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Reaching carbon neutrality in France by 2050: Optimal choice of energy sources, carriers and storage options

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Reaching carbon neutrality in France by 2050: Optimal choice of energy sources, carriers and storage options

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Atteindre la neutralité carbone en France d’ici 2050 : Choix optimal des sources d’énergie, des vecteurs énergétiques et des options de stockage

Mots clés

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Abstract

To stay in line with 1.5°C of global warming, the French government has adopted the target of net zero greenhouse gas emissions by 2050. The main greenhouse gas being carbon dioxide, and the majority of its emissions being due to energy combustion, this dissertation focuses on reaching carbon-neutrality in French energy-related CO_2 emissions by 2050. This thesis dissertation aims to study the relative role of different low-carbon mitigation options in the energy sector in reaching carbon-neutrality. More precisely, this thesis first studies the French power sector, first in a fully renewable power system, and second in a power system containing other mitigation options i.e. nuclear energy and carbon capture and storage. I study the impact of uncertainties related to cost development of renewables and storage options and address the robustness of a fully renewable power system to cost uncertainties. Later, adding other low-carbon mitigation options in the power sector, I analyze the relative role of different low-carbon options. Similarly, to incentivize the investments in variable renewable energy sources such as wind and solar power, I study the investment risk related to the price and volume volatility of renewable electricity technologies, and the performance of different public policy support schemes. The analysis in this thesis goes beyond the electricity system and it also considers the whole energy system in the presence of sector-coupling.

During this thesis, I have developed a family of models optimizing dispatch and investment to answer different questions regarding the French energy transition. These models minimize the cost of the considered system (electricity system or the whole energy system) by satisfying the supply/demand equilibrium at each hour over at least one year, respecting the main technical and operational, resource related and land-use constraints. Thus, both short-term and long-term variability of renewable energy sources are taken into account. Using these models, I address the questions raised above. These models are not used to find a single optimal solution, but several optimal solutions depending on different weather, cost, energy demand and technology availability scenarios. Therefore, the importance of robustness to the uncertainties is at the center of the used methodology beside optimality. The findings of my thesis show that renewable energy supply sources are the main enablers of reaching carbon neutrality in a cost-effective way, no matter the considered energy system; either only electricity or the whole energy system. While the elimination of nuclear power barely increases the cost of a carbon-neutral energy system, the elimination of renewables is associated with high inefficiencies both from the cost and emission points of view. In fact, if renewable gas is not available, even a social cost of carbon of €500/tCO_2 will not be enough to reach carbon-neutrality. This is partially due to the negative emissions that it can provide once combined with carbon capture and storage, and partially due to the cost-optimality of renewable gas-fired internal combustion engines in reaching carbon-neutrality in the transport sector.

This dissertation has several important policy-related messages; however, the central one is that reaching carbon-neutrality for the lowest cost requires a highly renewable energy system. Therefore, if we are to prioritize investment in low-carbon options, renewable gas and electricity technologies are of the highest importance.

Résumé

Pour contribuer à l’objectif de contenir le réchauffement climatique à 1,5°C, le gouvernement français a adopté l'objectif de zéro émission nette de gaz à effet de serre d'ici 2050. Le principal gaz à effet de serre étant le dioxyde de carbone, et la plupart des émissions de CO_2 étant dues à la combustion d'énergies fossiles, cette thèse porte sur l'atteinte de la neutralité carbone des émissions françaises de CO_2 liées à l'énergie d'ici 2050. Cette thèse vise à étudier le rôle relatif des différentes options bas-carbone dans le secteur de l'énergie pour atteindre la neutralité carbone. Plus précisément, cette thèse étudie d'abord le secteur électrique français, d'abord dans un système entièrement renouvelable, et ensuite dans un en intégrant d'autres options d'atténuation, c'est-à-dire l'énergie nucléaire et la capture et le stockage du carbone. J'étudie l'impact des incertitudes liées au développement des coûts des énergies renouvelables et des options de stockage et j'aborde la question de la robustesse d'un système électrique entièrement renouvelable face aux incertitudes liées aux coûts. Plus tard, en ajoutant d'autres options bas-carbone dans le secteur de l'électricité, j'analyse le rôle relatif des différentes options. De même, pour encourager les investissements dans des sources d'énergie renouvelables telles que l'énergie éolienne et solaire, j’étudie le risque d'investissement lié à la volatilité des prix et des volumes des technologies d'électricité renouvelable, et les performances de différents régimes de soutien publique. L'analyse de cette thèse va au-delà du système électrique et considère également l'ensemble du système énergétique en présence d'un couplage sectoriel.

Au cours de cette thèse, j’ai développé une famille de modèles d'optimisation de l’investissement et du fonctionnement pour répondre à différentes questions concernant la transition énergétique française. Ces modèles minimisent le coût du système considéré (système électrique ou système énergétique dans son ensemble) en satisfaisant l'équilibre offre/demande à chaque heure pendant au moins un an, en respectant les principales contraintes techniques et opérationnelles et liées aux ressources et à l’usage des sols. Ainsi, la variabilité à court et à long terme des énergies renouvelables est prise en compte. En utilisant ces modèles, je réponds aux questions soulevées ci-dessus. Ces modèles ne sont pas utilisés pour trouver une seule solution optimale, mais plusieurs solutions optimales en fonction de différents scénarios de conditions météorologiques, de coûts, de demande énergétique et de disponibilité des technologies. Par conséquent, l'importance de la robustesse face aux incertitudes est au centre de la méthodologie utilisée, ainsi que l'optimalité. Les résultats de ma thèse montrent que les sources d’énergie renouvelable sont les principaux facilitateurs de la transition énergétique, non-seulement dans le système électrique mais aussi dans l'ensemble du système énergétique. Bien que l'élimination de l'énergie nucléaire n'augmente que marginalement le coût d'un système énergétique neutre en carbone, l'élimination des énergies renouvelables est associée à des inefficacités élevées tant du point de vue des coûts que des émissions. En fait, si le gaz renouvelable n'est pas disponible, même un coût social du carbone de 500 €/tCO_2 ne suffira pas pour atteindre la neutralité carbone. Cela est dû en partie aux émissions négatives qu'il peut produire avec le captage et le stockage du carbone, et en partie à la rentabilité des moteurs à combustion interne alimentés au gaz renouvelable.

Le message central de cette thèse est que pour atteindre la neutralité carbone au moindre coût, il faut un système d'énergie largement renouvelable. Par conséquent, si nous voulons donner la priorité aux investissements dans les options à faible émission de carbone, les technologies de gaz et d'électricité renouvelables sont de la plus haute importance.

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Being a foreigner has its own difficulties, without entering to details I just want to highlight being homesick and missing all the cultural events. Thanks to my Iranian friends, I didn't really feel so much of homesick, we tried to celebrate our holidays among each other. On top of that, I always felt their support in my private life, in any help that I needed (financial and administrative) they were available and simply they were all lovely and very kind. Mostly graduates from the same engineering school that I'm graduated from, Sharif University of Technology, they were simply always there for me: Ali Meschi, Amir Keshavars, Amirbahador Mousavi, Amirhossein Asadollahi, Mehrdad Abdi, Mohammad Eftekhari Nasab, Saeedeh Vessal and Samin Mansourzadeh, thank you all for your strong presence in my life that made me feel home.

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Contents

Chapter 1

Introduction

In its Fifth Assessment Report, the Intergovernmental Panel on Climate Change (IPCC) concluded there's a more than 95 percent probability that human activities over the past 50 years have warmed our planet (Edenhofer et al, 2014). The same report suggests that there's a better than 95 percent probability that human-produced greenhouse gases such as carbon dioxide, methane and nitrous oxide (N_2O) have caused much of the observed increase in Earth's temperatures over the past 150 years.

Carbon dioxide represents 76% of the global GHG emissions caused by human activities (65% from fossil fuels and industrial processes and 11% from forestry and land-use activities), followed by methane (16%) and nitrous oxide (6%) and fluorinated gases accounting for 2% (Pachauri et al, 2014). Global CO_2 emissions from fossil fuels has increased by nearly 2000% from 1900’s to 2014, following an exponential path from 1950 until 2010, becoming linearly increasing from 2010 on (IPCC, 2014). Figure 1.1 shows the evolution of global carbon emissions from 1900 to 2014.

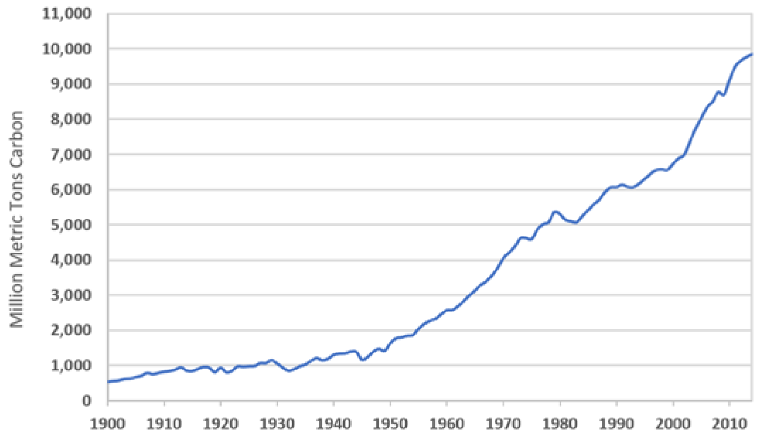

Figure 1.1. Global carbon emissions from fossil fuels from 1900 to 2014 (IPCC, 2014)

1.1. Mitigating climate change

Climate change risks and consequent impacts can be mitigated by limiting the global greenhouse gas emissions (IPCC, 2018). In 2015, the Paris Agreement under the United Nations Framework Convention on Climate Change (UNFCCC), has defined a global temperature limiting target. According to article 4.1 of Paris agreement 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” (UNFCCC, 2016). Paris agreement sets the goal of keeping global temperature increase “well below 2°C” and to “pursue efforts to 1.5°C’ above pre-industrial levels”. Followingly, the 1.5°C report of IPCC showed that limiting the global warming to 1.5°C would "reduce the probability of extreme drought, precipitation deficits, and risks associated with water availability in some regions" (IPCC, 2018). Although this report shows that limiting the global average temperature increase to 1.5°C is possible, it requires very rapid global CO_2 emission reductions and reaching carbon-neutrality by 2050 and negative emissions onwards.

In 'The European Climate Law' proposition, the European commission has set the target of achieving climate neutrality by 2050 (European Commission, 2019). Similarly, several European states have set ambitious GHG reduction targets; French 'Energy-Climate Law' approved in November 2019 consists of 69 articles setting medium-term and long-term fossil fuel reduction and clean energy promoting targets aiming to reach zero net GHG emissions by 2050 (DGEC, 2019). Germany's 2016 'Climate Action Plan' sets medium-term target of cutting the GHG emissions by at least 55% by 2030 compared to 1990's levels, and long-term ambition to become extensively greenhouse gas-neutral by 2050 (BMUB, 2016). In June 2019 UK parliament's 'Committee on Climate Change' has modified the 2008 'Climate Change Act' setting a "legally binding" net GHG neutrality target by 2050 (Walker et al, 2019).

These official commitments set the emission reduction targets to limit global warming, but they do not specify 'how' these targets can be achieved explicitly. Reaching these climate goals in the least-cost pathways requires future planning of energy systems, using modelling tools. According to Pfenninger et al. (2018) "*Models are idealized representations of real systems built to perform a specific analysis or answer a specific question, and so usually include code (e.g. for reading data, constructing and solving equations) and data (e.g. technology costs)*".

1.2. Energy systems modelling

Designing and planning energy systems requires modelling tools, to simulate the future energy system and to evaluate its feasibility, operation and the coexistence of different elements in an energy system and to identify the main challenges and requirements of such systems. Modelling energy systems has gained significant attention among the scientific community, particularly power systems, starting from the 1970s first by Sørensen (1975 and 1978). Driven by the increased share of renewables in the energy mix, numerous energy system models have been developed in recent years by policy makers, researchers and industrials for strategic planning of energy systems.

Since modelling complex systems is computationally demanding, energy system models vary depending on their functionality. According to Zhu (2020), energy system models can be classified depending on their purposes: (1) simulation models testing energy system characteristics and its operation mechanism based on technical and engineering equations (such as EnergyPLAN), (2) equilibrium models with a macroeconomic approach that study the energy in the whole economy (integrated assessment models such as PRIMES, WITCH, IMACLIM, MESSAGE etc.), and (3) optimization models that are microeconomic models considering only the energy system maximizing (minimizing) welfare (cost) related to energy systems subject to supply-demand equilibrium and several other constraints (such as DIETER, EMMA, ELMOD and other dispatch[1] and investment models).

Microeconomic energy models are bottom-up optimization models optimizing the investment and operation of energy systems; these models are either applying a two-stage optimization (first investment optimization and later dispatch optimization), such as PLEXOS[2] and TIMES (Loulou et al. 2007), or carrying out simultaneous optimization of dispatch and investment, such as ELMOD (Leuthold et al. 2008), EMMA (Hirth, 2016), DIFLEXIO (Villavicencio, 2017), FLORE (Perrier, 2018) and DIETER (Zerrahn et al. 2015). Two-stage optimization models first optimize a limited set of variables (installed capacities) and in second stage, the variables resulting from the initial optimization are used such as input data to optimize the dispatch (operation). Thus, each optimization is carried by less variables than simultaneous optimization. Therefore, they are faster to solve, and they can show the dynamics of the transition from and existing system to a future one. However, their solutions are not the absolute optimal solutions since optimizing the investment first (installed capacity) and the dispatch later (operation and fuel consumption) might favor technologies with low investment and high variable costs, since the initial optimization is based on the investment costs (capacity installation) and not the operation, by only considering approximate capacity factors. Simultaneous optimization of dispatch and investment solution is the absolute optimal but requires higher computation time.

Modelling energy systems is a challenging practice, especially when it comes to planning the future low-carbon energy systems. Decarbonization of power sector has gained particular attention in recent years since it is easier to decarbonize power sector than other major energy sectors such as industry and transport (Edenhofer et al. 2015). There is a wide literature on modelling power systems, such as Schlachtberger et al. (2018), Brouwer et al. (2016), Perrier (2018), Hirth et al. (2015), Zerrahn et al. (2015 and 2018), Krakowski et al. (2016) and several others. Each of these studies are based on optimization of dispatch and investment (simultaneously or sequentially). However, decarbonization of power sector alone is not sufficient to meet the CO_2 reduction goals, even for the 2°C of global warming scenario (Rogelj et al, 2015).

On the one hand, decarbonization targets must cover the whole energy sector and not only power sector. On the other hand, integrating other-than-power sectors and the interactions between different energy vectors (sector-coupling) can add flexibility to the energy system and reduce the overall cost of it since it includes optimization among interconnected energy sectors. Lund et al. (2017) introduce the term '*smart energy systems*'; which "*include the entire energy system in its approach to identifying suitable energy infrastructure designs and operation strategies*". The most efficient and least-cost solutions are obtained in smart energy systems, thanks to the sector-coupling between different sectors and sub-sectors. Sector-coupling has gained high attention in recent literature (Brown et al, 2018b, Victoria et al, 2019, Zhu et al, 2019, Pavičević et al, 2020). These studies demonstrated the important flexibility gains facilitating the operation of a highly renewable energy system and leading to lower costs, when buildings (heat and electricity) and transport sectors are considered. A complete integration of the whole energy sector in a dispatch and investment

[1] The term 'dispatch' refers to resource planning at a power plant by the plant's operator. Dispatch means allocation of the needed energy by different power plants, in an operationally optimal condition. In energy systems modelling, a dispatch model requires high temporal precision.

[2] http://energyexemplar.com/software/plexos-desktop-edition/

model, including the main emerging low-carbon technologies, remains a challenging task for the scientific community.

1.3. French energy system

To understand the required efforts for decarbonization of the energy system in the French context, one must first understand the existing energy system, the main energy sectors and the energy mix (thus carbon-intensity) of each sector in France. Understanding the existing characteristic and the required energy for different sectors can help classification of the low-carbon solutions for different sectors.

1.3.1. The current energy system in France

The primary energy [1] production of France was 138MToe in year 2018, consisting of 107.6Mtoe nuclear energy and 31Mtoe renewables and waste. The primary energy consumption of France in the same year was 249Mtoe. 124.5Mtoe of this primary energy consumption is the imported fossil sources (coal, natural gas and petroleum) and the remaining 124.5Mtoe consists of internal nuclear and renewable energy production (CGDD, 2019). Figure 1.2 shows the primary energy consumption of France in percentage for each energy source.

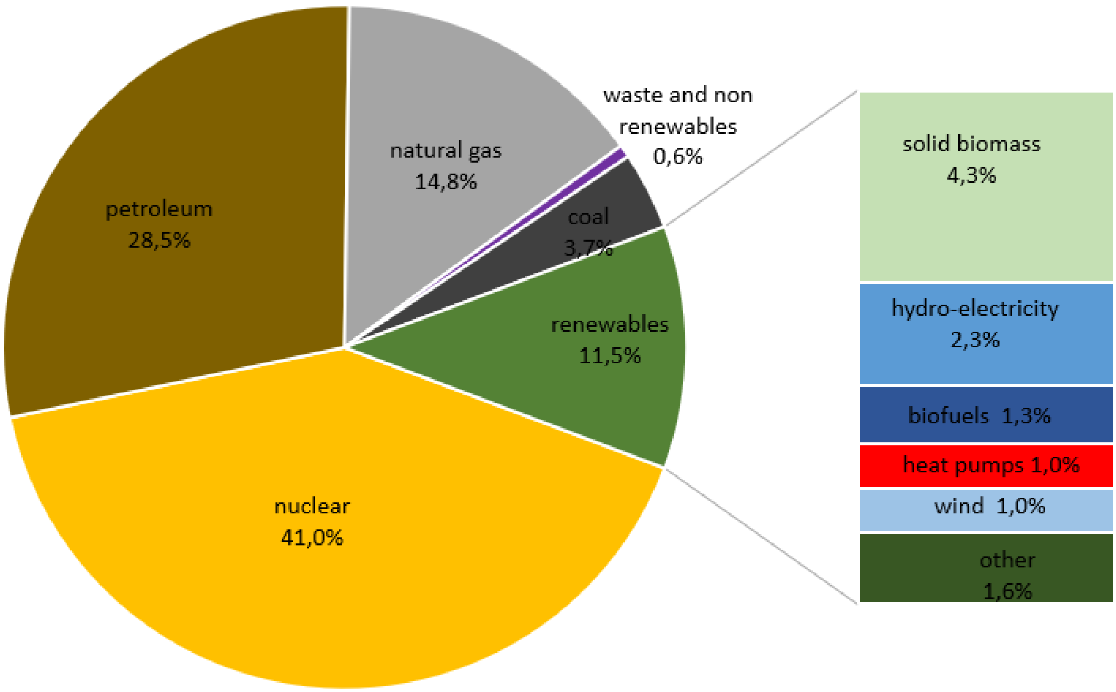

Figure 1.2. Primary energy consumption of France for year 2018 (CGDD, 2019)

This primary energy satisfies 144Mtoe of final energy demand, and 14Mtoe of non-energy petroleum demand. The remaining 95Mtoe is the loss of transport, distribution and conversion of

[1] Primary energy means the energy in its natural form without any human modification. Thus, for nuclear power, the transformation loss from power plants leads to one third of this primary energy in the consumption side. Similarly coal, petroleum, natural gaste and waste are associated with transformation infefficiencies, however, in this thesis, the variable renewables (wind blow and solar irradiation) are considered as the output from the wind turbines and solar panels, since in their natural form, they are present with much higher magnitudes.

energy. Final energy demand of each sector is shown in Figure 1.3. While the consumed energy sources for different sectors are diverse for buildings and industry sectors, transport and agriculture sectors depend highly on petroleum (91% and 74% respectively).

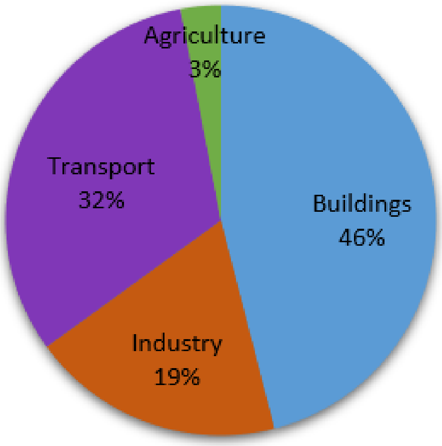

Figure 1.3. Final energy demand repartition between different major energy sectors for France for year 2018 (CGDD, 2019)

France (households, companies and government) has spent €153.3bn to satisfy the national energy demand during 2017. €35.2bn of this amount is spent for the net imports, and the remaining €118.1bn is spent on taxes, subsidies and national activities' remuneration (CGDD, 2019).

French GHG emissions in 2018 were 450MtCO_{2eq} (DGEC, 2019). Figure 1.4 shows the GHG emissions of each sector in carbon dioxide equivalent form.

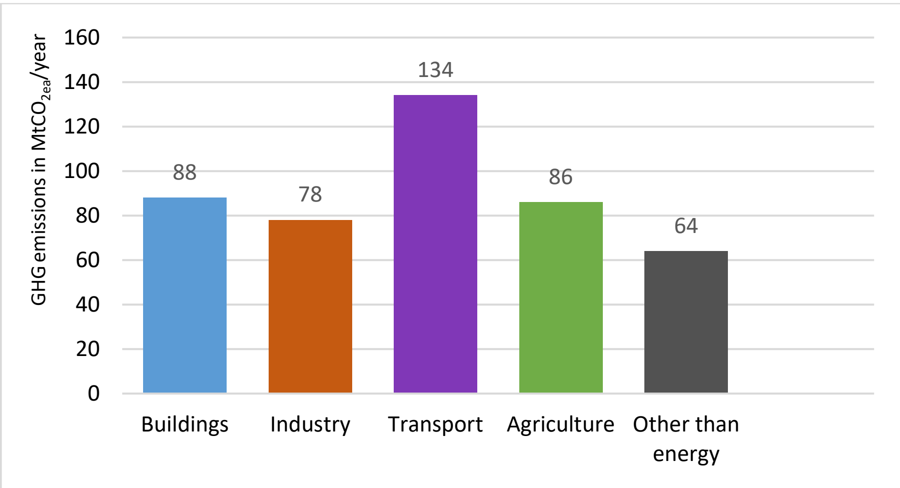

Figure 1.4. GHG emissions of each major energy sector for year 2018 (CGDD, 2019)

The 'French national low-carbon strategy' (SNBC, 2018) sets the greenhouse gas neutrality target by 2050, where 80MtCO_{2eq} of positive emissions from different sectors will be compensated by 15MtCO_{2eq} of carbon capture and storage and 67MtCO_{2eq} of forestation and land-use improvement.

1.3.2. French energy transition scenarios

Several public organizations and associations conducted studies on the energy transition of France with nearly carbon-neutral energy mix projections for 2050. Among these studies, 'French national low carbon strategy' conducted by French Ministry for Ecological Transition and Solidarity (SNBC, 2018) and négaWatt's 2050 energy mix scenario (négaWatt, 2017) project a fully carbon-neutral energy system for France by 2050 (currently the French energy-related greenhouse gas emissions amount to ~450MtCO_{2eq}/year; DGEC, 2019), and ADEME's (the French environment and energy agency) '2030-2050 visions' study forecasts up to 72% reduction in energy-related greenhouse gas (GHG) emissions for France for 2050 (ADEME, 2017).

In addition to different integrated assessment scenarios which do not rely on optimal allocation of different energy sources, the existing optimization literature for France focuses highly on the power sector. While power system of France is already highly decarbonized (35gCO_{2eq}/kWh_e), there is a lively debate on whether France should invest in new nuclear power plants or in renewables, and the existing literature mainly focuses on this issue. Krakowski et al.(2016) conclude that increasing the share of renewable electricity from 40% to 100% would increase the power system cost from €30bn/year to €60bn/year (nearly 3 times the actual electricity price in France), and Villavicencio (2017) argues that a fully renewable power system would cost even more (€180bn/year). Both studies conclude that reaching carbon-neutrality in power sector necessitates deployment of new nuclear power plants. On the other hand, ADEME's '100% renewable electricity mix' (ADEME, 2015) and 'electricity mix evolution trajectories 2020-2060' (ADEME, 2018) studies argue that a highly renewable power system (85% for 2050 and 95% for 2060) will cost slightly more expensive than the current electricity price, however, investment in new nuclear power plants is not an optimal choice.

While the optimal electricity mix literature for France concentrates on the relative role of nuclear energy and renewables, most of the European and world-wide studies agree on a relative dominance of renewables in the power system (Waisman et al, 2019, Rogelj et al, 2018 and Schlachtberger et al, 2018). These contradictory findings need further analysis to shed light on the cost parameters that create different visions of the future, as well as the relative role of different low-carbon options considering the most recent cost estimations of renewables and nuclear energy.

As discussed previously, sector-coupling can lead to more efficient allocation of different energy sources for different sectorial end-uses bringing flexibility to the energy system. The operation of an integrated energy system where energy can be transformed from one carrier to another with vector-change technologies, based on endogenous optimization, can facilitate the operation of the whole energy system and reduce the overall cost of energy system (Brown et al, 2018b). The existing energy transition scenarios (conducted by ADEME, négaWatt and French ministry of energy transition and solidarity) for France do not rely on optimization results they are all constructed by top-down resource allocation. Therefore, an integrated optimization model considering both hourly dispatch and the overall investment in a simultaneous way can shed light on the existing public debate.

1.4. Policy support for renewables

Considering an optimization from the social planner point of view will lead to higher shares of technologies with lower costs. The most recent literature suggests high penetration of renewable in the energy mix. However, from an investor's point of view, investment in renewables might be associated with several risks since their market behavior differs from the conventional technologies.

In a free market, the market price is defined by the marginal cost of supply options participating in the market. The merit-order effect imposes the exploitation of the options with the lowest marginal cost (variable cost) first. VRE technologies have no marginal cost since they do not consume any fuel, and their cost mainly comes from investment and fixed operation and maintenance cost. Therefore, in a highly renewable power market, the market price can be very low, and even zero for long periods when the sun shines and the wind blows, while the electricity demand is low.

The literature on climate policy and public support schemes to increase the competitiveness of VRE technologies is very wide. Several studies show that by introducing climate policy (for instance carbon budgets by Pommeret and Schubert, 2019) or direct support for renewables (such as feed-in tariffs and renewable portfolio standards by Ambec and Crampes, 2019) can play an important role in transitioning from fossil-based power system to a renewable one with storage by increasing the competitiveness of VRE sources. Thus, policy design can decrease the share of fossil fuels and increase the share of renewables by making the latter competitive. Nevertheless, in case renewables are already competitive, the non-traditional market behavior of VRE technologies stemming from their variable nature induces another problem beyond the competitiveness, the high market price variability and long periods with low market price. In an energy-only market, the only revenues of participating players are from selling electricity in market (in €/MWh_e). Therefore, in case of high initial investment and low market revenues, a renewable project may have negative cashflow over its lifetime or long periods during its operation.

As any project, VRE projects contain investment risk. The investment risk for VRE projects comes from price risk and volume risk (Pineda et al, 2018). Price and volume risks are directly related to the variability of VRE technologies. These price and volume related risks are not to be confused with competitiveness risk, since these technologies have zero or very low marginal cost and they always win the market participation bids (thanks to the merit-order effect). Several studies have analyzed the impact of public support schemes to reduce these risks and incentivize investment in VRE technologies (Pineda et al, 2018, Fagiani et al, 2013, etc.). Three main support schemes are feed-in tariffs, feed-in premiums and tradable renewable quotas.

Feed-in tariff is a fixed price above the electricity market price that is guaranteed to producers of VRE for a period of typically 10 to 20 years. Feed-in premium is a subsidy paid to VRE producers as an addition to the market price. Tradable renewable quotas oblige the fossil-generated electricity suppliers to buy 'green certificates' depending on their output. These green certificates are provided by renewable electricity suppliers. Quirion (2015) in a literature review framework, analyzes these support schemes and concludes that in a liberalized electricity market, tradable renewable quotas are not robust to uncertainties and they cause high transaction costs and higher investment risks.

1.5. The gaps in the literature

Many studies have studied the decarbonization of energy sector, particularly power sector in the scale of communities, countries and continents. Although these studies assess for the intra-daily, inter-daily and inter-seasonal weather variability, the inter-annual weather variability has been studied less. Renewable electricity technologies depend highly on the meteorological characteristics since they produce electricity from water flow, solar irradiation and wind blow. The inter-annual weather variability affecting the renewable power output has been highlighted by Collins et al. (2018) and Zeyringer et al. (2018). The impact of several years with low solar irradiation and/or wind potential in a highly renewable power system's operation and cost remains an open question. Therefore, **the uncertainties related to inter-annual weather variability** need further analysis.

Technical feasibility of a fully renewable power system has been demonstrated in the literature (Brown et al, 2018a and the references therein), and a variety of studies has concluded that fully renewable power system is not only technically feasible but economically optimal as well. These conclusions are based on debatable assumptions, especially the cost development of emerging low-carbon technologies. Therefore, **robustness of a fully renewable power system is yet to be studied to both weather variability and cost development assumptions for emerging renewable technologies**, especially solar PV and wind power technologies, as well as the flexibility options such as battery storage technologies.

High uncertainties on the future cost of emerging low-carbon technologies, especially renewables and nuclear power can lead to different visions of reaching carbon-neutrality in a cost-optimal way. For the French case, the role of different low-carbon technologies in the future electricity mix is a highly debated political subject. **The inclusion of recent technical and economic improvements in short-term and long-term storage technologies, as well as different low-carbon electricity supply technologies such as VRE sources, new nuclear power plants and carbon capture and storage (CCS) technologies in energy models are of high importance. Thus, not only the impact of cost uncertainties related to these technologies, but also their relative added value to the power system must be studied in a detailed way.**

From an investor's point of view, high inter-annual weather variability of VRE technologies imposes an investment risk as discussed above. In case of several years of low wind or low sun, the expected revenues of a variable renewable electricity supplier can be insufficient to balance a positive cashflow in its portfolio for long periods. Therefore, incentivizing the investment in VRE technologies in a liberalized energy-only market is necessary by different public support schemes or state-offered insurance in the form of risk premiums. **Different support schemes must be examined to assess both price and volume risks of variable renewable electricity suppliers, and an efficient support scheme for a risk-averse investor is yet to be identified.**

Energy transition is not only about transforming the power sector, and it should include the whole energy sector. Sector-coupling can be defined as following: allowing an endogenous energy carrier choice for different final end-use demands in different energy sectors through vector-change technologies. For instance, the choice of gas boiler or heat pump must be left endogenous in an integrated energy system model to reach the real optimal energy mix. While integrated assessment models (IAMs) consider different economic sectors in an integrated way, they do not rely on optimization results and they do not have enough temporal precision to account for the dynamics of variable energy supply technologies and the needed flexibility options such as storage technologies. Optimal energy system in the existence of sector-coupling has gained high attention recently. PyPSA (Python for Power System Analysis) developed by Brown et al. (2017) was the first to include sector-coupling between buildings (electricity and heat) and transport sectors. While sector-coupling studies have shed light upon the importance of interactions between energy sectors' diverse end-use demands and different energy carrier options, they do not cover the main energy sectors completely, with limited representation of different low-carbon technologies such as CCS and renewable gas supply technologies.

All the energy transition scenarios for France are based on top-down approaches, with no optimization. **An integrated optimization study considering the whole energy sector and the main emerging technologies can enrich the existing public debate in France on 'how' to reach the carbon-neutrality by 2050.**

1.6. Modelling framework

To fill the gaps identified in the previous section, I developed a family of optimization of dispatch and investment models entitled EOLES (Energy Optimization for Low Emission Systems). To this date, three EOLES models exist: EOLES_elecRES, EOLES_elec and EOLES_mv.

The EOLES family of models optimizes the investment and operation of an energy system in order to minimize the total cost while satisfying energy demand. It is based on optimization from a social planner's point of view, where each technology maximizes its profits, and in case of negative profit, there will be no investment on that technology. The EOLES family of models is based on linear optimization and all models are written in GAMS and solved by CPLEX solver.

First, I developed EOLES_elecRES (EOLES model for a fully renewable power system), to fill the first gap that we identified in the literature: the impact of weather-year and cost uncertainties on a fully renewable power system. Two versions of this model are available: a short version for one weather year, and a long version for 18 weather years.

To study the impact of cost uncertainties and relative role of different low-carbon options (renewables, nuclear energy, CCS and bioenergy with CCS – BECCS) in French energy transition, I developed EOLES_elec model (EOLES model for the power system). On top of the wider representation of power system in EOLES_elec model, the social cost of carbon[1] (SCC) is included in the optimal cost of power system, in a market equilibrium the SCC can be decentralized as a tax for positive CO_2-emitting technologies and as a remuneration for negative CO_2-emitting technologies.

Studying the whole energy system with endogenous allocation of different energy carriers for different end-use demands necessitates an integrated optimization of dispatch and investment, enabling a complete sector-coupling. To this end, I developed the EOLES_mv (EOLES multi-vector) model, which represents the key energy supply technologies, electricity, gas, heat and hydrogen as energy carrier options, and satisfies four main end-use demands (specific electricity, heat, transport and hydrogen for industry as replacement for coal) for the main energy sectors (residential and tertiary buildings, industry, agriculture and transport sectors) using different vector-change options between the energy carriers.

[1] Social cost of carbon (SCC) is the monetary value that society attributes to one ton of supplementary CO_2 emissions to internalize the damages caused by it.

1.7. Dealing with uncertainties

In this thesis, I studied a variety of uncertainties: related to future cost development of emerging technologies, weather variability of VRE technologies, availability of different low-carbon options, the energy demand level and the heat network coverage limit.

The definition of robustness can vary depending on different methods used for its assessment. When the value of a variable does not change remarkably by the uncertainties over a specific parameter, that variable is robust to those uncertainties. Therefore, 'unsensitive to variations' is one of these definitions. In Chapter 5, I define robustness of an energy system to several parameters (cost, demand level and availability of different technologies) in such a way. In case a specific characteristic of a system doesn't change much by a variation of a certain parameter, that characteristic is robust to the variations of that parameter. In this chapter, to guarantee a carbon-neutral energy system taking into account different uncertain parameters, I defined a robust social cost of carbon.

Another definition of robustness is a comparison between optimal results with erroneous future state assumptions. Multiplicity of uncertain parameters result in multiple optimal scenarios. In the existence of several optimal scenarios, a decision maker is interested in a strategy that performs well over a large set of hypotheses; a robust strategy. In Chapter 2, I study the robustness of a fully renewable power system to cost projections by asking the following question: "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 this end, I use robust decision-making framework (RDM) which was first developed in the context of climate change by Lempert (2006) and later applied to power systems by Nahmmacher (2016) and Perrier (2018).

Robustness assessment using RDM framework requires a particular variable to compare the difference between the optimal case with the initially projected future state, and the real optimal case for the state that is realized. This framework uses the concept of 'regret' first introduced by Savage (1950); which is defined as the difference between the performance of a strategy in the future state and the optimal strategy in the same future state. The strategy will be considered robust that has the lowest regret. Therefore, in Chapter 2, I use the installed capacities of generation and storage technologies optimized for the reference cost scenario, and fixing these capacities, I calculate the cost of the power system for this 'rigid capacity' across different cost scenarios. The cost of power system with this rigid capacity is necessarily equal to or higher than the optimal power system for that cost scenario, the difference being the 'regret' from basing the optimization on the wrong cost assumptions.

1.8. Organization of the thesis

This thesis is organized over six main research questions (in three main parts), each one in an academic article form. All the treated research questions can be applied to different zones (regions, countries, continents etc.) and time horizons. In this dissertation, I apply all the developed methods to the case study of France for the year 2050.

First part of this thesis deals with the economics of power systems: in Chapter 2, I study the robustness of a fully renewable power system to the cost uncertainties, taking into account weather variability in different time-scales (intra-day, inter-day, inter-seasonal and inter-annual intermittence of VRE production). Chapter 3 consists of a complete analysis of power sector, where I study the relative role of different low-carbon options in meeting climate goals in a cost optimal way. I analyze the impacts of inter-annual weather variability on the revenues of a VRE supplier in a fully renewable power system in Chapter 4, and I compare the efficiency of public support schemes to incentivize the investments in VRE technologies.

Part II extends the only electricity system approach to the whole energy system: it consists of one chapter (Chapter 5). In Chapter 5, I study the whole energy sector developing a sectorially coupled dispatch and investment model (EOLES_mv) and I apply a complete sector-coupling to the energy system.

Part III of this thesis deals with more technical research questions. During this thesis, a method has been developed to decrease the computation time of the EOLES_elecRES model: variable time-step method. Chapter 6 presents this method and its application to EOLES_elecRES model, and another power system optimization model (DIETER). The importance of hourly resolution in power systems modelling has been highlighted by many, but in the existence of a complete sector-coupling, the needed precision of temporal resolution is still to be studied. in Chapter 7, I study this question using several versions of EOLES_mv model differing in temporal resolution and representative periods.

Finally, chapter 8 concludes the thesis highlighting the main contribution of this thesis to the academic literature of the energy transition.

Contribution to the literature

Journal publications

The following is a list of journal publications in the order of thesis timeline and submission date:

Shirizadeh, B., Perrier, Q. & Quirion, P. (2022). How sensitive are optimal fully renewable systems to technology cost uncertainty? *the Energy Journal*, Vol 43. No 1. (Chapter 2)
https://doi.org/10.5547/01956574.43.1.bshi

Shirizadeh, B. & Quirion, P. (2020). Low-carbon options for French power sector: What role for renewables, nuclear energy and carbon capture and storage? *Energy Economics*, 105004. (Chapter 3)
https://doi.org/10.1016/j.eneco.2020.105004

De Guibert, P., Shirizadeh, B., & Quirion, P. (2020). Variable time-step: a method for improving computational tractability for energy system models with long-term storage. *Energy*, 119024. (Chapter 6)
https://doi.org/10.1016/j.energy.2020.119024

Shirizadeh, B. Relative role of electricity and gas in a carbon-neutral future: insights from an energy system optimization model. Submitted (Chapter 5)

Shirizadeh, B. & Quirion, P. Support schemes for risk-averse investors in variable renewables: Assessing weather-year variability**.** in progress. will be improved and submitted (Chapter 4).

Shirizadeh, B. & Quirion, P. On the importance of temporal resolution in energy systems modelling. Will be submitted (Chapter 7).

Conference proceedings

Shirizadeh, B. (2020). Solving the energy transition riddle: Renewable gas for transport and renewable electricity for heating. 17th international conference on European Energy Markets (EEM). IEEE. (Chapter 5).
https://doi.org/10.1109/EEM49802.2020.9221956

Conference presentations

Chapters 2, 3 and 5 were presented in different conferences, workshops and seminars during the thesis, under different titles and different development levels and several proceeding articles have been published. The final form of each research question is as it was published in the journal mentioned. Thus, I only precise the conferences, workshops and seminars that I participated to:

Risk Day 2019 (organized by EPSRC Supergen Energy Network Hub), 2019, Cambridge (UK)

38th International Energy Workshop (Organized by International Energy Agency), 2019, Paris (France)

6th annual conference of French Association of Environmental and Resource Economists (FAERE), 2019, Rennes (France)

Association of Energy Economists (AEE) student workshop, 2019, Grenoble (France)

25th annual conference of European Association of Environmental and Resource Economists (EAERE), 2020, Berlin (Germany)

4th South East European conference on Sustainable Development of Energy, Water and Environment Systems (SEE SDEWES), 2020, Sarajevo (Bosnia and Herzegovina)

15th conference on Sustainable Development of Energy, Water and Environment Systems *(SDEWES), 2020, Cologne* (Germany)

7th annual conference of French Association of environmental and Resource Economists *(FAERE), 2020, Grenoble* (France)

17th international conference on European Energy Markets (EEM – IEEE), 2020, Stockholm (Sweden)

Accepted but postponed conferences because of COVID-19 pandemic:

43rd conference of International Association of Energy Economists *(IAEE)*, 2021, Paris (France)

39th International Energy Workshop, 2021, Freiburg (Germany)

15th international conference on Greenhouse Gas control Technologies (Organized by IEA greenhouse gas control R&D program), 2021, Abu-Dhabi (UAE)

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Part I

Analysis of Low GreenHouse Gas Emission Power Systems

Chapter 2

A fully renewable power system

2.1. Introduction

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 (UNFCCC, 2016). The electricity sector will have a key role to play, as decarbonization is easier in this sector than in transport, industry or agriculture. According to some scholars, renewable energy will be the cornerstone of decarbonization, and it is expected to make a greater contribution than nuclear energy and fossil fuels with CO_2 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, I build a new open-source model called EOLES_elecRES (Energy Optimization for Low Emission Systems – fully renewable electricity) and apply it to continental France. EOLES_elecRES 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 PV, two types of hydro and biogas) and three storage technologies (batteries, pumped hydro and power-to-gas).

Using this model, I 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. I 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 chapter is organized as follows. Section 2.2 presents the EOLES_elecRES model, a 100% renewable electricity sector model from the EOLES family of models. Results are presented in Section 2.3 while Section 2.4 provides a discussion and section 2.5 concludes this chapter.

2.2. Materials and methods

2.2.1. Model description

EOLES_elecRES is the first model developed in the EOLES (Energy Optimization for Low Emission Systems) family of models. The EOLES family of models performs simultaneous optimization of the investment and operation of the energy system in order to minimize the total cost while satisfying energy demand. Therefore, it minimizes the costs associated with hourly power generation and storage profiles and capacity investment simultaneously, including the cost of connection to the grid. EOLES_elecRES considers only power sector with only renewable power production technologies and the main representative storage options. It includes six power generation technologies: offshore and onshore wind power, solar photovoltaics (PV), run-of-river and lake-generated hydroelectricity, 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 2.1.

All the models in the EOLES family optimize in a greenfield: they calculate a cost-optimal end point, taking into account the main technical and resource availability constraints. Therefore, this model does not show a dynamic trajectory but a static optimal destination. EOLES family considers a country as a single node using copper-plate assumption; therefore, spatial optimization is not considered in this model. Although enabling spatial optimization including transmission cost can increase or decrease the overall system cost, an aggregated representation of variable renewable's profiles can lead to near optimal spatial allocation of power plants with much lower calculation time (Subsection 2.2.3.2 and Appendix 2.10).

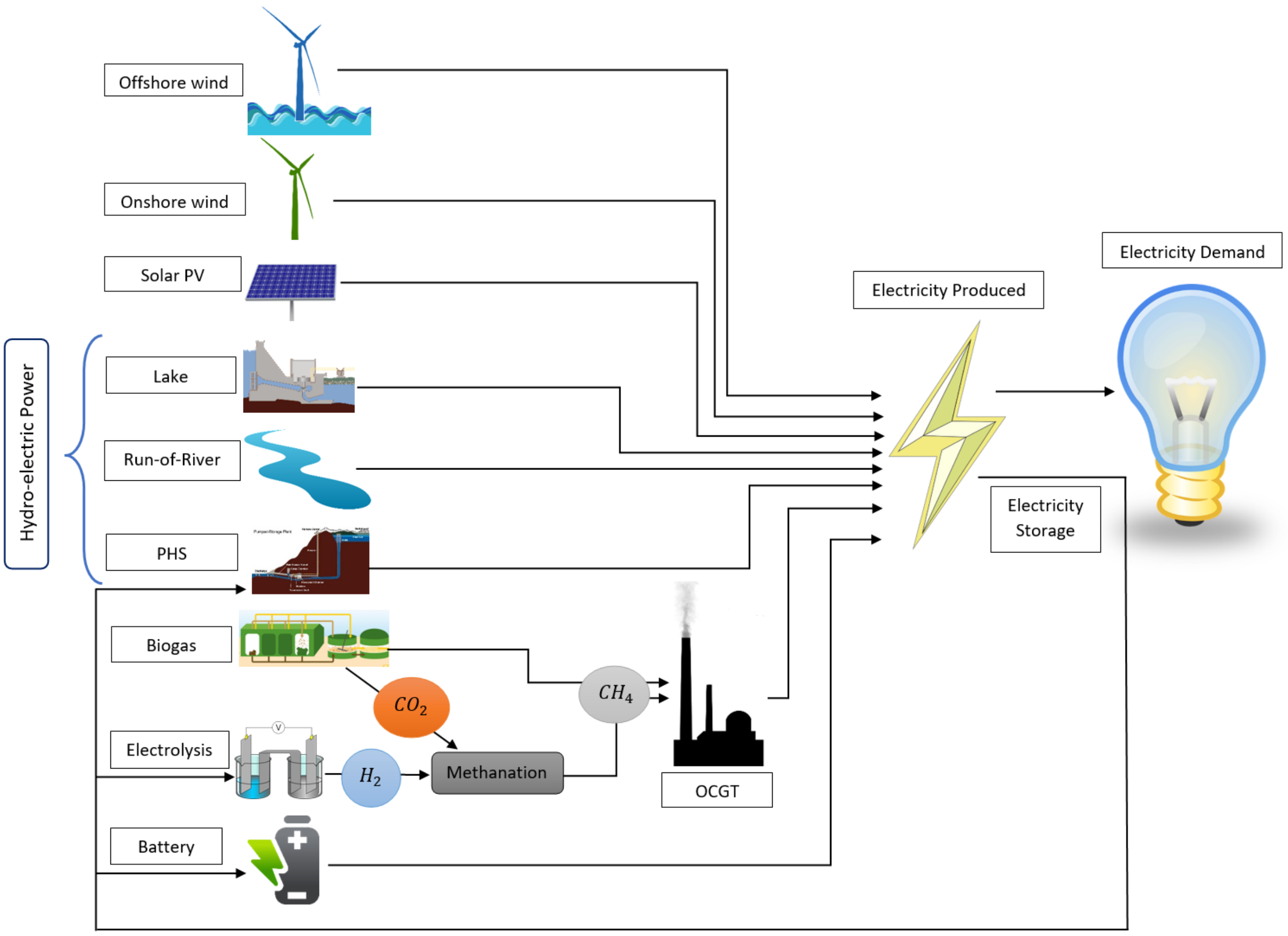

Figure 2.1. Graphical description of the EOLES_elecRES model

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, CO_2 emissions and investment estimations, but a speed-up by up to x1500. Similarly, according to Cebulla et al. (2017), in modelling thermal power plants, mixed-integer linear programming can capture the techno-economic characteristics more precisely compared to linear programming (LP), while LP has a superior computational performance. Linear programming merit order dispatch underestimates the storage demand compared to mixed-integer linear programming (MILP)[2], but this divergence is less visible for high renewable share in power system.

Figure 2.2 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.

[1] https://github.com/BehrangShirizadeh/EOLES_elecRES
[2] It can be considered as mixed-integer unit-commitment with economic dispatch.

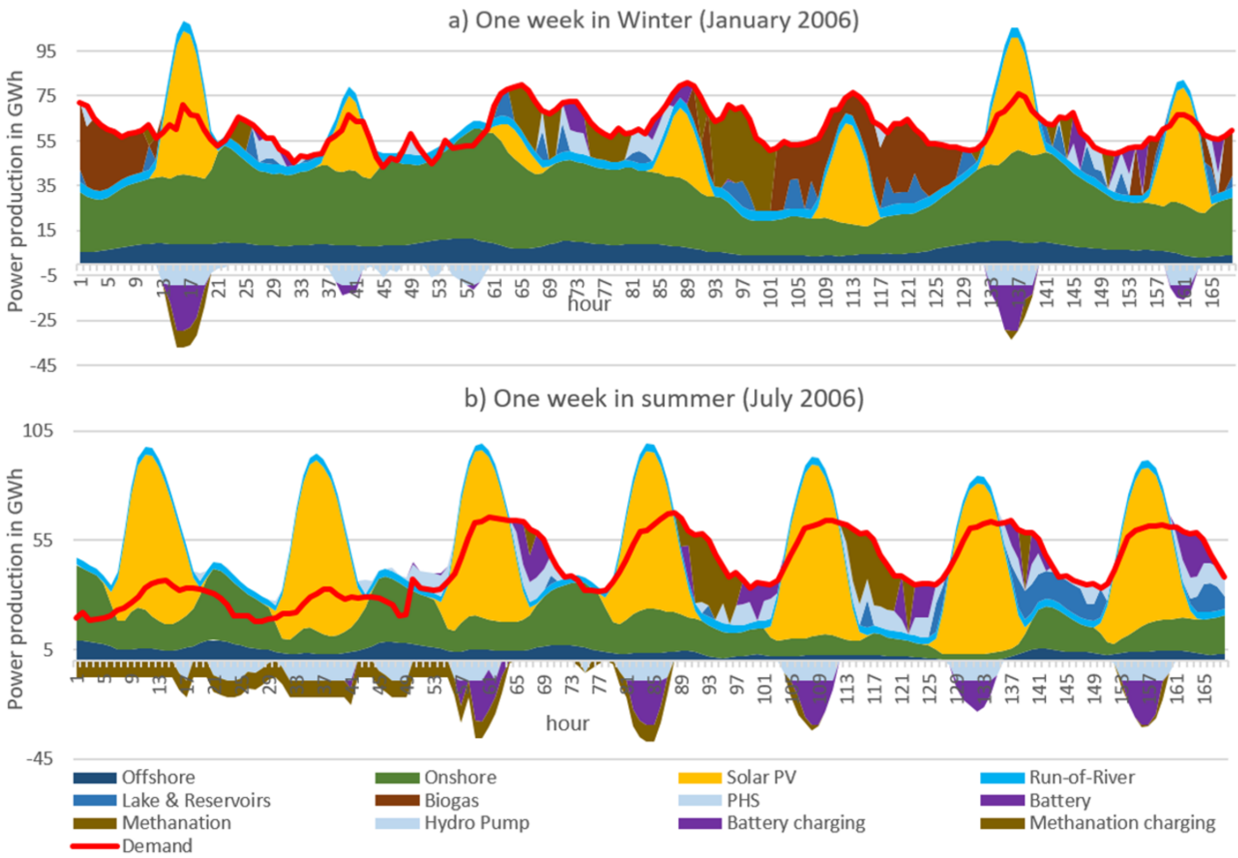

Figure 2.2. Hourly power generation, electricity demand, storage charge and discharge profiles for (a) the third week of January (Winter) and (b) the third week of July (Summer) 2006

The remainder of this section presents the main equations (2.2.2) and the input data (2.2.3). A detailed description of all sets, parameters and variables of the model is available in Appendix 2.4.

2.2.2. Model equations

2.2.2.1. 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 (2.1), 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$_e$.

$$COST = \left(\sum_{tec}[(Q_{tec} - q_{tec}^{ex}) \,.\, annuity_{tec}] + \sum_{str}(VOLUME_{str} \,.\, annuity_{str}^{en}) + \sum_{tec}(Q_{tec} . fO\&M_{tec}) + \sum_{str}\left(S_{str}\left(capex_{str}^{ch} + fO\&M_{str}^{ch}\right)\right) + \sum_{tec}\sum_{h}(G_{tec,h} .\ vO\&M_{tec})\right)/1000 \quad (2.1)$$

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), I use the following equation:

$$annuity_{tec} = \frac{DR \times CAPEX_{tec}}{1-(1+DR)^{-lt}} \quad (2.2)$$

Where *DR* is the discount rate.

2.2.2.2. Adequacy equation

Electricity demand must be met for each hour. If power production exceeds electricity demand, the excess electricity can be either sent to storage units or curtailed (Equation 2.3).

$$\sum_{tec} G_{tec,h} \geq demand_h + \sum_{str} STORAGE_{str,h} \quad (2.3)$$

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

2.2.2.3. 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 2.4).

$$G_{vre,h} = Q_{vre} \times cf_{vre,h} \quad (2.4)$$

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

2.2.2.4. Energy storage

Energy stored by storage option *str* at hour *h+1* is equal to the energy stored at hour *h* plus the difference between the energy entering and leaving the storage option at hour *h*, accounting for charging and discharging efficiencies (Equation 2.5):

$$STORED_{str,h+1} = STORED_{str,h} + (STORAGE_{str,h} \times \eta_{str}^{in}) - (\frac{G_{str,h}}{\eta_{str}^{out}}) \quad (2.5)$$

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

2.2.2.5. Secondary reserve requirement

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

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

In the EOLES_elecRES model, I 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, I consider only upward reserves.

The quantity of FRRs required to meet ENTSO-E's guidelines is given by Equation (2.6). These FRR requirements vary with the variation observed in the production of renewable energies. They also depend on the observed variability in demand and on forecast errors:

$$\sum_{frr} RSV_{frr,h} = \sum_{vre}(\varepsilon_{vre} \times Q_{vre}) + demand_h \times (1 + \delta^{load}_{variation}) \times \delta^{load}_{uncertainty} \quad (2.6)$$

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, $\delta^{load}_{variation}$ is the load variation factor and $\delta^{load}_{uncertainty}$ is the uncertainty factor in the load because of hourly demand forecast errors. The method for calculating these various coefficients according to ENSTO-E guidelines is detailed by Van Stiphout et al. (2017).

2.2.2.6. Power-production-related constraints

The relationship between hourly-generated electricity and installed capacity can be calculated using Equation (2.7). 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.

$$G_{tec,h} \leq Q_{tec} \quad (2.7)$$

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 (2.8).

$$Q_{frr} \geq G_{frr,h} + RSV_{frr,h} \quad (2.8)$$

Monthly available energy for the hydroelectricity generated by lakes and reservoirs is defined using monthly lake inflows (Equation 2.9). 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).

$$lake_m \geq \sum_{for\ h \in m} G_{lake,h} \quad (2.9)$$

Where $G_{lake,h}$ is the hourly power production by lakes and reservoirs, and $lake_m$ is the maximum electricity that can be produced from this energy resource during one month. This parameter is calculated by summing hourly power production from this hydroelectric energy resource over each month of the year to capture the meteorological variation of hydroelectricity, using the online portal of RTE[1] (the French transmission network operator).

The energy that can be produced by biogas is limited, since the main resources of this energy are methanization (anaerobic digestion) and pyro-gasification of solid biomass. Both processes are limited by several constraints and according to 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 (2.10).

$$\sum_{h=0}^{8759} G_{biogas,h} \leq e_{biogas}^{max} \tag{2.10}$$

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 (2.11);

$$G_{river,h} = Q_{river} \times river_h \tag{2.11}$$

As shown in Figure 2.1, two renewable gas technologies are considered; biogas and methanation. Both of them produce renewable methane, which can be used in gas power plants. In the model, the latter is considered to be an open cycle gas turbine (OCGT) due to its high operational flexibility and Equation (2.12) shows the relationship of the power production from these two methane resources;

$$G_{gas,h} = \sum_{comb} G_{comb,h} \tag{2.12}$$

Where $G_{comb,h}$ is the power production from each renewable gas source, 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 15TWh$_e$ of annual electricity production from biogas, and the discharge efficiency of the methanation process as defined in Equation (2.5).

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 (2.13) 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):

$$Q_{tec} \leq q_{tec}^{max} \tag{2.13}$$

2.2.2.7. Storage-related constraints

To prevent optimization leading to a very high amount of stored energy in the first hour represented and a low one in the last hour, I add a constraint to ensure the replacement of the consumed stored electricity in every storage option (Equation 2.14):

$$STORED_{str,h=0} \leq STORED_{str,h=8759} \tag{2.14}$$

While Equations (2.5) and (2.14) define the storage mechanism and constraint in terms of power, I also limit the available volume of energy that can be stored by each storage option (Equation 2.15):

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

$$STORED_{str,h} \leq VOLUME_{str} \tag{2.15}$$

Equation (2.16) 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.

$$STORED_{str,h} \leq S_{str} \leq Q_{str} \tag{2.16}$$

2.2.3. Input data

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

2.2.3.1. Cost data

The economic parameters for generation technologies are taken from JRC (2014, 2017) and summarized in Table 2.1. 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 2.1.

Table 2.1. Economic parameters of power production technologies

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

*For offshore wind power on monopiles at 30km to 60km from the shore, for onshore wind power, turbines with medium specific capacity (0.3kW/m^2) and medium hub height (100m) and for solar power, an average of the costs of utility scale, commercial scale and residential scale systems without tracking are taken into account. In this cost allocation, I consider solar power as a simple average of ground-mounted, rooftop residential and rooftop commercial technologies. For lake and reservoir hydro I 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 2.2. The cost of methanation is made up of the cost of electrolysis units and the Sabatier reaction[1].

Table 2.2. Economic parameters of storage technologies

Technology	Overnight costs (€/kW$_e$)	CAPEX (€/kWh$_e$)	Lifetime (years)	Annuity (€/kW$_e$/year)	Fixed O&M (€/kW$_e$/year)	Variable O&M (€/MWh$_e$)	Storage annuity (€/kWh$_e$/year)	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 (Li-Ion)	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%	ENEA (2016)

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

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

Considering a 100km long onshore pipeline (considering maximum 100km of distance between the methanation units and the biogas production units), the CO_2 transport cost for the methanation storage is €1/MWh (See Appendix 2.5), 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$_e$.

2.2.3.2. VRE profiles

Variable renewable energies' (offshore and onshore wind and solar PV) hourly capacity factors have been prepared using the renewables.ninja website[2], which provides the hourly capacity factor profiles of solar and wind power from 2000 to 2017 at the geographical scale of French counties (*départements*), following the methods elaborated by Pfenninger and Staffell (2016) and Staffell and Pfenninger (2016). These renewables.ninja hourly capacity 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).

The proportion of the installed capacity in each department remains the same in all simulations, at the level observed in 2017. I 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).

[1] The reaction that produces methane from hydrogen and carbon dioxide is called the Sabatier reaction.
[2] https://www.renewables.ninja/

To prepare hourly capacity factor profiles for offshore wind power, I first identified all the existing offshore projects around France using the "4C offshore" website[1], and using their locations, I 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 2.2 provides more information about the methodology used in the preparation of hourly capacity factor profiles of wind and solar power resources.

2.2.3.3. Electricity demand profile

Hourly electricity demand is ADEME (2015)'s central demand scenario for 2050. This demand profile falls in the middle of the four proposed demand scenarios for 2050 in France by Arditi et al. (2013) during the national debates on the French energy transition (DNTE). It amounts to 422TWh$_e$/year, 12% less than the average power consumption in the last 10 years. This takes into account foreseeable change in the demand profile up to 2050, including a reduced demand for lighting and heating and an increased demand for air conditioning and electric vehicles. In this demand scenario, almost half of the vehicles are electric or plug-in hybrids (10.7 million out of 22). I 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.

2.2.3.4. Discount rate

I 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).

2.2.4. Cost scenarios

To test the sensitivity of the optimal power to the costs of various technologies, the considered range of uncertainty is indicated in Table 2.3. 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.

For solar PV, the +/- 50% uncertainty range is chosen to reflect the various scenarios in the JRC (2017) study. I chose the same +/- 50% uncertainty range for batteries, the lower bound being based on the extrapolation 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. I also chose a +/- 50% uncertainty range since it can be considered to reach 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).

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

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 2.3. 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 2.3 would give 405 different cost scenarios ($5^1 \times 3^4$). Out of all these options, I 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 I 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 ($7 \times 5^1 \times 3^2$), 315 future cost scenarios are obtained.

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

2.3. Results

2.3.1. Weather-year selection

2.3.1.1. Testing sensitivity to the choice of a weather-year

The model is run for each year from 2000 to 2017 (henceforth “weather-years”) to test how the optimal mix of variable renewables varies for different weather-years.

The 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 2.3 and 2.4 and Appendix 2.3). 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 allowed[1]. High values for offshore wind are reached either for weather-years with a high average capacity factor for offshore wind (as in 2015) or for weather-years with a low average 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 2.4c). 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 2.4d1 and 2.4d2). In comparison, the system-wide LCOE and average power price (the dual variable of the adequacy constraint, i.e. Equation 2.3), as well as the sum of VRE curtailment and storage losses are much more stable (Figures 2.4e and 2.4f).

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

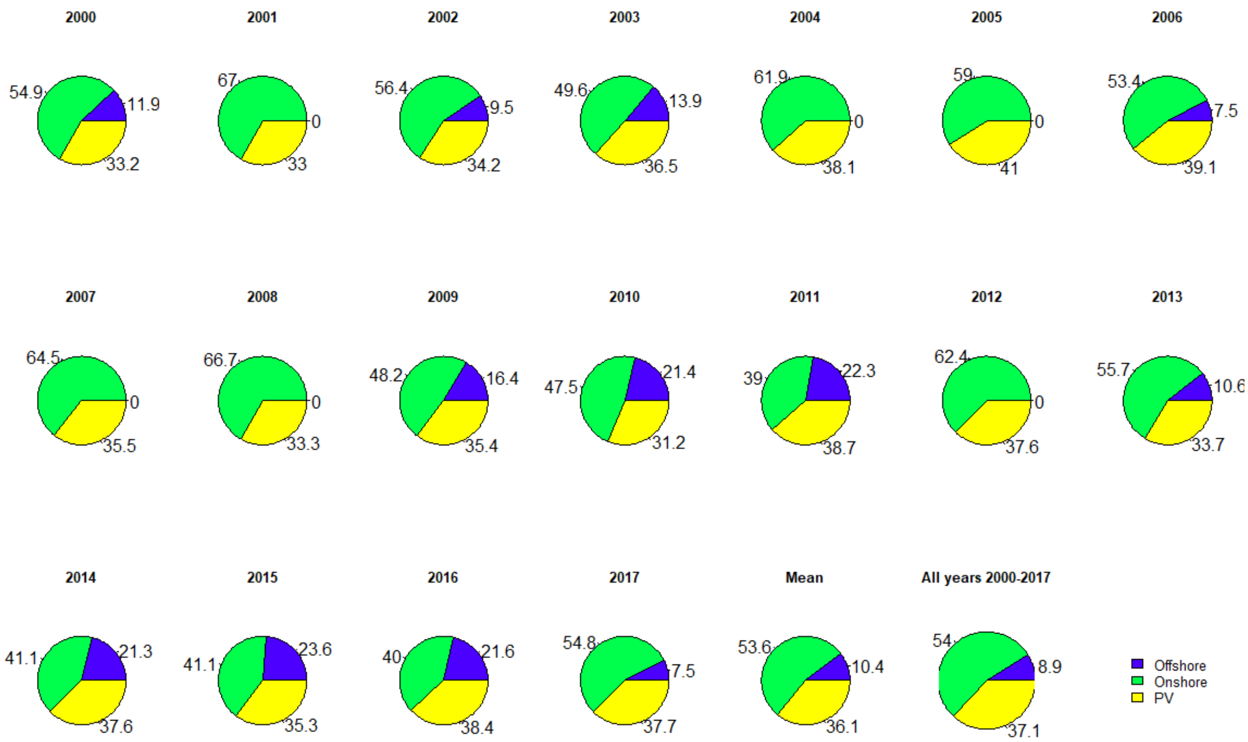

Figure 2.3. VRE generation mix for each weather-year in single-year optimization and over the whole 18-year long period

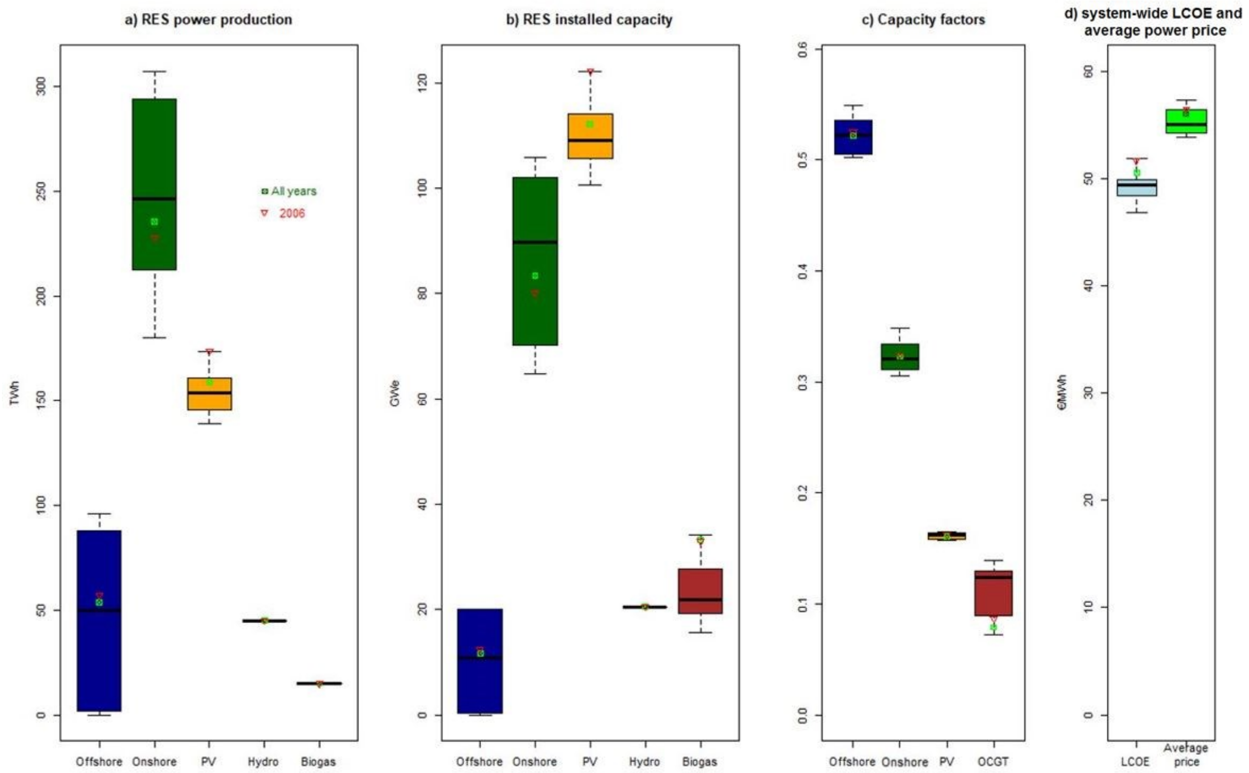

Figure 2.4. Optimization results for each weather-year from 2000 to 2017 and for the whole 18-year period. (a) power production; (b) installed capacity; (c) average capacity factor of each VRE and the gas power plant for biogas produced by anaerobic digestion and methane produced by methanation and (d) system-wide LCOE and average power price of electricity. The green dot shows the results of the optimization over the 18-year period and the red dot the results for weather-year 2006. The box plots show the first and third quartiles and the median for each scenario.

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 an 18-year simulation.

However, the drawback is a much longer optimization time, which prevents me from doing this for the 315 cost scenarios used in sensitivity analysis. Hence, another approach has been chosen: selecting a representative year that gives the results closest to the results when optimizing over 18 years.

2.3.1.2. Selecting a representative weather-year

The selection of a representative year could be made using several criteria. Here, it is based on selecting the year with a capacity factor closest to the 18-year optimal mix. I used the capacity factor because it is invariable with respect to technology costs, on which the sensitivity analysis is performed. To measure the distance to the 18-year optimal mix, I computed the sum of absolute difference[1] of the three VREs. I also calculated the mean squared error[2] which 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 A2.4 in Appendix 2.3).

I also launched the model with the optimal installed capacities found for 2006 over all other weather-years to test the adequacy of this installed capacity with respect to the other 18 weather-years, and I did not observe any operational inadequacy.

Figure 2.5 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.

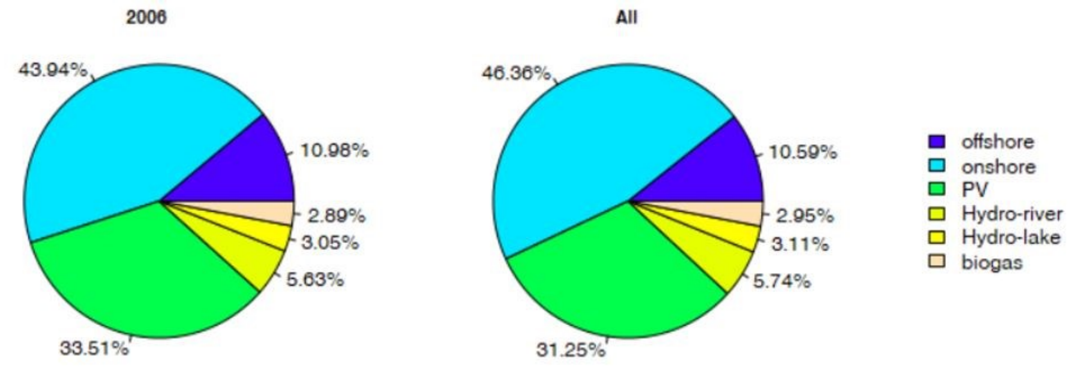

Figure 2.5. Energy mix for the chosen representative weather-year (2006, left) and for the 18-year optimization (right)

[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.

2.3.2. The optimal power mix is highly sensitive to technology cost assumptions

Figure 2.6 shows the results of the sensitivity analysis. These 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 2.6-a). Storage technologies also demonstrate such high sensitivity with the exception of PHS whose capacity is always fixed by the maximum allowed value. Battery capacity ranges from 7.6 to more than 279GWh$_e$, nearly four times the capacity in the reference cost scenario (Figure 2.6-d1), and methanation ranges from 7 to 33.5TWh$_e$, more than twice the capacity in the reference cost scenario (Figure 2.6-d2).

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 LCOE[1] and the average power price are much more influenced by the cost of generation technologies than by that of storage technologies[2]. Keeping the reference investment cost scenario for power production technologies, changing the investment cost of battery and 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.

[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 the conclusions of the EOLES_elecRES model.

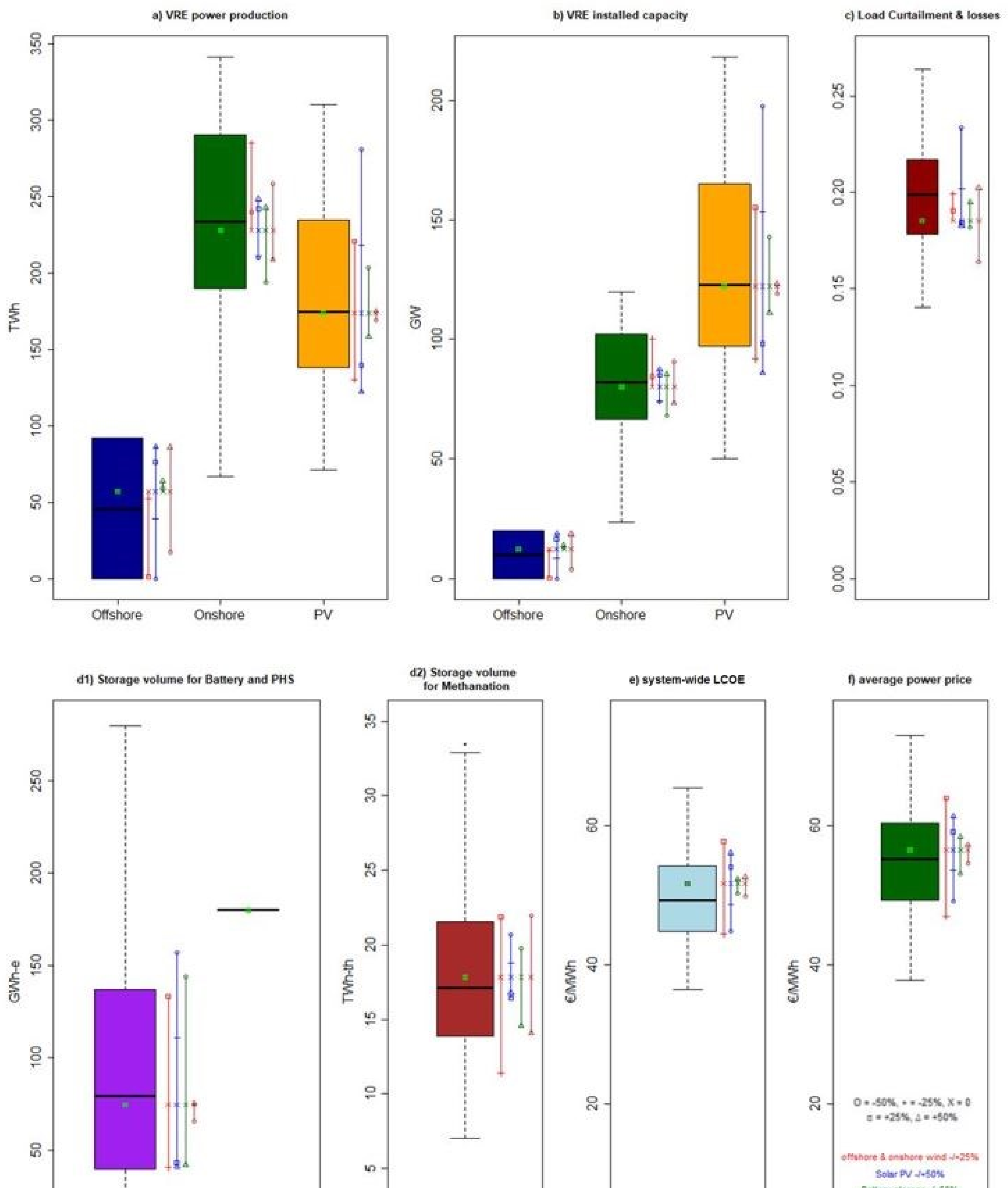

Figure 2.6. Optimization results for the representative year (2006) over the 315 future cost projection scenarios. (a) power production and (b) installed capacity of each VRE resource; (c) load curtailment and storage losses; (d) needed storage volume in GWh_e for batteries and pumped hydro storage (d1) and in TWh_e for methanation (d2); (e) system-wide LCOE in €/MWh_e; (f) average power price in €/MWh_e. The green point shows the reference cost scenario. The colored lines beside whisker plots show the impact of varying separately the cost of one technology, keeping all other technologies at their reference cost.

2.3.3. 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 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, I use the installed capacities of generation and storage technologies optimized for the reference cost scenario, and I calculate the system-wide LCOE for this “rigid capacity” across 315 cost scenarios (Figure 2.7). 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.

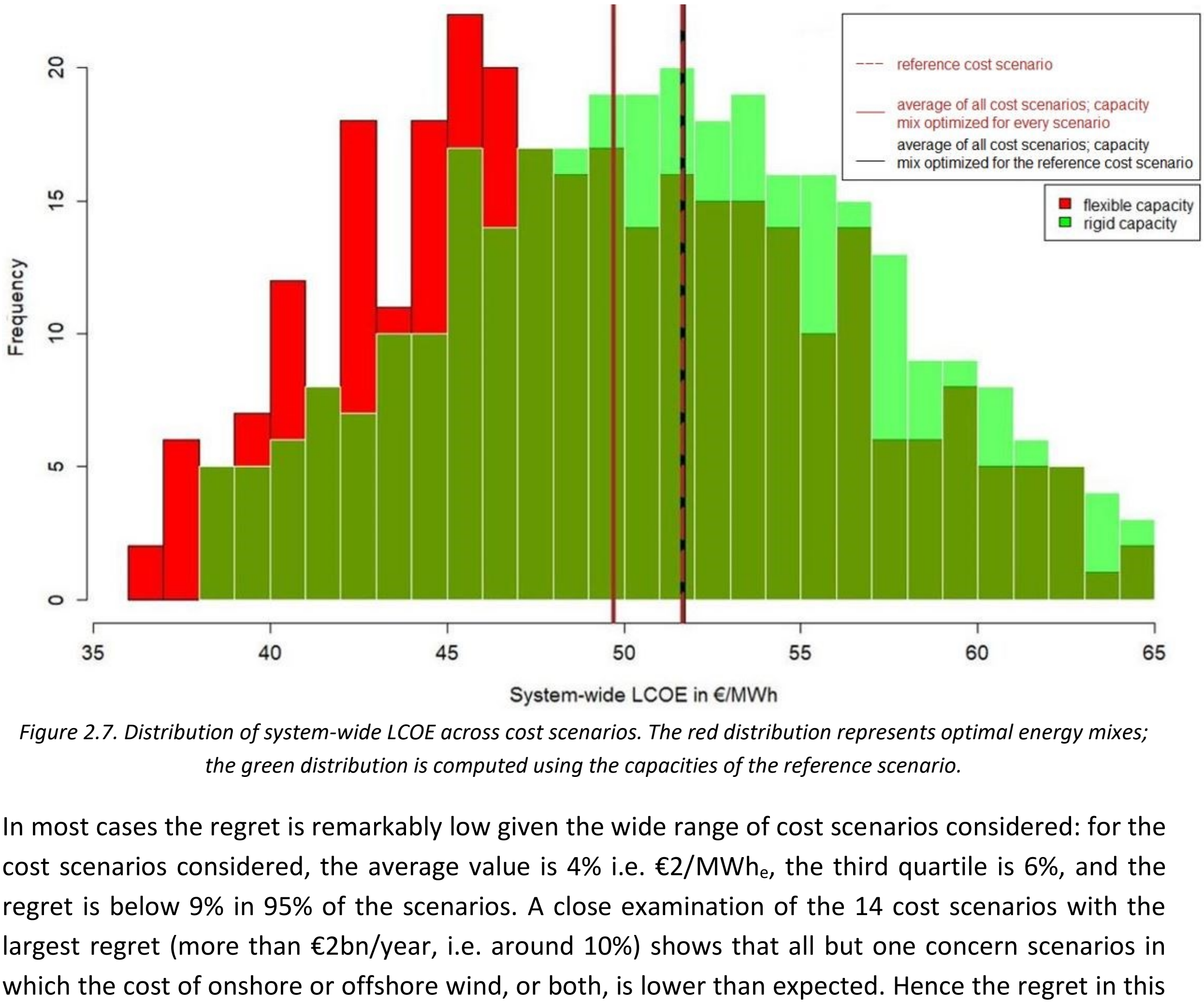

Figure 2.7. Distribution of system-wide LCOE across cost scenarios. The red distribution represents optimal energy mixes; the green distribution is computed using the capacities of the reference scenario.

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. €2/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 €2bn/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 wind power. The only exception is a scenario in which solar PV and batteries are 50% cheaper than in the reference scenario, onshore wind at the reference cost, offshore wind 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 2.7) equals the system-wide LCOE under the reference cost scenario (red 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 (red dashed vertical line in Figure 2.7).

The average system-wide LCOE for the flexible capacity mix (red vertical line in Figure 2.7) 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 *reduces* the expected system-wide LCOE – because the model allows optimizing the mix depending on uncertainty realizations.

2.4. Discussion

2.4.1. 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 the reference cost scenario of this study, storage (batteries, PHS and methanation) accounts for only 14.5% of the system cost, vs. 85.5% for electricity generation (Appendix 2.6). 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 €60bn/year. in their scenario 100RES2050 (cf. their Fig. 23) vs. €21bn/year in this chapter. The explanation does not stem from their investment cost assumptions, which are similar to the ones in this chapter (cf. their Table 1). One explanation might be that they take a higher discount rate, but they do not disclose it so this hypothesis cannot be verified. 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 €180bn/year for 100% renewables, i.e. more than 8 times the result of this chapter. Several factors may explain this huge difference. First, he takes a real discount rate of 7%/year. This is much higher than mine, which corresponds to the rate recommended for socio-economic analysis in France (4.5%/year). Second, his investment cost for PV is much higher than mine: €3.6/W_p, while the current investment cost at utility scale is around \$1/W_p (Lazard, 2019). This explains why solar PV does not appear in his reference scenario (F1) with 100% renewables. Third, total demand is higher than the one taken in this study (512TWh_e vs. 422TWh_e).

Moreover, recent market observations make the high-cost scenario for offshore wind in Table 2.3 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 the low-cost scenario of this chapter.

In the remainder of this section, I address several factors which could push my estimates up or down.

2.4.2. Model limitations

2.4.2.1. Factors which could push costs up

a) *Cost of the transmission and distribution network*

The system-wide LCOE includes storage costs, as well as some network costs: the connection costs are included in the JRC cost estimates used in this thesis, 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 four-node model), therefore, I applied a single-node model for weather-year selection, sensitivity analysis and robustness study. But to assess the importance of the internal congestion issue, I developed a four-node version of the 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 four-node version of this study for year 2006 and the central cost scenario can be found in Appendix 2.10.

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.
- EirGrid[1] (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 the EOLES_elecRES model.

b) *Discount rate*

Some studies use higher discount rates than 4.5% considered in this study, 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 interest rate available on financial markets and expected GDP growth over the next few decades. Using a higher rate in a socioeconomic analysis means than future generations would be penalized when compared to current ones, which can hardly be defended on ethical grounds.

Table 2A.10 in Appendix 2.9 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.

c) *Perfect weather forecasts*

The optimization in EOLES_elecRES 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.

d) *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.

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

Concerning supply, the production of wind farms and PV panels will be affected by climate change but based on 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).

2.4.2.2. Factors which could bring costs down

a) *Demand-side management*

The EOLES_elecRES model does not feature price-elastic electricity demand or flexibility in the power consumption profile, because this would have required debatable assumptions. Including these features would reduce the need for storage and the related energy losses. Demand side management (DSM) has been studied 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. I decided not to include DSM because its cost is difficult to estimate.

b) *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.

c) *Spatial optimization of renewable energy capacities*

As mentioned above, EOLES_elecRES does 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.

d) *Neither vehicle-to-grid nor second-hand batteries*

EOLES_elecRES does not 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 GWh_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 I 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, modeling this option would require precise assumptions on battery degradation.

2.5. Conclusion

In this chapter, I studied the sensitivity of optimal fully renewable power systems to technology cost. To that end, I 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. 315 cost scenarios have been built by combining assumptions about the long-term cost of the key power generation and storage technologies.

The 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 EOLES_elecRES 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/MWh_e). 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, this chapter 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.

The findings of this chapter 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 2.8), 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 CO_2 emissions: CO_2 capture and storage and nuclear power. The next chapter applies this extension and addresses the relative role of different low-carbon options in reaching carbon neutrality, by internalizing the cost of positive and negative emissions. 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. This extension is studied in Chapter 5, by coupling all the major energy sectors endogenously.

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Appendices 2

Appendix 2.1. Additional information on the JRC 2017 study

In the JRC's 2017 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 (A2.1) shows the main methodology used in the cost projection using the learning rate method:

$$Cost_t = Cost_0 \cdot \left(\frac{C_t}{C_0}\right)^{\delta} \quad \text{(A2.1)}$$

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 (A2.2);

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

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 (A2.1). These three scenarios are described in Table A2.1;

Table A2.1. The chosen scenarios by JRC (2017) for the 2050 cost projections of low carbon power production technologies

Scenario	
Baseline	This scenario is used to cover the lower end of RES-E deployment. It is based on the "6DS" scenario of the Energy Technology Perspectives published by the International Energy Agency in 2016. It represents a "business as usual" world in which no additional efforts are taken on stabilizing the atmospheric concentration of greenhouse gases. By 2050, primary energy consumption reaches about 940EJ/year, renewable energy supplies about 30% of global electricity demand and emissions climb to 55GtCO_2/year.
Diversified	The "Diversified" portfolio scenario is taken from the "B2DS" scenario of the International Energy Agency's 2017 Energy Technology Perspectives and is used as representative for the mid-range deployment of RES-E found in literature. To achieve rapid decarbonization in line with international policy goals, all known supply, efficiency and mitigation options are available and pushed to their practical limits. Fossil fuels and nuclear energy participate in the technology mix, and CCS is a key option to realize emission reduction goals. Primary energy consumption is comparable to 2015 levels (about 580EJ/year), the share of renewable electricity in the global supply mix is 74 % while emissions decline to about 4.7GtCO_2/year by 2050.
ProRES	The "ProRES" scenario results are the most ambitious in terms of capacity additions of RES-E technologies. In this scenario the world moves towards decarbonization by significantly reducing fossil fuel use, however, in parallel with rapid phase out of nuclear power plants. 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 430EJ/year, renewables supply 93 % of electricity demand and global CO_2 emissions are about 4.5GtCO_2/year 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 2.2. 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 solar panel is calculated using the relative PV performance model by Huld et al. (2010) which gives temperature dependent panel efficiency curves.

I first extracted the hourly VRE profiles for each of the 95 counties of France from 2000 to 2018. Then considering the near optimal assumption of proportional installation of new plants to the existing plants, I aggregated these 95 counties to one single node. Therefore, while the model is a single node model with no spatial optimization, the spatial distribution of VRE resources has been taken into account by the spatial aggregation, which can be considered a nearly optimal spatial distribution.

Appendix 2.3. Weather-year sensitivity

The results for each weather-year can be seen in Tables A2.2, A2.3 and A2.4.

Table A2.2. Installed capacities of each power production technology in GW_p and energy storage capacity of each storage technology during each optimization period

Year	Offshore Wind	Onshore Wind	Solar PV	Run-of-river	Lake & reservoir	Biogas	Battery (GWh)	PHS (GWh)	Methanation (TWh)
2000	11.46	84.14	105.74	7.50	13.00	18.24	60.17	180	5.52
2001	0.38	104.62	101.16	7.50	13.00	28.61	41.91	180	8.45
2002	17.12	69.66	105.55	7.50	13.00	19.16	74.70	180	4.60
2003	10.21	90.15	106.83	7.50	13.00	25.70	62.78	180	5.52
2004	0.00	105.29	113.38	7.50	13.00	21.88	70.32	180	15.30
2005	0.00	105.89	110.38	7.50	13.00	25.22	60.27	180	9.37
2006	12.36	80.08	122.17	7.50	13.00	32.89	74.62	180	12.90
2007	0.00	98.40	118.33	7.50	13.00	27.61	65.73	180	12.05
2008	0.78	101.95	105.20	7.50	13.00	21.76	52.03	180	12.05
2009	11.61	89.32	107.79	7.50	13.00	18.83	51.47	180	6.92
2010	20.00	83.64	100.50	7.50	13.00	22.88	40.53	180	15.81
2011	20.00	65.81	114.17	7.50	13.00	28.32	101.33	180	8.54
2012	0.00	103.38	114.49	7.50	13.00	20.36	62.43	180	11.32
2013	10.32	92.30	100.82	7.50	13.00	21.54	37.06	180	10.59
2014	20.00	70.23	111.40	7.50	13.00	18.57	80.03	180	7.69
2015	20.00	64.77	103.78	7.50	13.00	34.09	63.19	180	8.22
2016	20.00	69.77	114.07	7.50	13.00	23.96	81.68	180	8.66
2017	5.29	100.72	111.62	7.50	13.00	19.30	50.05	180	11.77
Mean	9.97	87.78	109.30	7.50	13.00	23.83	62.79	180	7.74
All	11.77	83.30	112.21	7.50	13.00	33.25	66.71	180	16

Table A2.3. Yearly power production of each production technology (in TWh_e/year) and capacity factor of VRE resources

Year	**Offshore Wind**	**Onshore Wind**	**Solar PV**	**Run-of-river**	**Lake**	**Biogas**	**Offshore Wind**	**Onshore Wind**	**Solar PV**	**OCGT plant**
2000	54.08	246.41	146.58	29.19	15.82	15	0.538	0.334	0.158	0.139
2001	1.77	307.32	143.64	29.19	15.82	15	0.537	0.335	0.162	0.089
2002	82.05	212.44	145.52	29.19	15.82	15	0.547	0.348	0.157	0.127
2003	44.99	245.26	153.46	29.19	15.82	15	0.503	0.311	0.164	0.088
2004	0.00	296.53	159.65	29.19	15.82	15	0.509	0.322	0.161	0.130
2005	0.00	290.19	159.98	29.19	15.82	15	0.507	0.312	0.165	0.102
2006	56.90	227.80	173.72	29.19	15.82	15	0.525	0.324	0.162	0.087
2007	0.00	294.71	170.24	29.19	15.82	15	0.532	0.341	0.164	0.100
2008	3.67	296.22	145.50	29.19	15.82	15	0.536	0.331	0.158	0.120
2009	51.41	246.86	153.65	29.19	15.82	15	0.504	0.315	0.162	0.130
2010	88.51	226.65	140.74	29.19	15.82	15	0.505	0.308	0.160	0.130
2011	91.47	179.83	165.84	29.19	15.82	15	0.522	0.311	0.165	0.085
2012	0.00	294.01	164.07	29.19	15.82	15	0.523	0.326	0.163	0.130
2013	48.17	259.67	138.87	29.19	15.82	15	0.533	0.320	0.157	0.128
2014	89.18	193.92	153.49	29.19	15.82	15	0.509	0.314	0.157	0.133
2015	96.26	190.85	148.57	29.19	15.82	15	0.549	0.335	0.163	0.072
2016	88.09	187.04	160.28	29.19	15.82	15	0.502	0.302	0.160	0.101
2017	23.35	272.47	160.58	29.19	15.82	15	0.504	0.309	0.164	0.135
Mean	45.55	248.23	154.69	29.19	15.82	15	0.522	0.323	0.161	0.113
All	53.79	235.53	158.75	29.19	15.82	15	0.522	0.323	0.161	0.079

Table A2.4 shows the total cost, marginal cost and the system-wide LCOE[1] 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 A2.4. 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 A2.5 shows the ranking of each weather-year in correlation with overall 18-year period.

Table A2.5. 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** **- with mean squared error**	2006 (value 0.015) 2006 (value 3.667e^{-6})	2012 (value 0.0236) 2012 (value 4.667e^{-6})	2004 (value 0.028) 2013 (value 5.667e^{-6})

According to the simulations done by EOLES_elecRES, 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 122GW, while it is 112GW 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 20GW 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 65GW to 106GW while the overall 18-year optimization results in 83GW of installed capacity. The 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 2.4. The EOLES_elecRES model

A2.4.1. Sets and parameters

Table A2.6 presents the sets (indices) of the EOLES_elecRES model and Table A2.7 presents its parameters. Throughout this chapter and Chapter 3, 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 it is indicated that $45MWh_e$ is stored in the natural gas network, it means that $100MWh_{th}$ of methane is stored, which will allow $45MWh_e$ of electricity to be generated.

Table A2.6. Sets (indices) of the EOLES_elecRES model

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

Table A2.7. Parameters of the EOLES_elecRES model

Parameter	Unit	Value[1]	Description
$month_h$	[-]		A parameter to show which month each hour is in
$cf_{vre,h}$	[-]		Hourly production profiles of variable renewable energies
$demand_h$	$[GW_e]$		Hourly electricity demand profile
$lake_m$	$[GWh_e]$		Monthly extractable energy from lakes
$river_h$	[-]		Hourly run-of-river capacity factor profile
ε_{vre}	[-]		Frequency restoration requirement because of forecast errors on the production of each variable renewable energy
q_{tec}^{ex}	$[GW_e]$		Existing capacity by technology

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

$annuity_{tec}$	[M€/GW_e/year]		Annualized capital cost of each technology
$annuity_{str}^{en}$	[M€/GWh/year]		Annualized capital cost of energy volume for storage technologies
$capex_{str}^{ch}$	[M€/GW /year]		Annualized capital cost of storage technology charging power
$fO\&M_{str}^{ch}$	[M€/GW /year]		Fixed operation and maintenance cost of storage technology charging power
$fO\&M_{tec}$	[M€/GW_e /year]		Annualized fixed operation and maintenance cost
$vO\&M_{tec}$	[M€/GWh_e]		Variable operation and maintenance cost of each technology
η_{str}^{in}	[-]		Charging efficiency of storage technologies
η_{str}^{out}	[-]		Discharging efficiency of storage technologies
q^{pump}	GW_e	9.3	Pumping capacity for Pumped hydro storage
e_{PHS}^{max}	GWh_e	180	Maximum energy volume that can be stored in PHS reservoirs
e_{biogas}^{max}	$TWh_e/year$	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

A2.4.2. Variables

The main variables resulting from the optimization are presented in Table A2.8.

Table A2.8. 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_e	Hourly electricity entering each storage technology (inflow)
$STORED_{str,h}$	GWh_e	Hourly energy stored in each technology (stock)
S_{str}	GW_e	Installed charging capacity by storage technology
$VOLUME_{str}$	GWh_e	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
$\boldsymbol{COST}$	$\boldsymbol{bn€/year}$	Total annualized power system cost (minus the fixed cost of already installed capacities). This is the objective function to be minimized.

Appendix 2.5. 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 carbon-dioxide with an efficiency of 80% and each mole of methane can produce 802.3kJ$_{th}$ of thermal energy, considering an OCGT combustion efficiency of 45% (JRC 2014):

$$\frac{1\ t\ CO_2}{1000000\ g\ CO_2} \times \frac{44\ g\ CO_2}{1\ mol\ CO_2} \times \frac{1\ mol\ CO_2}{0.8\ mol\ CH_4} \times \frac{1\ mol\ CH_4}{802.3\ kJ} \times \frac{1\ kJ_{th}}{0.00022277778\ kWh_{th}} \times \frac{1\ kWh_{th}}{0.45\ kWh_e} \times \frac{1000\ kWh_e}{1\ MWh_e} = 0.5486\,\frac{tCO_2}{MWh_e}$$

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

Appendix 2.6. Cost decomposition

Figure A2.1 shows the share of each technology in overall cost of power system (except distribution and transmission costs).

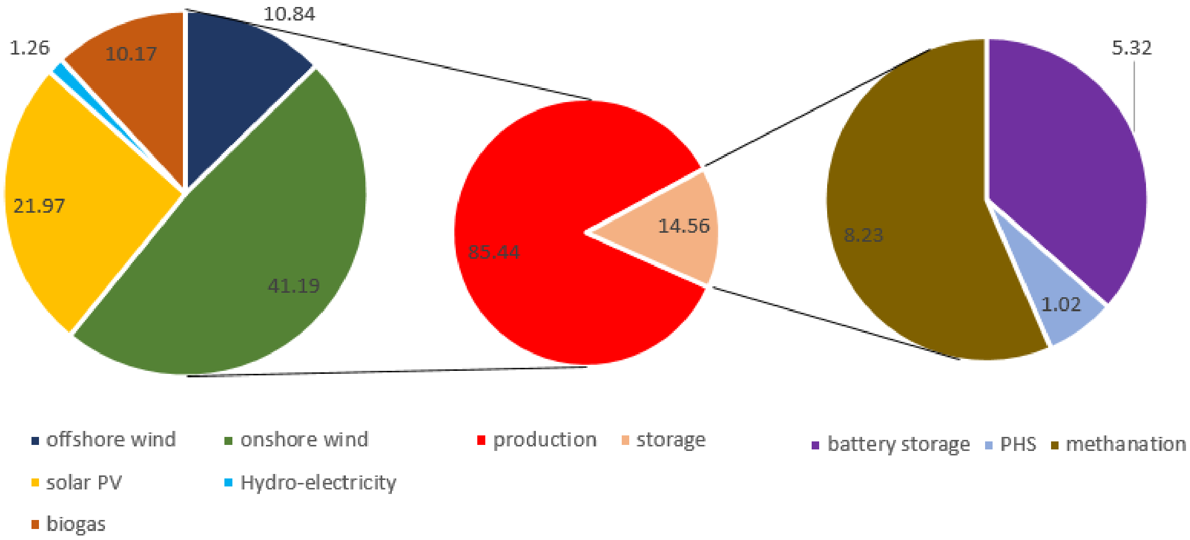

Figure A2.1. Overall decomposition of the system cost in percentage for the reference cost scenario

As we can observe, only 14.56% of the cost of the electricity system comes from storage options, of which the main part is the cost of the methanation (Power-to-CH_4), with 8.23% of the overall cost of the electricity, and 5.32% of the cost of short-term storage (Li-Ion batteries).

Appendix 2.7. Insights on profitability by technology

In this chapter, an economic optimum is modelled but not a decentralized economy. However, in this appendix, I provide some insights on the decentralization of this optimum in the form of a market economy, assuming perfect competition and an energy-only market[1]. To this aim, I consider that the Lagrange multiplier of the adequacy equation (Equation 2.3) represents the market price. Figure A2.2 below adds to Figure 2.2 the electricity spot price, defined this way.

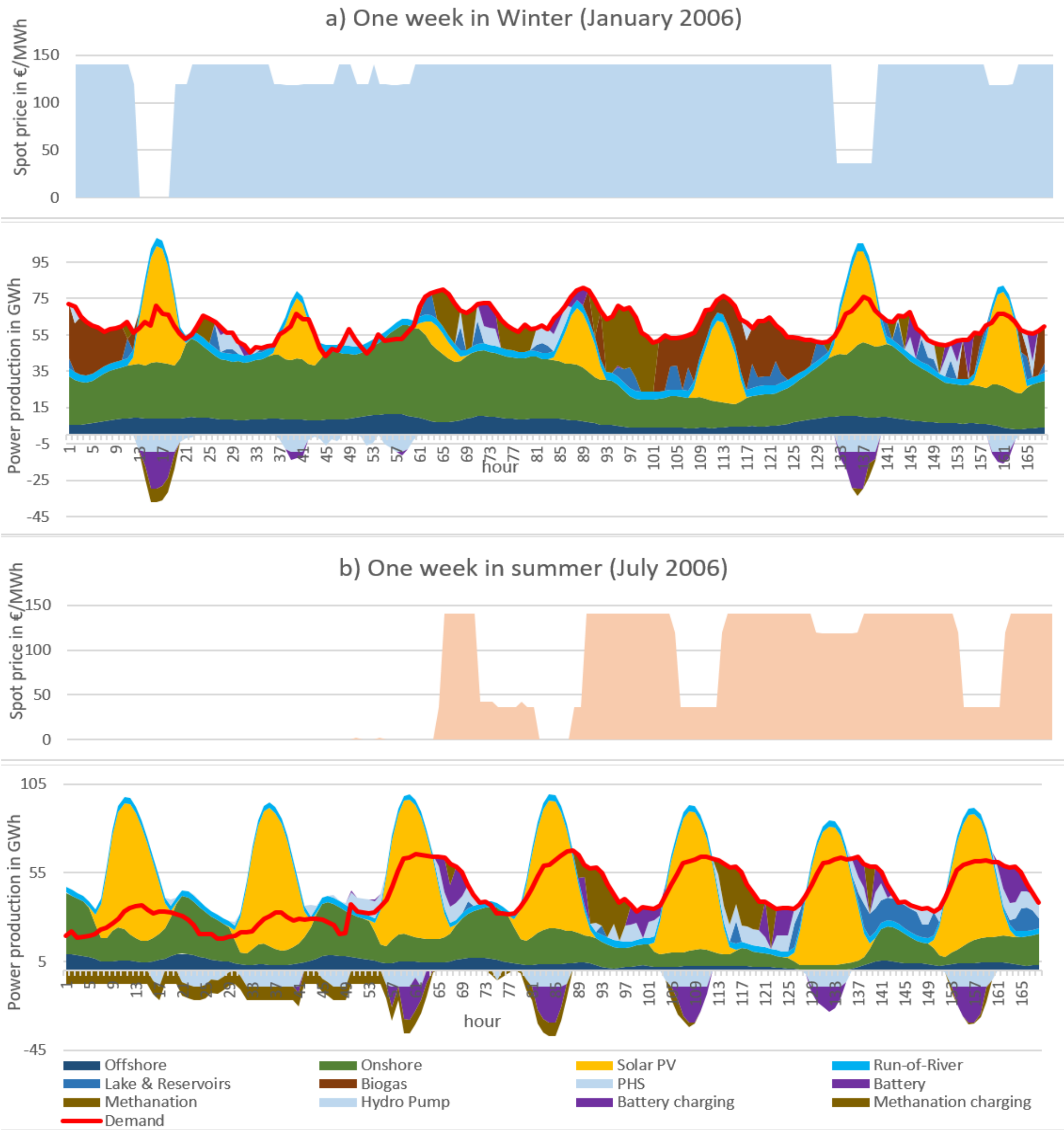

Figure A2.2. Hourly power generation, electricity demand, storage charge and discharge profiles and power prices for (a) third week of January (Winter) and (b) third week of July (Summer) 2006

As we can see, the price is often either zero (when there is some excess power generation) or around €140/MWh. Figure A2.3 below, which presents the price frequencies, confirms this result:

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

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.

On the basis of these 'market prices', one can calculate the average selling price for every technology, and the average buying price for storage technologies. These are presented in Table A2.9 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.

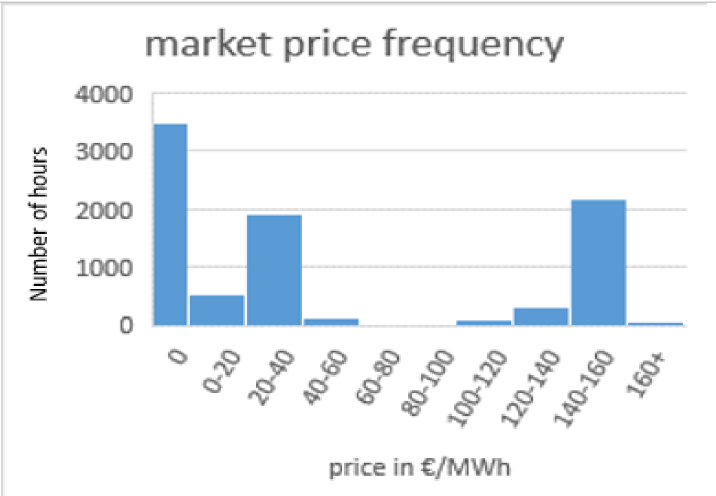

Figure A2.3. Market price frequency.

Table A2.9. LCOE/LCOS and average price of electricity sold and bought and unit profit for each technology, for weather-year 2006

Prices (€/MWh$_e$)	**offshore**	**onshore**	**PV**	**lake**	**river**	**biogas***	**OCGT***	**battery**	**PHS**	**methanation***
LCOE/LCOS	41.585	39.45	27.59	98.84	40.80	82.00	67.07	87.520	16.26	116.12
Av. selling price	41.68	39.597	28.01	1437.03	55.19	141.57	209.01	99.506	86.06	142.495
Av. buying price	-	-	-	-	-	-	141.93	21.529	22.98	26.375
Long-term profit	0.09	0.15	0.42	38.19	14.39	59.57	0	-9.543	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 I have not modelled such a market to keep the model simple.

Appendix 2.8. Renewable capacities compared to the potential and other scenarios

For the reference cost scenario, the optimal mix features 12GW of offshore wind (vs. 2MW as of mid-2019), 80GW of onshore wind (vs. 16GW, i.e. 5 times more) and 110GW of solar PV (vs. 9GW, 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?

Table A2.10. Renewable capacities in our study, capacities currently installed, capacities in other scenarios and available potential

	Optimum in reference cost scenario	**Current capacity, mid-2019 (RTE, 2019)**	**Other scenarios for 2050**			**Renewable potential**			
			ADEME (2015)	négaWatt (2017)	ADEME (2018)	ADEME (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

To address the first question, the last four columns of Table A2.10 show the renewable potential identified by several studies. For each of the three technologies at stake, the capacity resulting from 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 I have identified for the reference cost scenario. Indeed, reaching 80GW in 2050 means an increase of 2GW/year. 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 large substitutable, so our intuition is that a scenario with less onshore wind, more offshore wind and more PV would not be much costlier.

To address the second question, Table A2.10 (columns 3-6) shows 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 this study. The optimal mix resulting from EOLES_elecRES 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 2.6 based on 315 cost scenarios, except for offshore wind in the négaWatt scenario because it slightly exceeds the maximal prescribed potential in EOLES_elecRES (28GW vs. 20GW). To sum up, the results of this chapter do not cast doubts on the technological choices made by the authors of these scenarios.

Appendix 2.9. Sensitivity to the discount rate

Table A2.11 below shows, for a discount rate ranging from 2%/year to 7%/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 A2.11. Installed capacities and annual system cost for various discount rates

	Installed capacity (GW)						
Discount rate (%)	**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.)	**18.25**	**19.62**	**21.08**	**21.86**	**22.58**	**24.42**	**25.72**

Appendix 2.10. Impact of the inter-regional transmission network

I developed a four-node version of the EOLES_elecRES model, dividing France into four geographical divisions: North-East, North-West, South-East and South-West. I added the existing interconnections and the possibility of new investments in the 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, I 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, I took a weighted average proportional to the existing installed capacity in each county for each region, and I 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, I 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 four-node version and the single-node version of EOLES_elecRES for year 2006 are presented in tables A2.12 and A2.13 below. The codes can be found on GitHub[1].

Table A2.12. Installed capacity of each electricity production technology (in GW) and energy volume capacity of each storage technology for the single node and thefour4-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
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

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

Table A2.13. Yearly electricity produced by each technology (in TWh), imports and exports, for the single node and the four-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 the EOLES_elecRES model are presented in table A2.14.

Table A2.14 Main outputs from the single-node and the four-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 A2.15 provides the interconnection capacity between each of the four divisions, and Table A2.16 the energy flow between each pair of divisions.

Table A2.15. 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

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%.

Table A2.16 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	-

Chapter 3

Relative role of different low-carbon options in a carbon-neutral power mix

3.1. Introduction

In the previous chapter, I studied a fully renewable power system, however, renewables are not the only low-carbon supply options in reducing CO_2 emissions of power system and nuclear power and carbon capture and storage (CCS) technologies could be useful CO_2 mitigation options as well (Brouwer et al. 2016).

The economic interest of nuclear energy as a low-carbon supply technology has been questioned by many, because of high uncertainty on its construction time and its negative learning-by-doing rate in the latest projects such as Hinkley Point C in UK, Flamanville 3 in France and Olkiluoto 3 in Finland. Linares et al. (2013), in a Spanish case study, showed that the cost-competitiveness of nuclear power is highly questionable and for a liberalized market, a public support will be inevitable for investments for new nuclear power plants. Similarly, Kan et al. (2020) studied the cost of a future low-carbon Swedish power system and they concluded that once the old nuclear power plants are decommissioned (by 2040), there is no economic interest in the new nuclear power plants. Likewise, in previous chapter, we saw that a fully renewable power system is not only technically feasible, but economically attractive and the uncertainty in the future cost projection of variable renewable energy sources (VRE) does not increase the system cost by much (less than 4% in average).

The official target presented by the French government in its energy-climate law is to reach zero net greenhouse gas (GHG) emissions by 2050 (MTES, 2019). While the French electricity sector is relatively decarbonized, the relative proportions of renewable energy resources and nuclear power is a highly debated topic. With 63GW of installed capacity by the end of 2019, nuclear power dominates the French electricity mix, accounting for 70.6% of net electricity production in 2018 (CGDD, 2019). France is at the crossroads of the decision to invest in new nuclear power plants, or slowly decrease the proportion of nuclear power in favor of a renewables-dominated power mix (DNTE, 2013).

A very wide range of academic studies evaluate the optimal electricity mix for France by 2050. Krakowski et al. (2016) argue that increasing the proportion of RES from 40% to 100% would lead to a power system that would be twice as expensive (more than €60bn/year vs. €30bn/year), and similarly Villavicencio (2017) shows an even higher cost for a 100% RES power system (€180bn/year). The costs from the last two studies are equivalent to nearly three times and nine times the current electricity price in France respectively. On the other hand, both ADEME reports (ADEME, 2015 and ADEME, 2018) show that investing in new nuclear power plants is not an optimal choice and that in an optimal scenario, renewables will represent 85% and 95% of the electricity mix in 2050 and 2060 respectively. This very highly renewable electricity is expected to cost less than the current electricity price (€90/MWh vs. €100/MWh excluding taxes). Similarly, a big proportion of European and world-wide studies conclude that renewables would provide most of the electricity production. (Rogelj et al, 2018 and Waisman et al, 2019). Similarly, according to IPCC special report on 1.5°C of global warming, by 2050, "the share of electricity supplied by renewables increases from 23% in 2015 to 59–97% across 1.5°C pathways with no or limited overshoot" (IPCC, 2018).

The controversial findings in the existing literature for France raise the question of the impact of cost scenarios for the respective proportion of nuclear power and VRE technologies in the optimal power mix. Moreover, carbon capture and storage (CCS) and negative emission technologies such as bioenergy with carbon capture and storage (BECCS) are not included in any of the existing literature for France, while these technologies show promising potential for decarbonizing the electricity sector. The special 1.5°C global warming report published by the Intergovernmental Panel on Climate Change (IPCC, 2018) argues that "Significant near-term emissions reductions and measures to lower energy and land demand" is necessary to limit the carbon dioxide removal (CDR) technologies to a few hundred $GtCO_2$ without reliance on BECCS. Daggash et al. (2019) conclude that it is significantly cheaper (37% to 48%) to decarbonize the power sector using BECCS and DACCS than to consider only VRE technologies with storage options.

This chapter aims to evaluate the relative role of renewable energy technologies, nuclear power and carbon capture and storage technologies, the impact of different cost scenarios in the optimal electricity mix and the integration of the social cost of carbon (SCC) into these evaluations. To investigate these issues, I develop the EOLES_elec model, from the EOLES family of models, which considers only the power sector. This chapter examines the sensitivity of the optimal power mix to a wide range of SCC scenarios (from 0 to €500/tCO_2) and to the future cost development of new nuclear power plants (from €3,000/kW to €4,500/kW of capital expenditure) and VREs (three main scenarios; low, central and high cost for wind and solar power).

The remainder of this chapter is organized as follows. Section 3.2 presents the methods: the EOLES_elec model and the input parameters used. The results and discussion are presented in Sections 3.3 and 3.4 while Section 3.5 concludes this chapter.

3.2. Methods

3.2.1. The EOLES_elec model

EOLES_elec is the electricity version of the EOLES family of models. Like EOLES_elecRES, it minimizes the annualized power generation and storage costs, including the cost of connection to the grid. The EOLES_elec model adds natural gas, nuclear power and combined cycled gas turbines equipped with carbon capture and storage (CCS) bits to the EOLES_elecRES. Thus, two gas turbines (OCGT and CCGT with CCS) burn methane which can come from three sources: fossil natural gas, biogas from anaerobic digestion and synthetic gas from power-to-gas (methanation)[1]. These technologies are shown in Figure 3.1.

All the simplification assumptions of the EOLES_elec model are the same as in Chapter 2. In fact, these assumptions are same for the whole EOLES family of models. The code and data for this chapter are available on Github.[2] A big proportion of equations in EOLES_elec are the same as the ones in EOLES_elecRES. In the following, all the equations are presented, and the ones differing from EOLES_elecRES are explained.

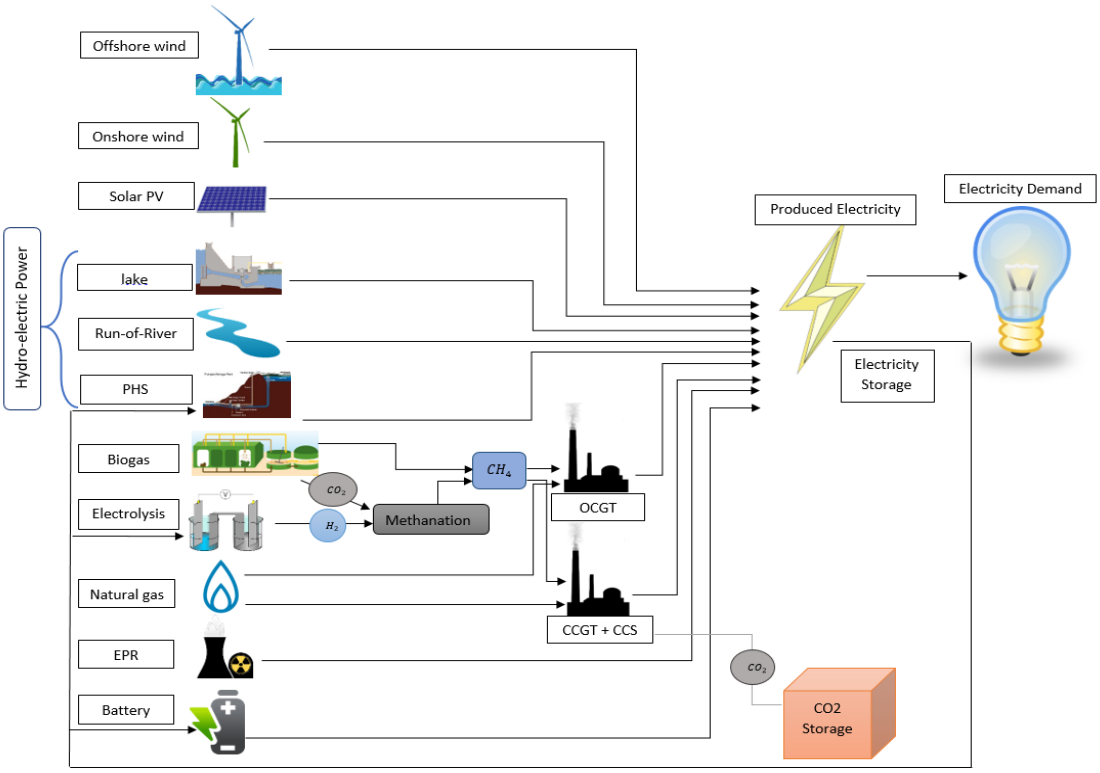

Figure 3.1. Graphical description of the EOLES_elec model

3.2.1.1. Objective function

The objective function, as shown in previous chapter, is the sum of all costs over the chosen period, including the annualized investment costs as well as the fixed and variable O&M costs (Equation 3.1):

$$COST = \Big(\sum_{tec}[(Q_{tec} - q_{tec}^{ex})\, annuity_{tec}] + \sum_{str}(VOLUME_{str}\,.\,annuity_{str}^{en}) + \sum_{tec}(Q_{tec}.\,fO\&M_{tec}) + \sum_{str}(S_{str}.\big(capex_{str}^{ch} + fO\&M_{str}^{ch}\big)) + \sum_{tec}\sum_{h}(G_{tec,h}\,.\,(vO\&M_{tec} + e_{tec}SCC_{CO_2}))\Big)/1000 \qquad (3.1)$$

[1] I chose the main representative technologies for three main storage types: short-term, mid-term and long-term storage options. Hydrogen as direct injection to gas network or separate storage in salt caverns could be two other power-to-gas storage options. An alternative scenario with both types of hydrogen is presented in Appendix 3.8. Since no visible change is observed by excluding these two power-to-hydrogen options from the present technologies in the model, and it increased the computation time of the model, I considered methanation as the only power-to-gas technology.

[2] https://github.com/BehrangShirizadeh/EOLES_elec

where Q_{tec} represents the production capacities, q_{tec}^{ex} represents the existing capacity (notably for hydro-electricity technologies with long lifetime), $VOLUME_{str}$ is the energy storage capacity in GWh, S_{str} is the storage capacity in GW, $annuity$ is the annualized investment cost, $fO\&M$ and $vO\&M$ respectively represents fixed and variable operation and maintenance costs, $G_{tec,h}$ is the hourly generation of each technology, $capex_{str}^{ch}$ is the charging annualized investment cost and $fO\&M_{str}^{ch}$ is the charging fixed operation and maintenance cost of the storage technology str, e_{tec} is the specific emission of each technology in tCO_2/GWh of power production and SCC_{CO_2} is the social cost of carbon in €/tCO_2.

3.2.1.2. Adequacy equation

$$\sum_{tec} G_{tec,h} \geq demand_h + \sum_{str} STORAGE_{str,h} \tag{3.2}$$

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

3.2.1.3. Variable renewable power production

$$G_{vre,h} = Q_{vre} \times cf_{vre,h} \tag{3.3}$$

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.

3.2.1.4. Energy storage

$$STORED_{str,h+1} = STORED_{str,h} + (STORAGE_{str,h} \times \eta_{str}^{in}) - (\frac{G_{str,h}}{\eta_{str}^{out}}) \tag{3.4}$$

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

3.2.1.5. Secondary reserve requirements

$$\sum_{frr} RSV_{frr,h} = \sum_{vre}(\varepsilon_{vre} \times Q_{vre}) + demand_h \times (1 + \delta_{variation}^{load}) \times \delta_{uncertainty}^{load} \tag{3.5}$$

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.

3.2.1.6. Power-production-related constraints

$$G_{tec,h} \leq Q_{tec} \tag{3.6}$$

$$Q_{frr} \geq G_{frr,h} + RSV_{frr,h} \tag{3.7}$$

$$lake_m \geq \sum_{h \in m} G_{lake,h} \tag{3.8}$$

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

$$G_{river,h} = Q_{river} \times river_h \quad (3.9)$$

As shown in Figure 3.1, in addition to natural gas, two renewable gas technologies are considered: biogas and synthetic gas from methanation. They can be sent either to OCGT power plants with high operational flexibility, with no emissions for renewable gas, or to CCGT power plants equipped with post-combustion CCS where renewable gas technologies have negative emissions and natural gas has residual positive emissions. Equations (3.10) and (3.11) show the operation of these two power plants with each of three gas production technologies:

$$G_{ocgt,h} = G_{biogas1,h} + G_{methanation1,h} + G_{ngas1,h} \quad (3.10)$$

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

$$G_{ccgt-ccs,h} = G_{biogas2,h} + G_{methanation2,h} + G_{ngas2,h} \quad (3.11)$$

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

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

Equation (3.12) limits the annual power production from biogas (with and without CCS), where e_{biogas}^{max} is the maximal annual power that can be produced from biogas:

$$\sum_{h=0}^{8759} G_{biogas1,h} + \sum_{h=0}^{8759} G_{biogas2,h} \leq e_{biogas}^{max} \quad (3.12)$$

For open-cycle and combined-cycle gas turbines, there are some safety- and maintenance-related breaks. Equations (3.13) and (3.14) limit the annual power production for each of these plants to their maximum annual capacity factors:

$$\sum_h G_{ocgt,h} \leq Q_{ocgt} \times cf_{ocgt} \times 8760 \quad (3.13)$$

$$\sum_h G_{ccgt-ccs,h} \leq Q_{ccgt-ccs} \times cf_{ccgt} \times 8760 \quad (3.14)$$

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

$$Q_{tec} \leq q_{tec}^{max} \tag{3.15}$$

3.2.1.7. Nuclear-power-related constraints

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

Nuclear power plants have limited flexibility, so definitions of hourly ramp-up and ramp-down rates are essential to model them accurately. Equations (3.16) and (3.17) limit the power production of nuclear power plants with these ramping constraints:

$$G_{nuc,h+1} + RSV_{nuc,h+1} \leq G_{nuc,h} + r_{nuc}^{up} \times Q_{nuc} \tag{3.16}$$

$$G_{nuc,h+1} \geq G_{nuc,h}(1 - r_{nuc}^{down}) \tag{3.17}$$

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

The nuclear power plants' capacity factor should also be limited by safety and maintenance constraints. Equation (3.18) quantifies this limitation:

$$\sum_h G_{nuc,h} \leq Q_{nuc} \times cf_{nuc} \times 8760 \tag{3.18}$$

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

3.2.1.8. Storage-related constraints

$$STORED_{str,0} = STORED_{str,8759} + (STORAGE_{str,8759} \times \eta_{str}^{in}) - (\frac{G_{str,8759}}{\eta_{str}^{out}}) \tag{3.19}$$

$$STORED_{str,h} \leq VOLUME_{str} \tag{3.20}$$

$$STORED_{str,h} \leq S_{str} \leq Q_{str} \tag{3.21}$$

Methanation is constrained by available green CO_2. In EOLES_elec, the only considered green CO_2 is the byproduct of anaerobic digestion, therefore methanation is limited by the available biogas from anaerobic digestion. Equation (3.22) applies this constraint;

$$\sum_h G_{methanation1,h}/\eta^{OCGT} + \sum_h G_{methanation2,h}/\eta^{CCGT-CCS} \leq \gamma_{methanation}^{CO_2} \times e_{total,biogas}^{max}$$

(3.22)

Where $\mathrm{G_{methanation1,h}}$ and $\mathrm{G_{methanation2,h}}$ are hourlypower production from methanation without and with carbon capture and storage respectively and η^{OCGT} and $\eta^{\mathrm{CCGT-CCS}}$ are the efficiencies of OCGT and CCGT with CCS power plants , $\gamma_{\mathrm{methanation}}^{\mathrm{CO_2}}$ is the molar ratio of CO_2 to CH_4 in the methanization process, and $\mathrm{e_{total,biogas}^{max}}$ is the total annual biogas production from methanization.

3.2.2. Input parameters

3.2.2.1. VRE profiles

All the VRE profiles are the same as in Chapter 2.

3.2.2.2. Electricity demand profile

Hourly electricity demand profile is taken from ADEME's central demand scenario for 2050 (ADEME, 2015), same as in Chapter 2.

3.2.2.3. Limiting capacity and power production constraints

As in Chapter 2, I use the maximal capacities of VRE technologies from ADEME (2018), the maximal and existing hydro-electricity capacities from ADEME (2015), and the run-of-river and lake-generated hydro-electricity profiles from RTE's (the French transmission network operator) online portal for year 2016[1].

3.2.2.4. Economic parameters

Table 3.1 summarizes the economic parameters (and their sources) used as input data in the EOLES_elec model. Although most of the technologies are the same as in Chapter 2, in this chapter, I take into account the impact of construction period in the annualized costs, since nuclear power has a long construction time, leading to higher financial costs.

Construction time is the period between the date of the first expenditure on public works and the last day of construction and tests, when the plant starts operation; local authority permit processes and the preliminary business studies are, therefore, not included in this period.

It should be noted that the annuity includes the interest during construction (IDC) relating to the construction time, and the decommissioning cost for nuclear power plants. The construction time for nuclear power plants can be as little as seven years, while the three projects at Olkiluoto in Finland, Hinkley Point C in the UK and Flamanville 3 in France show much longer construction times. According to NEA (2018), an average construction time of 10 years can be considered for new nuclear power plants. The same report provides a labor-during-construction profile: the annual construction expenditure has been calculated assuming expenditure to be proportional to labor each year. Using the formula provided by the GEN IV international forum (2007), the interest during construction can be calculated using Equation (3.23):

$$IDC = \sum_{j=1}^{ct} C_j[(1+r)^{t_{op}-j} - 1] \tag{3.23}$$

Where IDC is the interest during construction, C_j is the money spent during year j of construction, ct is the construction time and t_{op} is the year the power plant starts operating. Solving this equation leads to IDC=€1,078/kW. According to the same GEN IV study, decommissioning of a nuclear power plant accounts for 10% of the overnight costs. Including these interest-during-

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

construction and decommissioning costs, the final investment cost is found to be €5,311/kW, which is the value used to calculate the annuity.

Table 3.1. Economic parameters of power production technologies

Technology	**Overnight costs (€/kW$_e$)**	**Lifetime (years)**	**Annuity (€/kW$_e$/year)**	**Fixed O&M (€/kW$_e$/year)**	**Variable O&M (€/MWh$_e$)**	**Construction time (years)**	**Efficiency (%)**	**Source**
Offshore wind farm	2,330	30	150.9	47	0	1	-	JRC (2017)
Onshore wind farm	1,130	25	81.2	34.5	0	1	-	JRC (2017)
Solar PV	423	25	30.7	9.2	0	0.5	-	JRC (2017)
Hydroelectricity – lake and reservoir	2,275	60	115.2	11.4	0	1	-	JRC (2017)
Hydroelectricity – run-of-river	2,970	60	150.4	14.9	0	1	-	JRC (2017)
Biogas (Anaerobic digestion)	2,510	25	141.6	83.9	3.1	1	-	JRC (2017)
Natural gas	-	-	-	-	50/61**	-	-	IEA (2018)
Nuclear power	3,750	60	262.6	97.5	9.5***	10	38%	JRC (2014)
CCGT with CCS	1,280	30	82.1	32	18****	1	55%	JRC (2017)
OCGT	550	30	35.3	16.5	-	1	45%	JRC (2014)

+The LCOE of each technology is an output of the model since the capacity factor of each non-vre technology is chosen endogenously in the EOLES_elec model. But to have an initial idea about the unit cost of electricity, I used estimated capacity factors of 80% for nuclear power, 15% for the OCGT and 60% for CCGT power plants.
*€84/MWh$_e$ for CCGT power plants with 55% efficiency, and €103/MWh for OCGT power plants with 45% efficiency.
**€50/MWh$_e$ for CCGT power plants with 55% efficiency, and €61/MWh for OCGT power plants with 45% efficiency (accounting for $9/MBtu, projected for Europe for the year 2040 by the IEA in the World Energy Outlook 2018).
***This variable cost accounts for €2.5/MWh$_e$ of fuel cost and €7/MWh of other variable costs, excluding waste management and insurance costs.
****This variable cost accounts for a 500km CO_2 transport pipeline (in €/tCO_2) and offshore storage costs estimated by Rubin et al. (2015).

Table 3.2 shows the economic parameters of power storage technologies.

Table 3.2. Economic parameters of storage technologies

Technology	**Overnight costs (€/kW$_e$)**	**CAPEX (€/kWh$_e$)**	**Lifetime (years)**	**Annuity (€/kW$_e$/year)**	**Fixed O&M (€/kW$_e$/year)**	**Variable O&M (€/MWh$_e$)**	**Storage annuity (€/kWh$_e$/year)**	**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 (Li-Ion)	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%	ENEA (2016)

The construction time for storage options is considered as one year for both PHS and methanation and 6 months for battery storage. It is worth mentioning that OCGT and CCGT with CCS power plants are technologies using natural gas, biogas and renewable methane (from power-to-gas) as fuel; therefore, the full cost of electricity generated through these technologies is the sum of the combustion technology cost and the used fuel cost.

3.2.2.5. Model parametrization

Equations (3.13), (3.14), (3.16), (3.17) and (3.18) need technology-related input parameters. These parameters such as ramp rate, annual maximal capacity factor (availability limits due to maintenance) and efficiencies of different processes need to be introduced into the model. Similarly, equation (3.5), the reserve requirement definition, consists of several input parameters relating the required secondary reserves to installed capacities of VRE technologies and hourly demand profiles. Natural gas with CCS is not a zero-emission technology and according to JRC (2014), it captures only 86% of the carbon dioxide produced by the combustion, thus leaving residual emissions. The values of these input parameters, as well as their sources are presented in Table 3.3.

Table 3.3. Technical parameters of the model

parameter	definition	value	source
$\boldsymbol{cf_{ocgt}}$	Annual maximal capacity factor of OCGT	90%	JRC (2014)
$\boldsymbol{cf_{ccgt}}$	Annual maximal capacity factor of CCGT	85%	JRC (2014)
$\boldsymbol{cf_{nuc}}$	Annual maximal capacity factor of nuclear plants	90%	JRC (2017)
$\boldsymbol{r_{nuc}^{up}}$	Hourly ramping up rate of nuclear plants	25%	NEA (2011)
$\boldsymbol{r_{nuc}^{down}}$	Hourly ramping down rate of nuclear plants	25%	NEA (2011)
$\boldsymbol{\varepsilon_{offshore}}$	Additional FRR requirement for offshore wind	0.027	Perrier (2018)
$\boldsymbol{\varepsilon_{onshore}}$	Additional FRR requirement for onshore wind	0.027	Perrier (2018)
$\boldsymbol{\varepsilon_{PV}}$	Additional FRR requirement for solar PV	0.038	Perrier (2018)
$\boldsymbol{\delta_{variation}^{load}}$	Load variation factor	0.1	Van Stiphout et al.(2017)
$\boldsymbol{\delta_{uncertainty}^{load}}$	Load uncertainty because of demand forecast error	0.01	Van Stiphout et al.(2017)
$\boldsymbol{\eta_{ccgt-ccs}}$	The capture efficiency of CCS	86%	JRC (2014)
$\boldsymbol{\gamma_{methanation}^{CO_2}}$	The relative share of CO_2 to methane in methanization process	3/7	ADEME (2018b)
$\boldsymbol{e_{total,biogas}^{max}}$	Total biogas from methanization projected for France for 2050	152TWh	ADEME (2018b)

Equations (3.8), (3.9), (3.12) and (3.15) also have some input parameters with respect to the chosen country. These parameters are the maximal available energy from the constrained technologies, maximum available capacities and hourly and monthly profiles of hydro-electricity technologies. In this chapter I study the French power sector, therefore I use the values provided for France. Table 3.4 summarizes these values and their resources.

Table 3.4. Country-specific limiting input parameters of model

parameter	definition	value	source
$\boldsymbol{lake_m}$*	Monthly maximum electricity from dams & reservoirs	See GitHub[1]	RTE (2016)
$\boldsymbol{river_h}$**	Hourly maximal power production from run-of-river	See GitHub[2]	RTE (2016)
$\boldsymbol{e_{biogas}^{max}}$	Annual maximal power production from Biogas	15TWh	ADEME (2013)
$\boldsymbol{q_{tec}^{max}}$	Maximum installable capacity limit for each technology	See GitHub[3]	ADEME (2018)

* This parameter is calculated by summing hourly power production from this hydroelectric energy resource over each month of the year to capture the meteorological variation of hydroelectricity, using the online portal of RTE[4] (the French transmission network operator). ** Hourly run-of-river power production data from the RTE online portal has been used to prepare the hourly capacity factor profile of this energy resource.

3.2.2.6. Choice of discount rate

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

$$annuity_{tec} = \frac{DR \times CAPEX_{tec}((DR \times ct_{tec})+1)}{1-(1+DR)^{-lt_{tec}}} \tag{3.24}$$

Where DR is the discount rate, ct_{tec} is the construction time, lt_{tec} is the technical lifetime and $annuity_{tec}$ is the annualized investment of the technology tec. Appendix 3.3 provides a sensitivity analysis, varying this rate from 2% to 7%.

3.2.3. Studied scenarios

Following Chapter 2, I use 2006 as the weather year for the hourly capacity factor profiles of VRE technologies. I run the EOLES_elec model for 126 cost scenarios: 6 social cost of carbon scenarios, from 0 to €500/tCO_2 in steps of €100/tCO_2, 7 nuclear power cost scenarios and 3 VRE cost scenarios. For nuclear power, the central scenario is €3,750/kW, ranging from €3,000/kW to €4,500/kW in steps of 250€/kW. VRE cost scenarios are labeled low cost (offshore wind: €1,747.5/kW, onshore wind: €847.5/kW and solar PV: €318/kW), central cost (offshore wind: €2,330/kW, onshore wind: €1,130/kW and solar PV: €423.3/kW) and high cost (offshore wind: €2,912.5/kW, onshore wind: €1,412.5/kW and solar PV: €530/kW), where the variation from the central cost scenario is 25%.

The choice of central scenarios has been made from the cost resources (Tables 3.1 and 3.2), while the 25% variation for VRE resources is taken from the expert elicitation survey by Wiser et al. (2016). The cost variation boundaries for nuclear power plants are based on simulations, where the highest cost scenario for this technology is chosen as the scenario where the optimization for central VRE cost scenario and any SCC scenario leads to zero installed capacity of this technology. To retain symmetry, the same relative variation is applied for the lowest cost scenario for nuclear power. The size of the step (6.66%) is chosen because of the high sensitivity of the optimal mix to the cost variation of this technology. The SCC values are based on the official 'value for climate action' social

[1] https://github.com/BehrangShirizadeh/EOLES_elec/blob/master/lake_inflows.csv
[2] https://github.com/BehrangShirizadeh/EOLES_elec/blob/master/run_of_river.csv
[3] https://github.com/BehrangShirizadeh/EOLES_elec/blob/master/max_capas.csv
[4] https://www.rte-france.com/fr/eco2mix/eco2mix-telechargement

cost of carbon introduced by Quinet et al. (2019) for France for 2050, (between €600/tCO_2 and €900/tCO_2), but the results presented are for a maximum €500/tCO_2 SCC, since no particular change has been observed for higher values.

3.3. Results

3.3.1. Central cost scenario

3.3.1.1. Power mix

Figure 3.2 shows the annual power production of each technology for central VRE and nuclear power cost scenarios. Whatever the SCC scenario, approximately 75% of the electricity is generated by renewable energy resources. The remaining 25% is shared between nuclear power and natural gas, with or without carbon capture and storage technologies. For low SCC scenarios, nuclear power accounts for only 10% of annual electricity production, while for high social cost of carbon, the whole remaining 25% is produced by nuclear power.

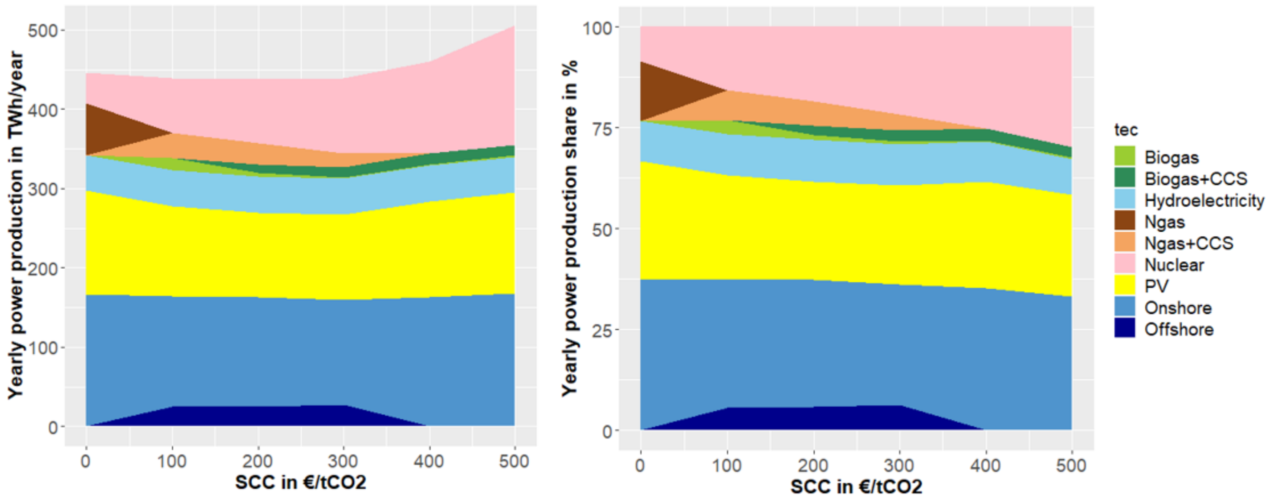

Figure 3.2. Optimal power mix for central VRE and nuclear power cost scenarios with respect to different SCC scenarios for the studied time horizon (2050)

Figure 3.3 shows the annual power production from storage options for each social cost of carbon scenario. As we saw from Figure 3.2, natural gas without CCS exists only for the zero SCC scenario, and once the social cost of carbon is €100/tCO_2 or more, natural gas without CCS is abandoned and replaced by natural gas with CCS and by bio-energies. Because of residual emissions, for high SCCs (€400/tCO_2 and more), natural gas with CCS is also eliminated. One can observe from Figure 3.3 that natural gas with CCS is also abandoned and replaced by the supply chain decarbonized electricity-methanation-CCGT with CCS from a social cost of carbon of €400/tCO_2 upwards.

The installed capacities of each technology and a summary of the main model outputs (such as overall cost and load curtailment) for different SCC scenarios are presented in Appendix 3.1 (Tables A3.1, A3.2 and A3.3). Appendix 3.6 shows that the wind and solar installed capacities stay well below the potential figures identified for France.

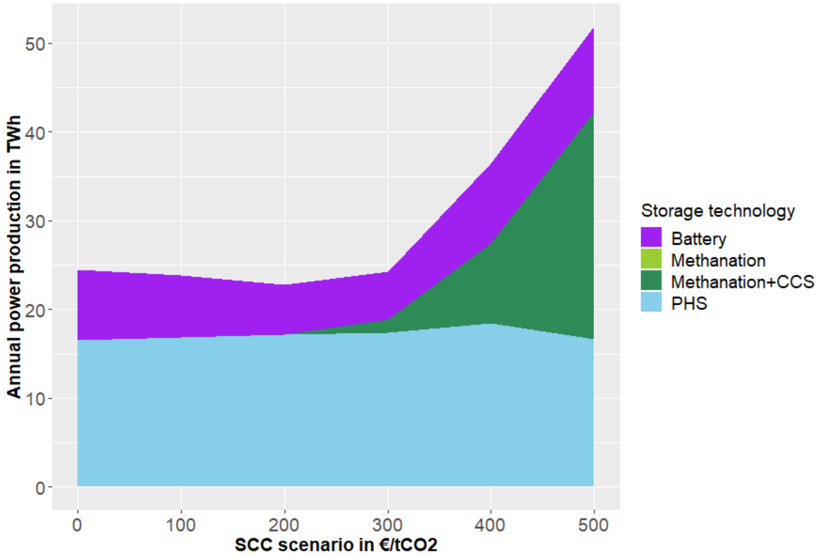

Figure 3.3. Annual power production by storage technology for the central VRE and nuclear power cost scenario for the considered time horizon (2050)

3.3.1.2. CO_2 Emissions

The relationship between the social cost of carbon and the system's overall CO_2 emissions is presented in Figure 3.4. The power system becomes nearly carbon neutral for €100/tCO_2 and for €200/tCO_2 and above, emissions fall below zero. These negative emissions increase with the SCC, and at €500/tCO_2 the power system captures 12MtCO_2/year.

One of the main hurdles to the deployment of CCS is the availability of enough safe storage sites. Hence Figure 3.4 presents the amount of captured CO_2 (from both fossil fuels and biomass), which gives a useful insight into the CO_2 storage required for each year.

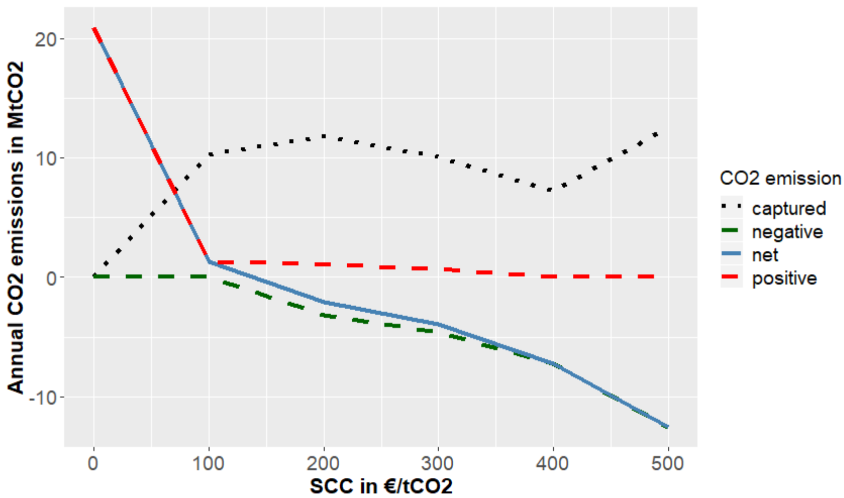

Figure 3.4. Annual positive, negative and net (net = positive – negative) CO_2 emissions and CO_2 captured by CCS technologies in MtCO_2/year for different SCC scenarios, for central VRE and nuclear power cost scenarios for 2050

3.3.1.3. Cost and revenues

We can define two different system cost definitions: the technical cost (Eq. (3.1) excluding the last part) and the cost including the social cost of carbon, i.e. the whole of Eq. (3.1). In a decentralized equilibrium, the gap between these two costs would include the remuneration earned by negative CO_2-emitting plant operators and the tax paid by CO_2-emitting plant operators. Figure 3.5 shows these two costs for different SCC scenarios, for the central nuclear power and VRE cost scenarios. At €200/tCO_2 of SCC and more, these costs diverge significantly, and for €500/tCO_2, this gap reaches around €6bn/year i.e. around 20% of the technical cost.

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

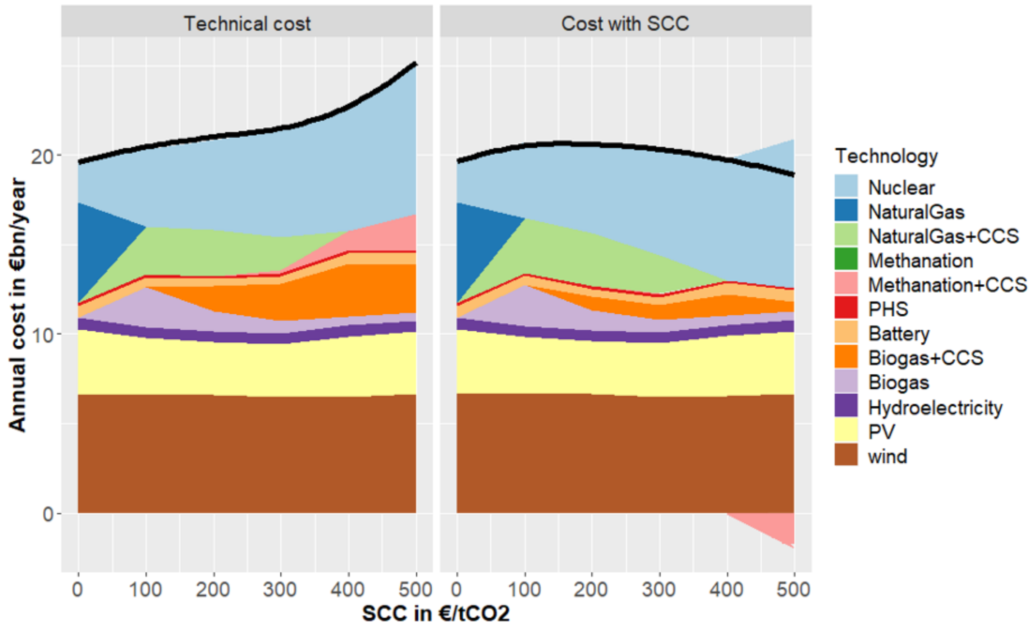

Figure 3.5. Annual technical cost and cost with social cost of carbon for central VRE and nuclear power cost scenarios, split by technology, for different SCC scenarios for 2050

This large difference between the technical cost and the cost including the social cost of carbon raises another question: what is the proportion of CO_2-related revenues from CCS technologies in the overall revenues of the operators of technologies that include CCS? To answer this question, I calculated the annual revenues from the electricity 'market' for each CCS technology and then the revenue (or expenditure) relating to negative (or positive) emissions. Figure 3.6 shows the revenues for each technology with CCS, from each of these two 'markets'.

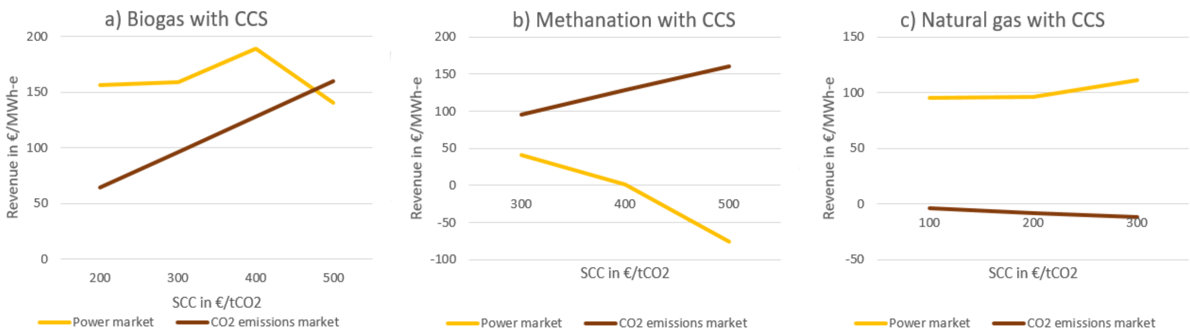

Figure 3.6. Proportion of revenues from electricity market and CO_2 emissions market for each technology with CCS, for central nuclear power and VRE cost scenarios for the considered time horizon (2050)

The electricity 'market' price is calculated from the dual of the adequacy equation (Eq. 3.2). This hourly dual can be interpreted as the wholesale electricity price at each hour[1]. The overall market revenues for each technology can be calculated by using this dual and the amount of electricity sold at each hour. For the storage technologies, money spent on buying electricity when the storage technologies are in the charging phase are deducted from the revenues. For the fuel technologies (biogas, natural gas and methanation), the revenues come from the gas market, whose price can be found using the dual of the combustion equations (Equations 3.10 and 3.11).

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

3.3.1.4. Social acceptability of onshore wind power

To study the importance of social acceptability of onshore wind power, I define an alternative limited social acceptability scenario for the onshore wind power with a maximal capacity limit of 34GW (i.e. twice the existing fleet).

Comparison of Figures 3.7 and 3.2 shows that while the power production by onshore wind decreases, an increase in the power production by offshore wind power keeps the wind power share higher than 25%. This slight decrease in the share of wind power in the overall power production leads to a slight increase in the share of nuclear power in the final electricity mix, but renewables still dominate the power sector and the share of nuclear power never surpasses 30% of the electricity production.

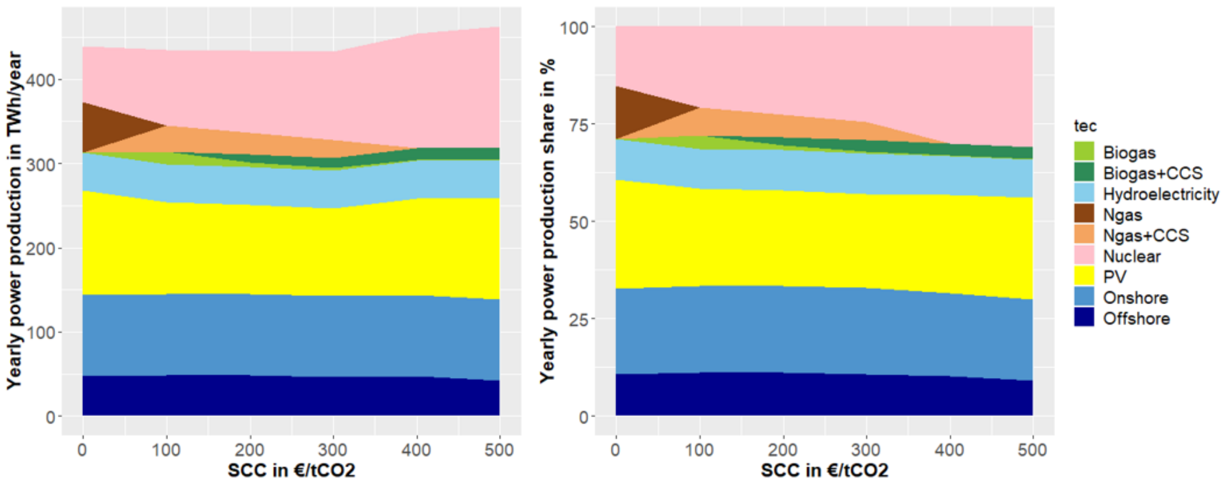

Figure 3.7. Electricity mix in TWh and in percentage share for the low social acceptability of onshore wind scenario as function of SCC for 2050

[1] The dual of adequacy equation is equal to the derivative of objective variable on the adequacy equation's main parameter, thus hourly electricity demand: $p_h = \frac{\partial C}{\partial d_h}$; where p_h is hourly electricity market price, C is the overall cost and d_h is the hourly electricity demand.

For every SCC scenario, we observed a negligible difference in system cost (less than 1% nearly for all SCC scenarios). The difference in CO_2 emissions is also lower than 2 Mt CO_2/year, except for an SCC of €500/tCO_2: 4.7 Mt CO_2/year. The main characteristics of this scenario can be found in Appendix 3.2.

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

In this section, I study the importance of the nuclear power and the carbon capture and storage technologies, by removing first each of them separately, then both at once. This part of the study has only been performed for the central VRE and nuclear power cost scenarios. Figure 3.8 shows the system-wide Levelized Cost of Electricity (LCOE), i.e. the average system cost per unit power production, for each SCC scenario and for 4 different technology availability cases: a) with all technologies, b) without nuclear power, c) without CCS and d) with neither nuclear power nor CCS. The cost considered here includes the social cost of carbon.

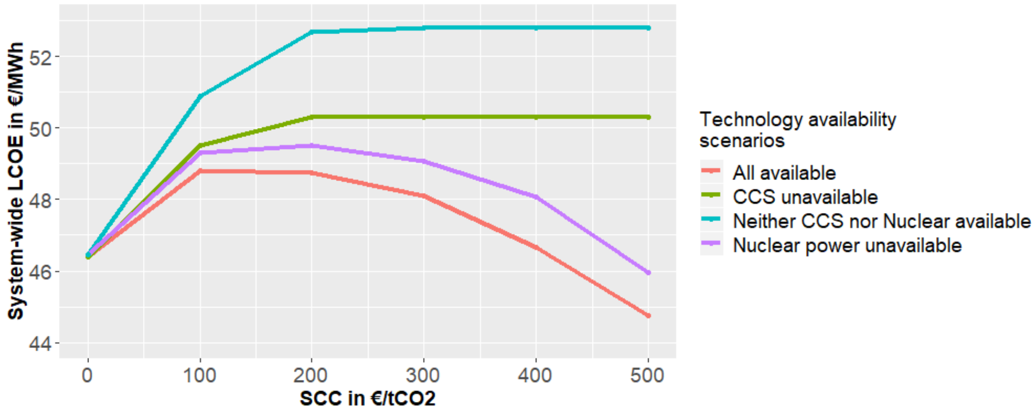

Figure 3.8. System-wide LCOE of the system for different technology availability scenarios, for central VRE and nuclear power cost scenario and different SCC scenarios for 2050

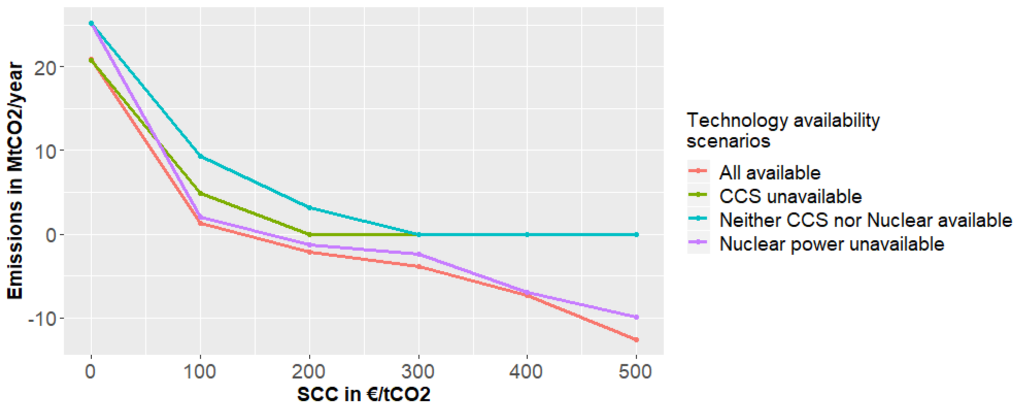

Figure 3.9. Annual CO_2 emission of power system for central VRE and nuclear power cost scenario, and different availability and SCC scenarios for 2050

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

The sensitivity of CO_2 emissions to the availability of technologies is presented in Figure 3.9. As shown previously, a nearly carbon-neutral power system can be reached for an SCC of €100/tCO_2, but this happens only if CCS is available. If CCS is available, an SCC of €200/tCO_2 will result in negative emissions, while for the same SCC, the system with none of the technologies discussed above will not even reach carbon neutrality. To sum up, the system cost and emissions are more sensitive to the availability of CCS than to that of nuclear power.

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

Figure 3.10 shows the proportion of power produced by each technology. The proportions of renewables and nuclear are inversely related to their relative cost. Even for the most expensive VRE and cheapest nuclear scenario, nuclear power does not exceed 75% of the power mix. Conversely, for the low cost VRE scenario, it provides less than 15% of power production, and for most of the nuclear power cost scenarios (including the central one), nuclear power does not even enter the optimal power mix. On the other hand, the proportion of RES in power production almost never drops below 25%, while it can reach 100%.

While increasing the SCC leads to lower and even negative emissions, if decentralized in the form of public subsidies for negative emissions it also leads to a significant cost to the public purse. Figure 3.11 shows the annualized technical cost and the cost with the social cost of carbon. As we saw in Figure 3.5, for high SCC scenarios the gap between these two costs is large. The implied transfer can go up to €10.5bn/year for the low VRE cost and high SCC (€500/tCO_2) scenario, which also leads to higher negative emissions (approximately -22MtCO_2/year).

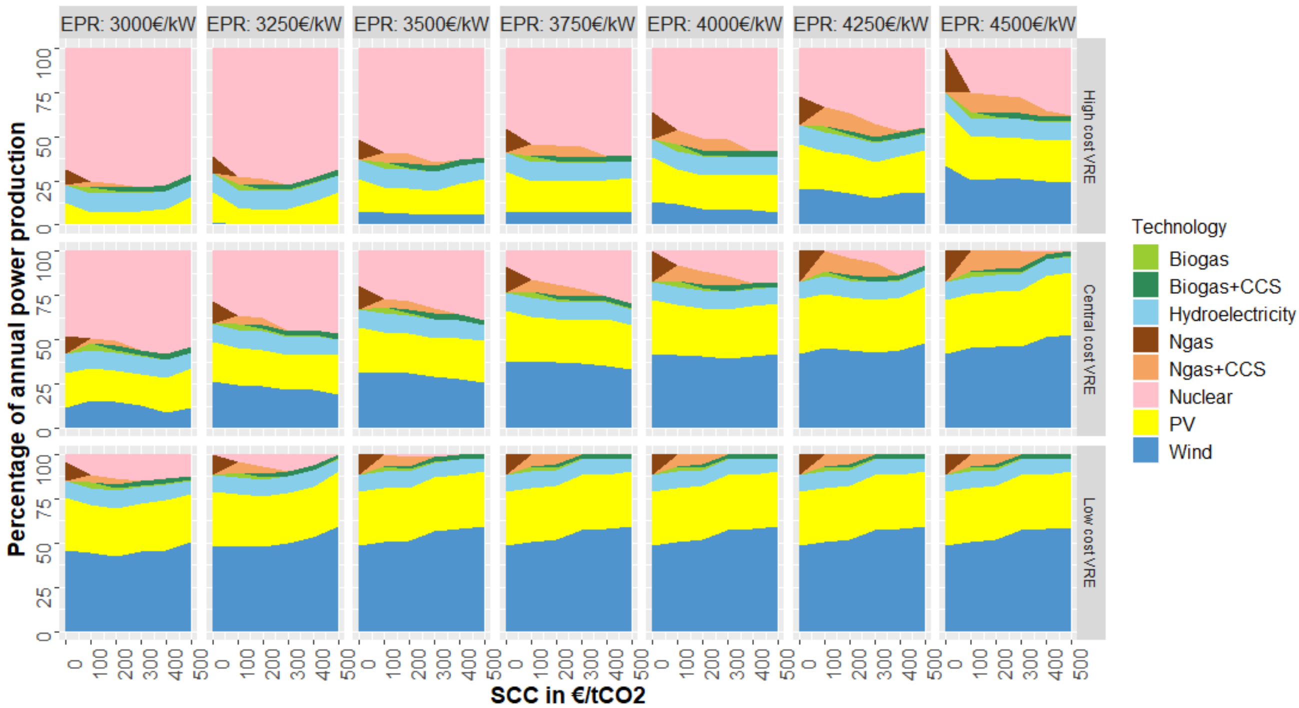

Figure 3.10. Annual percentage of power production for each technology for different VRE and nuclear power cost and SCC scenarios for 2050

As argued in Subsection 3.3.1.2, the overall CO_2 emission gives helpful insights about the overall CO_2 balance, and the real carbon impact of the power system, but the required storage volume depends on the overall captured CO_2. Figure 3.12 shows the annual CO_2 emissions and annual captured CO_2 by CCS options for different VRE and nuclear power cost scenarios and different SCCs.

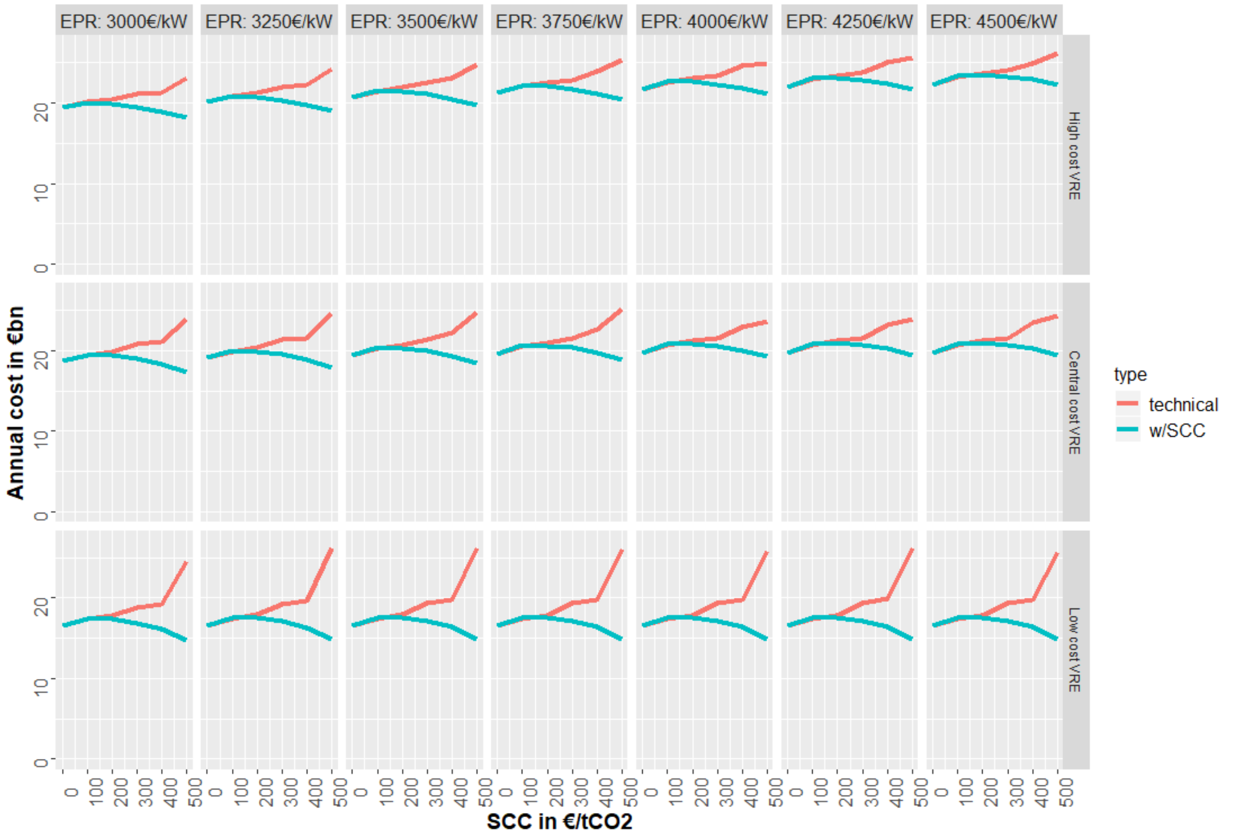

Figure 3.11. Annualized technical cost and cost with social cost of carbon (including SCC) for different VRE and nuclear power cost and SCC scenarios for 2050

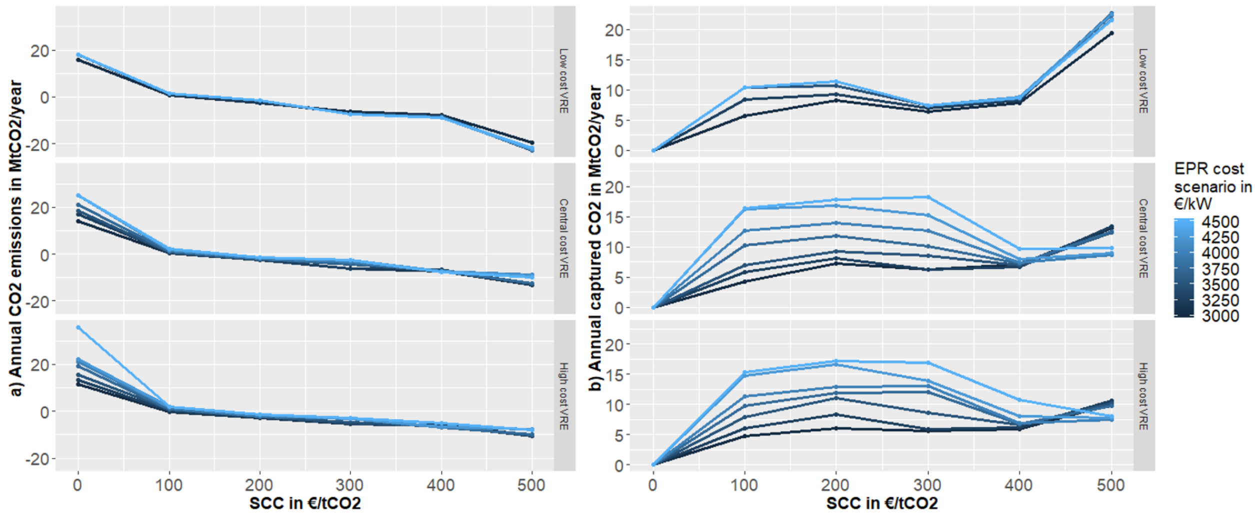

Figure 3.12. Overall a) annual net CO_2 emissions and b) annual captured CO_2 by CCS options for different VRE and nuclear power cost and SCC scenarios for 2050

Varying these cost scenarios can make a big difference to the amount of CO_2 captured. While for high and central VRE cost scenarios, the required storage does not exceed 18MtCO_2/year, the low

VRE cost scenario leads to a storage capacity in excess of 20MtCO_2/year for €500/tCO_2 of SCC. The reason for this surge in negative emissions is the increased proportion of VRE technologies in the final electricity mix, which leads to an increased use of methanation. Similarly, high cost VRE leads to a high proportion of power production from nuclear power technology (60 to 75% of power production), which entails much less need for dispatchable options such as combustible technologies, which eventually capture more CO_2 for high SCC scenarios.

3.3.3. Importance of reduction in electricity demand

In these two first chapters of thesis, I use ADEME's central electricity demand hourly profile for 2050 (ADEME, 2015). This demand accounts for 422TWh$_e$/year, which is equivalent of the EFF (efficiency) scenario of the four main demand scenarios proposed in the French national energy transition debate (DNTE, 2013). The other scenarios are DIV (divergence – 534TWh$_e$/year), SOB (sobriety – 280TWh$_e$/year) and DEC (decarbonization – 651TWh$_e$/year). To study the importance of reducing the electricity consumption, I ran the EOLES_elec model for two alternative demand scenarios: SOB (low demand) and DIV (high demand). Figure 3.13 shows the emission and system-wide LCOE of the power system for different SCC values and different demand levels.

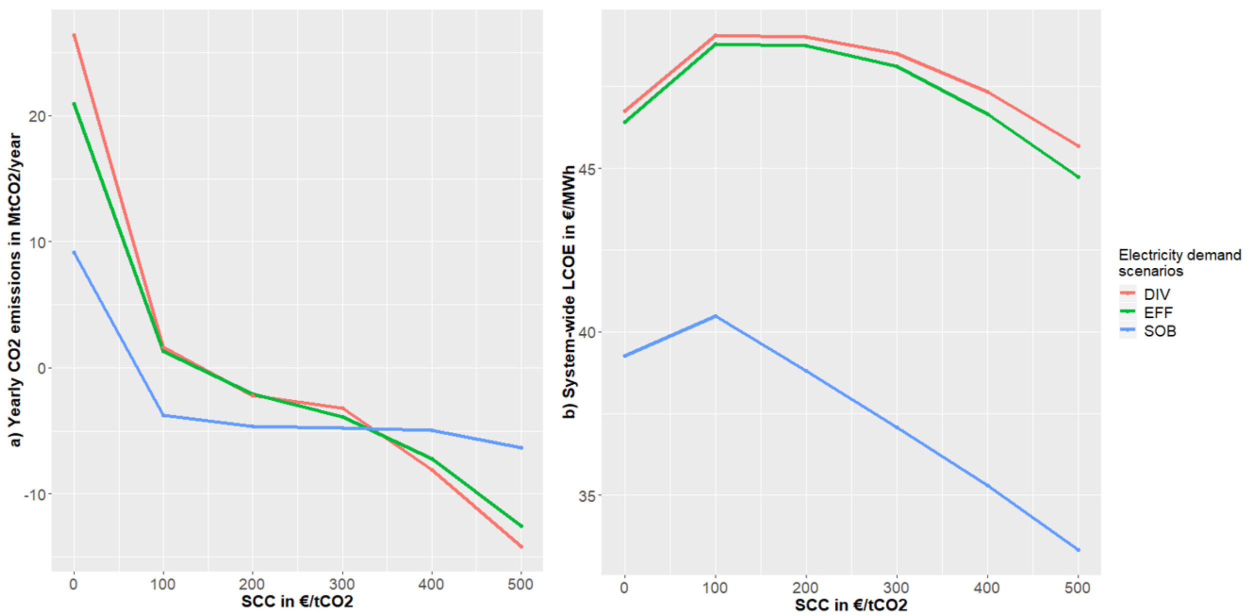

Figure 3.13. Impact of the electricity demand scenario on a) net CO_2 emissions and b) the system-wide levelized cost of electricity (including the social cost of carbon) for 2050

A low electricity demand leads to negative emissions for low SCC values (even 100€/tCO_2), but for a very high SCC, the amount of negative emissions decreases with electricity demand. Similarly, demand reduction does not only lower the total system cost (which is obvious) but also the system-wide LCOE, i.e. the cost per MWh$_e$ consumed. The latter result stems mostly from the capacity and production constraints to hydro and biogas, which become less stringent (in percentage of electricity demand) under a lower electricity demand.

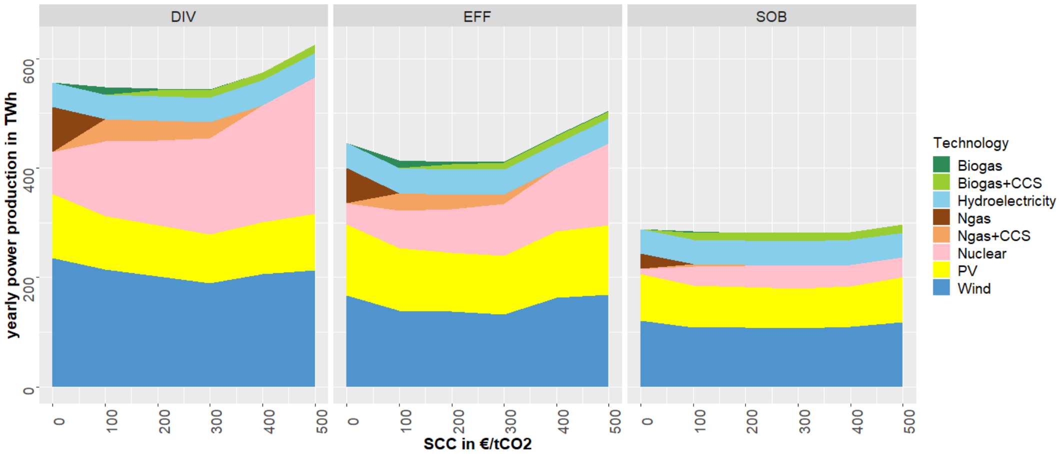

Figure 3.14. Electricity mix for alternative demand scenario as a function of social cost of carbon

Figure 3.14 shows the electricity mix for the central cost scenario, six SCC scenarios and three different electricity demand scenarios. A steep increase in the nuclear power share in the electricity mix is observed by increasing electricity demand (DIV). On the opposite, for a low electricity demand (SOB), nuclear power does not contribute significantly to electricity production and the use of fossil natural gas is massively reduced. Therefore, under a low demand scenario, the electricity mix is massively renewable (>90%) whatever the SSC.

3.4. Discussion

3.4.1. Comparison with existing studies for France

According to the findings of this chapter, for moderate SCCs (€200/tCO_2 and less), the system-wide LCOE will be between €46/MWh$_e$ and €50/MWh$_e$, depending on the availability of nuclear power and CCS technologies. If none is available, even for a very high social cost of carbon, this value will be less than €53/MWh$_e$. According to the latest quarterly report from the French energy regulator (CRE, 2019), 35% of a typical electricity bill (varying between €170/MWh$_e$ and €200/MWh$_e$ depending on the tariff chosen and consumption profile) represents electricity production, which costs between €59-€70/MWh$_e$. Therefore, even for high SCC scenarios, the power production side (including storage, grid connection and secondary reserve requirements) is estimated to cost less than today.

These results contrast with those of Krakowski et al. (2016), where the least costly scenario for France is presented as being "business as usual", and increasing the proportion of RES gradually increases the annualized cost of the power system by approximately 20% for an electricity mix with 80% of RES (€40bn/year). The main reasons for this difference are the ones explained in Chapter 2.

In a European-wide study Schlachtberger et al. (2018) find an annualized system cost that is very close to the results of EOLES_elec (€20bn to €25bn depending on the wind availability scenario) for France, and in a further similarity to the previous chapter (a fully renewable power system) they observe considerable robustness of total system cost to the weather data and cost assumptions, but they find a higher proportion of power production by onshore wind. This difference in the installed capacity comes from small differences in the relative cost of technologies (the relative cost of onshore wind to offshore wind and solar PV is lower in Schlachtberger's study) and their exclusion of nuclear power, renewable gas and negative emissions technologies. Another difference that leads to a higher share of wind power in the final energy mix is the difference in the discount rate (4.5% vs. 7%), the impact of the discount rate in the final energy mix is studied and presented in Appendix 3.3. The results confirm that a higher discount rate leads to a higher wind installed capacity.

According to another European-wide study (Brouwer et al, 2016), increasing the proportion of renewables in the final electricity mix from 40% to 80% raises the total system cost, even in the presence of demand response. The average system cost (average LCOE) is approximately €91/MWh_e for the case of 80% RES. This big difference in results can be explained by (i) the difference in the chosen future cost projections, where they use IEA's world energy investment outlook study (IEA, 2014), carried out in 2012, and projected for 2035, while since 2012 we have seen a very big cost decrease in solar PV and storage technologies, (ii) the non-negligible higher annual power demand (547TWh/year vs. 423TWh/year), (iii) a low calculated capacity factor for wind power (25% vs. 32.5%) which is also weakly correlated with the historical data (86% correlation), (iv) the choice of 2013 as the weather data year without studying the importance of this choice (in this chapter the chosen representative weather year is 2006, which results from a correlation study with a 19-year weather data simulation), and finally (v) the methodological difference in the calculation, where they use a two-stage procedure, first optimizing the installed capacity before optimizing the dispatch, while the EOLES_elec model optimizes dispatch and investment simultaneously.

In their study of the French power sector, Petitet et al. (2016) find an LCOE of €90/MWh_e for wind power and show that for a carbon price of less than €65/tCO_2 wind power is competitive with neither coal nor CCGT power plants. They also show that in the case of considering the existing nuclear power plants of France, for carbon prices below €150/tCO_2, wind power does not become economically competitive enough to enter the energy mix, while in the current article, we observe a very high proportion of RES, as shown in Subsection 3.3.2. This big difference from our results comes from (i) not considering any storage options, (ii) using very different cost projection data (IEA and NEA's 2010 cost projections for electricity generation), (iii) the absence of negative emission technology options and (iv) considering onshore wind power as the only renewable source, moreover with a very low capacity factor (21.6% vs. 32.5%), based on the observation of the wind turbines installed at this time, which are much less efficient than state-of-the-art turbines (Hirth et al, 2016).

Several studies by ADEME focus on power mix planning for France. Among them, the "*100% renewable power mix"* study (ADEME, 2015), and "*electricity mix development trajectories 2020-2060"* (ADEME, 2018) explicitly optimize the power system and study the role of renewables in the French energy transition. The findings of chapter 2 (fully renewable power mix study) were very close to those of these two studies. But other options, especially CCS, may play an important role in cost reduction and reaching zero/negative emissions. Comparing the findings of this chapter with ADEME's results, I highlight the importance of negative emission technologies.

To sum up, the main drivers of the different results from different studies are the assumptions about the cost components, availability of different technologies and the limiting constraints. More recent studies with up-to-date cost projections conclude with higher proportions of VRE in the final optimal electricity mix. Similarly, introduction of more precise weather data, as well as flexibility options and simultaneous optimization of dispatch and investment (which takes into account variable costs in the total cost minimization objective) can overcome the underestimation of the proportion of VRE in the power mix.

Finally, interconnections with neighboring countries, which are not included in our model, can significantly reduce the cost of a highly renewable system (Annan-Phan and Roques, 2018) because it allows benefitting from the differences in climatic and weather conditions between the countries concerned.

3.4.2. CO_2 emissions and storage capacity

For a social cost of carbon of €100/tCO_2 and more, the CO_2 emissions are expected to be either zero or negative. Without any SCC, the CO_2 emission is approximately 20MtCO_2/year, which can be translated as 50kgCO_2/MWh_e. This figure is even higher for the expensive VRE and nuclear power cost scenarios. According to RTE's online portal (eco2mix)[1] the average emission rate of power production in France in 2018 was 60kgCO_2/MWh_e. Thus, in the absence of an SCC, the carbon dioxide emissions from the power sector would not decrease.

According to the IPCC (2005) special report on carbon capture and storage, the worldwide carbon dioxide storage capacity in saline formations is between 1,000GtCO_2 and 10,000GtCO_2 and the main onshore CO_2 storage option for France is considered to be these saline formations. Kearns et al. (2017) estimate 8,000 to 55,000GtCO_2 of worldwide geological (onshore) CO_2 storage capacity. Fuss et al. (2018) find the global carbon storage potential to be between 320GtCO_2 and 50,000GtCO_2, where the global estimates for aquifers is estimated at between 200GtCO_2 and 50,000GtCO_2. According to the *"Feasibility study for Europe-wide CO_2 infrastructure"* by the European commission (EC Directorate-General Energy, 2010), France is one of the few European countries having abundant carbon storage capacity for its own domestic production (more than 50 years of potential storage), and its total CO_2 storage capacity is estimated between 6GtCO_2 and 26GtCO_2. Yet according to CCFN (The Franco-Norwegian Chamber of Commerce)[2] *"(1) Onshore CO_2 storage in France, even if possible, could face strong social acceptance issues, (2) Up to 17-20 MtCO_2/year could be sent by ship from France (Le Havre and Dunkerque clusters mainly) to the North Sea for storage or CO_2 Enhanced Oil Recovery, (3) In the longer term, an additional 20 MtCO_2/year capacity pipeline could be laid parallel to the NorFra gas pipeline from a hub in Dunkerque"*. Hence, although the need for annual CO_2 storage is lower than these upper limits, French access to the North Sea and the availability of internal onshore storage still remain open questions.

I considered an upper limit of 15TWh_e/year for biogas from anaerobic digestion which is fully exploited in each SCC scenario equal to and higher than 100€/tCO_2. On the other hand, power-to-gas option of methanation can reach up to 20TWh_e/year for very high SCC scenarios. Therefore, one of the main enablers of a highly renewable zero or negative CO_2-emitting power is the biogas and biomethane injected to the gas network. In this study I did not take into account the methane leakage from gas network but using the existing gas infrastructure for biogas transmission and distribution might lead to methane leakage (Alvarez et al, 2012), eroding all the associated climate benefits (Union of concerned scientists, 2017). Therefore, a future work in analyzing methane leakage and its impact in the climate goals can be a complementary study with this paper.

[1] https://www.rte-france.com/fr/eco2mix/chiffres-cles#chcleco2
[2] https://www.ccfn.no/actualites/n/news/french-norwegian-collaboration-on-carbon-capture-and-storage.html

3.4.3. Funding negative CO_2 emissions

In the case of a decentralized equilibrium, the difference between the technical cost and the cost with SCC requires pricing CO_2 by this amount, which could either be achieved by price instruments (taxes and subsidies) or by a CO_2 market. This market would reach up to €6bn/year for central nuclear power and VRE cost scenarios, and up to €10.5bn/year for the highest SCC scenarios. Considering the power system alone, negative emissions would need to be funded from the public purse, but since decarbonization of other CO_2 emitting sectors such as agriculture, industry and transport is more difficult, negative emissions in the power sector could be funded by taxing (or selling auctioned emission allowances for) the positive emissions from these sectors. In the second French national low carbon strategy report, the residual emissions for France are evaluated to be more than 80MtCO_{2eq}/year, assuming no negative emissions (SNBC, 2018). Negative emissions from the electricity sector could be one of the compensation options to help achieve net zero emissions by 2050.

3.4.4. Policy implications

For the vast majority of the scenarios studied, renewable technologies dominate the energy mix. The proportion of VRE in final electricity production varies from 60% to 70%, and it can go up to 90% for low VRE cost, high SCC scenarios. These findings are in line with the 70% to 85% of renewables in final electricity production obtained by Waisman et al. (2019). Therefore, a fast development scheme for VRE technologies is of key importance in order to come into line with the Paris agreement objectives under the most cost-optimal conditions. Similarly, social acceptability of onshore wind power, as the main contributor to the electricity production, remains an important open question. My findings indicate that limited social acceptability of this technology can lead to significant losses in the negative emission potential of the French power system.

Since EOLES_elec performs a greenfield optimization, I have not included the option to refurbish the existing nuclear reactors. Provided that safety concerns do not preclude such refurbishment; the latter would likely be cheaper than building new nuclear plants. However, in 2050, only seven reactors out of the 56 currently operating in France will be less than 60 years old[1], and the youngest one will be 51 years old (excluding Flamanville III which is still under construction). Intuitively, if those seven existing reactors were included, they would replace the new reactors, presumably without changing the main results, beyond a small decrease in system cost.

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

The projected CO_2 storage capacity, in the order of ~10MtCO_2/year, shows an emerging need for geological storage which might be achieved either by exploiting the available French saline formations or transporting the captured carbon dioxide to the North Sea. Since the literature about the available storage capacity in France is very vague, further research is needed to quantify the

[1] The French nuclear industry does not claim that existing reactors may operate beyond 60 years, even following deep refurbishment.

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

3.5. Conclusion

This chapter examines the cost-optimal low-CO_2 energy mix for the French electricity sector. To that end, I developed the EOLES_elec model, an electricity model from the EOLES family, which includes six renewable technologies, conventional power production technologies (natural gas and nuclear power), natural gas with carbon capture and storage, and negative emission technologies (biogas with CCS and methanation storage with CCS). 126 cost scenarios have been built to assess a wide range of future cost projections for VRE and nuclear power technologies, as well as a wide range of social cost of carbon (SCC) scenarios.

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

Setting an SCC of €100/tCO_2 leads to the effective exploitation of CCS technology, where for most cost scenarios, the power system becomes carbon neutral and an SCC of €200/tCO_2 can be enough for the power system to reach negative emissions thanks to the appearance of BECCS technology in the optimal mix. While increasing SCC leads to an increased need for carbon storage, this required storage capacity does not exceed 20MtCO_2/year. Whether this amount of CO_2 can be stored in the French context remains an open question.

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

Finally, the gap between the cost with and without the social cost of carbon shows an emerging need for a public support scheme for negative emission technologies. This gap also shows the importance of carbon businesses which may emerge in high SCC scenarios, where the main incentive for negative emission technologies will only be to generate negative emissions which can be sold or subsidized, with less incentive to actually produce electricity.

This work could be extended in several directions, for instance, adding the interconnections with the neighboring countries can decrease the overall cost of the power system and help further exploitation of VRE technologies by adding the spatial aggregation possibility as a flexibility option for the intermittent energy sources. Similarly, while in this study the electricity demand is considered as inelastic series of parameters, separating different end-use demands by allowing the different energy carriers to satisfy each end-use demand endogenously would lead to more optimal allocation of supply, vector-change and storage capacities. In ADEME's electricity demand scenario half of the transport sector is electrified, while an optimal allocation of energy vectors for different transport end-use demands using plug-in battery electric vehicles, fuel cell electric vehicles, internal combustion engines with compressed biogas and biodiesel as well as existing conventional transport options might lead to different energy demand for different energy carriers. Inclusion of these flexible demand and interconnection would reinforce the findings of this study.

On the other hand, a highly renewable power system depends highly on the availability of bio-energies injected to the gas network, and in case of methane leakage, all the benefits from using biogas and synthetic gas options can be eroded. Thus, quantifying methane leakage and minimizing it in a narrower study of gas network is an important research question worth special attention.

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Appendices 3

Appendix 3.1. Installed capacities for the central cost scenarios

Table A3.1. Installed capacity of each power production technology in GW for the central VRE and nuclear power cost scenarios

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

Table A3.2. Installed capacity (and energy volume) of each storage technology in GW (and GWh/TWh) for the central VRE and nuclear power cost scenarios

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

Table A3.3. The main model outputs for the central VRE and nuclear power cost scenarios

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

Appendix 3.2. Installed capacities for limited onshore wind acceptability

Table A3.4. Installed capacity of each power production technology in GW for the central VRE and nuclear power cost scenarios for limited onshore wind power acceptability

SCC (€/tCO₂)	**Offshore Wind**	**Onshore Wind**	**Solar PV**	**Run-of-river**	**Lake & reservoir**	**OCGT**	**CCGT w/CCS**	**Nuclear power**
0	10.31	34	86.8	7.5	12.9	31.6	0	8.96
100	10.48	34	76.63	7.5	12.9	19.88	9.41	12.89
200	10.48	34	74.71	7.5	12.9	13.16	14.71	14.35
300	10.03	34	73.13	7.5	12.9	9.84	17.26	15.76
400	10.22	34	80.54	7.5	12.9	7.63	15.14	18.56
500	9.06	34	85.23	7.5	12.9	6.98	15.03	18.77

Table A3.5. Installed capacity (and energy volume) of each storage technology in GW (and GWh/TWh) for the central VRE and nuclear power cost scenarios for limited onshore wind power acceptability

SCC (€/tCO₂)	**Battery (GW)**	**PHS (GW)**	**Battery (GWh)**	**PHS (GWh)**	**Methanation (TWh)**	**Methanation w/CCS (TWh)**
0	13.33	9.3	30.68	180	0	0
100	11.32	9.3	20.42	180	0	0
200	11.20	9.3	21.19	180	0	0
300	10.50	9.3	16.91	180	0	0
400	12.31	9.3	26.05	180	0	14.60
500	14.8	9.3	31.23	180	0	16.52

Table A3.6. The main model outputs for the central VRE and nuclear power cost scenarios for limited onshore wind power acceptability

SCC (€/tCO₂)	**Annualized cost with SCC (€bn/year)**	**Annualized technical cost (€bn/year)**	**System-wide LCOE (€/MWh)**	**Average 'market price' (€/MWh)**	**Load curtailment (%)**	**CO₂ emissions (MtCO₂/year)**
0	19.66	19.66	46.55	49.87	3.05	19.32
100	20.64	20.52	48.86	49.78	2.03	1.23
200	20.61	21.02	48.80	49.78	1.77	-2.05
300	20.34	21.30	48.15	49.78	1.63	-3.2
400	19.80	22.56	46.87	50.09	1.16	-6.91
500	19.06	22.99	45.14	50.19	1.25	-7.84

Appendix 3.3. Sensitivity to the discount rate

As explained in subsection 3.2.2.6, the discount rate chosen is that proposed by Quinet (2014) for public socio-economic analyses, 4.5%. A sensitivity analysis has therefore been carried out for the discount rate (DR), from 2% to 7%. Figures A3.1, A3.2 and A3.3 show the installed capacities, annual costs and annual CO_2 emissions for each SCC and DR scenario.

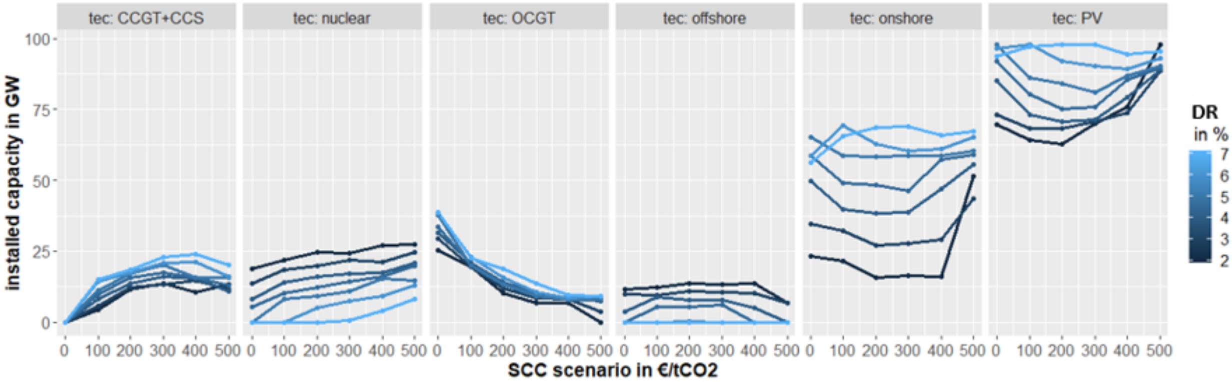


Figure A3.1. Installed capacity of each technology for different discount rate and social cost of carbon scenarios

Raising the discount rate increases the installed capacities of onshore wind and solar PV technologies, as well as gas turbines (both OCGT and CCGT with CCS); meanwhile, a higher discount rate reduces the proportion of nuclear and offshore wind power because of their longer lifetime (60 and 30 years vs. 25 for onshore wind and PV). Moreover, the discount rate increases the annualized cost (Figure A3.2), and Figure A3.3 shows the linearity of this relationship.

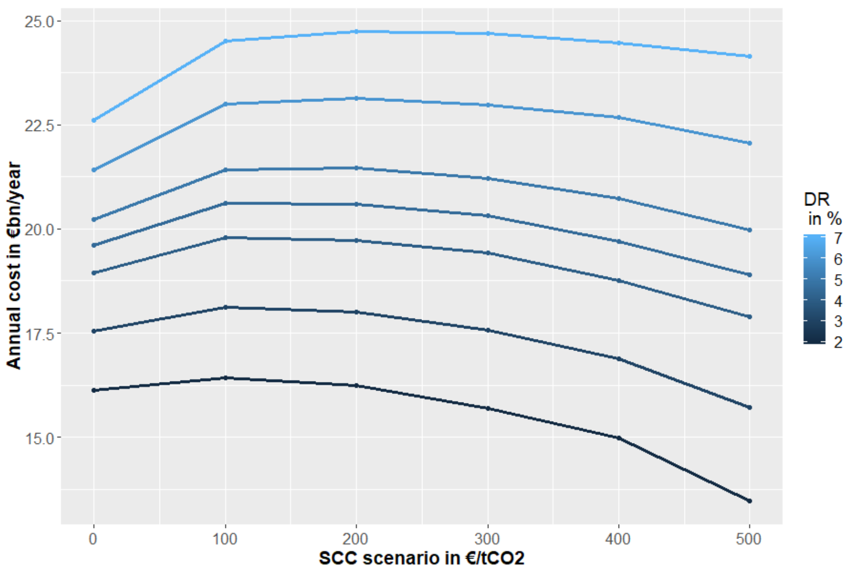


Figure A3.2. Annual total cost for each social cost of carbon and discount rate scenario

Figure A3.3 shows that by increasing the SCC, the slope of this relationship increases, therefore the degree of cost dependence on the discount rate also increases. This can be explained as follows: increasing the discount rate favors the technologies with negative or positive emissions (OCGT and CCGT with CCS power plants) because of the low contribution of capital expenditure to their total costs. Therefore, the sensitivity to the SCC (impacting the total cost to an even greater extent) also increases in this case.

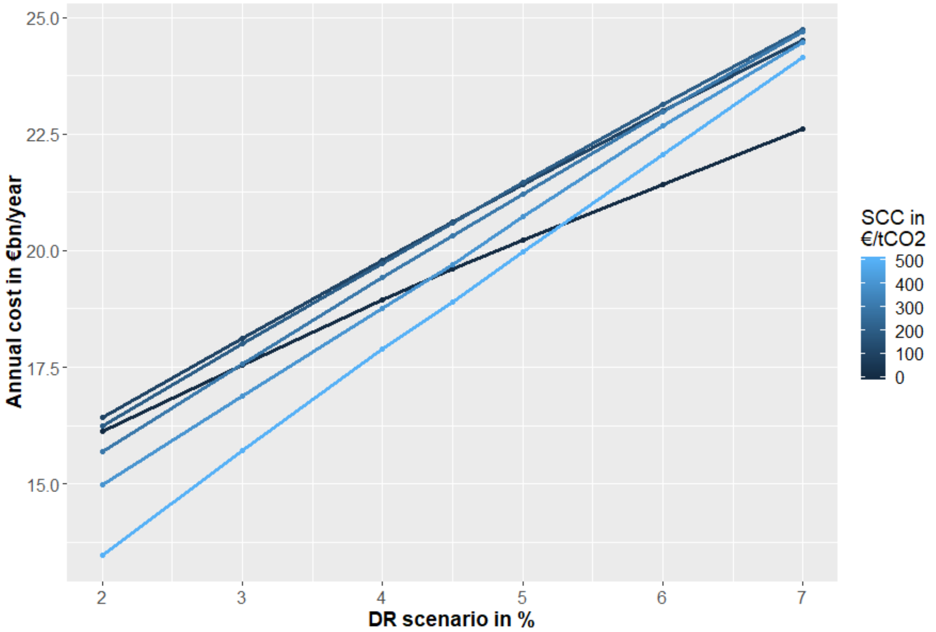


Figure A3.3. Annual cost with respect to different SCC and discount rate scenarios

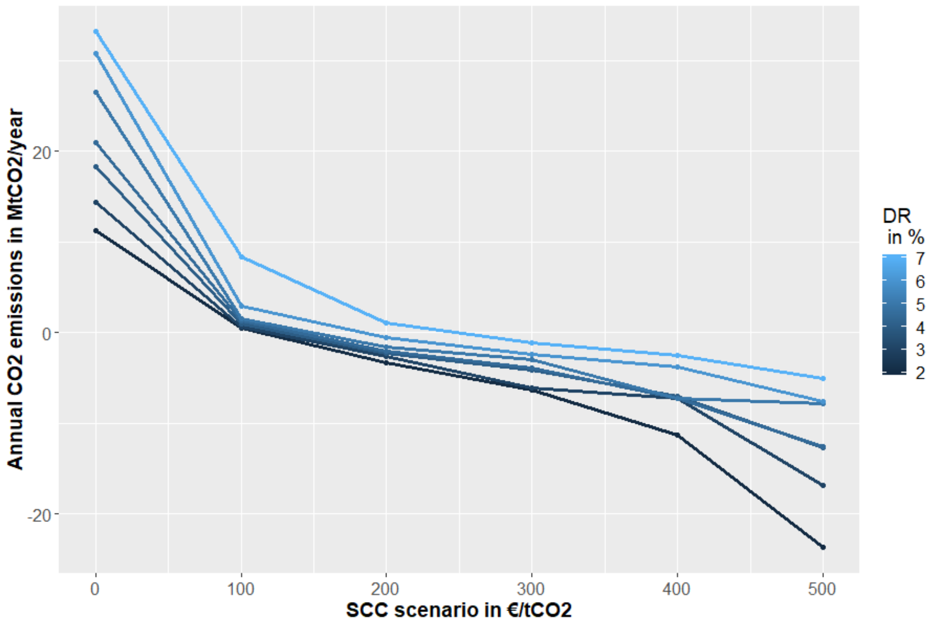


Figure A3.4. Annual CO_2 emission for each social cost of carbon and discount rate scenario

Figure A3.4 shows the impact of the discount rate on annual CO_2 emissions. As the discount rate increases, the proportions of zero-emission technologies (VRE technologies and nuclear power) decrease in comparison with both gas turbine technologies, therefore, the impact of variable costs (where fuel costs and SCC values are applied) becomes less significant in comparison with the investment costs. Emissions thus become higher e.g. with a discount rate of 7%, even for €200/tCO_2 of SCC value, annual CO_2 emissions are still positive, while for a discount rate of 2%, the lowest emissions are observed for each SCC scenario.

Appendix 3.4. Installed capacities and power mix for the case with hydrogen storage and hydrogen injection to the gas network

I studied the impact of presence of hydrogen in two different types of usage: direct injection to the gas network (limit to 6.35% of energetic volume of gas transport network - GRTgaz, 2019), and storage in salt caverns and separate hydrogen combustion with adapted CCGT power plants. Tables A3.7 to A3.9 present the installed capacities and the main power system characteristics for this variant scenario. The hydrogen storage with dedicated salt caverns never came out as an optimal technology, thus I excluded it from table A3.8. Neither in energy mix, nor in other energy system characteristics a significant change is observed compared to the case with only methanation as power-to-gas option. Therefore, to reduce the computation time of the model, I excluded both hydrogen options.

Table A3.7. Installed capacity of each power production technology in GW for the central VRE and nuclear power cost scenarios for limited onshore wind power acceptability

SCC ($€/tCO_2$)	**Offshore Wind**	**Onshore Wind**	**Solar PV**	**Run-of-river**	**Lake & reservoir**	**OCGT**	**CCGT w/CCS**	**Nuclear power**
0	0	59.65	93.20	7.5	12.9	33.35	0	5.11
100	5.28	49.36	80.74	7.5	12.9	20.64	8.98	10.55
200	5.55	48.28	75.58	7.5	12.9	14.55	15.06	12.07
300	5.71	47.63	78.48	7.5	12.9	10.13	15.91	14.87
400	0	57.14	86.47	7.5	12.9	7.82	15.75	15.78
500	0	59.26	89.25	7.5	12.9	8.11	12.26	18.50

Table A3.8. Installed capacity (and energy volume) of each storage technology in GW (and GWh/TWh) for the central VRE and nuclear power cost scenarios for limited onshore wind power acceptability

SCC ($€/tCO_2$)	**Battery (GW)**	**PHS (GW)**	**Hydrogen injection (GW)**	**Battery (GWh)**	**PHS (GWh)**	**Methanation (TWh)**	**Methanation w/CCS (TWh)**	**Hydrogen injection (TWh)**
0	15.21	9.3	2.12	40.76	180	0	0	0.74
100	12.84	9.3	1.31	29.74	180	0	0	2.17
200	11.18	9.3	0.92	20.73	180	0	0	0.81
300	12.08	9.3	0.64	25.68	180	0	6.3	0.34
400	14.32	9.3	0.50	37.21	180	0	14.9	0.19
500	14.69	9.3	0.28	39.46	180	0	15.37	0.19

Table A3.9. The main model outputs for the central VRE and nuclear power cost scenarios for limited onshore wind power acceptability scenario

SCC ($€/tCO_2$)	**Annualized cost with SCC (€bn/year)**	**Annualized technical cost (€bn/year)**	**System-wide LCOE (€/MWh)**	**Average 'market price' (€/MWh)**	**Load curtailment (%)**	**CO_2 emissions ($MtCO_2$/year)**
0	19.60	19.60	46.41	49.47	3.05	19.99
100	20.57	20.46	48.71	49.50	2.03	1.16
200	20.57	20.96	48.70	49.50	1.77	-1,97
300	20.27	21.84	47.99	49.75	1.63	-5,23
400	19.52	22.73	46.22	49.92	1.16	-8,03
500	18.26	24.78	43.24	50.12	1.57	-13.03

Figure A3.5 shows the power supply mix. the difference of this figure from figure 3.2, and the tables A3.7, A3.8 and A3.9 with tables A3.2, A3.3 and A3.4 shows that exclusion of hydrogen has a negligible impact from the energy mix and economic optimality point of view.

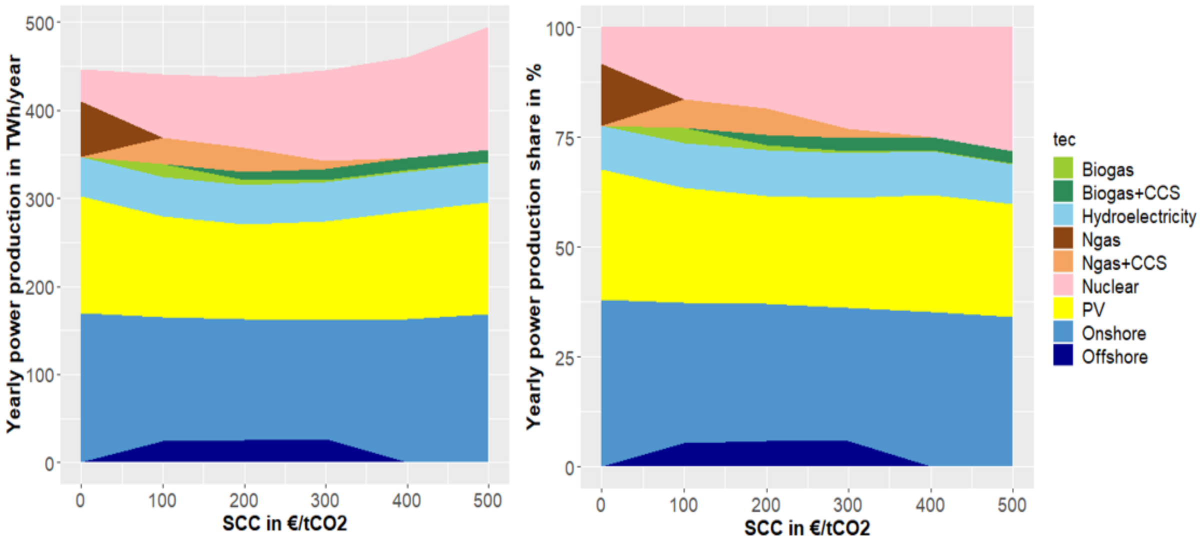


Figure A3.5. The yearly power supply mix in TWh_e/year (left) and share in % (right) for the scenario including hydrogen direct injection and storage

Chapter 4

Support schemes for risk-averse investors in variable renewables: Assessing weather-year variability

4.1. Introduction

Most of the existing literature agrees that a carbon-neutral power sector will include large shares of variable renewable energy sources such as wind power and solar photovoltaics (Waisman et al, 2019, Schlachtberger et al, 2018, Rogelj et al, 2018, Zeyringer et al, 2018, Olauson et al, 2016, previous chapters etc.). While the optimization considering future cost development of low-carbon technologies contains high shares of VRE technologies, their market behavior differs from the conventional technologies. Variable renewable energy technologies have no marginal cost since they do not consume any fuel, and their cost mainly comes from investment and fixed operation and maintenance cost (Hirth, 2013 and Keppler et al, 2016). Therefore, as we also saw in Chapter 2, in a highly renewable power market, the market price can be very low, and even null for long periods when the sun shines and the wind blows.

Different climate policy and subsidy schemes have been studied in the literature to incentivize the investments in renewable energy sources and decrease the share of fossil-based power supply technologies. All these studies show that policy support schemes are useful tools in decarbonizing electricity production, by increasing the competitiveness of renewables compared to fossil-based power generation options (Pommeret and Schubert, 2019, Ambec and Crampes, 2019 etc.). Therefore, the public support schemes to incentivize investments in renewables has been identified and addressed in the existing literature. However, currently renewables are competitive thanks to rapid reduction in the cost of renewables (3.5x for onshore wind power and 10x for solar PV in 11 years, LAZARD, 2020). While the competitivity of variable renewables is no more a question, there are other investment risks that are associated with their variable nature. In an energy-only market, the only revenues of participating players are from selling the energy in the market (in MWh_e). Therefore, in case of high initial investment and low market revenues, a renewable project may have negative cash flow over its lifetime or long periods during its operation.

The investment risk for these technologies contains price and volume risks (Pineda et al, 2018). The volatility of energy production from variable renewables is the main driver of volume risk, which also induces the price risk that is a direct consequence of the former. These risks are not to be confused with the competitiveness of renewables, which is based on the balance of expenses and revenues and long-term profitability of renewables. Most of the support scheme propositions are based on a comparison over the market revenues and the associated costs of power plant construction and operation over the lifetime of these projects, considering only an overall monetary balance for the investor.

The ‘variability’ or ‘intermittence’ of variable renewables does not only imply short-term volatility in electricity generation but also inter-seasonal (Pfenninger, 2017) and inter-annual variations (Collins et al, 2018 and Zeyringer et al, 2018). The optimal power mix changes from one weather-year to another because of the long-term variations (cf. Chapter 2) and these long-term variations lead to volume and investment risks over longer periods. In case of several years of low wind or low sun, the expected revenues of a variable renewable electricity supplier can be insufficient to balance a positive cash flow in its portfolio for long periods. Therefore, in a market where renewables are already competitive, a public support scheme to incentivize investments in renewables in an efficient manner must minimize the risks associated with both long-term and short-term variability of their revenues.

Fagiani et al. (2013) compare the performance of two policy support mechanisms with risk-aversion: feed-in tariffs and certificate markets and they conclude that in case regulator fixes the tariffs high enough, they reduce the needed risk premium, thus, the unit cost, more efficiently than the certificate markets. In another study based on integration of variability of renewables in the risk assessment, Tietjen et al. (2016) identify the price risk of renewables based on their production variability, and they conclude that this risk declines as the market share of renewables increases. In this chapter, I study this investment risk of renewables, stemming from the price and volume volatility (the price risk is induced by the volume risk) for a fully renewable power system.

In a traditional electricity market, the price of the market is determined by the marginal cost of the most expensive technology participating in the market: the ‘marginal technology’ (Boiteux, 1949). In this traditional approach, most of the participating technologies are dispatchable power plants with variable (fuel) costs, thus, with non-zero marginal costs (i.e. nuclear power, gas power plants etc.). However, in a highly renewable power market, the market pricing is based on also the operation of storage options which are integrated to deal with both short-term and long-term volatility of renewables (Crampes and Trochet, 2019). In such a market, the marginal cost of technologies will change by time since the charging and discharging of storage options, depending on the hourly market price and the marginal cost of the state of charge of the storage options are based on hourly electricity prices, thus variable in time.

In this chapter, I first identify the price variability for a fully renewable power system that was studied in Chapter 2, and by showing the operation of different technologies for different electricity market prices, I show the temporality of marginal pricing because of existence of the energy storage technologies. I analyze the performance of two policy support schemes: feed-in tariffs and capacity remuneration mechanisms and with a comparative analysis, I evaluate their relative efficiency in reduction of investment risks.

The remainder of this chapter is organized as follows. Section 4.2 explains the used methodology and the modelling framework. Section 4.3 shows the results for a fully renewable power system: the price risk, the seasonality of turnover of renewables and the roles of support schemes in reducing the investment risks and provides a small discussion. Finally, Section 4.4 presents the concluding remarks of this chapter.

4.2. Methods

I first study the future French electricity market for a fully renewable optimal power sector, using a 19-year long weather data, to assess not only for intra-daily, inter-daily and inter-seasonal variability of variable renewable energies (VRE), but also their inter-annual weather variability. In the following the model is explained briefly.

4.2.1. Modelling framework

I use the long version of EOLES_elecRES. As a modification to this model, I added the possibility of non-served demand, with a value of lost load equal to €10,000/MWh_e to limit the maximal market price to this value. Moreover, the reserve requirement equations are removed from the model since they penalized battery storage technology and they added additional income to VRE technologies. In the presence of the reserve requirement constraints, dispatchable technologies are called upon to present a reserve capacity as a function of the installed capacity of renewables (and their historical variability) and hourly electricity demand (and its historical variability). Without representing the reserves market (therefore, no remuneration for the reserve technologies), battery storage option with low power capacity cost (€/kW) is the main technology participating in reserve allocation. Because of this constraint, battery storage technology has a negative scarcity rent in an energy only market, and variable renewables have slightly positive scarcity rents. However, according to microeconomic theory, a technology that is not capped by its constraints should have zero long-term profit in a market (I present an analytical solution for the EOLES_elecRES model in Appendix 4.1, and the resulting long-term profit for VRE technologies in Appendix 4.2 confirms this deduction). This modification leads to zero long-term profit for non-constrained technologies in the studied energy-only market.

All the input parameters (electricity demand, technology costs, limiting availability and technical constraints etc.) are 2050 projections, same as in Chapter 2.

4.2.2. The optimal power mix resulting from the EOLES_elecRES model

Table 4.1 shows the installed capacities and annual power production of different technologies in a fully renewable electric system for the year 2050 with historical VRE profiles from 2000 to 2018. The optimal energy mix depends highly on wind power, particularly onshore wind power. 47% of the electricity supply comes from this technology, followed by solar power (30% of the electricity generation) and hydroelectricity (11% taking account both run-of-river and lake & reservoirs).

Table 4.1. Installed power capacity (in GW_e) of each technology and energy volume capacity (in GWh_e) of each storage technology resulting from optimization over 19 years. OCGT is open cycled gas turbines fueled with either biogas or bio-methane from power-to-gas, PHS is pumped hydro storage and P2G is power-to-gas, here methanation (hydrogen production from water electrolysis and Sabatier reaction of this hydrogen with green CO_2 leading to methane production).

Technology	*Offshore wind*	*Onshore wind*	*Solar PV*	*Run-of-river*	*Lake & reservoir*	*OCGT*	*Battery*	*PHS*	*P2G*
Installed capacity (GW)	9.7	85.3	107	10.5	10.1	31.4	9.6	9.3	5.6
Storage volume	-	-	-	-	-	-	47.7	180	16,000

(GWh)									
Yearly power production (TWh/year)	44	241	151	42	16	15	-	-	-

The electricity price is defined based on marginal pricing. EOLES_elecRES is an optimization model from the social planner's point of view: thus, the result is the social optimum. To study the decentralization of this social optimum through an energy-only competitive market, I use the Lagrange multiplier of the adequacy equation (the supply/demand equation), and since the dual of this equation is the derivative of the cost over hourly electricity demand (Eq. 4.1), I interpret this Lagrange multiplier as the hourly electricity price:

$$p_h = \frac{\partial C}{\partial d_h} \tag{4.1}$$

Where C is the cost of the electricity system, d_h is the electricity demand and p_h is the hourly electricity price at hour h.

Figure 4.1 shows the histogram of hourly electricity price over 19 weather-years. In 43.3% of the hours the electricity price is zero, and for 88 hours the electricity demand was not satisfied (lost load), accounting for an overall lost load of 315GWh$_e$ (0.0039% of the overall electricity demand).

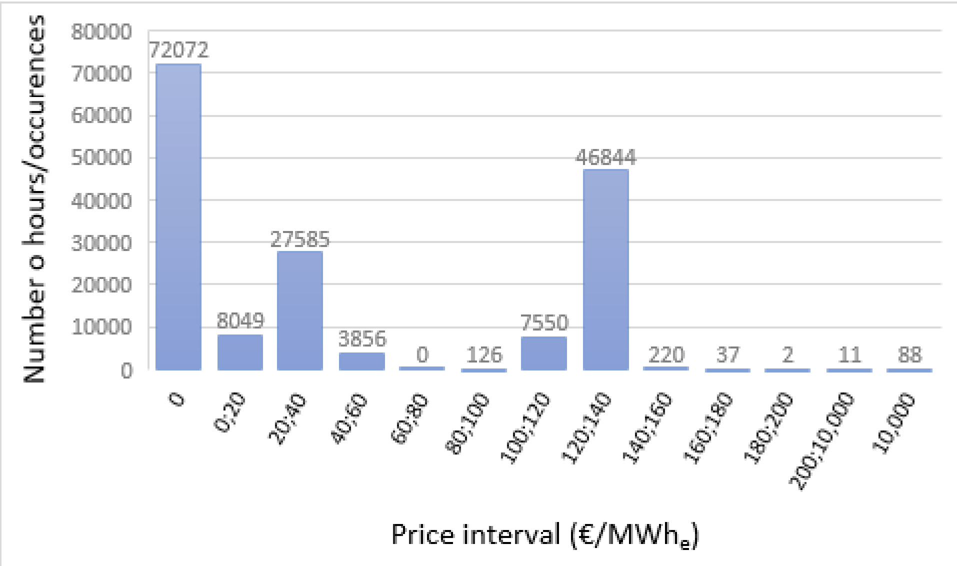


Figure 4.1. Histogram of electricity price over 19 years

The pricing mechanism based on marginal cost in a fully renewable power system leads to a big proportion of hours with zero market price for electricity. It is a typical behavior of an energy system containing high shares of variable renewables. The hours with zero market price are the hours where the variable renewables with no marginal cost are enough to supply the demand and no technology with variable cost (storage options and gas turbines fueled with biogas or bio-methane) is called for the market participation, and storing this electricity does not induce any marginal cost.

4.3. Results and discussion

4.3.1. Price regimes

In Chapter 2 and in the previous section we saw that the market price is highly variable. Table 4.2 shows the prices with the highest occurrence and the number of hours and percentage over 19 years of these hours with these market prices.

Table 4.2. Electricity market prices and hours with each price during the whole 19-year period

Price (€/MWh)	Number of hours	Percentage of hours
0	72,072	43.3
136.55	46,668	28.04
34.82	22,622	13.6
2	6,663	4
116.75	5,219	3.14
29.77	2,816	1.69
40.73	2,448	1.47
115.04	2,320	1.39
42.73	1,228	0.74
1.71	1,208	0.73
…		
10,000	88	0.05
…		

There are 56 different market prices, of which the 10 most frequent ones and the maximal price of €10,000/MWh are presented in Table 4.3. The most frequent price is zero (43.3% of the hours), and secondly it is €136.55/MWh (28.04% of hours), followed by €34.82/MWh (13.6% of hours) and €2/MWh (4% of hours). For 88 hours (0.05% of hours) electricity demand is not served by introduction of a value of lost load of €10,000/MWh. The analysis of the hourly power production and consumption data shows that the zero price happens mostly during the mid-day hours of the three sunniest seasons (spring, summer and autumn). The second most frequent price (€136.55/MWh) occurs mainly in the cold season (winter), especially at the hours when sun doesn't shine, and wind blows weakly.

Heterogeneity of the market price is expected from the theory and without storage, the limited number of technologies (six supply and three storage options, and possibility of unserved demand) would lead to a limited number of market prices (equal to number of supply and storage options). However, this optimization leads to 56 different prices, and this is because of the presence of storage options which brings the temporality dimension to the marginal costs of technologies (Appendix 4.3).

To understand the price regimes, first I analyze the operation of different technologies for each price. Table 4.3 shows the operation of different power supply technologies and charging and discharging operation form of different storage technologies. The operation of variable renewables (offshore and onshore wind, solar PV and run-of-river) is not presented in this table, since they always operate in full load unless when there is no sun or wind doesn't blow or not enough water flux in the rivers (because their marginal cost is zero).

Table 4.3. Operation of different technologies depending on different price regimes, "FL" means the plant operates in full load, "No" means it doesn't operate and "PL" means the plant operates in partial load.

Price (€/MWh)	Lake	Biogas	Battery discharge	PHS discharge	P2G discharge	LL[1]	Battery charge	PHS charge	P2G charge
0	No	No	No	No	No	No	FL/PL/No	FL/PL/No	FL
137	FL/PL/No	No	FL/PL/No	FL/PL/No	No	No	No	No	No
34.8	FL/PL/No	No	FL/PL/No	FL/PL/No	No	No	FL/PL/No	FL/PL/No	FL/PL/No
2	FL/PL/No	No	FL/PL/No	FL/PL/No	No	No	No	FL/PL/No	FL
117	FL/PL/No	No	FL/PL/No	FL/PL/No	No	No	No	FL/PL/No	No
29.8	FL/No	No	PL/No	No	No	No	FL/PL/No	FL/PL/No	FL
40.7	FL/PL/No	No	FL/PL/No	FL/PL/No	No	No	PL/No	No	No
115	FL/No	No	No	FL/No	No	No	FL/PL	FL/PL/No	No
42.7	FL/PL/No	No	FL/PL/No	FL/PL/No	No	No	FL/PL/No	FL/PL/No	No
1.71	PL/No	No	No	FL/PL/No	No	No	FL/PL/No	FL/PL/No	Yes
…									
10,0000	FL	FL/No	FL/PL/No	FL/PL/No	FL/No	FL/PL/No	No	No	No
…									

Not only several price regimes exist, but also for each price several electricity supply and storage regimes exist (with identical prices). According to the micro-economic theory, the technology whose marginal cost is equal to the market price is the marginal technology, however, several technologies can behave as marginal technologies at the same time and several combinations of power supply and storage can be observed for each of these 56 prices. For instance, for the electricity price of zero, marginal technologies can be either load curtailment (four VRE technologies, producing more than the demand and storage charging), or charging of batteries, or charging of pumped storage, or the discharge of pumped hydro storage, where the methane storage is always in full charging power, sometimes battery storage and some other times pumped storage is in their maximal capacities and sometimes the discharge of PHS is in its full capacity. In this chapter, I do not calculate the details of these marginal costs, however, it is necessary to analyze the marginal cost of different technologies for different market prices to assess different price regimes and the pricing mechanism in the presence of storage options. In a case study with 56 different prices, made by several combinations, this study can be complicated, but a simpler model with less technologies can also lead to an understanding of the different rice regimes in more depth.

[1] Loss of Load

4.3.2. Annual profits of an energy-only market

Understanding the investment behavior and identifying its risks requires a profitability analysis. Figure 4.2 shows the annual profit and cumulated profits[1] (in €/$€_{inv}$) of each VRE technology (offshore and onshore wind and solar PV) if the cost is annualized and amortized during the whole lifetime of the power plants. The unit of €/$€_{inv}$ means the profit made in € for €1 of investment, therefore, it is a rate of the return to the investment made. In case this rate is 0, the profit is zero, and if it is positive, there is a positive profit and vice versa.

We can see that the annual profit of each VRE technology is highly variable, because of the price and volume risks explained previously. Although the longest negative annual profit period for each of these technologies is three years (2012 to 2014), Figure 4.2-b shows that the cumulated profit can remain negative for much longer periods. For onshore wind and solar power, this period is six years but for offshore wind, it is as long as 11 years over the 19-year period. These results show that, for a market where renewables are highly competitive, the investment in renewables can have long periods of negative monetary balance, which would discourage investments in VRE technologies.

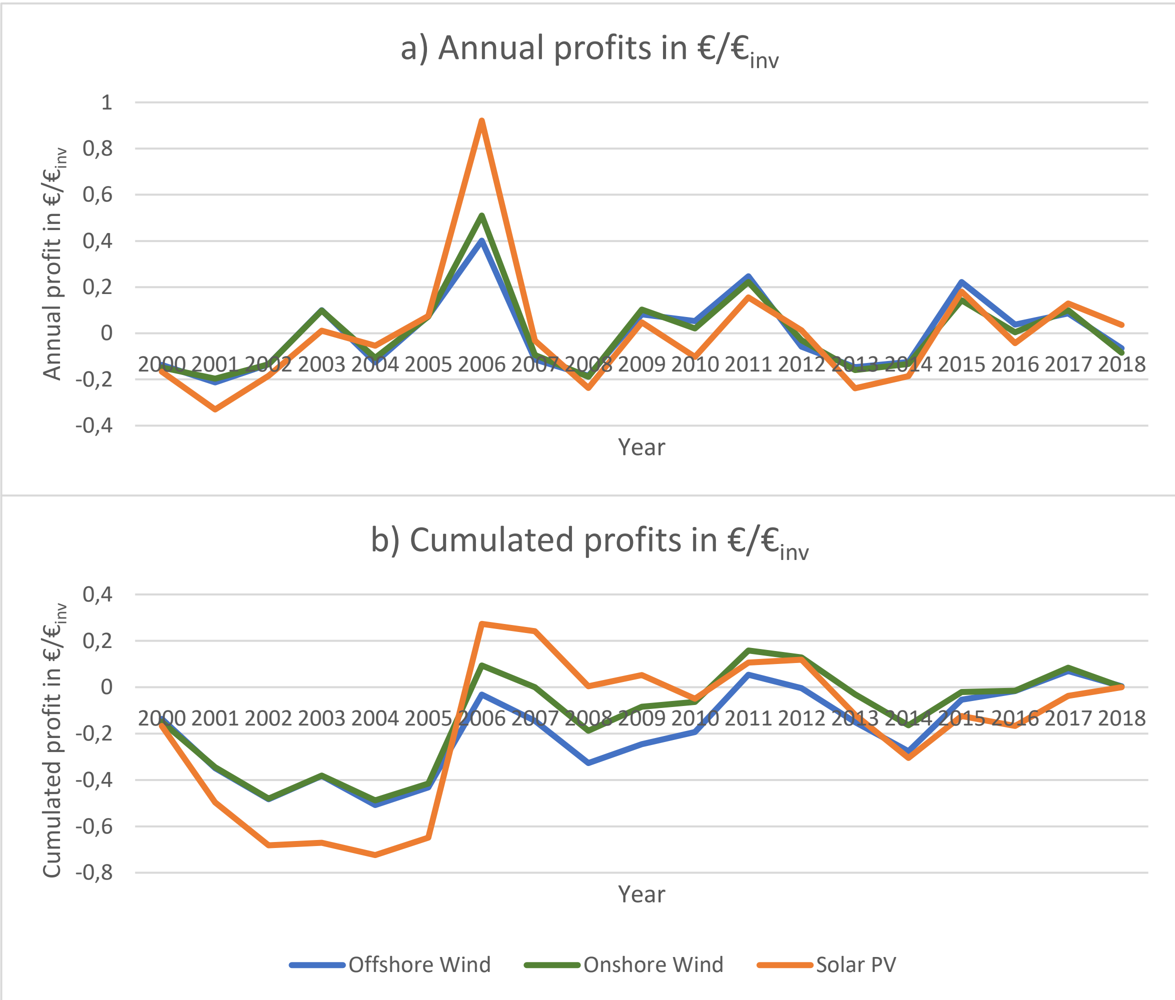


Figure 4.2. a) Annual net and b) cumulated profits in €/$€_{inv}$ for each of the three VRE technologies with no policy support scheme

[1] Cumulated profit means the sum of the profits from the first observed period until the period under discussion. Thus, in case the annual profit for a technology at each year is $\pi_{y,tec}$, the cumulated profit for the same technology at year n is $\pi_{n,tec}^{cumulated} = \sum_{y=1}^{y=n} \pi_{y,tec}$.

What we observed in Figure 4.2 is the investment risk of VRE technologies, stemming from price and volume risk. To compare the relative importance of these two risks, I calculated the correlation coefficients between the annual profit and annual power production (volume risk) and the annual average electricity price sold (price risk) for each of the main VRE technologies (Table 4.4).

Table 4.4. Correlation coefficients between annual profits, annual sold energy and annual average selling price for three main VRE technologies

Offshore	***Price***	***Volume***	***Profit***
Price	-	-	-
Volume	-0.353	-	-
Profit	0.932	-0.191	-
Onshore	***Price***	***Volume***	***Profit***
Price	-	-	-
Volume	-0.469	-	-
Profit	0.931	-0.308	-
Solar PV	***Price***	***Volume***	***Profit***
Price	-	-	-
Volume	0.335	-	-
Profit	0.945	0.393	-

For both, offshore and onshore wind power, there is a high correlation between the profit and the average selling price of electricity, and a very low correlation between the volume sold and the profit. The relatively high negative correlation between the volume of electricity sold and the average selling price shows that, when the renewable production is low, because of entry of other supply (and discharge for storage) options to the market, the marginal technology changes from VRE technologies to another with a marginal cost which increases the market price, leading to higher electricity price, and thus higher unit profit from selling electricity. However, for solar power, all the three characteristics are positively correlated. To understand the reason, I studied the correlation between solar and wind power production (Table 4.5):

Table 4.5. Correlation coefficients between the annual power production from offshore and onshore wind power and solar power technologies

Production	***Offshore***	***Onshore***	***PV***
Offshore	-	-	-
Onshore	0.849	-	-
PV	-0.129	-0.147	-

When solar power production is high, wind power production is low and vice versa. Comparison of Tables 4.4 and 4.5 show that the wind power technologies are highly correlated among each other, and the negative correlation of market price with the production of wind power technologies (especially onshore wind) and the low correlation of market price with the production of solar power implies that the electricity price is set by wind power, especially onshore wind power. Similarly, the positive correlation of both price and volume of sold PV with its profitability is because of the negative correlation between solar and wind power technologies, otherwise, increasing the volume of a technology would lead to reduced market price, and thus reduced profits. However, since the market price is set by wind power, the observed correlations do not reflect this expectation.

While the variation of annual profits is high for all three VRE technologies, to understand the relative riskiness of each of these three VRE technologies, they must also be compared among each other. To this end, I calculate the standard deviation of profit (in €/€$_{inv}$ as in Figure 4.2) for each of the three main VRE technologies from the Equation (4.2):

$$SD_{\pi_{vre}} = \sqrt{\sum_{y=1}^{Y} \frac{(\pi_{y,vre} - \overline{\pi_{vre}})^2}{Y}} \tag{4.2}$$

$SD_{\pi_{vre}}$ is the standard deviation of profit (in €/€$_{inv}$) for the technology vre over the whole duration of Y (19 years), $\pi_{y,vre}$ is the annual profit of that technology at year y and $\overline{\pi_{vre}}$ is the mean annual profit over the whole observation period. Table 4.6 shows these coefficients for each VRE technology.

Table 4.6. Standard deviation of annual profits for each of the three emerging VRE technologies

	Offshore wind	**Onshore wind**	**Solar PV**
Standard deviation of profit (€/€$_{inv}$)	0.1656	0.1749	0.2653

The standard deviation of annual profits (thus, variability) is the lowest for offshore wind power thanks to its relatively low production variation. However, this profit variation is higher for onshore wind power, and much higher for solar PV. Therefore, not only all three of VRE technologies are associated with high investment risk, but also among them, solar PV is associated with the highest. In Table 4.4 we saw that the profit risk of solar PV is positively correlated with its volume and price risks, therefore, one explanation for this high variability of solar power's annual profits is the positive impact of both its price and volume variability, however, it is not the case for the wind power technologies.

To deal with this investment risk, I study two of the existing support mechanisms: feed-in tariffs and capacity remuneration. They are explained in in the following section.

4.3.3. Policy support schemes

Two well-known policy support tools in the energy sector are feed-in tariffs and feed-in premiums. Feed-in tariff is a fixed price above the electricity market price that is guaranteed to producers of VRE for a period of typically 10 to 20 years. Feed-in premium is a subsidy paid to VRE producers as an addition to the market price (Quirion, 2015). Since feed-in premiums do not address the volatility of the market price, they do not reduce the price risk. Thus, I study feed-in tariff among two feed-in options. The main interest in studying the feed-in tariffs is the fact that by guaranteeing an agreed fixed remuneration price, they eliminate the price risk completely, however the volume risk remains. Another support mechanism for the energy providers is capacity remuneration. Capacity remuneration is based on two revenues: first from the energy sold in the electricity market (in €/MWh$_e$), and second, a complementary remuneration from the capacity market (in €/MW) during the hours that the power plant is available. Capacity remuneration (which take a form of capacity subsidy) reduces both price and volume risk by decreasing the revenues from highly variable electricity market and increasing a fixed remuneration based on the available capacity. However, both of these risks still exist.

I first apply a feed-in tariff, fixing the price of electricity market to a single value for each hour over the 19 years. This tariff is the price that leads to the same profit over the 19 years as with no feed-in tariff, thus, monetary balance is assured. This price should satisfy Equation (4.3):

$$\sum_{h=1}^{H}(E_{vre,h} \times p_h) = \bar{p}\sum_{h=1}^{H} E_{vre,h} \tag{4.3}$$

Where $E_{vre,h}$ is the electricity sold in the market by technology vre at hour h in MWh_e, p_h is the hourly electricity market price in €/MWh_e, H is the overall considered period (in this case 19 years multiplied by 8,760 hours, which is 166,440 hours) and $\bar{p}$ is the fixed market price (feed-in tariff) over 19 years for each hour in €/MWh_e. Figure 4.3 shows the annual net and cumulated profits in (€/$€_{inv}$) for each VRE technology in the presence of feed-in tariff.

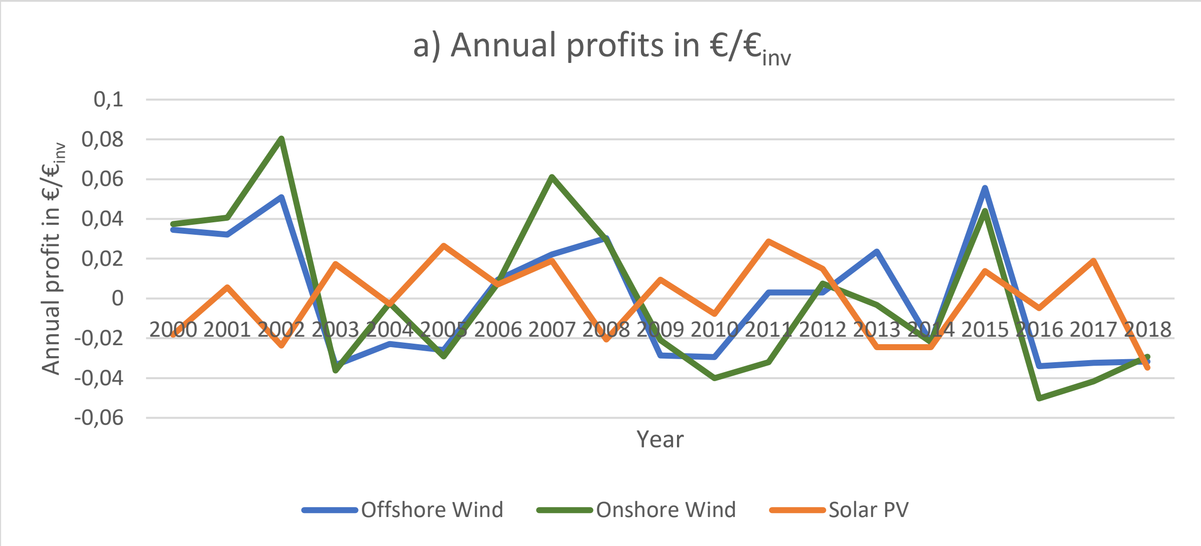
We can see that feed-in tariff, eliminating the price risk, reduces the amplitude of variation by a factor of more than 10 (Figures 4.2 vs. 4.3). The efficiency of feed-in tariff in reduction of amplitude of variability is very high, but it also reduces the negative profit periods: for instance, the annual profit of solar power never becomes negative for two consecutive years except for 2013 and 2014, both with very small magnitude of negative profits. Similarly, cumulated profits of offshore and onshore wind power technologies stay above zero during the whole 19-year period, reaching zero just at the end of this period, but this is because of the year that the simulation has started, and it can be different if the meteorological order was different, or the starting year of the simulation was different. In the case with no feed-in tariff, the cumulated profits of onshore wind and solar power are negative for six consecutive years, and the cumulated profit of offshore wind power is negative for 11 consecutive years. Therefore, the efficiency in reducing the cashflow variation of VRE technologies (both in amplitude and the frequency of variation) can be confirmed.

A capacity remuneration scheme can take different forms. To keep the overall revenue balance equal to a case with no policy support scheme, we consider a capacity remuneration which is paid on an annual basis (which can be considered as suppression of a part of the annualized fixed cost) in €/(MW.year) and a tax on the market revenue (proportional to the market price). The sum of the remunerated capacity and electricity market revenues after the tax deduction is equal to the sum of the electricity market revenues in the absence of this tax. Equation (4.4) explains this balance:

$$\sum_{h=1}^{H}(E_{vre,h} \times p_h) = Q_{vre} \times cr_{vre} \times C_{vre}^{annualized} + \sum_{h=1}^{H}(E_{vre,h} \times p_h \times (1 - tax_{vre}) \tag{4.4}$$

Where Q_{vre} is the capacity in technology vre in kW, cr_{vre} is the annual capacity remuneration ratio for the technology vre (in %), $C_{vre}^{annualized}$ is the annualized fixed costs of technology vre (in €/(kW.year)) and tax_{vre} is the tax ratio to be reduced from the hourly market price for each VRE technology in %. We define several capacity remuneration ratios (from 20% to 80%), and Figure 4.4 shows the annual profits of each VRE technology for each of these capacity remuneration ratios. Since both the electricity market tax and the capacity remuneration ratio are unitless and their impact is symmetrical keeping the overall zero scarcity rent balance, they are equal. Thus, for a capacity remuneration ratio of 0.2, a 20% of market tax is applied.

Although increasing the capacity remuneration reduces the intensity of the profit variability, it doesn't decrease the period where the annual profits are zero, thus it doesn't decrease the length of the negative monetary balance period for the investors. Cumulated profits are presented in Figure 4.5.



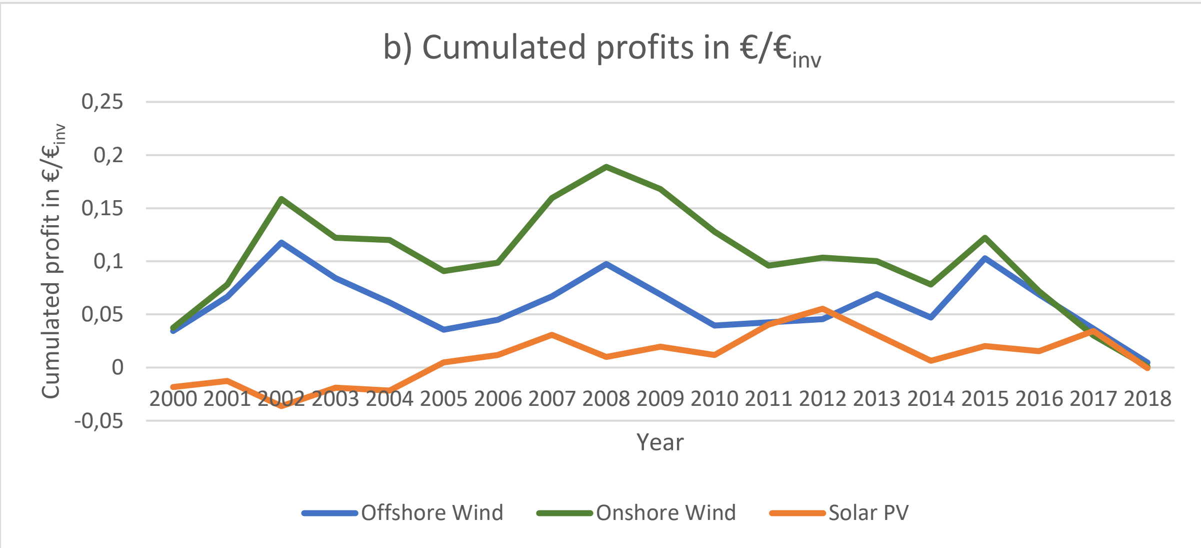


Figure 4.3. a) Annual net and b) cumulated profits in €/€$_{inv}$ for each of the three VRE technologies in the existence of Feed-in tariff

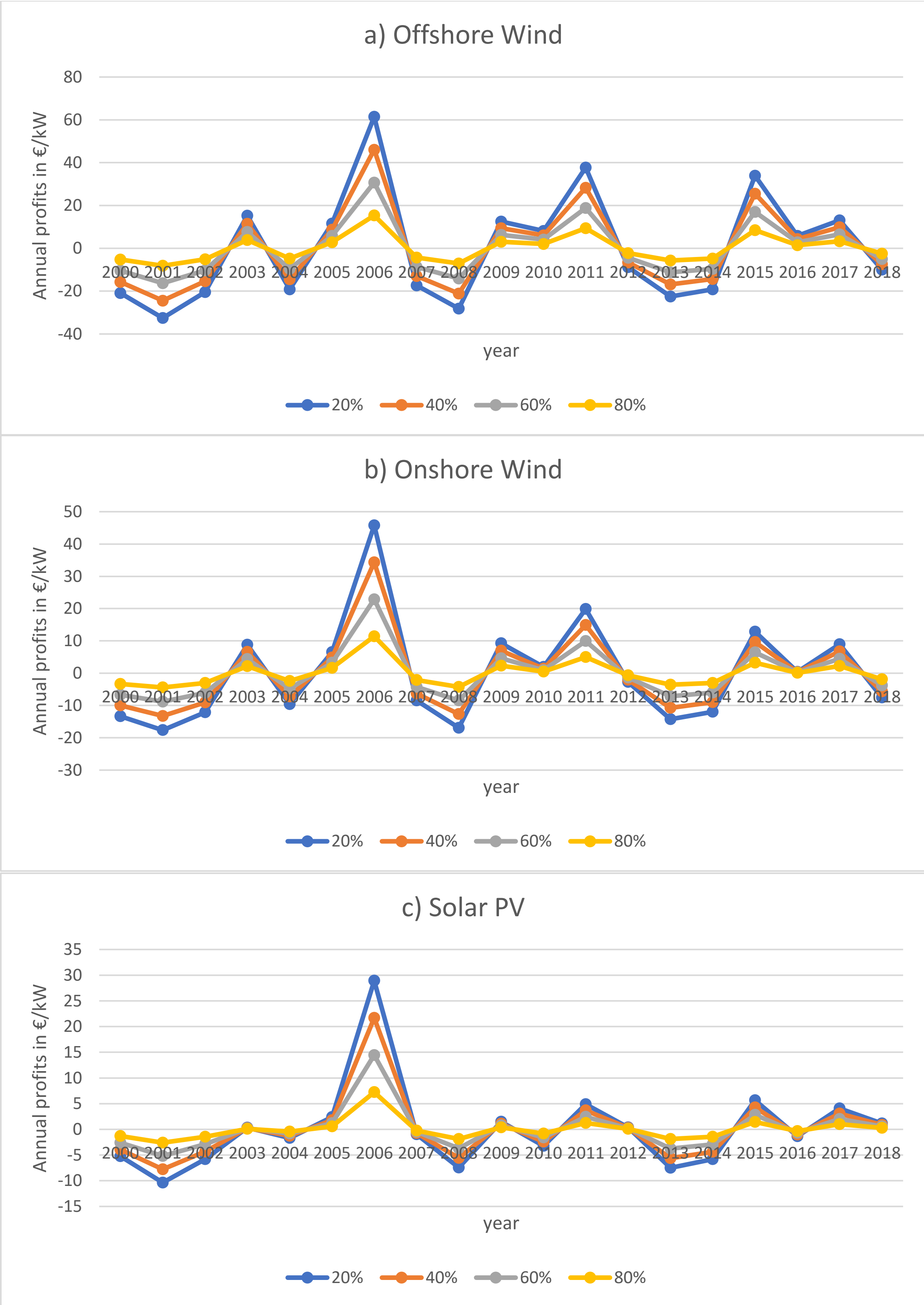


Figure 4.4. Annual net profits in €/kW for each of the a) offshore wind, b) onshore wind and c) solar PV technologies in the existence of capacity remuneration scheme varying from a remuneration rate of 20% to 80%

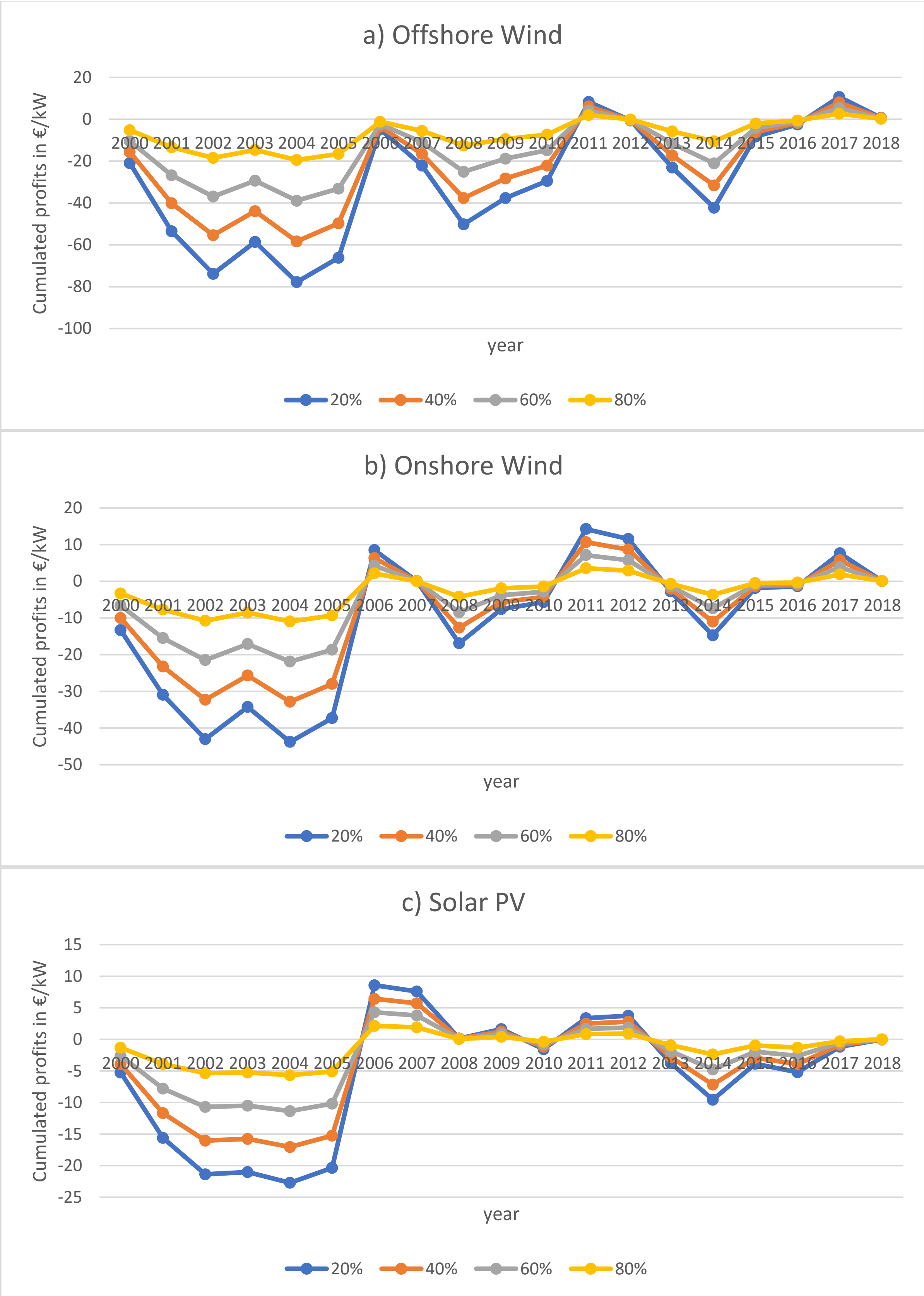


Figure 4.5. Cumulated net profits in €/kW for each of the a) offshore wind, b) onshore wind and c) solar PV technologies in the existence of capacity remuneration scheme varying from a remuneration rate of 20% to 80%

Both feed-in tariff and capacity remuneration schemes can help reduce the amplitude of variations in profits. In case of feed-in tariff, it also reduces the period over which the cumulated profit is negative. However, there are still long periods over which a VRE provider's profit is negative. Therefore, the investment risk still exists; while feed-in tariff eliminates the price risk, the volume risk still remains, but its impact is marginal compared to the price risk. Capacity remuneration reduces both the price and the volume risks but does not eliminate any of them.

To quantify the variability of the annual profits for each VRE technology in presence of different support schemes, I calculated the standard deviation of annual profits for each VRE technology over the 19 considered weather years for the cases with feed-in tariff and with capacity remuneration. Table 4.7 presents these standard deviation values for each VRE in the presence of these support schemes.

Table 4.7. Standard deviation of annual profits in the presence of different support schemes for each of the three emerging VRE technologies

Standard deviation of profits	Offshore wind	Onshore wind	Solar PV
Feed-in tariff	0.0313	0.0387	0.0196
Capacity remuneration	0.1656	0.1749	0.2653

Feed-in tariffs decrease the variability of annual profits by a factor of more than 5 for offshore wind, 4.5 for onshore wind power and 13.5 for solar power. However, the capacity remuneration does not decrease the variability of annual profits (equal to the case with no support for any remuneration rate), it only decreases the amplitude of variability. The profit is considered in €/$€_{inv}$, therefore, reducing the market revenues and adding a fixed annual remuneration based on capacity with the equal ratio (capacity remuneration mechanism) does not change this profit (Appendix 4.4 shows this argument based on Equation 4.4).

4.4. Conclusion

In this chapter I identified the economic characteristics of a fully renewable power system. In such a power system, the most frequent market price is zero (43.3% of the time). The second most occurring market price is €136.55/MWh (i.e. twice the actual electricity price), which happens mainly in the cold season, and in the evening when there is not enough solar energy, but high electricity demand (28% of the time). I identified 56 price regimes, and each price regime can account for several technology market participation regimes. The study of the price regimes shows that in a power system with storage options, the constant marginal cost of different energy supply technologies are not the only market price setting costs, and introduction of storage options can make the market price setting more complicated, because of the introduction of temporality. The electricity bought by one storage technology must be sold for a higher price, and since the storage volume has its own cost, the storage options buy electricity for numerous prices, and sell it for even more numerous prices.

The price variation of electricity in a fully renewable electricity market stems from the power supply variability of intermittent renewable energy supply technologies. Both price and production volume variability of VRE technologies has a direct impact on the profitability of VRE technologies, inducing two investment risks: volume risk and price risk.

In an energy only market, the comparison of correlation between the price and volume of electricity sold and the profits of different VRE technologies shows that the main reason for the profit variability of VRE technologies is the variability of the price of sold electricity, which is an indirect result of the variability of the quantity of electricity produced. Negative correlation between the power production by solar PV and wind power technologies, combined with the previous reasoning leads to the conclusion that the price of the electricity market is mainly set by onshore wind power. Since the power production from wind power and solar PV technologies are negatively correlated, the price and volume of solar power are positively correlated with its annual profit.

The variability in the annual profits of VRE technologies are not similar. The least variable being offshore wind power, followed by onshore wind power, the highest investment risk is associated with solar PV. By introduction of a feed-in tariff for the VRE technologies, the price risk is eliminated and the variability in the annual profits of VRE technologies decreases drastically. Feed-in tariff leads to a more than 5-fold reduction in the standard deviation of annual profits of offshore wind power, a 4.5-fold reduction for onshore wind power and a 13.5-fold reduction for solar power. Offshore wind power remaining the technology with the lowest annual profit variability, and thus lowest investment risk, onshore wind and solar power become nearly equally the technologies with the highest investment risk. However, a capacity subsidy scheme (such as capacity remuneration) reducing both price and volume risk, does not eliminate any of them and the profit variability remains at the same level, but the amplitude of this variability is reduced. Thus, feed-in tariff shows a higher performance in incentivizing the investments in VRE technologies, by decreasing the investment risk more efficiently.

Findings of Chapters 2 and 3 show that a cost-optimal low-carbon electricity mix will be highly renewable, consisting of mainly variable renewables. Although from a social planner point of view, the most cost-optimal solutions are renewables, their integration in the electricity mix is associated with investment risk which can lead to long periods of negative cashflow for the investor. In such a market, investors with high liquidity can continue their economic activities, however these long negative cashflow periods can demotivate smaller investors from investing in renewables, leading to a concentrated electricity market. Thus, the classical liberalized electricity market with marginal pricing must be replaced by new market structures for a competitive non-concentrated electricity market, far from monopolistic behaviors.

This chapter is a preliminary study on the quantification of the risks associated with inter-annual variability of variable renewable technologies and the efficiency of different policy support mechanisms in the reduction of these risks. Therefore, this analysis can be extended for deeper analysis by identification of different price regimes using the Lagrange multipliers and calculation of marginal costs of different technologies, particularly storage technologies that have varying marginal costs for different hours. Although the variability of VRE technologies is the main research question identified for this chapter, these findings are based on a single node model for France, associated with aggregation effect of VRE profiles of different counties of France. Therefore, the variability of a single wind farm or solar farm will be more than what I identified in this chapter, leading to higher investment risks. A practical extension of this study is its application to one single wind or solar farm, which can be used to assess the real investment risk of a project.

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Appendices 4

Appendix 4.1. The analytical solution of the EOLES_elecRES model

This Appendix provides the analytical solution of the cost minimization problem that is numerically solved using the EOLES_elecRES model. The solution method is based on the methodology proposed by Cretì and Fontini (2019 – Ch. 9).

Looking from a social planner point of view, the optimal case will be the case meeting the demand at each hour, with the highest possible welfare. I define the utility function over the demand, considering a positive value in case demand is met. Later I will define the constraints in the way that this utility function becomes a single value parameter (in other words, I won't allow any blackout possibility in the results).

The welfare maximization problem for the supply side of the power system can be defined as in Equation (A4.1):

$$\max_{Q_i, E_{i,t}} U(d_t) - C(Q_i, E_{i,t}) \tag{A4.1}$$

Where $U(.)$ represents the utility function, d_t represents the electricity demand at hour t, $C(.)$ represents the cost function, Q_i and $E_{i,t}$ represent the installed capacity and power produced (in hour t for power production) of plant i.

Since demand is considered to be a fixed value at each hour, with no load shedding possibility, we can define $U(.)$ a positive constant function, therefore; $U'(.)$ is zero and the dual problem of the welfare maximization is simply cost minimization as in Equation (A4.2).

$$\min_{Q_i, E_{i,t}} C(Q_i, E_{i,t}) \tag{A4.2}$$

In this problem, the dispatch optimality condition requires the merit order dispatching of plants at each hour (lowest marginal cost plant to be dispatched first), and the investment optimality condition requires an optimal choice of installed capacity for each of these plants. These two optimality conditions, solved together, will result on a solution optimal both in investment and dispatch.

Let's assume the cost function to be linear with respect to installed capacity of each plant and power production at each hour by each plant, in other words a cost function in the form $C(Q_i, E_{i,t}) \sim aQ_i + bE_{i,t}$, a homogenous function from first degree where we can simply add up all the costs linearly, and the overall cost function can be considered as the sum of the cost functions for all plants $C\left(\sum_i Q_i, \sum_i \sum_t E_{i,t}\right) \sim \sum_i a_i Q_i + \sum_i \sum_t b_i E_{i,t}$.

Now let's consider the EOLES_elecRES model, where besides the production technologies and their limiting constraints, there are storage technologies, reserve requirements and different technical and resource availability constraints for some technologies, where some equations become binding. Let's consider cost as a function of installed capacities and hourly generation by power production technologies and installed charge and discharge capacities, energy related capacity and hourly charge and discharge of storage technologies. And let's add reserve and storage related variables into the minimization problem, then the optimization objective becomes:

$$\min_{Q_i, E_{i,t}, \bar{S}_s^{out}, \bar{S}_s^{in}, S_{s,t}^{out}, S_{s,t}^{in}, \tilde{S}_{s,t}, V_s, R_{f,t}} C(Q_i, E_{i,t}, \bar{S}_s^{out}, \bar{S}_s^{in}, S_{s,t}^{out}, S_{s,t}^{in}, V_s) \quad \text{(A4.3)}$$

Variable Q_i represents the installed capacity and variable $E_{i,t}$ the hourly electricity production of technology i. $\bar{S}_s^{in}$ and $\bar{S}_s^{out}$ are the installed charging and discharging capacities and $S_{s,t}^{out}$ and $S_{s,t}^{in}$ are the hourly charging and discharging powers of storage technology s. V_s is the installed energy capacity and $\tilde{S}_{s,t}$ is the hourly state of charge of storage option s. Finally, $R_{f,t}$ is the hourly capacity allocation for the secondary reserves by technology f.

The indices are defined in table 1; three variable renewable energy technologies (offshore and onshore wind power and solar PV) displayed with v, three storage technologies (Battery storage, pumped hydro storage and methanation from power to gas) displayed with s, three hydroelectric power technologies (lakes with dams, run-of-river and pumped hydro storage) represented with indices h and the technologies including combustion (biogas and methanation) are represented by c. All technologies together are summed under the indices i.

Table A4.1. Indices in EOLES_elecRES: technologies and time-slices.

Indices	Explanation	Technologies considered
i	All technologies	off, on, pv, river, lake, bio, gas, phs, bat, metha
g	Power production technologies	off, on, pv, river, lake, bio, gas
v	VRE technologies	off, on, pv, river
s	Storage technologies	phs, bat, metha
f	Frr reserve contributing technologies	lake, phs, bat, gas
h	Hydro-electric technologies	river, lake, phs
c	Technologies burnt in OCGT	bio, metha
t	Time slice used, hourly data for one year	0,1,…,8759
m	Months in one year	1,…,12

Equation (A4.4) is the supply demand equilibrium (adequacy equation) for the electricity market, and the following equations are the constraints:

$$\sum_{g \neq c} E_{g,t} + \sum_s S_{s,t}^{out} \geq d_t + \sum_s S_{s,t}^{in} \quad \text{(A4.4)}$$

$$Q_i \geq E_{i,t} \quad \text{(A4.5)}$$

$$Q_v \times cf_{v,t} = E_{v,t} \quad \text{(A4.6)}$$

$$Q_f \geq E_{f,t} + R_{f,t} \quad \text{(A4.7)}$$

$$E_{gas} = \sum_c E_{c,t} \quad \text{(A4.8)}$$

$$e_{bio}^{max} \geq \sum_t E_{bio,t} \quad \text{(A4.9)}$$

$$\tilde{S}_{s,t+1} = \tilde{S}_{s,t} + S_{s,t}^{in} \eta_s^{in} - \frac{S_{s,t}^{out}}{\eta_s^{out}} \quad \text{(A4.10)}$$

$$V_s \geq \tilde{S}_{s,t} \quad \text{(A4.11)}$$

$$\bar{S}_s^{in} \geq S_{s,t}^{in} \quad \text{(A4.12)}$$

$$\bar{S}_{s}^{out} \geq S_{s,t}^{out} \quad (A4.13)$$

$$\tilde{S}_{s,0} = \tilde{S}_{s,8759} + S_{s,8759}^{in}\eta_{s}^{in} - \frac{S_{s,8759}^{out}}{\eta_{s}^{out}} \quad (A4.14)$$

$$e_{lake,m}^{max} \geq \sum_{t \epsilon m} E_{lake,t} \quad (A4.15)$$

$$\sum_{f} R_{f,t} = \sum_{v} Q_{v}\epsilon_{v} + d_{t}l(1+\Delta) \quad (A4.16)$$

$$q_{v}^{max} \geq Q_{v} \quad (A4.17)$$

$$q_{h}^{max} \geq Q_{h} \quad (A4.18)$$

$$Q_{h} \geq q_{h}^{min} \quad (A4.19)$$

$$Q_{i} \geq 0 \quad (A4.20)$$

$$E_{i,t} \geq 0 \quad (A4.21)$$

$$R_{f,t} \geq 0 \quad (A4.22)$$

$$\tilde{S}_{s,t} \geq 0 \quad (A4.23)$$

$$V_{s} \geq 0 \quad (A4.24)$$

$$\bar{S}_{s}^{in} \geq 0 \quad (A4.25)$$

$$\bar{S}_{s}^{out} \geq 0 \quad (A4.26)$$

$$S_{s,t}^{in} \geq 0 \quad (A4.27)$$

$$S_{s,t}^{out} \geq 0 \quad (A4.28)$$

Equation (A4.5) limits the maximal hourly power production by each technology to its installed capacity, Equation (A4.6) integrates hourly capacity factors of VRE technologies to the former, Equation (A4.7) integrates the capacity needed to put aside for the secondary reserves at each hour to Equation (A4.5) for the technologies used in reserve options. Equation (A4.8) shows that biogas (as renewable gas) and methanation (as storage option) should be sent to the combustion units (in our model OCGT) and Equation (A4.9) puts a constraint on the level of yearly available power from biogas. Equations (A4.10) to (A4.14) represent the mechanism of charge and discharge of the storage options and the related installed capacity, hourly power production and energy volume constraints. Equation (A4.15) relates the hourly power production by reservoirs and dams to the maximum monthly possible levels (related to monthly rainfall) and Equation (A4.16) quantifies the needed hourly secondary reserve as a function of installed capacity of VRE technologies and the hourly demand. Equations (A4.17) and (A4.18) limit the installed capacity of VRE and hydropower technologies with respect to land-use constraints, while Equation (A4.19) puts a minimal value to the installed capacity of hydro power plants, which is the existing installed capacity of each hydro technology. Equations (A4.20) to (A4.28) highlight the fact that all the variables are non-negative, but definition of Equations (A4.5), (A4.11), (A4.12) and (A4.13) combined with Equations (A4.21), (A4.23), (A4.27) and (A4.28) already imply that installed capacities are all non-negative, thus I eliminate equations (A4.20), (A4.24), (A4.25) and (A4.26) from the system. The Lagrange equation for this minimization problem becomes (Equation A4.29):

$$\mathcal{L} = -C\big(Q_i, E_{i,t}, \bar{S}_s^{out}, \bar{S}_s^{in}, S_{s,t}^{out}, V_s\big) + \sum_t \lambda_t\big(\sum_{g\neq c} E_{g,t} + \sum_s S_{s,t}^{out} - d_t - \sum_s S_{s,t}^{in}\big) + \sum_t \sum_i \delta_{i,t}\big(Q_i - E_{i,t}\big) + \sum_t \sum_v \delta'_{v,t}\big(Q_v cf_{v,t} - E_{v,t}\big) + \sum_t \sum_f \delta''_{f,t}\big(Q_f - E_{f,t} - R_{f,t}\big) + \sum_t \beta_t^{gas}\big(E_{gas,t} - \sum_c E_{c,t}\big) + \beta^{bio}\big(e_{bio}^{max} - \sum_t E_{bio,t}\big) + \sum_t \sum_s \varepsilon_{s,t}^1\left(\tilde{S}_{s,t+1} - \tilde{S}_{s,t} - S_{s,t}^{in}\eta_s^{in} + \frac{S_{s,t}^{out}}{\eta_s^{out}}\right) + \sum_t \sum_s \varepsilon_{s,t}^2\big(V_s - \tilde{S}_{s,t}\big) + \sum_t \sum_s \varepsilon_{s,t}^3\big(\bar{S}_s^{in} - S_{s,t}^{in}\big) + \sum_t \sum_s \varepsilon_{s,t}^4\big(\bar{S}_s^{out} - S_{s,t}^{out}\big) + \sum_s \varepsilon_s^5\left(\tilde{S}_{s,0} - \tilde{S}_{s,8759} - S_{s,8759}^{in}\eta_s^{in} + \frac{S_{s,8759}^{out}}{\eta_s^{out}}\right) + \sum_m \beta_m^{lake}\big(e_{lake,m}^{max} - \sum_{t\epsilon m} E_{lake,t}\big) + \sum_t \gamma_t\left(\sum_f R_{f,t} - \sum_v Q_v\epsilon_v - d_t l(1+\Delta)\right) + \sum_v \pi_v^{vre}(q_v^{max} - Q_v) + \sum_h \pi_h^{hydro}(q_h^{max} - Q_h) + \sum_h \rho_h^{hydro}\big(Q_h - q_h^{min}\big) + \sum_t \sum_i \vartheta_{i,t}^e E_{i,t} + \sum_t \sum_f \vartheta_{f,t}^r R_{f,t} + \sum_t \sum_s \vartheta_{s,t}^s \tilde{S}_{s,t} + \sum_t \sum_s \vartheta_{s,t}^{ch} S_{s,t}^{in} + \sum_t \sum_i \vartheta_{s,t}^{dch} S_{s,t}^{out} \quad \text{(A4.29)}$$

Equations A4.30 to A4.36 show the Kuhn-Tucker conditions at the equilibrium of load d_t existing in the cost function:

$$\frac{\partial L}{\partial Q_i} = -\frac{\partial C(.)}{\partial Q_i} + \sum_t \delta_{i,t} + \left[\sum_t \delta'_{v,t}\, cf_{v,t} + \sum_t \delta''_{f,t} - \sum_t \gamma_t \epsilon_v - \pi_v^{vre} - \pi_h^{hydro} + \rho_h^{hydro}\right] \quad \text{(A4.30)}$$

$$\frac{\partial L}{\partial E_{i,t}} = -\frac{\partial C(.)}{\partial E_{i,t}} + \lambda_t - \delta_{i,t} + \vartheta_{i,t}^e + \left[-\delta'_{v,t} - \delta''_{f,t} \pm \beta_t^{gas} - \beta^{bio} - \beta_m^{lake}\right] \quad \text{(A4.31)}$$

$$\frac{\partial L}{\partial S_{s,t}^{in}} = -\frac{\partial C(.)}{\partial S_{s,t}^{in}} - \lambda_t - \varepsilon_{s,t}^1\eta_s^{in} - \varepsilon_{s,t}^3 + [-\varepsilon_s^5\eta_s^{in}] + \vartheta_{s,t}^{ch} \quad \text{(A4.32)}$$

$$\frac{\partial L}{\partial S_{s,t}^{out}} = -\frac{\partial C(.)}{\partial S_{s,t}^{out}} + \lambda_t + \varepsilon_{s,t}^1/\eta_s^{out} - \varepsilon_{s,t}^4 + [+\varepsilon_s^5/\eta_s^{out}] + \vartheta_{s,t}^{dch} \quad \text{(A4.33)}$$

$$\frac{\partial L}{\partial \bar{S}_s^{in}} = -\frac{\partial C(.)}{\partial \bar{S}_s^{in}} + \sum_t \varepsilon_{s,t}^3 \quad \text{(A4.34)}$$

$$\frac{\partial L}{\partial \bar{S}_s^{out}} = -\frac{\partial C(.)}{\partial \bar{S}_s^{out}} + \sum_t \varepsilon_{s,t}^4 \quad \text{(A4.35)}$$

$$\frac{\partial L}{\partial V_s} = -\frac{\partial C(.)}{\partial V_s} + \sum_t \varepsilon_{s,t}^2 \quad \text{(A4.36)}$$

The terms in brackets are to mention some cases where the technology is the one indicated in the indices. According to Kuhn-Tucker conditions in the optimal case, each of these derivatives must be equal to zero. Consequently, we have:

$$C_{Q_i} = \sum_t \delta_{i,t} + \left[\underbrace{\sum_t \delta'_{v,t}\, cf_{v,t}}_{i\in v} + \underbrace{\sum_t \delta''_{f,t}}_{i\in f} - \underbrace{\sum_t \gamma_t \epsilon_v}_{i\in v} - \underbrace{\pi_v^{vre}}_{i\in v} - \underbrace{\pi_h^{hydro}}_{i\in h} + \underbrace{\rho_h^{hydro}}_{i\in h}\right] \quad \text{(A4.37)}$$

$$C_{E_{i,t}} = +\lambda_t - \delta_{i,t} + \vartheta_{i,t}^e + \left[\underbrace{-\delta'_{v,t}}_{i\in v}\underbrace{-\delta''_{f,t}}_{i\in f} + \underbrace{\beta_t^{gas}}_{i=gas} - \underbrace{\beta_t^{gas}}_{i\in c} - \underbrace{\beta^{bio}}_{i=bio} - \underbrace{\beta_m^{lake}}_{i=lake}\right] \quad \text{(A4.38)}$$

$$C_{S_{s,t}^{in}} = -\lambda_t - \varepsilon_{s,t}^1\eta_s^{in} - \varepsilon_{s,t}^3 + [\underbrace{-\varepsilon_s^5\eta_s^{in}}_{t=8759}] + \vartheta_{s,t}^{ch} \quad \text{(A4.39)}$$

$$C_{S_{s,t}^{out}} = +\lambda_t + \varepsilon_{s,t}^1/\eta_s^{out} - \varepsilon_{s,t}^4 + [\underbrace{+\varepsilon_s^5/\eta_s^{out}}_{t=8759}] + \vartheta_{s,t}^{dch} \quad \text{(A4.40)}$$

$$C_{\bar{S}_s^{in}} = \sum_t \varepsilon_{s,t}^3 \quad \text{(A4.41)}$$

$$C_{\bar{S}_s^{out}} = \sum_t \varepsilon_{s,t}^4 \tag{A4.42}$$

$$C_{V_s} = \sum_t \varepsilon_{s,t}^2 \tag{A4.43}$$

C_{Q_i} can be interpreted as the marginal cost of capacity of each technology which is a value in (€/kW).year and one can define $C_{E_{i,t}}$ as the marginal cost of power production by that technology at hour t. Here λ_t is the Lagrange multiplier of adequacy equation. This can be interpreted as the hourly market equilibrium price. Therefore, with quantifying these Lagrange multipliers one can see if the marginal cost of a power plant is higher, lower or equal to the market price, and consequently, we can understand the place of the power plant in the wholesale market at each hour. We will see this later, let's now consider the slackness conditions:

i. $\delta_{i,t}(Q_i - E_{i,t}) = 0;$ $\quad \delta_{i,t} \geq 0\,,\ Q_i \geq E_{i,t}$

ii. $\delta'_{v,t}(cf_{v,t}Q_v - E_{v,t}) = 0;$ $\quad \delta'_{v,t} \geq 0\,,\ cf_{v,t}Q_v \geq E_{v,t}$

iii. $\delta''_{f,t}(Q_f - E_{f,t} - R_{f,t}) = 0;$ $\quad \delta''_{f,t} \geq 0\,,\ Q_f \geq E_{f,t} + R_{f,t}$

iv. $\beta_t^{gas}(E_{gas,t} - \sum_c E_{c,t}) = 0;$ $\quad \beta_t^{gas} \geq 0\,,\ E_{gas,t} \geq \sum_c E_{c,t}$

v. $\beta^{bio}(e_{bio}^{max} - \sum_t E_{bio,t}) = 0;$ $\quad \beta^{bio} \geq 0\,,\ e_{bio}^{max} \geq \sum_t E_{bio,t}$

vi. $\varepsilon_{s,t}^1\left(\tilde{S}_{s,t+1} - \tilde{S}_{s,t} - S_{s,t}^{in}\eta_s^{in} + \frac{S_{s,t}^{out}}{\eta_s^{out}}\right) = 0;$ $\quad \varepsilon_{s,t}^1 \geq 0\,,\ \tilde{S}_{s,t+1} \geq \tilde{S}_{s,t} + S_{s,t}^{in}\eta_s^{in} - \frac{S_{s,t}^{out}}{\eta_s^{out}}$

vii. $\varepsilon_{s,t}^2(V_s - \tilde{S}_{s,t}) = 0;$ $\quad \varepsilon_{s,t}^2 \geq 0\,,\ V_s \geq \tilde{S}_{s,t}$

viii. $\varepsilon_{s,t}^3(\bar{S}_s^{in} - S_{s,t}^{in}) = 0;$ $\quad \varepsilon_{s,t}^3 \geq 0\,,\ \bar{S}_s^{in} \geq S_{s,t}^{in}$

ix. $\varepsilon_{s,t}^4(\bar{S}_s^{out} - S_{s,t}^{out}) = 0;$ $\quad \varepsilon_{s,t}^4 \geq 0\,,\ \bar{S}_s^{out} \geq S_{s,t}^{out}$

x. $\varepsilon_s^5\left(\tilde{S}_{s,0} - \tilde{S}_{s,8759} - S_{s,8759}^{in}\eta_s^{in} + \frac{S_{s,8759}^{out}}{\eta_s^{out}}\right) = 0;$ $\quad \varepsilon_s^5 \geq 0\,,\ \tilde{S}_{s,0} \geq \tilde{S}_{s,8759} + S_{s,8759}^{in}\eta_s^{in} - \frac{S_{s,8759}^{out}}{\eta_s^{out}}$

xi. $\beta_m^{lake}(e_{lake,m}^{max} - \sum_{t\epsilon m} E_{lake,t}) = 0;$ $\quad \beta_m^{lake} \geq 0\,,\ e_{lake,m}^{max} \geq \sum_{t\epsilon m} E_{lake,t}$

xii. $\gamma_t\left(\sum_f R_{f,t} - \sum_v Q_v\epsilon_v - d_t l(1+\Delta)\right) = 0;$ $\quad \gamma_t \geq 0\,,\ \sum_f R_{f,t} \geq \sum_v Q_v\epsilon_v + d_t l(1+\Delta)$

xiii. $\pi_v^{vre}(q_v^{max} - Q_v) = 0;$ $\quad \pi_v^{vre} \geq 0\,,\ q_v^{max} \geq Q_v$

xiv. $\pi_h^{hydro}(q_h^{max} - Q_h) = 0;$ $\quad \pi_h^{hydro} \geq 0\,,\ q_h^{max} \geq Q_h$

xv. $\rho_h^{hydro}(Q_h - q_h^{min}) = 0;$ $\quad \rho_h^{hydro} \geq 0\,,\ Q_h \geq q_h^{min}$

xvi. $\vartheta_{i,t}^e E_{i,t} = 0;$ $\quad \vartheta_{i,t}^e \geq 0\,,\ E_{i,t} \geq 0$

xvii. $\vartheta_{f,t}^r R_{f,t} = 0;$ $\quad \vartheta_{f,t}^r \geq 0\,,\ R_{f,t} \geq 0$

xviii. $\vartheta_{s,t}^s \tilde{S}_{s,t} = 0;$ $\quad \vartheta_{s,t}^s \geq 0\,,\ \tilde{S}_{s,t} \geq 0$

xix. $\vartheta_{s,t}^{ch} S_{s,t}^{in} = 0;$ $\quad \vartheta_{s,t}^{ch} \geq 0\,,\ S_{s,t}^{in} \geq 0$

xx. $\vartheta_{s,t}^{dch} S_{s,t}^{out} = 0;$ $\quad \vartheta_{s,t}^{dch} \geq 0\,,\ S_{s,t}^{out} \geq 0$

Note that some of the equations are binding (Equations A4.6, A4.8, A4.10, A4.14 and A4.16), therefore the Lagrange multipliers for these equations are always positive: $\delta'_{v,t} > 0\,, \beta_t^{gas} >$

0 , $\varepsilon^1_{s,t} > 0$, $\varepsilon^5_s > 0$, γ_t>0. On the other hand, if there is no installed capacity of a technology available, no power can be produced from that technology.

As identified above, the marginal cost of each technology is found using these Lagrange multipliers, and by knowing the market price of electricity at each hour, and these multipliers, we can understand the position of each technology in the market at that hour. Since λ_t is interpreted as the hourly market price, we can classify the marginal cost of each technology in one of three groups below:

a) $C_{E_{i,t}} > \lambda_t$: The technology has a higher marginal cost than market price, so it is out of market.
b) $C_{E_{i,t}} = \lambda_t$: The technology has a marginal cost equal to the market price, it is a 'marginal plant'.
c) $C_{E_{i,t}} < \lambda_t$: The technology's marginal cost is cheaper than the market price, it will be on 'full load' condition.

Let's consider three power plants, "1", "2", and "3". The marginal cost of each power plant is represented by c_i and hourly power production of each of them is represented by $E_{i,t}$ and the demand for electricity for each hour is d_t. Let's suppose that $c_1 < c_2 < c_3$ and $d_t > E_{i,t}$ and $d_t < \sum_i E_{i,t}$. We can graphically see the classification made above for these three power plants in Figure A4.1. Here, plant "1" is in full load, whose marginal cost is lower than the market clearing price. Plant "2" is the marginal plant, it is the plant setting the market price, and $\lambda_t = c_2$. As we can see plant "2" is not fully exploited, and since plant "3" has a higher marginal cost than the market clearing price, it is not producing any electricity at this hour.

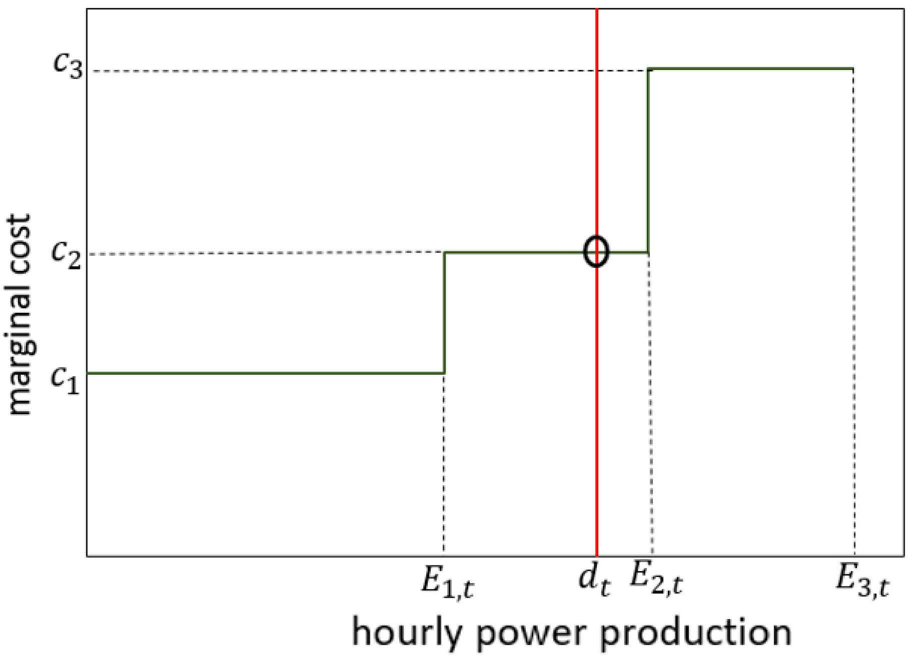

Figure A4.1. Market equilibrium for plants with different marginal costs and inelastic fixed hourly demand

The way to understand if a technology has an installed capacity or not, if it produces electricity or not and if it is in full load or not is straightforward, using the Lagrange multipliers and slackness conditions. For any binding constraint, the Lagrange multipliers should be positive and non-zero. For non-binding constraints, if the Lagrange multiplier is zero, the remaining of the slackness condition should be positive, and vice versa. For example, if a technology produces power ($E_{i,t} > 0$), according to slackness condition (xvi), the corresponding Lagrange multiplier should be zero, i.e. $\vartheta_{i,t}^{e} = 0$.

Let's consider all the technologies are installed (since it is the solution of the optimization). In case a technology i produces power at the corresponding hour t it means that $\vartheta_{i,t}^{e}$ is equal to zero and according to the slackness condition (i), we know that if the Lagrange multiplier $\delta_{i,t}$ is equal to zero, we will have $Q_i > E_{i,t}$, which means the technology is not in full load, and it is the marginal technology at this hour, in other words this technology is the one setting the price, in partial load (except for the renewables where the hourly capacity factors lead to this inequality in every hour). Similarly, in case we have a positive Lagrange multiplier for this equation, the technology will be in full load, and it will have a lower price than the price of the market. The equation of marginal cost above shows this market behavior clearly.

Appendix 4.2. The impact of reserve allocation in the long-term profit of VRE technologies

To understand the market behavior of each technology, the marginal cost of each technology ($C_{E_{i,t}}$) should be calculated, and in case it is lower than market price (λ_t), it should be exploited without being marginal technology at the full load operation, in case it is higher than this market price, this technology is not exploited and does not participate to the supply of electricity, and if the marginal cost of a technology is equal to the market price, that technology is the marginal one. Equation (A4.37) for each technology set is as below:

$$C_{E_{v,t}} = +\lambda_t + \vartheta_{v,t}^{e} - \delta'_{v,t} \tag{A4.44}$$

$$C_{E_{biogas,t}} = +\beta_t^{gas} - \delta_{biogas,t} + \vartheta_{biogas,t}^{e} - \beta^{bio} \tag{A4.45}$$

$$C_{E_{gas,t}} = +\lambda_t - \beta_t^{gas} - \delta_{gas,t} + \vartheta_{gas,t}^{e} + -\delta''_{gas,t} \tag{A4.46}$$

$$C_{E_{lake,t}} = +\lambda_t - \delta_{lake,t} + \vartheta_{lake,t}^{e} - \delta''_{lake,t} - \beta_m^{lake} \tag{A4.47}$$

Equation (A4.40) for storage technologies becomes:

$$C_{S_{battery,t}^{out}} = +\lambda_t + \frac{\varepsilon_{battery,t}^{1}}{\eta_{battery}^{out}} - \varepsilon_{battery,t}^{4}\left[\underbrace{+\frac{\varepsilon_{battery}^{5}}{\eta_{battery}^{out}}}_{t=8759}\right] + \vartheta_{battery,t}^{dch} - \delta''_{battery,t} \tag{A4.48}$$

$$C_{S_{phs,t}^{out}} = +\lambda_t + \frac{\varepsilon_{phs,t}^{1}}{\eta_{phs}^{out}} - \varepsilon_{phs,t}^{4}\,\underbrace{[+\varepsilon_{phs}^{5}/\eta_{phs}^{out}]}_{t=8759} + \vartheta_{phs,t}^{dch} - \delta''_{phs,t} \tag{A4.49}$$

$$C_{S_{metha,t}^{out}} = +\beta_t^{gas} + \frac{\varepsilon_{metha,t}^{1}}{\eta_{metha}^{out}} - \varepsilon_{metha,t}^{4}\,\underbrace{[+\varepsilon_{metha}^{5}/\eta_{metha}^{out}]}_{t=8759} + \vartheta_{metha,t}^{dch} \tag{A4.50}$$

Calculation of short-term profit is based on marginal cost, however calculation of long-term profit (scarcity rent) needs fixed costs too. For instance, short-term profit of VRE technologies can be calculated by subtraction of their marginal costs from the market price:

$$\pi_{v,t} = \lambda_t - C_{E_{v,t}} = -\vartheta_{v,t}^{e} + \delta'_{v,t} \tag{A4.51}$$

Long-term profit is the sum of the short-term profits and subtraction of the fixed costs (C_{Q_i}) from it, thus:

$$\bar{\Pi}^{v} = \frac{\sum_t(\delta'_{v,t} - \vartheta_{v,t}^{e}) \times E_{v,t} - \sum_t \delta'_{v,t}\, cf_{v,t} \times Q_v + \sum_t \gamma_t \epsilon_v Q_v}{\sum_t E_{v,t}} \tag{A4.52}$$

Knowing the fact that $Q_v cf_{v,t} = E_{v,t}$, and that $\sum_t E_{v,t} = Q_v \times \overline{cf_v} \times 8760$, we can rewrite it as:

$$\bar{\Pi}^{vre} = \frac{\sum_t({\delta'}_v^t - \nu_v^t) \times Q_v \times cf_{v,t} - \sum_t {\delta'}_v^t \times cf_{v,t} \times Q_v + \sum_t \gamma_t \epsilon_v Q_v}{Q_v \times \overline{cf_v} \times 8760} = \frac{Q_v[\sum_t {\delta'}_v^t cf_{v,t} + \sum_t \nu_v^t cf_{v,t} - \sum_t {\delta'}_v^t cf_{v,t}]}{Q_v \times \overline{cf_v} \times 8760} = \frac{\sum_t \nu_v^t cf_{v,t} + \sum_t \gamma_t \epsilon_v}{\overline{cf_v} \times 8760} \tag{A4.53}$$

And we know that if power production by a VRE technology is zero, $cf_{v,t}$ is equal to zero and in case it is positive, ν_v^t is zero, thus in any case $\sum_t \nu_v^t cf_{v,t}$ will be equal to zero. Therefore, the scarcity rent of a VRE technology is as in Equation (A4.54).

$$\bar{\Pi}^{vre} = \frac{\sum_t \gamma_t \epsilon_v}{\overline{cf}_v \times 8760} \tag{A4.54}$$

Therefore, the reason why the long-term profit of VRE technologies are positive without reaching their capacity constraints is the presence of the reserve requirement equations (γ_t is the Lagrange multiplicator for reserve requirements equation). To study the profitability of VRE technologies correctly, these extra income because of the additional reserve capacity resulting from the variability of VRE technologies should be eliminated.

Appendix 4.3. Marginal cost of all technologies

In case reserve requirements are eliminated (as it is the case in the analysis of this chapter), Equations (A4.44) to (A4.50) become:

$$C_{E_{v,t}} = +\lambda_t + \vartheta^{e}_{v,t} - \delta'_{v,t} \tag{A4.55}$$

$$C_{E_{biogas,t}} = +\beta^{gas}_{t} - \delta_{biogas,t} + \vartheta^{e}_{biogas,t} - \beta^{bio} \tag{A4.56}$$

$$C_{E_{gas,t}} = +\lambda_t - \beta^{gas}_{t} - \delta_{gas,t} + \vartheta^{e}_{gas,t} \tag{A4.57}$$

$$C_{E_{lake,t}} = +\lambda_t - \delta_{lake,t} + \vartheta^{e}_{lake,t} - \beta^{lake}_{m} \tag{A4.58}$$

$$C_{S^{out}_{battery,t}} = +\lambda_t + \varepsilon^{1}_{battery,t}/\eta^{out}_{battery} - \varepsilon^{4}_{battery,t}\ \underbrace{[+\varepsilon^{5}_{battery}/\eta^{out}_{battery}]}_{t=8759} + \vartheta^{dch}_{battery,t} \tag{A4.59}$$

$$C_{S^{out}_{phs,t}} = +\lambda_t + \frac{\varepsilon^{1}_{phs,t}}{\eta^{out}_{phs}} - \varepsilon^{4}_{phs,t}\ \underbrace{[+\varepsilon^{5}_{phs}/\eta^{out}_{phs}]}_{t=8759} + \vartheta^{dch}_{phs,t} \tag{A4.60}$$

$$C_{S^{out}_{metha,t}} = +\beta^{gas}_{t} + \frac{\varepsilon^{1}_{metha,t}}{\eta^{out}_{metha}} - \varepsilon^{4}_{metha,t}\ \underbrace{[+\varepsilon^{5}_{metha}/\eta^{out}_{metha}]}_{t=8759} + \vartheta^{dch}_{metha,t} \tag{A4.61}$$

Although these Lagrange multiplicators defining the market behavior of different technologies remain constant over one year (because their marginal costs do not change over time) for non-constrained technologies, for the monthly constrained lake it can have 12 values: either zero in case the limiting constraint is not reached, or positive values (the same over the whole constrained period). However, presence of storage options introduces the temporality dimension since the electricity bought from the market in a moment has its price and selling it in another time requires a minimum profit of zero. The Lagrange multiplicator connecting the charging and discharging of storage options is $\varepsilon^{1}_{s,t}$. Thus, the price regimes are much more than the expected limited possibilities.

Using the propositions elaborated by Crampes and Trochet (2019), the charging behavior of the storage options can also be visualized by Lagrange multiplicators using Equations (A4.62) to (A4.64).

$$C_{S^{in}_{battery,t}} = -\lambda_t - \varepsilon^{1}_{battery,t}\eta^{in}_{battery} - \varepsilon^{3}_{battery,t}\ [-\underbrace{\varepsilon^{5}_{battery}\eta^{in}_{battery}}_{t=8759}] + \vartheta^{ch}_{battery,t} \tag{A4.62}$$

$$C_{S^{in}_{phs,t}} = -\lambda_t - \varepsilon^{1}_{phs,t}\eta^{in}_{phs} - \varepsilon^{3}_{phs,t}\ \underbrace{[-\varepsilon^{5}_{phs}\ \eta^{in}_{phs}]}_{t=8759} + \vartheta^{ch}_{phs,t} \tag{A4.63}$$

$$C_{S^{in}_{metha,t}} = -\lambda_t - \varepsilon^{1}_{metha,t}\eta^{in}_{metha} - \varepsilon^{3}_{metha,t}\ \underbrace{[-\varepsilon^{5}_{metha}\eta^{in}_{metha}]}_{t=8759} + \vartheta^{ch}_{metha,t} \tag{A4.64}$$

In case the marginal cost of charging of a storage technology is lower than the negative of market price $-\lambda_t$, it will store energy with its full capacity, in case it is equal, this storage technology will be the marginal (storage) technology and in case the marginal cost of charging is higher than the negative of market price, the storage option will not operate in charging mode.

Appendix 4.4. The annual profit calculation in the presence of a capacity remuneration mechanism

Equations (A4.65) and (A4.66) show the calculation of profit for the cases with capacity remuneration and with no support scheme in €/€$_{inv}$:

$$\pi_{vre,y}^{capacity\ rem} = \frac{\sum_{h\in y}(E_{vre,h}\times p_h)(1-\tau^{rem}) - C^{fixed}{}_{vre}(1-\tau^{rem})}{C^{fixed}{}_{vre}(1-\tau^{rem})} \qquad \text{(A4.65)}$$

$$\pi_{vre,y}^{no\ support} = \frac{\sum_{h\in y}(E_{vre,h}\times p_h) - C^{fixed}{}_{vre}}{C^{fixed}{}_{vre}} \qquad \text{(A4.66)}$$

Where $\pi_{vre,y}^{capacity\ rem}$ is the annual profit (in €/€$_{inv}$) of technology vre at year y in the presence of capacity remuneration mechanism, and $\pi_{vre,y}^{no\ support}$ is the annual profit of the same technology, at the same year with no capacity remuneration. τ^{rem} is the remuneration rate (capacity remuneration ratio of cr_{vre} or the income tax ratio tax_{vre} that was defined in Equation 4.4). Both of these two equations result in the same annual profit value of Equation (A4.67):

$$\pi_{vre,y}^{capacity\ rem} = \pi_{vre,y}^{no\ support} = \frac{\sum_{h\in y}(E_{vre,h}\times p_h)}{C^{fixed}{}_{vre}} - 1 \qquad \text{(A4.67)}$$

Part II

Analysis of Low GreenHouse Gas Emission Energy Systems

Chapter 5

Sector-coupling to reach carbon-neutrality in the whole energy system

5.1. Introduction

In order to meet the 1.5°C global warming objective, the European commission's 'European Climate Law' proposal sets the target of achieving climate neutrality by 2050 (European Commission, 2019). Similarly, several European states have set ambitious greenhouse gas (GHG) emission reduction targets; for instance, the official target in the French 'energy-climate law' is to reach net zero GHG emissions by 2050 (DGEC, 2019). Energy scenarios aiming at carbon-neutrality by 2050 vary with respect to the role of different energy carriers, particularly gas and electricity. For instance, the French Environment and Energy Management Agency's (ADEME) 'energy-climate scenario 2035-2050' and the French Ministry of Ecological Transition and Solidarity's 'national low-carbon strategy', predict highly electrified heating and transport sectors in France with up to 60% of the primary energy supply being electrified (ADEME, 2017 and SNBC, 2018). However, négaWatt's scenario suggests 35% of electrification for the primary energy supply (négaWatt, 2017), with the transport sector dominated by gas-fueled internal combustion engines.

These national scenarios are based on top-down allocation of energy sources and carriers and do not result from optimization. Considering the entire energy system as an integrated whole and optimizing it on a national scale is complicated and highly demanding in computational terms. However, a rigorous energy policy that fully considers the relative role of different energy sources, carriers and storage options must be based on the optimal allocation of those options. This optimization must include endogenous choice of energy carriers and should include the main low-carbon options (renewable electricity and gas, carbon capture and storage and nuclear power), since choice of technology and optimal allocation of energy carriers are interdependent. For instance, considering power-to-gas as a long-term storage option in the context of the electricity sector alone requires highly inefficient gas-to-power conversion technologies which may be difficult to render profitable (Van Leeuwen and Molder, 2018). To avoid overestimation of storage needs, the studies should analyze the entire energy system, not a single sector (Blanco and Faaj, 2018). Therefore, the endogenous technology choice must include a multi-sectorial approach to enable sector-coupling. Sector-coupling enables optimal allocation of different energy sources, carriers and storage options to satisfy the main end-use demands by allowing an endogenous choice of energy carrier and conversion options for different end-uses (Lund et al, 2017).

Correct dimensioning of short-term and long-term storage options requires high temporal resolution. A coarser-than-hourly temporal resolution lowers the model accuracy due to short-term variations in wind speed and solar irradiation, leading to underestimation in the dimensioning of short-term storage options, at least in the electricity system (Brown et al, 2018a). Similarly, long-term storage options (typically inter-seasonal storage) are among cost-optimal solutions due to annual cycles of wind, solar irradiation and temperature (Chapter 2 and Schill and Zerrahn, 2018), and correct dimensioning of long-term storage options requires the modeling of a continuous, long period of time, rather than defining representative periods (Pfenninger, 2017). Therefore, modelling an optimal energy mix must consider at least one full year at an hourly resolution, at least at the first stage where the effect of flexibility gains from sector-coupling in reduction of short-term variability of VRE technologies and end-use demand is not assessed (in case short-term variations are fully compensated by the flexibility gains from sector-coupling, coarser-than-hourly temporal resolution can keep a high accuracy in energy mix – Chapter 7).

Social cost of carbon must be included in the optimization from the social planner perspective to internalize the cost of positive and negative emissions to the society. To sum up, identification of the relative role of different energy carriers requires an integrated optimization that (1) includes the main energy sectors, (2) is based on endogenous energy carrier and technology choice, (3) includes the main low-carbon options, (4) has a high temporal resolution over at least a full year and (5) internalizes both positive and negative CO_2 emissions.

A very big proportion of the existing literature on energy system optimization is based on a single sector (Chapters 2 and 3, Olauson et al, 2016, Schlachtberger et al, 2017, Schlachtberger et al, 2018, Zeyringer et al, 2018, etc.). Although sector-coupling has gained significant attention recently, the existing energy system optimization studies that include sector-coupling either lack the required temporal precision by choosing discrete representative periods (Doudard, 2018), or lack complete endogeneity in the interactions between energy carriers and end-use demands. They also suffer from limited representation of the main low-carbon options, especially negative emission technologies (Bloess et al, 2018, Brown et al, 2018b, Victoria et al, 2019, Victoria et al, 2020, Zhu et al, 2019 and Zhu et al, 2020). Moreover, none of these studies include internalization of both negative and positive CO_2 emissions, which is a key element in studying the potential of different mitigation options. To include all the conditions mentioned above in an optimal decision-making process aiming at carbon-neutrality, I develop the EOLES_mv (Energy Optimization for Low Emission Systems, multi-vector) model, which meets all the conditions highlighted above. EOLES_mv simultaneously optimizes dispatch (providing an hourly supply-demand balance) and investment in production, storage, network and energy conversion capacities, in order to minimize the total cost of energy systems.

Applying this model to the French energy situation, I study the optimal energy system for different social cost of carbon[1] scenarios (from 0 to €500/tCO_2), and I study the relative role of the main energy carriers and the importance of the key low-carbon technologies in achieving carbon-neutrality in cost-optimal ways. Finally, accounting for the main uncertainties, I propose a robust social cost of carbon to ensure carbon neutrality in the French energy sector.

The remainder of this chapter is organized as follows. Section 5.2 presents the methods: the EOLES_mv model and the input parameters. Section 5.3 presents the results, which are discussed in section 5.4. Section 5.5 highlights the main findings and concludes.

[1] Social cost of carbon (SCC) is the monetary value that society attributes to one ton of supplementary CO_2 emissions to internalize the damages caused by it.

5.2. Methods

5.2.1. The EOLES_mv model

The EOLES_mv model is one of the models in the EOLES family of models, therefore, it performs simultaneous optimization of the investment and operation of the energy system in order to minimize the total cost while satisfying energy demand. The "mv" in EOLES_mv stands for multi-vector and this model minimizes the annualized energy generation, conversion and storage costs, including the cost of connection to the grid. EOLES_mv considers all the major energy sectors (residential and tertiary buildings, industry, transport and agriculture) in an integrated manner, enabling sector-coupling. EOLES_mv is one of the EOLES models, therefore all the simplifying assumptions discussed in previous chapters hold for EOLES_mv as well: greenfield optimization with static end-point but not a dynamic trajectory, performing linear optimization and considering a country as a single node with aggregated weather data. This model considers perfect competition and full information, where the energy demand in EOLES_mv is inelastic[1].

The EOLES_mv model includes seven power generation technologies: floating and monopile offshore wind power, onshore wind power, photovoltaic solar power (PV), run-of-river and lake-generated hydro-electricity and nuclear power (EPR, i.e. third generation European Pressurized Water Reactors) and three gas production technologies: natural gas, methanization from anaerobic digestion and pyro-gasification of solid biomass. Sector-coupling is enabled by vector-change (energy conversion) technologies: open-cycle gas turbines (OCGT), combined-cycle gas turbines (CCGT) and CCGTs equipped with post-combustion carbon capture and storage (CCS) technologies are used to convert gas to electricity. Vector-change from electricity to gas is enabled by electrolysis (power to hydrogen to inject into the gas network with a volume share limit) and methanation (hydrogen production from electrolysis of water and the Sabatier reaction between the hydrogen produced and green CO_2 to produce synthetic methane) as power-to-gas options. Similarly, centralized and decentralized boilers are used to produce heat from gas and centralized and individual heat pumps and resistive heat production technologies are used to produce heat from electricity. The model includes two electricity storage technologies (Li-Ion batteries and pumped hydro storage), the existing gas network as the gas storage option and two heat storage technologies (centralized and decentralized hot water tanks). This model also allows demand for transport to be met with an endogenous choice between electric vehicles and internal combustion engine vehicles, for four main transport categories: light vehicles, heavy vehicles, buses and trains. The interaction of different energy end-use demands, supply side, storage and energy carriers are presented in Figure 5.1.

EOLES_mv uses representative technologies chosen from groups of technologies with similar technical and economic behavior. For instance, only two engine types are considered in the transport sector: gas-fueled internal combustion engine (ICE) vehicles and battery electric vehicles (BEV). Other transport options include liquid-fueled ICE vehicles and hydrogen-fueled fuel cell electric vehicles but since they have similar economic and technical behaviors to gas-fueled ICE vehicles and BEVs respectively, they have been excluded in order to maintain computational tractability.

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[1] The inelastic demand assumption cannot be realistic for low social cost of carbon values. This is discussed briefly in section 4.5.

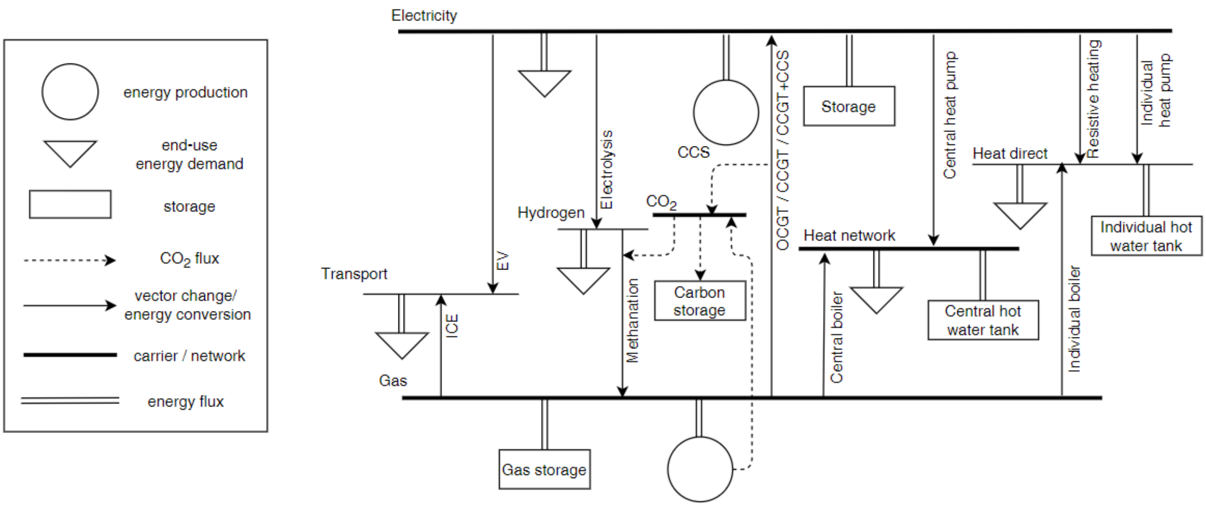

Figure 5.1. Schematic diagram of the EOLES_mv model; the figure on the right shows the interactions between energy supply, demand, storage and carriers by energy flux and CO_2 exchanges. The box on the left provides the key to the shapes. The two energy supply technologies are electricity and gas production, each connected to its own network.

The model is written in GAMS and solved using the CPLEX solver. The GAMS scripts and the input data are available on GitHub[1]. The model's indices, parameters, variables and equations are presented in Appendix 5.1.

5.2.2. Input parameters

5.2.2.1. VRE profiles

The preparation of VRE profiles is explained in detail in Chapter 2. In this chapter the same weather data has been used as input data, and 2006 is the representative year for this chapter is in Chapters 2 and 3).

5.2.2.2. Energy demand

The energy demand is categorized for each end-use, i.e. electricity, heat, transport and hydrogen (as a substitute for coal in industry) covering all the main energy sectors: residential and tertiary buildings, industry and construction, agriculture and transport. Unlike the existing literature, I define the end-uses and allow the model to make the optimal choice to satisfy demand in different sectors for different end-uses. As an example, the EOLES_mv model optimizes the required transport energy carrier (electricity for EV or gas for ICE) for three of the four main transport categories (light and heavy vehicles and buses), while trains are all considered to be electrically powered as they mostly are today. Similarly, EOLES_mv optimizes heat production to satisfy hourly heat demand profiles, and the choice of heat production is optimized over five energy conversion technologies from electricity or gas to heat. Therefore, the model chooses the optimal heat production mix endogenously among different central/decentralized and power-to-heat/gas-to-heat options to satisfy the exogenous hourly heat demand.

The annual energy requirement for each energy sector is taken from ADEME's update of the 'Energy climate' scenario for 2050 (ADEME, 2017). While different end-uses are provided in detail for the residential sector, this detail is not included for the tertiary, agriculture and industry sectors.

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

Another future annual demand projection for France is provided by the French National Low Carbon Strategy (DGEC, 2019). The sectorial demands are very similar in these two studies, but the latter provides more detail about energy end-use for the transport and tertiary sectors. Therefore, taking the same values found in ADEME (2017), I use the final energy demand allocation for the tertiary sector from the second report. I took transport demand from ADEME's "energy climate scenario" (ADEME, 2017) in Gp.km and Gt.km units, and using the occupation rate of different passenger and freight transport demands presented in DGEC (2019), I calculated the annual transport demand for each transport category in vehicle-kilometers. The demand for agriculture and industry are separated by end-use in négaWatt's '2017-2050 scenario' study (négaWatt, 2017). Therefore, using the overall energy demand in industry and agriculture provided by ADEME (2017), I use the allocation of heat and electricity demand provided by négaWatt to find the end-use demand for each of these technologies. The preparation of each end-use demand profile is presented in Appendix 5.2. Table 5.1 summarizes the assumed annual demand for each sector and its end-use, and the sources of these annual values and hourly profiles.

Table 5.1. Assumed sectorial demands for each end-use

Sector	End-use		Annual Value (TWh)	Source	Profiles from
Residential	Electricity		72.11	ADEME (2017), DGEC (2019)	ADEME (2015)
	Heat		215.16		Doudard (2018)
Tertiary	Electricity		83.74	ADEME (2017), DGEC (2019)	ADEME (2015)
	Heat		82.57		Doudard (2018)
Agriculture	Electricity		16.28	ADEME (2017), négaWatt (2017)	ADEME (2015)
	Heat		18.61		
Industry	Electricity		77.92	ADEME (2017), négaWatt (2017)	ADEME (2015)
	Heat		147.70		Flat
	Hydrogen		40.71	ADEME (2017)	Flat
Transport	Passengers (in Gp.km)	Light	554	ADEME (2017)	Doudard (2018)
		Public	51		
		Train	187		Flat
	Freight (in Gt.km)	Heavy	347		Doudard (2018)
		Train	127		Flat

5.2.2.3. Limiting capacity and energy production constraints

The maximal capacities of VRE and hydro-electricity technologies are the same as in Chapters 2, 3 and 4, taken from ADEME's 'Electric system trajectories 2020-2060' (ADEME, 2018a) and '100% renewable electricity system' (ADEME, 2015) studies. The hourly run-of-river and lake-generated hydro-electricity profiles are taken from the French national open data forum, provided by RTE (French transmission network operator) for each year from 2000 to 2018. By summing the hourly lake-generated hydro-electricity profiles for each month, I calculated the maximum amount of electricity that can be produced from this technology for each month from 2000 to 2018. Similarly, the maximum non-synthetic renewable gas[1] production (methanization and pyro-gasification) are taken from the upper limits of ADEME's '100% renewable gas mix' study (ADEME, 2018b). According

[1] Renewable gas, also known as bio-methane, is a biogas which has an upgraded quality similar to fossil natural gas or methanation as a power-to-gas option (hydrogen production from water electrolysis and methanation by the Sabatier reaction between hydrogen and green CO2) that can be injected directly into the gas network. In its biogas form, it is produced using biochemical processes from organic waste (methanization) and gasification of energy wood and biomass.

to the same study, the production of bio-methane from methanization leads to 60% of methane and 30% of carbon dioxide, which is used as the green CO_2 for the methanation process.

5.2.2.4. Economic parameters

Table 5.2 summarizes the economic parameters (and their sources) of energy supply technologies used as input data in the EOLES_mv model. Since four energy carriers are considered (electricity, gas, hydrogen and heat), the values are either in kW_e and MWh_e (for electricity) or in kW_{th} and MWh_{th} (for gas, hydrogen and heat). The economic parameters used are all forecasts for 2050.

Table 5.2. Economic parameters of energy production technologies; electricity supply technologies are in kW_e and gas supply technologies are in kW_{th}

Technology	**Overnight costs (€/kW)**	**Lifetime (years)**	**Annuity (€/kW/year)**	**Fixed O&M (€/kW/year)**	**Variable O&M (€/MWh)**	**Construction time (years)**	**Source**
Offshore wind farm - floating	3,660	30	236.2	73.2	0	1	JRC (2017)
*Offshore wind farm - monopile**	2,330	30	150.9	47	0	1	JRC (2017)
*Onshore wind farm**	1,130	25	81.2	34.5	0	1	JRC (2017)
*Solar PV**	423	25	30.7	9.2	0	0.5	JRC (2017)
Hydroelectricity – lake and reservoir	2,275	60	115.2	11.4	0	1	JRC (2017)
Hydroelectricity – run-of-river	2,970	60	150.4	14.9	0	1	JRC (2017)
Nuclear power	3,750	60	262.6	97.5	9.5**	10	JRC (2014)
Natural gas	-	-	-	-	23.5***	-	IEA (2019)
Methanization	370****	20	29.7	37	50	1	ADEME (2018b)
Pyro-gasification	2500	20	200.8	225	32*****	1	ADEME (2018b)

*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, I consider solar power as a simple average of ground-mounted, rooftop residential and rooftop commercial technologies. For lake and reservoir hydro I take the mean value of low-cost and high-cost power plants.

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

*** The price projected for Europe in 2040 in the sustainable development scenario, standing for $7.5/MBtu.

****The overnight cost for methanization is the investment cost of the purification plants for syngas.

*****The overnight cost only accounts for the gasification plants, while the wood used for energy is accounted for in variable costs.

Table 5.3 shows the economic parameters of energy conversion technologies.

Table 5.3. Economic parameters of conversion technologies

Technology	**Overnight costs (€/kW)**	**Lifetime (years)**	**Annuity (€/kW/year)**	**Fixed O&M (€/kW/year)**	**Variable O&M (€/MWh)**	**Construction time (years)**	**Conversion efficiency**	**Source**
OCGT	550	30	35.28	16.5	0	1	0.45	JRC (2014)
CCGT	850	30	54.53	21.25	0	1	0.63	JRC (2014)
CCGT-CCS	1280	30	82.12	32	5.76*	1	0.55	JRC (2017)
Electrolysis (Power-to-H2)	450	25	31.03	6.75	0	0.5	0.8	ENEA (2016)
Methanation	450/700	25/20	86.05	59.25	5***	0.5	0.8/0.79	ENEA

(Power-to-CH4)**								(2016)
Resistive	100	20	7.86	2	0	0.5	0.9	Brown et al. (2018b)
Individual heat pump	1050	20	82.54	36.75	0	0.5	3.5	Henning and Palzer (2014)
Central heat pump	700	20	55.02	24.5	0	0.5	2	Henning and Palzer (2014)
Central gas boiler	63	20	4.95	0.945	0	0.5	0.9	Brown et al. (2018b)
Decentral gas boiler	175	20	13.76	3.5	0	0.5	0.9	Brown et al. (2018b)

* This variable cost accounts for a 500km CO_2 transport pipeline and offshore storage costs estimated by Rubin et al. (2015).
**Methanation is the combination of hydrogen production from electrolysis and the Sabatier reaction of green CO_2 as a by-product from methanization with the hydrogen produced, therefore the economic parameters of each production are presented as electrolysis/Sabatier.
***As in Chapter 3.

The conversion efficiency is in the output energy form over the input energy form. Therefore, for Gas-to-Power technologies (OCGT, CCGT and CCGT-CCS) it is kW_e/kW_{th}, for Power-to-Gas technologies (electrolysis and methanation) it is kW_{th}/kW_e, for Power-to-Heat technologies (resistive heating and electric heat pump) it is also kW_{th}/kW_e and for Gas-to-Heat technologies (gas heat pump and central and non-central gas boilers) it is kW_{th}/kW_{th}.

Table 5.4 shows the economic parameters of power storage technologies, and Table 5.5 shows the economic parameters for transport technologies.

Table 5.4. Economic parameters of storage technologies

Technology	Overnight costs (€/kW)	CAPEX (€/kWh)	Lifetime (y)	Annuity (€/kW/y)	Fixed O&M (€/kW/y)	Variable O&M (€/MWh)	Storage annuity (€/kWh/y)	Const. time (y)	Efficiency (input/ output)	Source
Pumped hydro storage (PHS)	500	5	55	25.8050	7.5	0	0.2469	1	95%/90%	FCH-JU (2015)
Battery storage (Li-Ion)	140	100	12.5	15.2225	1.96	0	10.6340	0.5	90%/95%	Schmidt (2019)
ITES	0	18.38	20	-	0	0	1.4127	0.5	90%/90%	Brown et al. (2018b)
CTES	0	0.64	40	-	0	0	0.0348	1	90%/75%	Brown et al. (2018b)
Gas storage*	0	0	80	0	0	2	0	-	100%/99%	CRE (2018)

*The French gas network is already operational for methane injection; therefore, no network development cost is considered. However, the network usage fee of 2€/MWh_{th} for the gas network is derived from the French energy regulation commission (CRE, 2018).

Table 5.5. Economic parameters for two transport engine types

Technology	Charging infrastructure (€/kW)	Reservoir (€/kWh)	Lifetime (years)	Charging annuity (€/kW/year)	Reservoir annuity (€/kWh/year)	Source
Electric vehicles	81.7*	100	10	11.08	12.64	CGDD (2017)

ICE vehicles	180**	0	15	17.14	0	Doudard (2018)

*I consider a charging point cost of €600 for 7kW of charging power.
**According to Doudard (2018), a gas charging station which can serve 400 vehicles per day costs €300,000: assuming nearly 100kWh$_{th}$ (384km of autonomy) of charging at each charge, I obtain this cost.

All the remaining technical, land-use related, and country-specific parametrization of the model is presented in Appendix 5.3.

5.2.2.5. Choice of the discount rate

As in the previous chapters, the discount rate recommended by the French government for use in public socio-economic analyses is taken in the calculation of annuity (4.5% - Quinet, 2014).

5.2.3. The chosen SCC scenarios

As in Chapter 3, the SCC values are based on the official 'value for climate action' social cost of carbon introduced by Quinet et al. (2019) for France for 2050, (between 600€/tCO_2 and 900€/tCO_2). However, the results I present are for a maximum €500/tCO_2 of SCC, since for higher values, I have not observed any significant change in the energy mix or emissions.

5.3. Results

5.3.1. Energy mix

Figure 5.2 shows primary energy production. With no SCC, about 75% of primary energy comes from natural gas. But from an SCC of €100/tCO_2 upwards, the proportion of natural gas in primary energy production more than halves and for an SCC of €200/tCO_2 it is completely abandoned and replaced by increased electrification and bio-methane from methanization. Although introducing an SCC value leads to an increase in the proportion of nuclear power in primary energy production, this never exceeds 25%.

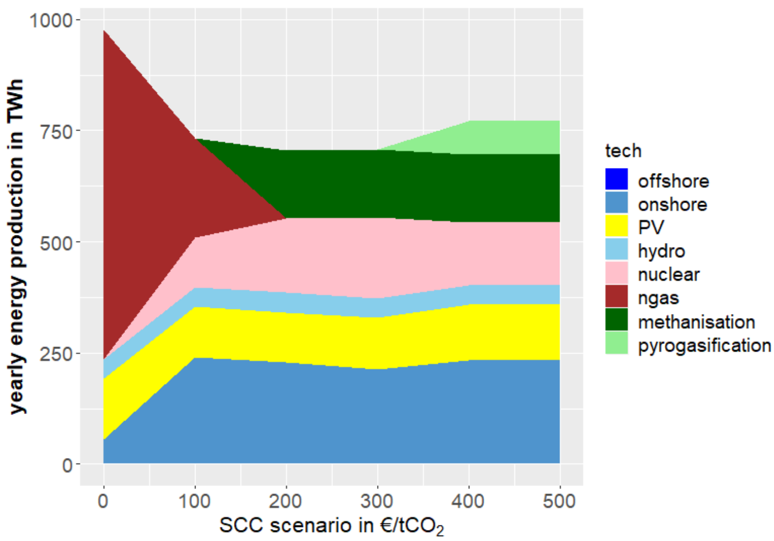

Figure 5.2. Primary energy production for each SCC scenario

The gas network provides 30% to 75% of primary energy production. Once natural gas is phased out, renewable gas from methanization alone provides 22% of the primary energy supply, and as SCC increases (for €400/tCO_2 and €500/tCO_2) pyro-gasification of biomass enters the optimal mix, and the proportion of renewable gas increases to 30% of primary energy production. Starting from an SCC value of €200/tCO_2, methanization is fully exploited and the upper limit of annual renewable gas production from this technology (152TWh_{th}/year) is reached. Once pyro-gasification enters the optimal mix, it also reaches its upper limit of 77TWh_{th}/year. The only energy supply technologies that are fully exploited are renewable gas production technologies. Installed capacity and annual energy production by primary energy source are presented in Appendix 5.5.

With no SCC, nearly half of the electricity production comes from natural gas (Figure 5.3). When the SCC value increases, nuclear energy and variable renewables replace natural gas while combined cycled gas turbines (CCGT) without carbon capture units (CCS) are replaced by nuclear power and CCGT equipped with CCS. The proportion of electricity in the primary energy supply increases from 25% to up to 78% as SCC increases, thanks to electrification of the heat sector, replacement of natural gas in electricity production by nuclear power and an increased proportion of power-to-gas.

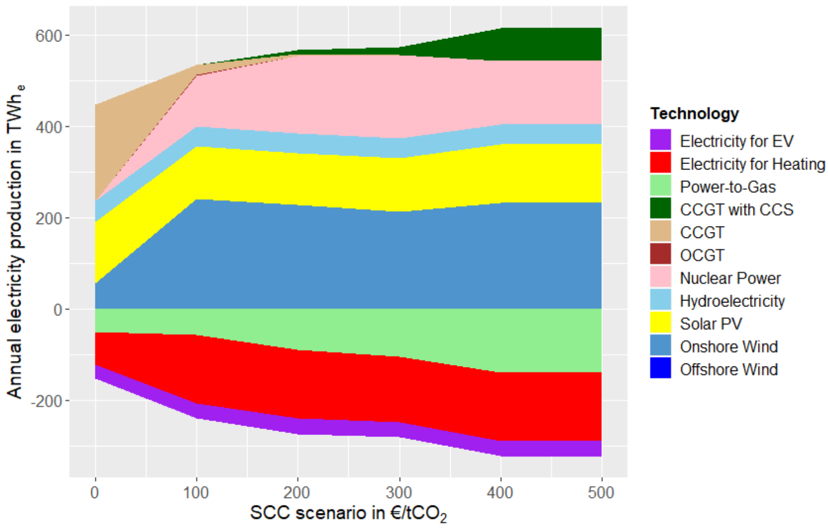

Figure 5.3. Electricity production (positive) and its conversion to other sectors (negative) in TWh_e/year as a function of SCC

For zero social cost of carbon, natural gas dominates the gas supply side, with a very small proportion of hydrogen for industry (Figure 5.4). Half of the natural gas is used for electricity production while the other half is used in the heat and transport sectors. As the social cost of carbon increases, gas for electricity production falls 10-fold leading to a steep decrease in natural gas production from 740TWh_{th}/year to 220TWh_{th}/year, and for €200/tCO_2 the gas supply becomes fully decarbonized and biogas from methanization replaces natural gas. While from this SCC value upwards, gas is mainly used for transport, by increasing the SCC value, gas production from pyro-gasification of biomass becomes cost-effective enough to be sent to CCGT power plants equipped with CCS to provide negative carbon-emitting electricity. Power-to-gas, including both methane from methanation and hydrogen from electrolysis, can provide up to 100TWh_{th}/year of synthetic gas. When the renewable gas supply is added, the gas network can account for 330TWh_{th}/year of energy.

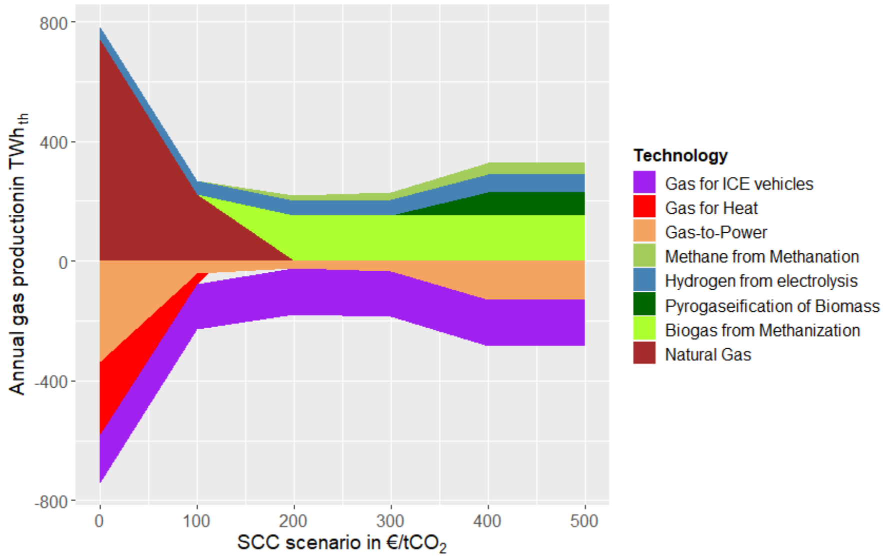

Figure 5.4. Gas production (positive) and its conversion to other sectors (negative) in TWh_{th}/year as a function of SCC

Figure 5.5 shows annual heat production as a function of SCC. For zero SCC half of the heat is produced from gas, by increasing the SCC value the proportion of electric heating (resistive and electric heat pumps) increases remarkably (to more than 90% for an SCC of €100/tCO_2), and from an SCC of €200/tCO_2 upwards, heating is fully electrified.

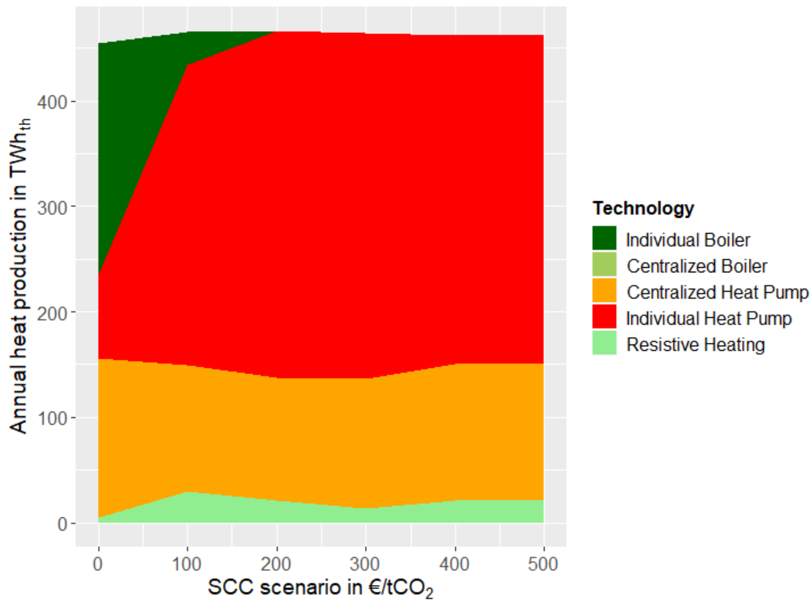

Figure 5.5. Annual heat production in TWh_{th}/year as a function of SCC

Although as the SCC value increases the heat sector becomes more and more electrified (heating, cooking and hot water), the transport sector remains highly dependent on internal combustion engines (ICE) using fossil fuels (for SCCs of 0 and €100/tCO_2) or renewable gas (for SCC of €200/tCO_2 and above) as the energy carrier (Figure 5.6). All heavy vehicles and buses (public transport except trains) are ICE vehicles, and light vehicles are also mainly fueled by gas (ICE) while the proportion of electric vehicles is very small in the transport sector[1].

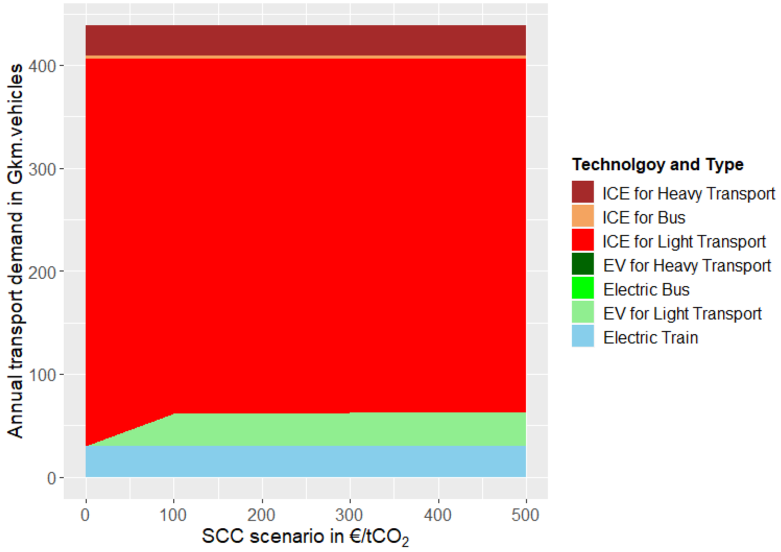

Figure 5.6.3 Transport supply by mobility type and vehicle technology type in Gkm.vehicles/year as function of SCC (the rail demand satisfied by electric trains is expressed in TWh$_e$/year

5.3.2. Cost of the energy system

As it was defined in Chapter 3, there are two system costs: technical cost (Equation A5.1 in Appendix 5.1 excluding the last part) and social cost, i.e. the cost including the social cost of carbon (the whole of Equation A5.1). In the EOLES_mv model, the social cost is optimized while the technical cost is calculated without optimization. In a decentralized equilibrium, the gap between these two costs would include the remuneration of negative CO_2-emitting plant operators and the tax paid by CO_2-emitting sources.

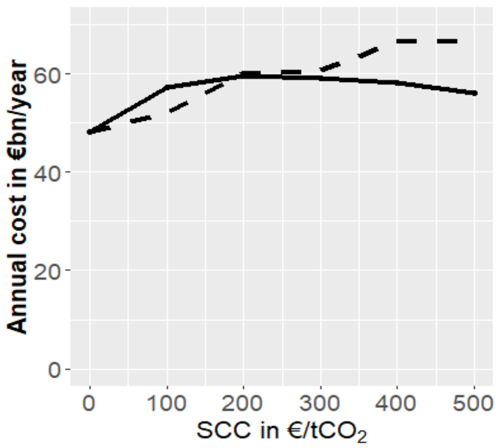

Figure 5.7. Annual social (including SCC) and technical costs for each SCC scenario; the dashed line represents the technical cost, and the solid line represents the optimized cost including the SCC value

Positive and negative emissions are valued at the same price. Therefore, a carbon neutral system has equal technical and social costs while for a negative emission system the latter is lower. The

[1] A back-of-the-envelope calculation is presented in Appendix 5.9 to provide an intuitive assessment of the relative cost-optimality of electric vehicles and internal combustion engines.

intersection between the technical and social cost curves is at an SCC of nearly €200/tCO_2 while increasing the SCC value, leading to negative emissions, increases the gap between these two curves to €10.5bn/year (nearly 16% of the technical cost) for an SCC scenario of €500/tCO_2 (Figure 5.7).

Figure 5.8 shows the system-wide levelized cost[1] of each energy carrier. With no SCC, the average LCOEs of gas and heat are very low thanks to cheap natural gas with no carbon tax. On increasing the SCC value, the price of gas increases because first the carbon tax equals the cost of fossil gas, and by further increasing the SCC value, it is fully replaced by expensive biogas from methanization. Once the SCC is high enough, even more expensive renewable gas from pyro-gasification of biomass enters the optimal mix, increasing the system-wide LCOE of gas (from €400/tCO_2 upwards). The price of electricity remains nearly stable since power production is mainly from renewable and nuclear sources (for an SCC of €100/tCO_2 and above), and none of these technologies' costs increase as SCC is increased since they are considered to be carbon neutral. Thanks to the electrification of heat production, the price of heat also remains stable once it is fully electrified, i.e. from an SCC of €200/tCO_2 upwards.

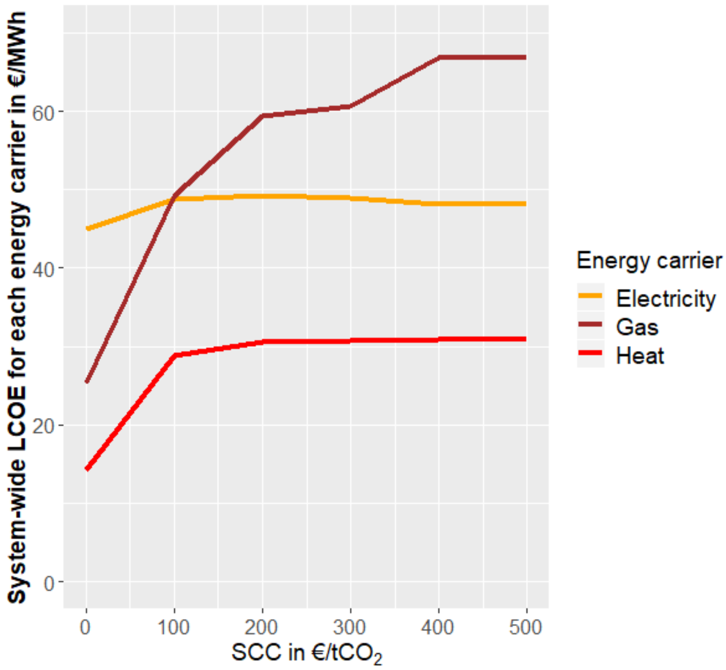

Figure 5.8. Average system-wide levelized cost of energy for each energy carrier in €/MWh_e for electricity and €/MWh_{th} for gas and heat

5.3.3. Availability of different low-carbon technologies

In order to study the importance of each energy production technology, I defined four alternative availability scenarios: without nuclear (noEPR), without CCS (noCCS), without renewable gas (noRG) and without variable renewable electricity (noVRE). The overall CO_2 emissions and the total cost for each case are compared to evaluate their relative importance (Figure 5.9).

[1] System-wide LCOE for each energy carrier is the average annual cost of each MWh of energy in the form of the discussed vector, in other words, the average money spent in providing each MWh of energy in the form of each energy carrier to satisfy the end-use demand or vector-change demand to provide energy in another vector.

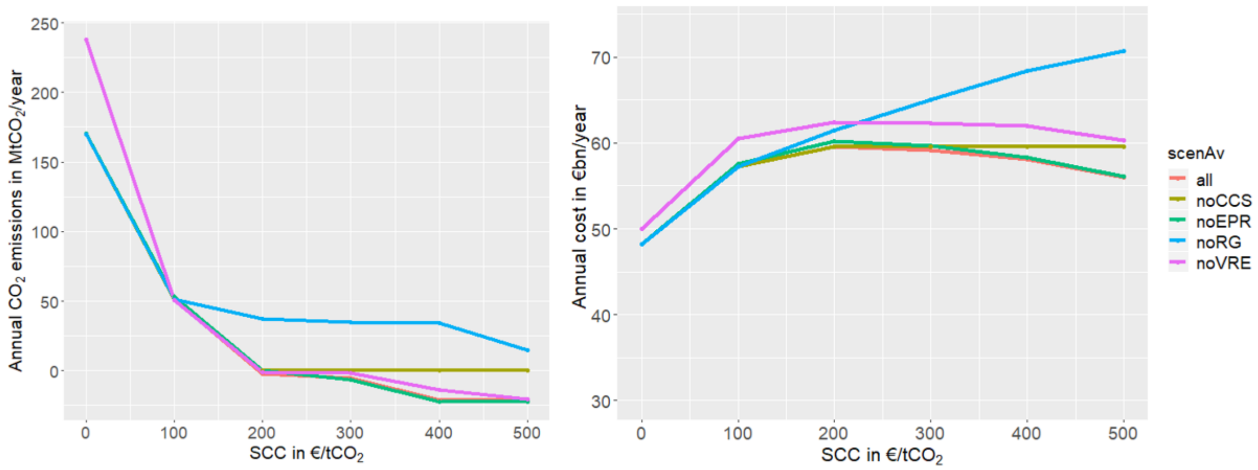

Figure 5.9. Annual CO2 emissions (left) and the annual social cost (right) of the energy system for different technology availability scenarios

When all the technologies are available the energy system emits 170MtCO_2/year for zero SCC[1]. The introduction of an SCC leads to an efficient emission reduction: 51.1MtCO_2/year of CO_2 emissions for an SCC value of €100/tCO_2, and -2.4MtCO_2/year for an SCC of €200/tCO_2. Increasing the SCC value results in negative emissions, up to 21MtCO_2/year of captured and stored CO_2 for an SCC of €500/tCO_2.

While having all options available is by definition the optimal case, for all the availability scenarios including renewable gas, the energy system reaches carbon neutrality for an SCC of €200/tCO_2. For zero SCC, VRE technologies can help reduce emissions, but as the SCC value increases, the annual CO_2 emissions of the scenario with no VRE technologies becomes nearly the same for the scenario with all the technologies available. Similarly, the scenario with no nuclear power leads to the same CO_2 emissions as the scenario where all the technologies are available.

Since the only negative emission technology considered is CCS combined with CCGT power plants, the scenarios excluding CCS do not reach negative emissions, and their emissions stay zero from €200/tCO_2 upwards. On the other hand, achieving carbon neutrality requires the replacement of fossil gas by renewable gas, and carbon neutrality cannot be achieved without renewable gas since fossil gas with CCS will still produce residual emissions. Therefore, for an efficient emission reduction target, renewable gas and CCS technologies are of greater importance than VRE and nuclear power technologies, which are substitutable with respect to their emission reduction potential. The primary energy production and the energy mix of each end-use demand are presented in Appendix 5.7.

The exclusion of both renewable gas and VRE technologies leads to the highest cost increases among different technology availability scenarios (Figure 5.9 – right). The scenario with no nuclear power has nearly the same cost as the scenario with all technologies available (a difference of less than 1% of the energy system cost for any SCC value), which means that the economic benefit of nuclear power is negligible. On the other hand, the availability of VRE technologies can reduce the social cost of the energy system by up to 6% and renewable gas can reduce it by up to 20%. While both CCS and renewable technologies are of key importance, nuclear energy does not play an important role, either in achieving low emissions, or in decreasing the system cost.

[1] Current French CO_2 emissions are around 420MtCO_2/year. The reason for this big difference in the absence of an SCC value is explained in Appendix 6.

5.3.4. How high should the social cost of carbon be to ensure carbon-neutrality?

For all the availability scenarios including renewable gas, an SCC of €200/tCO_2 can be enough to completely decarbonize the energy sector (Figure 5.9 – left). The impact of some other uncertain hypotheses such as the cost of emerging technologies, the level of final energy demand and the development of the heat network should be studied in order to assess the robustness of the proposed SCC.

To study a wide variation in the future cost of key emerging technologies, I varied the cost of variable renewable electricity, renewable gas supply, nuclear power, Li-Ion batteries (for both stationary use and electric vehicles) and natural gas supply by +/-50% from the central cost scenario (presented in Tables 5.2, 5.3, 5.4 and 5.5). Figure 5.10 shows a) the annualized total cost and b) annual CO_2 emissions of the energy system for SCC values of €200/tCO_2 and €300/tCO_2.

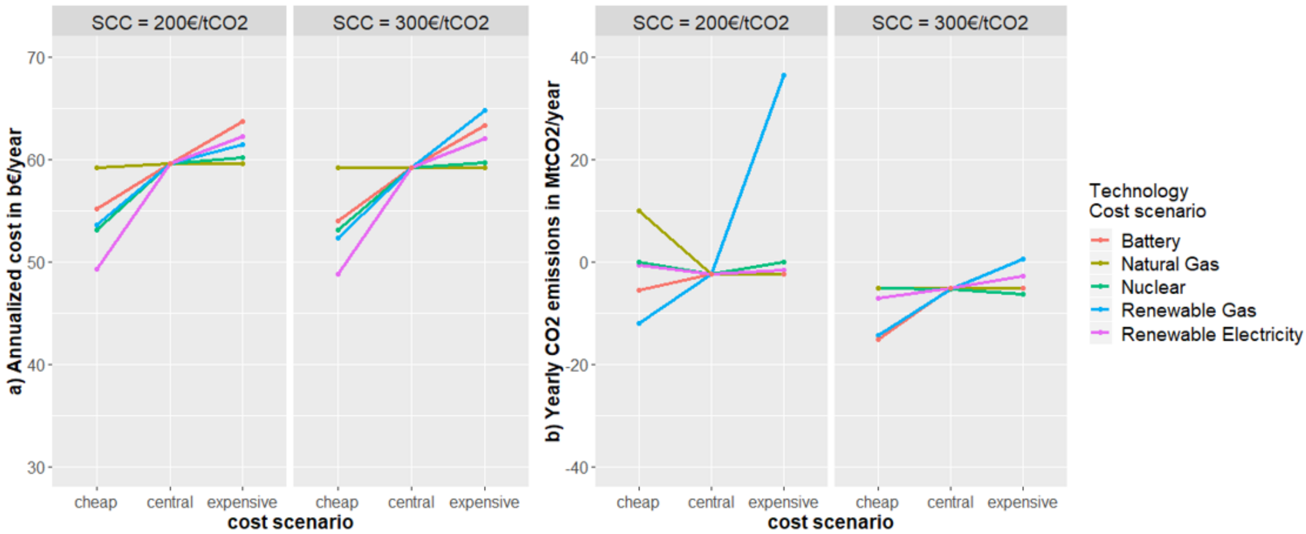

Figure 5.10. Sensitivity of (a) the yearly total cost and (b) the emissions of the energy system to a +/-50% cost variation in battery (for both stationary and electric vehicles), fossil gas, nuclear energy, renewable gas and variable renewable electricity technologies

While fossil gas has no impact on system cost for these two SCC values, the cheap technology cost scenario for batteries, nuclear power and renewable gas and electricity can reduce the system cost by up to 11%. However, increasing the cost of key technologies has a smaller impact on overall cost. From the emissions point of view (Figure 5.10-b), while for an SCC value of €200/tCO_2 the energy system can be positively CO_2-emitting for both cheap fossil gas and expensive renewable gas scenarios, for an SCC of €300/tCO_2 whatever the cost scenario, the energy system is either carbon-neutral or provides negative emissions.

The central demand scenario in this study is ADEME's update of the energy climate scenario, with a final energy demand of 82Mtoe/year (953.7TWh/year). To assess the impact of energy demand on decarbonization, I define a high demand scenario equal to the actual final energy demand (142Mtoe/year i.e. 1,651.5TWh/year).

The system-wide levelized costs of energy carriers do not vary with, and remain nearly robust to, the energy demand level (Figure 5.11-a). For an SCC of €200/tCO_2 energy system's emissions vary from -2.4MtCO_2/year to 1.5MtCO_2/year which is a minor variation while for the high SCC of €300/tCO_2, even for the high energy demand scenario, the energy system provides negative emissions (Figure 5.11-b).

To sum up, an SCC of €300/tCO_2 will be enough to decarbonize the energy system considering different technology costs and uncertainties in energy demand and heat network coverage[1]. The Sankey flow diagrams for the central availability scenario and the scenario without nuclear energy for the proposed robust SCC of €300/tCO_2 are presented in Appendices 5.10 and 5.11.

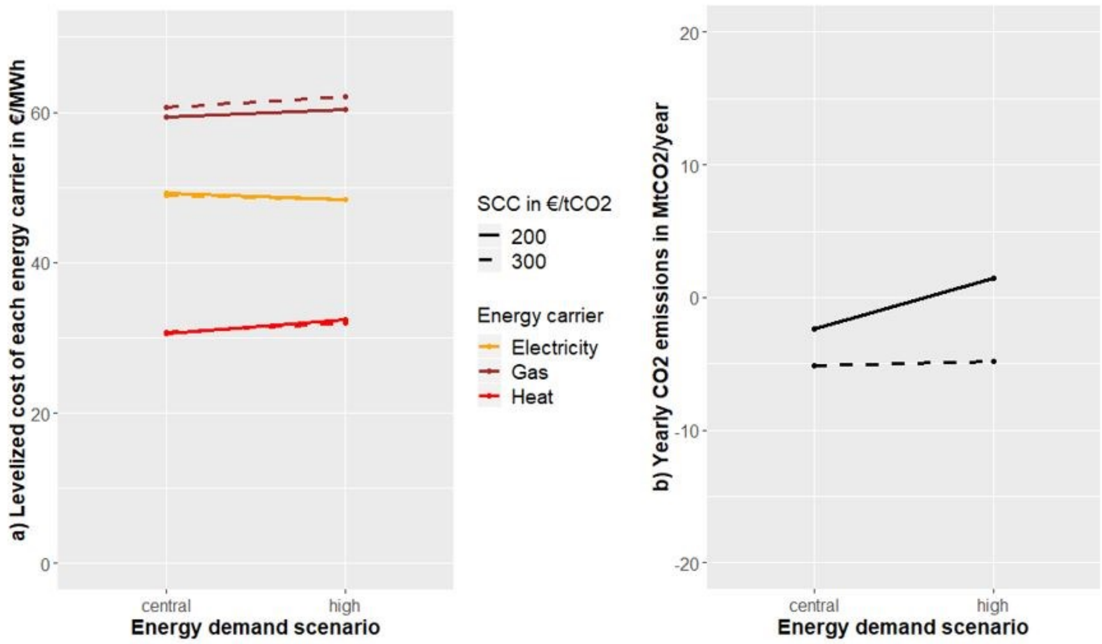

Figure 5.11. Sensitivity of (a) levelized cost of each energy carrier and (b) emissions of the energy system to the demand scenario as a function of two chosen social cost of carbon scenarios (the high scenario accounts for the current energy demand of France and the central scenario accounts for the future energy demand projection by the French Ministry of Ecological Transition and Solidarity).

5.4. Discussion

5.4.1. Comparison with existing scenarios

The second 'French national low carbon strategy' (SNBC, 2018) proposes a high electrification in the transport (50% share of electricity in the final transport demand) and industry (74% vs. less than 40% currently) sectors. The high efficiency improvements in the residential and tertiary sectors and modal change strategies in the transport sector, as well as the elimination of coal from industry are the main enablers of the French energy transition in this scenario. Similarly, ADEME's update of the 'energy-climate scenario 2035-2050' study (ADEME, 2017) shows an energy mix consisting of 49% to 69% renewable energies with the remainder from conventional energy resources. Table 5.6 shows the share of each energy carrier (network) in the final energy consumption for each of SNBC, ADEME and négaWatt scenarios, and the results from EOLES_mv for the SCC of €300/tCO_2.

[1] The importance of heat network coverage limitations has also been studied using an uncertainty range of 50%, and no change was observed in cost or emission levels. Appendix 5.9 shows the findings of the study of sensitivity to heat network coverage.

By making the choice of energy carrier endogenous for different end-uses we see that in optimal scenarios, the energy system will be highly electrified. More than 70% of a carbon neutral energy system's primary energy production comes from electricity. The transport sector is presented as a highly electrified sector in the ADEME and SNBC scenarios. The findings of this chapter show that even for very high SCC scenarios, the transport sector remains highly dependent to internal combustion engines, with an insignificant proportion of electric vehicles in the final transport demand. Only two to three million light vehicles are found to be electric, which contrasts strongly with both SNBC (2018) and ADEME (2017). This result is very close to négaWatt's scenario which suggests 15.7% of electrification in the transport sector.

Table 5.6. The comparison of share of each energy carrier in final energy consumption in different scenarios and the results of the EOLES_mv model. Heat in this table accounts for heat network and not the overall heat consumption.

Scenario	**Energy carrier**	**Share in final energy consumption**
ADEME	Electricity	39%
	Heat	8%
	Gas	24%
	Others/direct usage	29%
SNBC	Electricity	57.3%
	Heat	5%
	Gas	13.3%
	Others/direct usage	24.4%
négaWatt	Electricity	35%
	Heat	7%
	Gas	36%
	Others/direct usage	22%
EOLES_mv (SCC = €300/tCO_2)	Electricity	58%
	Heat	16.5%
	Gas	20%
	Others/direct usage	5.5%

Sector-coupling can accelerate the decarbonization of the energy sector and decrease the costs and load curtailment providing additional flexibility (Brown et al, 2018b, Victoria et al, 2019, BNEF 2020 and Pavičević et al, 2020). My findings, which agree with this conclusion, highlight the importance of full endogeneity in energy carrier choice including the key representative technologies that make this choice possible. Brown et al. (2018b) conclude that with no commercial power exchange with neighboring countries, at the optimal conditions, more than 80% of France's primary energy consumption is satisfied by VRE resources, and only about 5% of this primary energy is provided by fossil gas. This study excludes renewable gas as a possible energy supply option. While the results of EOLES_mv model for SCC values of €200/tCO_2 and above are very close to these results, fossil gas is abandoned at these SCC values. These findings show that in an optimal case a significant proportion of future transport demand is met by gas-powered internal combustion engines, and a very small proportion by electric vehicles.

5.4.2. The cost of carbon-neutrality

A nearly carbon-neutral energy system requires an SCC of €200/tCO_2 and accounting for uncertainties related to energy demand and technology cost development, it requires an SCC of

€300/tCO_2. The technical costs of the optimal energy system for these SCC values are €60.04bn/year and €60.69bn/year respectively. In the absence of an SCC value, the optimal energy system costs €48.19bn/year. The difference between the cost of a carbon-neutral energy system and one without SCC is between €11.85bn/year and €12.50bn/year. France's gross domestic product (GDP) was €2,332.68bn/year in 2019[1]. Assuming an average increase in GDP by 1%/year, in 2050 France's GDP would be €3,175.54bn/year. The 2050 energy system for zero SCC would cost 1.5% of this estimated annual GDP. Considering the technical cost of a decarbonized national energy system for SCC values of €200/tCO_2 and €300/tCO_2, decarbonization of the energy system would cost between 0.37% and 0.39% of France's estimated GDP for 2050.

5.4.3. The role of renewable gas

We saw earlier in this chapter that while the proportion of renewable gas in primary energy production does not exceed the proportion of renewable electricity in it, it is of the greatest importance. In the absence of renewable gas, the energy system cannot achieve carbon neutrality even for a high SCC value of €500/tCO_2. Moreover, sensitivity analysis also confirms this key role of renewable gas in both cost optimality and emission reduction; The energy system with central cost scenario reaches carbon-neutrality for €200/tCO_2, however, increasing the cost of renewable gas by 25% leads to more than 35MtCO_2/year of CO_2 emissions in energy system. Although these findings imply that renewable gas is of key importance in achieving carbon-neutrality for the lowest cost, using the existing gas infrastructure for biogas transmission and distribution might lead to methane leakage (Alvarez et al, 2012), eroding all the associated climate benefits (Union of concerned scientists, 2017). Similarly, particulate pollution by gas-fueled ICE vehicles has been highlighted as an important environmental disadvantage of this transport technology (Suarez-Bertoa et al, 2019). Therefore, it is essential to limit methane leakage and particulate pollution and take them into account correctly in environmental impact assessments.

In this study, I chose gas-fueled ICE as a representative technology for all ICE vehicles (fueled with biofuels and liquefied biogas), since they have similar economic characteristics and the main difference between them would be the relative cost of these fuels. Therefore, the idea of gas being the carrier for transport fuel can be expanded to include biofuels and liquefied biogas. The high relative proportion of ICE vehicles in the transport sector is confirmed by the results of several integrated assessment models (Yeh et al, 2017). However, the environmental damage caused by biofuel production and its high energy demand, as well as the competition between biofuels and food crops (due to land-use changes caused by biofuel production) are highly debated topics casting doubt on scenarios that include liquid biofuels (Kleiner, 2008, Searchinger et al, 2008, Lapola et al, 2010 and Rulli et al, 2016).

5.4.4. The role of short-term storage

In Chapter 2, we saw that a fully renewable power system would require roughly 75GWh_e of battery storage energy capacity. In Chapter 3 we saw that allowing natural gas and nuclear power in the power system increases the flexibility of the system, reducing the battery storage volume to 20GWh_e to 40GWh_e depending on the SCC scenario. However, in this chapter, the required storage volume from battery storage is nearly zero, and the main reason of the installation of battery is its

[1] https://tradingeconomics.com/france/gdp

participation to the reserve previsions (Appendix 5.5). Therefore, modelling only the power system overestimates the required battery storage and the flexibility gains from sector-coupling nearly eliminate battery from the energy system. Instead of battery, thermal storage options and gas storage result from the optimization to balance the intermittence of energy demand and VRE production.

5.4.5. Negative emissions

From the SCC of €200/tCO_2 upwards, the energy system can provide negative emissions, and for an SCC of €500/tCO_2 the negative emissions reach 21MtCO_2/year. These negative emissions are provided only by exploitation of BECCS and without other negative emission and carbon dioxide removal technologies such as direct air capturing (DAC), because of high uncertainties in their future costs. Thus, 21MtCO_2/year is not an upper limit for negative emissions, but only what the energy system can add by only post-combustion carbon capture from renewable gas. In the second French national low carbon strategy report, the residual emissions for France are evaluated to be more than 80MtCO_{2eq}/year (Mainly because of agriculture and land-use), assuming no negative emissions (SNBC, 2018). These emissions are not covered by the EOLES_mv model but negative emissions from the energy sector could be one of the compensation options to help achieve net zero emissions by 2050. Thus, although from an energy-only modelling perspective achieving carbon-neutrality does not necessarily require carbon capture and storage, in order to deal with the residual emissions, carbon capture and storage combined with bio-energies represent a pivotal mitigation option as stated in the IPCC's 'Special Report on 1.5°C of Global Warming' (IPCC, 2018) and in the IEA's 'Special Report on Carbon Capture, Utilisation and Storage' (IEA, 2020).

5.4.6. Limits and further research

In this chapter, I have considered France in isolation which means there is no exchange of energy between France and its neighboring countries (except natural gas imports). Several findings of this study might be different in a highly inter-connected European energy system. For example, renewable gas can play an important role in balancing wind fluctuations, but inter-connections with neighboring countries can also help balance intermittent power production technologies. Therefore, the role of renewable gas would be less important, at least in the electricity sector. On the other hand, I consider only anaerobic digestion of organic waste and pyro-gasification of wood and biomass as sources of bioenergy, which would only be used by injection into the gas network to satisfy either transport, heating or electricity final end-uses. Renewable gas can also be used as a raw material in several industries, and its by-products also have an economic value. Thus, a more detailed analysis of the whole bio-methane value chain considering different production and end-use options could be the next step in evaluating the importance of renewable gas in a carbon-neutral energy system. However, as explained in Subsection 5.4.3, methane leakage and particulate pollution resulting from the increased use of renewable gas in the energy sector could erode all the assumed benefits. The direct and indirect environmental impacts of renewable gas production, distribution and consumption need further analysis.

In my analysis, I used inelastic end-use demand profiles. The energy demand scenario from the French low-carbon strategy that I used is based on significant efforts being made to achieve energy efficiency and modal shift in different sectors. Thus from one side, the adaptation of demand to a high social cost of carbon would induce the energy consumption from a temporal point of view (shifting the demand from one hour to another) leading to energy demand profiles that are more adapted to the energy supply options. From the other side, it will modify the consumption mode in several sectors (such as shifting to public transport and bicycles instead of individual vehicles) and it will increase the efforts to eliminate or reduce the energy demand in different sectors (such as replacement of incandescent lamps by LED for lighting and thermal isolation of buildings). Although these assumptions may be realistic for high SCC values, the situation will be very different for low SCC values (especially 0€/tCO_2 and 100€/tCO_2), leading to different final energy demand levels and profiles in different sectors. By including the option of weekly charging for EVs and ICE vehicles, I accounted for the temporal modification of energy demand in transport sector which takes into account the load shifting in this sector by modifying charging profiles in the transport sector, but it doesn't take into account the possibility of modal shift in transport sector. Moreover, the energy demand levels, and profiles of other sectors are all inelastic in EOLES_mv, thus none of the two possible elasticities (temporal demand profile modification and energy consumption mode shifting) is taken into account, and only for the transport sector. Therefore, the energy demand profiles, and the annual end-use demand levels should be different for different SCC values not only in the transport sector, but in all the other energy sectors. Inclusion of this elasticity in the energy system modelling, although very challenging, would lead to an energy consumption that is better adapted to the 'variable' energy supply technologies.

5.5. Conclusion

This chapter studies the cost-optimal low-CO_2 energy mix, relative role of energy carriers and different low-carbon options applied to the case of France for the year 2050. To that end, I developed a first-of-its-kind integrated optimization of the energy system model (EOLES_mv). Allowing the end-use demand for each major energy sector to choose endogenously among four different energy carriers (electricity, heat, gas and hydrogen), I maintained high temporal resolution, and I studied different availability and future cost development scenarios for the key low-carbon technologies as a function of SCC.

The results imply that the optimal carbon-neutral energy system is highly electrified (exceeding 70% of the primary energy supply), but that non-fossil gas, even though accounting for a smaller proportion of energy supply, plays a very important role in emission reductions. In the presence of renewable gas, a carbon-neutral energy sector can be achieved for an SCC of €200/tCO_2, while for high energy demand or unfavorable conditions in the future cost reduction of renewable gas, carbon neutrality can be achieved for an SCC of €300/tCO_2. In cases where non-fossil gas is not available, carbon-neutrality cannot be achieved even for the very high SCC scenario of €500/tCO_2.

On the one hand, renewable electricity and gas technologies play a crucial role in achieving carbon-neutrality, and their absence from the energy supply side can lead to high inefficiencies in cost-optimality and emission reductions for future energy systems. On the other hand, exclusion of nuclear energy from the energy supply side has a minor impact on both emission reduction and cost-optimality. Therefore, one important policy-related outcome of this study is to invest in renewable gas and variable renewable electricity production technologies, and to prioritize them over other low-carbon options, particularly nuclear energy.

Finally, unlike the existing literature, the results of this chapter suggest that, in a cost-optimal coupled energy system, electricity would satisfy the demand for heat while gas would satisfy that for transport. Therefore, this study suggests that further development of gas charging stations is required, as well as individual and central heat pumps.

The near elimination of battery storage from an energy system with full sector-coupling also questions the importance of temporal resolution in modelling, because hourly temporal resolution was necessary for correct dimensioning of the short-term storage (batteries). Thus, coarser-than-hourly temporal resolution might also lead to precise results reducing the calculation time. In Chapter 7, I examine the importance of temporal resolution in multi-energy systems.

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Appendices 5

Appendix 5.1. The EOLES_mv model

A5.1.1. Sets and parameters

Table A5.1 presents the sets and indices of the EOLES_mv model and Table A5.2 the parameters. Throughout the paper, every energy unit (e.g. MWh) or capacity unit (e.g. MW) is expressed in useful form. For instance, some energy is converted from gas to electricity by OCGT. The input energy in MWh is in the gas carrier, therefore the unit is MWh_{th} and conversion efficiency by OCGT is 45%. The output energy is in MWh_e equivalent to the value in MWh_{th} multiplied by 0.45.

Table A5.1. Sets and indices of the EOLES_mv model

Index	Set	Description
h	∈ H	**Hour:** the number of hours in a year, from 0 to 8759
d	∈ D	**Day:** The number of days in a year, from 1 to 365
w	∈ W	**Week:** The number of weeks in a year, from 1 to 52 (the 52nd week accounts for 10 days)
m	∈ M	**Month:** the twelve months, from January to December
tec	∈ TEC	**Technologies:** The set of all energy supply, conversion, storage and non-existing carrier technologies (floating offshore, monopile offshore, onshore, PV, river, lake, nuclear, natural gas, methanization, pyro-gasification, OCGT, CCGT, CCGT with CCS, electrolysis, methanation, heat network, resistive heating, electric heat pump, gas heat pump, central boiler, decentralized boiler, heavy EV, light EV, EV bus, train, heavy ICE, light ICE, ICE bus, PHS, battery, gas storage, individual thermal energy storage -ITES- and central thermal energy storage -CTES)
gen	∈ GEN ⊆ TEC	**Generation:** Energy supply technologies (floating offshore, monopile offshore, onshore, PV, river, lake, nuclear, natural gas, methanization and pyro-gasification)
$elec$	∈ ELEC ⊆ TEC	**Electricity:** The technologies providing electricity by supply, conversion or storage (floating offshore, monopile offshore, onshore, PV, river, lake, nuclear, OCGT, CCGT, CCGT with CCS, PHS and battery)
gas	∈ GAS ⊆ TEC	**Gas:** The technologies providing gas by supply, conversion or storage (natural gas, methanization, pyro-gasification, electrolysis, methanation and gas storage)
$heat$	∈ HEAT ⊆ TEC	**Heat:** The technologies providing heat by conversion and storage (heat network, resistive heating, electric heat pump, gas heat pump, central boiler, decentralized boiler, individual thermal energy storage and central thermal energy storage)
$transport$	∈ TRANSPORT ⊆ TEC	**Transport:** The technologies that meet different types of transport demand (heavy EV, light EV, EV bus, train, heavy ICE, light ICE and ICE bus)
gen_{elec}	∈ ELECGEN ⊆ ELEC	**Electricity supply:** The technologies generating electricity (floating offshore, monopile offshore, onshore, PV, river, lake and nuclear)
gen_{gas}	∈ GASGEN ⊆ GAS	**Gas supply:** Technologies supplying gas (natural gas, methanization and pyro-gasification)
$biogas_{gas}$	∈ BIOGAS ⊆ GAS	**Renewable gas:** biogas supply technologies (methanization and pyro-gasification)

vre	∈ VRE ⊆ ELEC	**VRE:** variable renewable electricity generation technologies (offshore, onshore, PV and run-of-river)
str	∈ STR ⊆ TEC	**Storage:** energy storage technologies (PHS, battery, gas storage, individual thermal energy storage and central thermal energy storage)
str_{elec}	∈ STRELEC ⊆ ELEC	**Electric storage:** technologies providing storage for electricity (battery and PHS)
str_{gas}	∈ STRGAS ⊆ GAS	**Gas storage:** technologies providing storage for gas (gas storage)
str_{heat}	∈ STRHEAT ⊆ HEAT	**Heat storage:** technologies providing storage for heat (ITES and CTES)
$conv$	∈ CONV ⊆ TEC	**Conversion:** energy vector-change technologies (OCGT, CCGT, CCGT with CCS, electrolysis, methanation, resistive heating, electric heat pump, gas heat pump, central boiler and decentralized boiler)
$conv_{elec}$	∈ CONVELEC ⊆ TEC	**Conversion from electricity:** energy vector-change technologies from electricity to other vectors (electrolysis, methanation, resistive heating and electric heat pump)
$conv_{gas}$	∈ CONGAS ⊆ TEC	**Conversion from gas:** energy vector-change technologies from gas to other vectors (OCGT, CCGT, CCGT with CCS, gas heat pump, centralized boiler and decentralized boiler)
$central$	∈ CENTRAL ⊆ HEAT	**Central heating:** heating technologies needing heat network (electric heat pump, gas heat pump and centralized boilers)
$vector_t$	∈ TVECTOR	**Transport vector:** two different engine types for transport sector (EV and ICE)
cat_t	∈ TCAT	**Transport category:** four categories of transport demand (heavy, light, bus and train)
$ev_{transport}$	∈ EV ⊆ TRANSPORT	**Electric transport:** the electric transport technologies (heavy EV, light EV, EV bus and train)
$ice_{transport}$	∈ ICE ⊆ TRANSPORT	**Gas transport:** the ICE transport technologies using gas as fuel (heavy ICE, light ICE and ICE bus)
frr	∈ FRR ⊆ TEC	**Frequency restauration reserves:** Technologies contributing to secondary reserves requirements (lake, PHS, battery, OCGT, CCGT, CCGT with CCS and nuclear)
co_2	∈ CO2	**Social cost of carbon scenario:** The scenarios are 1, 2, 3, 4, 5 and 6

Table A5.2. Parameters of the EOLES_mv model

Parameter	Unit	Description
day_h	[-]	A parameter to show which day each hour is in
$week_h$	[-]	A parameter to show which week each hour is in
$month_h$	[-]	A parameter to show which month each hour is in
$cf_{vre,h}$	[-]	Hourly production profiles of variable renewable energies
$profile_h^{transport}$	[-]	Hourly charging profile of each transport technology
$demand_{heat,h}$	$[GW_{th}]$	Hourly heat demand profile
$demand_{hydrogen,h}$	$[GW_{th}]$	Hourly hydrogen demand profile (for industry)
$demand_{elec,h}$	$[GW_e]$	Hourly electricity demand profile
$demand_h^{heavy}$	$[Gkm.vehicle]$	Hourly transport demand for heavy vehicles

$demand_h^{light}$	$[Gkm.vehicle]$	Hourly transport demand for light vehicles
$demand_h^{bus}$	$[Gkm.vehicle]$	Hourly transport demand for buses
$demand_h^{train}$	$[GWh_e]$	Hourly transport demand for trains (flat)
$lake_m$	$[GWh_e]$	Monthly extractable energy from lakes
ε_{vre}	[-]	Frequency restoration requirement because of forecast errors on the production of each variable renewable energy
q_{tec}^{ex}	$[GW_e]$	Existing installed capacity by each hydroelectric technology
$annuity_{tec}$	[M€/GW/year]	Annualized capital cost of each technology
$annuity_{str}^{en}$	[M€/GWh/year]	Annualized capital cost of energy volume for storage technologies
$annuity_{transport}^{vol}$	[M€/GWh/year]	Annualized capital cost of energy reservoir volume of transport technology
$fO\&M_{tec}$	[M€/GW /year]	Annualized fixed operation and maintenance cost
$vO\&M_{tec}$	[M€/GWh]	Variable operation and maintenance cost of each technology
η_{str}^{in}	[-]	Charging efficiency of storage technologies
η_{str}^{out}	[-]	Discharging efficiency of storage technologies
η_{conv}	[-]	Conversion efficiency for vector change technologies
$\eta_{cat_t}^{vector_t}$	$[Gkm.vehicle/kWh]$	Transport efficiency of each transport technology
q^{pump}	$[GW_e]$	Pumping capacity for Pumped hydro storage
e_{PHS}^{max}	$[GWh_e]$	Maximum energy volume that can be stored in PHS reservoirs
g_{biogas}^{max}	$[TWh_{th}]$	Maximum yearly energy that can be generated from renewable gas supply technologies
$\delta_{uncertainty}^{load}$	[-]	Uncertainty coefficient for hourly electricity demand
$\delta_{variation}^{load}$	[-]	Load variation factor
r_{nuc}^{up}	[-]	Maximal ramping up rate of nuclear power
r_{nuc}^{down}	[-]	Maximal ramping down rate of nuclear power
cf_{nuc}	[-]	The maximal annual capacity factor for nuclear power
cf_{ocgt}	[-]	The maximal annuity capacity factor for OCGT plant
cf_{ccgt}	[-]	The maximal annual capacity factor for CCGT plant
$cf_{ccgt-ccs}$	[-]	The maximal annual capacity factor for CCGT with CCS plants
e_{tec}	$[tCO_2/GWh]$	Emission rate of each technology

scc_{co_2}	$[€/tCO_2]$	Social cost of carbon for each SCC scenario
$\varphi_{CO_2}^{max}$	$[MtCO_2/year]$	The maximal carbon dioxide that can be stored annually
$\gamma_{methanization}^{CO_2}$	[-]	The green CO_2 available as a byproduct of methanization for methanation
$\tau^{hydrogen}$	[-]	The maximal penetration rate of hydrogen in the gas network

A5.1.2. Variables

The variables resulting from the optimization are presented in Table A5.3.

Table A5.3. Variables of EOLES_mv model

Variable	*Unit*	*Description*
$G_{tec,h}$	GWh	Hourly energy generation by technology
Q_{tec}	GW	Installed capacity by technology
$STORAGE_{str,h}$	GWh	Hourly energy entering each storage technology (inflow)
$SOC_{str,h}$	GWh	Hourly state of charge of each storage technology (stock)
S_{str}	GW	Installed charging capacity by storage technology
$CONVERT_{conv,h}$	GWh	Hourly converted energy by each conversion technology
$CHARGE_{transport,h}$	GWh	Hourly charging of each transport technology
$RESERVOIR_{transport}$	GWh	The energy reservoir volume for each transport 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 energy system cost annualized (minus the investment cost of already installed capacities). This is the objective function to be minimized.

A5.1.3. Equations

A5.1.3.1. Objective function

The objective function is similar to the one in Chapter 3 where the social cost of carbon is included (Equation A5.1):

$$COST = \left(\sum_{tec}[(Q_{tec} - q_{tec}^{ex}) \times annuity_{tec}] + \sum_{str}(VOLUME_{str} \times annuity_{str}^{en}) + \sum_{tec}(Q_{tec} \times fO\&M_{tec}) + \sum_{tec}\sum_{h}(G_{tec,h} \times (vO\&M_{tec} + e_{tec}SCC_{CO_2}))\right)/1000 \quad \text{(A5.1)}$$

where Q_{tec} represents the production capacities, q_{tec}^{ex} represents the existing capacity (notably for hydro-electricity technologies with long lifetime), $VOLUME_{str}$ is the energy storage capacity in GWh, S_{str} is the storage capacity in GW, $annuity$ is the annualized investment cost, $fO\&M$ and $vO\&M$ respectively represents fixed and variable operation and maintenance costs, $G_{tec,h}$ is the hourly generation of each technology, e_{tec} is the specific emission of each technology in tCO_2/GWh of power production and SCC_{CO_2} is the social cost of carbon in €/tCO_2.

A5.1.3.2. Adequacy equations

Energy demand must be met for each hour. If energy production exceeds energy demand, the excess energy can be either sent to storage units or curtailed (Equations A5.2, A5.3, A5.4, A5.5a-d and A5.6).

$$\sum_{elec} G_{elec,h} \geq demand_{elec,h} + \sum_{str_{elec}} STORAGE_{str_{elec},h} + \sum_{conv_{elec}} CONVERT_{conv_{elec},h} + \sum_{ev} CHARGE_{ev,h} \quad \text{(A5.2)}$$

$$\sum_{gas} G_{gas,h} \geq \sum_{str_{gas}} STORAGE_{str_{gas},h} + \sum_{conv_{gas}} CONVERT_{conv_{gas},h} + \sum_{ice} CHARGE_{ice,h} + demand_{hydrogen,h} \quad \text{(A5.3)}$$

$$\sum_{heat} G_{heat,h} \geq demand_{heat,h} + \sum_{str_{heat}} STORAGE_{str_{heat},h} \quad \text{(A5.4)}$$

$$G_{heavy_t,h} \times \eta_{heavy_t}^{vector_t} = demand_{transport,h}^{heavy_t} \quad \text{(A5.5a)}$$

$$G_{light_t,h} \times \eta_{light_t}^{vector_t} = demand_{transport,h}^{light_t} \quad \text{(A5.5b)}$$

$$G_{bus,h} \times \eta_{bus_t}^{vector_t} = demand_{transport,h}^{bus_t} \quad \text{(A5.5c)}$$

$$G_{train_t,h} \times \eta_{train_t}^{ev_t} = demand_{transport,h}^{train_t} \quad \text{(A5.5d)}$$

$$G_{electrolysis,h} \geq demand_{hydrogen,h} \quad \text{(A5.6)}$$

Where $G_{elec,h}$, $G_{gas,h}$, $G_{heat,h}$ is the energy produced by electricity, gas and heat technologies at hour *h* and $STORAGE_{str_{elec},h}$, $STORAGE_{str_{gas},h}$, $STORAGE_{str_{heat},h}$ is the energy entering storage electricity, gas and heat storage technologies at hour *h*. $CONVERT_{conv_{elec},h}$ is the energy conversion from electricity to other vectors and $CONVERT_{conv_{gas},h}$ is the energy conversion from gas to other vectors at hour *h* and $CHARGE_{ice,h}$ is the charging of internal combustion engine vehicles and $CHARGE_{ev,h}$ is the charging of electric vehicles at hour *h*. For each transport category the energy demand in vehicle.km should be satisfied either by *ev* or *ice* as transport energy vector options ($vector_t$), and the conversion from the energy in the gas or electricity form to the demand by transport category ($demand_{transport,h}^{heavy_t}$, $demand_{transport,h}^{light_t}$ and $demand_{transport,h}^{bus_t}$) in vehicle.km is done by the vehicle efficiency changing by both the energy vector and the transport category; $\eta_{cat_t}^{vector_t}$. We only consider the electricity to satisfy the trains' demand.

According to Vogl et al. (2018), the coal demand for steel industry can be replaced by hydrogen. Therefore, we define an hourly hydrogen demand for steel industry ($demand_{hydrogen,h}$) which should be satisfied (equation A5.6) beside other adequacy equations.

A5.1.3.3. Variable renewable power production

For each variable renewable energy (VRE) technology, for each hour, the hourly power production is given by the hourly capacity factor profile multiplied by the installed capacity available (Equation A5.7).

$$G_{vre,h} = Q_{vre} \times cf_{vre,h} \quad \text{(A5.7)}$$

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

A5.1.3.4. Energy storage

Energy storage for each energy vector in an hourly precision, follows the same mechanism as in Chapter 2:

$$SOC_{str,h+1} = SOC_{str,h} + (STORAGE_{str,h} \times \eta_{str}^{in}) - (\frac{G_{str,h}}{\eta_{str}^{out}}) \quad \text{(A5.8)}$$

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

A5.1.3.5. Secondary reserve requirements

As explained in Chapter 2, secondary reserves are defined as in Equation (A5.9):

$$\sum_{frr} RSV_{frr,h} = \sum_{vre}(\varepsilon_{vre} \times Q_{vre}) + demand_h \times (1 + \delta_{variation}^{load}) \times \delta_{uncertainty}^{load} \quad \text{(A5.9)}$$

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.

A5.1.3.6. Energy-generation-related constraints

$$G_{tec,h} \leq Q_{tec} \quad \text{(A5.10)}$$

$$Q_{frr} \geq G_{frr,h} + RSV_{frr,h} \quad \text{(A5.11)}$$

$$lake_m \geq \sum_{h \in m} G_{lake,h} \quad \text{(A5.12)}$$

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

A5.1.3.7. Energy conversion

Energy generated by any energy conversion technology should include the conversion efficiency of the conversion technology. Equation (A5.13) relates the energy generation and generation by each conversion technology.

$$G_{conv,h} = \eta^{conv} \times CONVERT_{conv,h} \quad \text{(A5.13)}$$

Where η^{conv} is the conversion efficiency of the energy conversion technology $conv$, and $CONVERT_{conv,h}$ is the converted energy by the same conversion technology at hour *h*.

A5.1.3.8. Charging of transport technologies

Electric vehicles and internal combustion engine vehicles have different charging profiles. Equation (A5.14) applies these charging profiles;

$$CHARGE_{transport,h} = profile_h^{transport} \times Q_{transport} \quad \text{(A5.14)}$$

Where $CHARGE_{transport,h}$ is the hourly charging of each transport technology (both EVs and ICEs four all four transport categories), $profile_h^{transport}$ is the predefined hourly charging profile of each of the transport technologies and $Q_{transport}$ is the charging capacity of transport technology $transport$.

I consider an average of one charge per week for each transport technology, and since the energy can be stored in the vehicle during the whole one week, the transport demand that should be satisfied is considered to have a weekly adequacy. The hourly demand of transport in vehicle.km should be satisfied from Equations (A5.5a-d) and the charging profiles should be applied to account for the charging behavior of different transport technologies from Equation (A5.14). I define Equation (A5.15) to keep both charging and demand constraints above and to let the vehicles choose the day of charging during the week;

$$\sum_{h \in w} CHARGE_{transport,h} = \sum_{h \in w} G_{transport,h} \quad \text{(A5.15)}$$

The storage volume of each transport technology accounts for an upper limit for the weekly charge and weekly energy consumption of it. While this storage volume is free of charge for ICE vehicles, electric vehicles' main cost component is this battery storage volume. Therefore, I define the reservoir size (storage volume) for each transport technology (Equation A5.16).

$$\sum_{h \in w} CHARGE_{transport,h} \leq RESERVOIR_{transport} \quad \text{(A5.16)}$$

Where $RESERVOIR_{transport}$ accounts for the reservoir size of each transport technology (kWh_e for electric vehicles and kWh_{th} for ICE vehicles).

A5.1.3.9. Inclusion of heat networks

Heat can be produced by two different technology classes: distributed technologies such as resistive heating technology, and centralized technologies such as central boilers. Decentralized heating technologies use electricity or gas from the network and provide heating for the local demand, therefore no heat network is needed. On the other hand, the centralized technologies produce heat in large quantities and distribute it to the points of the demand in different locations, which require a heat network. Equation (A5.17) separates the central heating technologies and define a heat network capacity for the distribution of produced heat:

$$Q_{heat-net} \geq Q_{central} \quad \text{(A5.17)}$$

Where $Q_{heat-net}$ is the heat network capacity and $Q_{central}$ is the installed capacity of each central heat production technology in kW_{th}.

Equation (A5.17) allows the heat network to have lower capacity than all the central heating technologies combined, depending on the optimal dispatching of each of them. Another equation is needed to restrict the central heating technologies to pass through the heat network (Equation A5.18).

$$G_{heat-net,h} = \sum_{central} G_{central,h} \quad \text{(A5.18)}$$

Where $G_{heat-net,h}$ is the heat generation passed through heat network and $G_{central,h}$ is the heat generation by each central heating technology at hour *h*.

A5.1.3.10. Operational constraints of conversion technologies

For open-cycle and combined-cycle gas turbines, there are some safety- and maintenance-related breaks. Equations (A5.19), (A5.20) and (A5.21) limit the annual power production for each of these plants to their maximum annual capacity factors:

$$\sum_h G_{ocgt,h} \leq Q_{ocgt} \times cf_{ocgt} \times 8760 \tag{A5.19}$$

$$\sum_h G_{ccgt,h} \leq Q_{ccgt} \times cf_{ccgt} \times 8760 \tag{A5.20}$$

$$\sum_h G_{ccgt-ccs,h} \leq Q_{ccgt-ccs} \times cf_{ccgt-ccs} \times 8760 \tag{A5.21}$$

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

The hydrogen produced from electrolysis (power-to-gas conversion) is either consumed directly in the industry (therefore I assume local electrolysis for industrials) or injected to the gas network. Because of different thermochemical properties of hydrogen, it cannot be injected in any rate to the gas network. Equations (A5.22), (A5.23) and (A5.24) limit the hydrogen that can exist in the gas network as a proportion of the overall existing gas in this network both in the storage level and in the distribution/transmission level;

$$G_{electrolysis,h} \leq \tau^{hydrogen} \times SOC_{gastank,h} + demand_{hydrogen,h} \tag{A5.22}$$

$$G_{electrolysis,h} \leq \tau^{hydrogen} \times \sum_{gas} G_{gas,h} + demand_{hydrogen,h} \tag{A5.23}$$

$$\sum_h G_{electrolysis,h} \leq \tau^{hydrogen} \times \sum_{gas \neq gastank,h} G_{gas,h} + \sum_h demand_{hydrogen,h} \tag{A5.24}$$

Where $G_{electrolysis,h}$ is the energy value of hydrogen injected to gas network from electrolysis at hour *h*, $\tau^{hydrogen}$ is the maximal relative energy share of hydrogen to the overall gas in the gas network which can be different for different countries depending on the capability of gas network in hosting hydrogen. $SOC_{gastank,h}$ is the state of charge of gas storage, which is the energy value of overall existing gas in the gas network and $\sum_{gas} G_{gas,h}$ is the overall gas production at hour h. Equation (A5.22) limits the relative share of hydrogen to other gas options in the storage infrastructures and Equation (A5.23) limits the relative share of hydrogen in the gas network. Equation (A5.24) makes sure that the overall hydrogen that is produced is not more than the capacity of the gas network.

A5.1.3.11. Nuclear-power-related constraints

As defined in Chapter 3, operational constraints of nuclear power are formulated in Equations (A5.25) to (A5.27):

$$G_{nuc,h+1} + RSV_{nuc,h+1} \leq G_{nuc,h} + r_{nuc}^{up} \times Q_{nuc} \tag{A5.25}$$

$$G_{nuc,h+1} \geq G_{nuc,h}(1 - r_{nuc}^{down}) \tag{A5.26}$$

$$\sum_h G_{nuc,h} \leq Q_{nuc} \times cf_{nuc} \times 8760 \tag{A5.27}$$

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

A5.1.3.12. Storage-related constraints

All the storage related constraints are the same as defined in Chapter 2.

$$SOC_{str,0} = SOC_{str,8759} + (STORAGE_{str,8759} \times \eta_{str}^{in}) - (\frac{G_{str,8759}}{\eta_{str}^{out}}) \quad \text{(A5.28)}$$

$$SOC_{str,h} \leq VOLUME_{str} \quad \text{(A5.29)}$$

$$SOC_{str,h} \leq S_{str} \leq Q_{str} \quad \text{(A5.30)}$$

A5.1.3.13. Resource availability related constraints

The maximum installed capacity of each technology is defined in Equation (A5.31) where q_{tec}^{max} is this capacity limit:

$$Q_{tec} \leq q_{tec}^{max} \quad \text{(A5.31)}$$

Renewable gas production technologies are limited due to land-use and agricultural constraints. Equation (A5.32) limits the annual renewable gas production from each of two renewable gas production technologies; methanization and pyro-gasification of biomass.

$$\sum_{h=0}^{8759} G_{biogas,h} \leq g_{biogas}^{max} \quad \text{(A5.32)}$$

Where $G_{biogas,h}$ is the hourly biogas production from each of renewable gas production technologies and g_{biogas}^{max} is the maximal yearly biogas that can be produced from each of renewable gas production technologies, both in energy values.

Methanation consists of the Sabatier reaction of hydrogen produced from electrolysis of water and green CO_2 produced as a by-product of methanization process. Implication of this limit in the overall methane production from methanation process is presented in Equation (A5.33):

$$\sum_{h=0}^{8759} CONVERT_{methanation,h} \leq \sum_{h=0}^{8759} G_{methanization,h} \times \gamma_{methanization}^{CO_2} \quad \text{(A5.33)}$$

Where $CONVERT_{methanation,h}$ accounts for the hourly methane produced from power-to-methane (methanation) process, $G_{methanization,h}$ is the hourly biogas production from methanization process and $\gamma_{methanization}^{CO_2}$ is the relative share of carbon dioxide to biogas produced from methanization process.

The captured carbon dioxide can't be stored infinitely, and geographical and social constraints limit the exploitation of CCS technology. Equation (A5.34) limits the captured CO_2 to the available offshore and onshore storage formations;

$$\varphi_{CO_2}^{max} \geq \sum_h G_{ccgt-ccs,h} \times \tau_{ccgt-ccs} \times e_{ccgt} \quad \text{(A5.34)}$$

Where $\varphi_{CO_2}^{max}$ is the maximal CO_2 storage potential, $G_{ccgt-ccs,h}$ is hourly power production from CCGT power plants equipped with CCS units, $\tau_{ccgt-ccs}$ is the carbon capture rate of post combustion

CCS units, and e_{ccgt} is the specific emission of CCGT power plant with natural gas (considered with no CCS input).

Heat network can't be extended in every area and it requires a specific density, and very distant rural areas with low population densities are better off without it. Equation A5.35 introduces a maximal limit of heat network coverage to meet the heat demand:

$$\sum_h G_{heat-net,h} \leq g_{heat-net}^{max} \times \sum_h demand_{heat,h} \quad \text{(A5.35)}$$

Where $g_{heat-net}^{max}$ accounts for the maximal share of the heat demand that can be satisfied by heat network.

Appendix 5.2. Demand profiles preparation

A5.2.1. Heat demand profile

The heat demand profiles for residential and tertiary sector for different usages (heating, hot water and cooking) are prepared using hourly, daily and monthly demand profiles presented in Doudard (2018). Hourly profiles for each weekday and weekend day are expanded using the daily profiles to the whole week, later using the monthly demand profiles we expanded these hourly demand profiles for one week to each month of the year, and with a final normalization process, I kept the annual heat demand for each usage in each of residential tertiary sector equal to the projected demand for 2050 by ADEME (2017) and DGEC (2019) scenarios.

According to Brown et al. (2018) the population density should be high enough to have heat network viable. According to Persson et al. (2011), 60% of the urban areas can be considered dense enough for a cost-effective development of district heating. Considering 87% of urban population share for France (projection for 2050 by Sénat[1]), only 52.2% of residential and tertiary sectors' heating can be provided by central heating (I assume that for agriculture and industry it is not possible to use central heating), therefore 13.36Mtoe (155.38TWh) of heating demand can be provided by central heating at maximum. On the other hand, ADEME predicts a 50% of heating from buildings sector can be satisfied by heat pumps by 2050 (ADEME, 2015). Therefore, I limit the central heating to 155.38TWh/year.

A5.2.2. Transport demand profile

Like the previous section, hourly profiles for each day type (weekday or weekend) as well as a daily profile for a week, and a monthly profile for one year are available in Doudard (2018) for each passenger and freight transport category. The considered transport modes are: light vehicles (particular or utility scale), buses/public transportation and trains as passenger modes and heavy vehicles, utility vehicles and trains as the freight transport modes. I excluded aerial and water transport options because of the lack of data, and the insignificance of these modes in comparison with the other transportation modes. Using the same method presented above, I prepared annual hourly demand profile for each of the transport modes and categorized them in four main categories of light vehicles, heavy vehicles, buses and trains[2]. Using daily, monthly and annual correction factors, I maintained the annual transport demand projected by ADEME (2017) and DGEC (2019) scenarios in vehicle-kilometers.

A5.2.3. Electricity demand profile

ADEME's (2015) central scenario hourly demand profile for 2050 is taken as the electricity demand profile for the model. This demand profile amounts to 423TWh$_e$/year, 12% less than the average power consumption in the last 10 years. This takes into account foreseeable change in the demand profile up to 2050, including a reduced demand for lighting and heating and an increased demand for air conditioning and electric vehicles. This demand profile includes heating, cooking, hot water usage and electric vehicle charging demand, therefore they should be subtracted from this demand

[1] https://www.senat.fr/rap/r10-594-1/r10-594-14.html

[2] Because of lack of data and continuity of the public transportation services, we considered a flat hourly demand profile for the transport demand by train.

profile to reach to an only electricity demand. By subtracting the heat and transport demand profiles (normalized again since only a part of these demands is satisfied by electricity), I build an hourly specific electricity demand profile for 2050.

A5.2.4. Hydrogen demand profile

The needed coal for the steel production is estimated to be 3.5Mtoe (40.71TWh) (ADEME, 2017 and DGEC, 2019). I consider the same amount of energy intensity but instead of coal, hydrogen meets this demand. The annual hydrogen demand is divided by 8760 (number of time-slices in in year) to produce a flat demand profile for hydrogen.

A5.2.5. Industry demand profiles

The energy demand for industry is the same value as ADEME (2017), but since no repartition between the usages are provided, I use the heat-electricity usage repartition provided by négaWatt's "scenario négaWatt 2017-2050" (négaWatt, 2017). Because of lack of data and high flexibility of industrials' energy demand with respect to the energy price, I consider a flat electricity and heat profile for industry, and I add them to the heat and electricity profiles constructed in previous sections.

Appendix 5.3. Model parametrization

Equations (A5.19), (A5.20), (A5.21), (A5.25), (A5.26), (A5.27) and (A5.33) need technology-related input parameters. These parameters such as ramp rate, annual maximal capacity factor (availability limits due to maintenance) and the limiting factors of different processes need to be introduced into the model. Similarly, equation (A5.9), the reserve requirement definition, consists of several input parameters relating the required secondary reserves to installed capacities of VRE technologies and hourly demand profiles. Natural gas with CCS is not a zero-emission technology and according to JRC (2014), it captures only 86% of the carbon dioxide produced by the combustion, thus leaving residual emissions. The values of these input parameters, as well as their sources are presented in Table A5.4.

It is worth to mention that according to Agora energiewende (2017), the ramping rates (both upward and downward) for OCGT and CCGT power plants can go easily 100% in less than an hour. While CCGT power plants show enough flexibility in hourly scales, the addition of carbon capture units to these power plants can decrease their flexibility. Nevertheless, according to Mac Dowell et al. (2016) the CCGT power plants equipped with CCS units have enough flexibility to reach to ramping rates as high as the full load power in less than one hour. Therefore, I consider full hourly-flexible operations for both OCGT and CCS-equipped CCGT power plants.

Table A5.4. Technical parameters of the model

parameter	definition	value	source
cf_{ocgt}	Annual maximal capacity factor of OCGT	90%	JRC (2014)
cf_{ccgt}	Annual maximal capacity factor of CCGT	85%	JRC (2014)
cf_{nuc}	Annual maximal capacity factor of nuclear plants	90%	JRC (2017)
r_{nuc}^{up}	Hourly ramping up rate of nuclear plants	50%	NEA (2011)
r_{nuc}^{down}	Hourly ramping down rate of nuclear plants	50%	NEA (2011)
$\varepsilon_{offshore}$	Additional FRR requirement for offshore wind	0.027	Perrier (2018)
$\varepsilon_{onshore}$	Additional FRR requirement for onshore wind	0.027	Perrier (2018)
ε_{PV}	Additional FRR requirement for solar PV	0.038	Perrier (2018)
$\delta_{variation}^{load}$	Load variation factor	0.1	Van Stiphout et al. (2017)
$\delta_{uncertainty}^{load}$	Load uncertainty because of demand forecast error	0.01	Van Stiphout et al. (2017)
$\tau_{ccgt-ccs}$	The capture rate of CCS	86%	JRC (2014)
$\gamma_{methanization}^{CO_2}$	The relative share of CO_2 to methane in methanization process	3/7	ADEME (2018b)
e_{ccgt}	The specific emission of CCGT power plant with natural gas	$340tCO_2/GWh_e$	JRC (2014)
e_{ocgt}	The specific emission of OCGT power plant with natural gas	$510tCO_2/GWh_e$	JRC (2014)

Equations (A5.7), (A5.12), (A5.14), (A5.22), (A5.23), (A5.24), (A5.31), (A5.32) and (A5.34) also have some input parameters with respect to the chosen country. These parameters are the maximal available energy from the constrained technologies, maximum available capacities and hourly and monthly profiles of hydroelectricity and variable renewable energy technologies. In this thesis I study the French energy sector, therefore I use the values provided for France. Table A5.5 summarizes these values and their sources.

Table A5.5. Country-specific limiting input parameters of model

parameter	definition	value	source
$lake_m$*	Monthly maximum electricity from dams & reservoirs	See GitHub[1]	RTE (online)
$cf_{vre,h}$**	Hourly power production profiles for VRE technologies (floating and monopole offshore wind power, onshore win power, solar PV and run-of-river)	See GitHub[2]	Renewables.ninja & RTE (online)
g_{biogas}^{max}	Annual maximal biogas production from methanization and pyro-gasification	Methanization: 152TWh$_{th}$ Pyro-gasification: 122TWh$_{th}$	ADEME (2018b)
q_{tec}^{max}	Maximum installable capacity limit for each technology	See GitHub[3]	ADEME (2018a)
$profile_h^{transport}$	Hourly charging profiles for each transport category for each engine type (EV or ICE)	See Github[4]	Doudard (2018)
$\tau^{hydrogen}$	Maximal energy share of hydrogen that can be hosted in French gas network	6.35%	GRTgaz (2019)
$\varphi_{CO_2}^{max}$	The maximal available CO_2 storage capacity for France in 2050	93MtCO_2***	BRGM (2009) & CCFN (2019)[5]
$g_{heat-net}^{max}$	The maximal share of the heat demand that can be satisfied by heat network in France for the year 2050	52.2%	Appendix 5.2.1

* This parameter is calculated by summing hourly power production from this hydroelectric energy resource over each month of the year to capture the meteorological variation of hydroelectricity, using the online portal of RTE[6].

** 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, while other VRE profiles are prepared from renewables.ninja website explained in chapter 2.2.1.

***The average of 4 scenarios presented in BRGM leads to 53MtCO_2/year of available onshore storage for France. The French Norwegian collaboration on carbon capture and storage approves 20MtCO_2/year of storage in the North Sea, and a possible extension of the collaboration for a supplementary 20MtCO_2/year.

[1] https://github.com/BehrangShirizadeh/EOLES/blob/master/inputs/lake2006.csv
[2] https://github.com/BehrangShirizadeh/EOLES/blob/master/inputs/vre_profiles2006f.csv
[3] https://github.com/BehrangShirizadeh/EOLES/blob/master/inputs/max_capas.csv
[4] https://github.com/BehrangShirizadeh/EOLES/blob/master/inputs/t_profiles.csv
[5] https://www.ccfn.no/actualites/n/news/french-norwegian-collaboration-on-carbon-capture-and-storage.html
[6] https://www.rte-france.com/fr/eco2mix/eco2mix-telechargement

Appendix 5.4. Acronyms of energy production, conversion and storage technologies

Table A5.6. Technology labels and their definitions

Technology label	Explanation	Technology label	Explanation
Offshore	Offshore wind power (both floating and grounded)	**G2P**	Gas-to-power options (OCGT, CCGT and CCGT-CCS)
Onshore	Onshore wind power	**G2H**	Gas-to-heat options (centralized and decentralized boilers)
PV	Solar PV (ground and utility and residential rooftop)	**G2ICE**	Gas for transport by ICEs
Hydro	Hydroelectricity (both run-of-river and lake generated)	**Resistive**	Electrical heating by resistive heaters
Nuclear	New nuclear power (EPR)	**Hpc**	Centralized electrical heat pumps
OCGT	Open-cycle gas turbine	**Hpd**	Decentralized (individual) electrical heat pumps
CCGT	Combined-cycle gas turbine	**Boilerc**	Centralized gas boilers
CCGT-CCS	Combined-cycle gas turbine with post-combustion CCS	**Boilerd**	Decentralized (individual) gas boilers
P2G	Power-to-gas options	**EV_train**	Electric trains
P2H	Power-to-heat options	**EV_light**	Electric vehicles for light individual transport
P2EV	Power for transport by EVs	**EV_bus**	Electric buses
Ngas	Natural (fossil) gas	**EV_heavy**	Electric heavy transport vehicles
Methanization	Renewable gas from anaerobic digestion	**ICE_light**	Light transport vehicles with internal combustion engines
Pyrogaseification	Renewable gas from pyro-gasification of biomass	**ICE_bus**	Buses with internal combustion engines
P2CH4	Methanaton (electrolysis of water and Sabatier reaction with green CO_2)	**ICE_heavy**	Heavy transport vehicles with internal combustion engines
P2H2	Power-to-hydrogen (electrolysis of water)		

Appendix 5.5. The main results for the central availability scenario

Table A5.7 shows the installed capacity of each energy production, storage and vector change technology;

Table A5.7. installed capacities of energy production, conversion and storage technologies for different SCC scenarios in GW

SCC (€/tCO₂)	**0**	**100**	**200**	**300**	**400**	**500**
technology	**Installed capacity in GW**					
Offshore wind	0	0	0	0	0	0
Onshore wind	19.41	84.58	80.34	74.58	81.74	81.71
Solar PV	96	80.36	79.32	82.20	89.20	89.79
Run of river	7.5	7.5	7.5	7.5	7.5	7.5
Lake and reservoir	12.86	12.86	12.86	12.86	12.86	12.86
Nuclear	0	15.28	22.64	23.87	18.19	18.11
Natural gas	-	-	-	-	-	-
Methanization	0	0	17.35	17.35	17.35	17.35
Pyro-gasification	0	0	0	0	8.79	8.79
OCGT	2.75	4.58	2.09	0.69	0	0
CCGT	35.51	14.13	5.20	0.75	0	0
CCGT with CCS	0	0	5.47	11.5	17.24	17.31
Power-to-hydrogen	4.65	6.11	6.37	6.74	7.16	7.16
Power-to-methane	0	0	3.37	5.29	6.27	6.25
Heat network	18.23	34.29	46.66	43.73	45.68	45.63
Central HP	18.23	26.59	26.79	28.80	30.97	34.01
Individual HP	9.23	37.40	41.50	41.90	40.08	40
Resistive heating	6.14	21.15	17.92	13.51	14.53	14.82
Central boiler	0	0	0	0	0	0
Decentralized boiler	60.04	16.30	0	0	0	0
Battery	3.83	5.56	4.78	4.83	5.87	5.92
PHS	9.30	9.30	9.30	9.30	9.30	9.30
Gas storage	0	0	24.29	25.48	27.68	27.67
CTES	18.23	34.29	46.66	43.73	45.68	45.63
ITES	20.27	41.26	39.31	37.23	38.48	33.95

Table A5.8 presents the annual energy production (conversion) by each energy production, storage and vector change technology;

Table A5.8. Annual energy production of each energy production, conversion and storage technology for different SCC scenarios in TWh

SCC (€/tCO₂)	**0**	**100**	**200**	**300**	**400**	**500**
technology	**Annual energy production in TWh**					
Offshore wind	0	0	0	0	0	0
Onshore wind	55.22	240.58	228.53	212.13	232.51	232.99
Solar PV	136.51	114.27	112.79	114.89	126.84	127.68
Run of river	28.48	28.48	28.48	28.48	28.48	28.48
Lake and reservoir	15.30	15.30	15.30	15.30	15.30	15.30
Nuclear	0	111.35	167.70	182.99	140.42	139.60
Natural gas	740.62	222.60	0	0	0	0
Methanization	0	0	152	152	152	152
Pyro-gasification	0	0	0	0	77	77
OCGT	1.75	2.29	1.04	0.33	0	0
CCGT	208.97	22.70	4.74	0.40	0	0

CCGT with CCS	0	0	8.26	17.66	71.63	71.75
Power-to-hydrogen	40.71	46.34	51.20	52.66	59.04	59.04
Power-to-methane	0	0	16.24	24.14	41.38	41.38
Central HP	151.06	120.16	116.75	123.55	129.42	129.26
Individual HP	79.87	285.205	328.30	326.89	311.46	311.17
Resistive heating	4.37	29.20	20.86	13.29	20.93	21.44
Central boiler	0	0	0	0	0	0
Decentralized boiler	219.30	30.59	0	0	0	0
Light EV	0	3.94	3.97	3.98	4.02	4.14
Heavy EV	0	0	0	0	0	0
Electric bus	0	0	0	0	0	0
Train (electric)	30	30	30	30	30	30
Light ICE	97.92	89.71	89.65	89.63	89.54	89.30
Heavy ICE	56.97	56.97	56.97	56.97	56.97	56.97
ICE bus	6.47	6.47	6.47	6.47	6.47	6.47
Battery	0.55	0.34	0.35	0.40	0.57	0.61
PHS	14.14	20.59	20.30	19.86	17.21	17.42
Gas storage	0	0	25.28	41.99	58.51	58.62
CTES	0.13	31.03	34.44	27.64	21.77	21.93
ITES	8.91	9.72	7.78	8.53	8.90	8.84

The main economic and emission related outputs of this study for different SCC values are presented in Table A5.9.

Table A5.9. Main economic and emission related outputs

SCC (€/tCO_2)	**0**	**100**	**200**	**300**	**400**	**500**
Cost with SCC (b€/an)	48.19	57.29	59.55	59.15	58.06	55.97
Technical cost (b€/an)	48.19	52.19	60.04	60.69	66.43	66.45
CO_2 emission (MtCO_2/an)	169.97	51.09	-2.41	-5.16	-20.91	-20.95
CO_2 captured (MtCO_2/an)	0	0	2.41	5.16	20.91	20.95
Electricity LCOE (€/MWh_e)	45.04	48.77	49.23	48.92	48.14	48.14
Gas LCOE (€/MWh_{th})	25.36	49.17	59.31	60.60	66.85	68.86
Heat LCOE (€/MWh_{th})	14.22	28.74	30.63	30.71	30.90	30.87

Appendix 5.6. The CO_2 emissions for no social cost of carbon and the emissions from the actual French energy system

In section 5.3.3 we saw the CO_2 emissions for different SCC values. In the absence of an SCC, the CO_2 emissions of the energy sector are relatively low in comparison with current emissions of the energy sector (170MtCO_2/year vs. 450MtCO_2/year). This low emission in the absence of an SCC value can be explained considering several factors: First, the existing energy system in France does not rely on an optimal allocation of installed capacities of energy production technologies. This study is a greenfield optimization, which does not consider the existing energy system, but it allocates an absolute optimal case regarding the taken hypothesis for a given year. While most of the existing power plants will be decommissioned by 2050, the hydro-electric power plants will remain, that's why I fixed a minimum installed capacity for these power plants equal to the existing capacities. Likewise, in case of retrofitting the nuclear power plants, the last historic nuclear power plant in France will be decommissioned by 2052 (Perrier, 2018). The Flamanville 3 nuclear reactor which is not commissioned yet will also be in the energy supply that is not considered in this optimization. Moreover, the lifetime of buildings, factories and the infrastructures are not taken into account. Therefore, a greenfield optimization does not reflect the existing energy system precisely. The existing energy system is highly dependent on fossil fuels especially in industry and transport sectors.

Second, the demand projections for 2050 for France are based on several energy consumption reduction assumptions in residential, tertiary and transport sectors. The final energy demand for residential and tertiary sectors for year 2015 were 490TWh and 295TWh respectively, while in the future final energy demand projections, these values are considered to be 293TWh and 168TWh respectively (SNBC, 2019). The high reduction in the final energy demand for each sector is thanks to increased efficiency of electronic appliances, increased isolation of buildings and replacement of light bulbs with LEDs. The final energy demand for the transport sector was 509TWh for 2015 (SNBC, 2019), and it is projected to be less than 200TWh in 2050. ADEME projects a final energy demand reduction from 149Mtoe (1,732.9TWh) to 82Mtoe (953.7TWh) from 2010 to 2050 (ADEME, 2017). Moreover, all the existing scenarios for future French energy mix (négaWatt, 2017, ADEME, 2017 and SNBC, 2019) project a much lower energy loss from the primary energy production to final energy consumption. According to SNBC (2019), a primary energy consumption of 250Mtoe (2,907.5TWh) for France for the year 2015 satisfies the 142Mtoe (1,651.5TWh) of final energy demand at this year. Therefore, one can easily predict the impact of each of these assumptions: the emissions will be much higher because of increased usage of cheap natural gas.

Appendix 5.7. Energy mix for different availability scenarios

Figure A5.1 shows the primary energy mix of each end-use for different availability and the final energy consumption. In case of unavailability of nuclear power, the energy mix becomes fully renewable from the SCC value of €300/tCO_2 on, with no change in emission or cost of the energy system. On the other hand, without VRE technologies, the primary energy contains 71% of nuclear energy from an SCC of €100/tCO_2 on. While in all the availability scenarios, the natural gas is phased out for €200/tCO_2 or €300/tCO_2 of SCC, in case of absence of renewable gas, natural gas remains an important part of primary energy even for the SCC of €500/tCO_2.

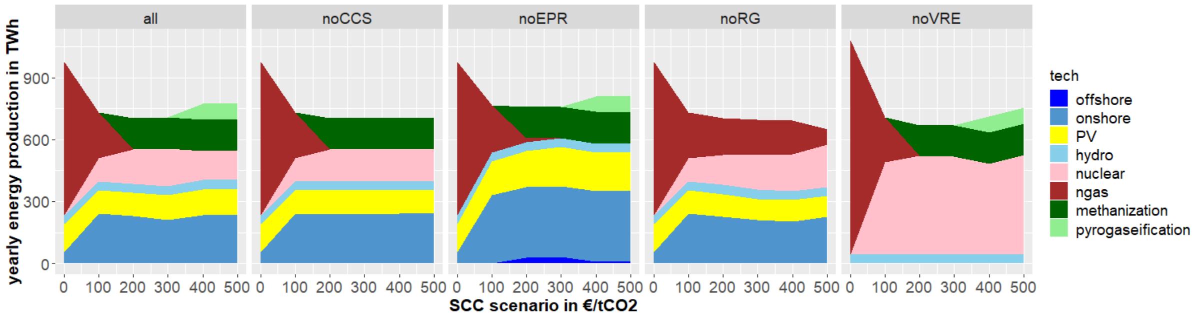

Figure A5.1. Primary energy mix for each technology availability scenario for different SCC values

Figures A5.2 and A5.3 show the electricity and the gas mix for each availability scenario and SCC value. In the absence of nuclear power, offshore wind power appears in the energy mix for SCC of €200/tCO_2. By increasing the SCC value from €200/tCO_2 on, this technology is phased out thanks to the increased usage of renewable gas and the flexibility gains from it. For all the availability scenarios in the presence of VRE technologies, the share of nuclear power in energy mix never exceeds 25% and the remaining is provided by renewable energy sources.

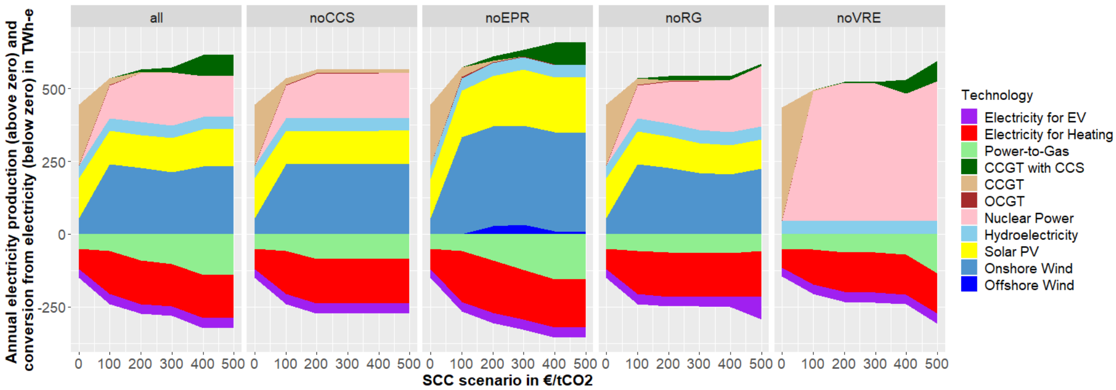

Figure A5.2. Electricity production mix for different technology availability scenarios

For all the scenarios, the main function of gas is the fuel for the transport sector, and electricity production for zero SCC, where cheap natural gas is used to produce electricity. From the SCC of €200/tCO_2 on, the gas production is dominated by renewable gas technologies, and synthetic gas from power-to-gas. For the scenario where no renewable gas is available, the gas supply is dominated by fossil gas, even for the highest SCC values, as we observed in figure A5.1 as well.

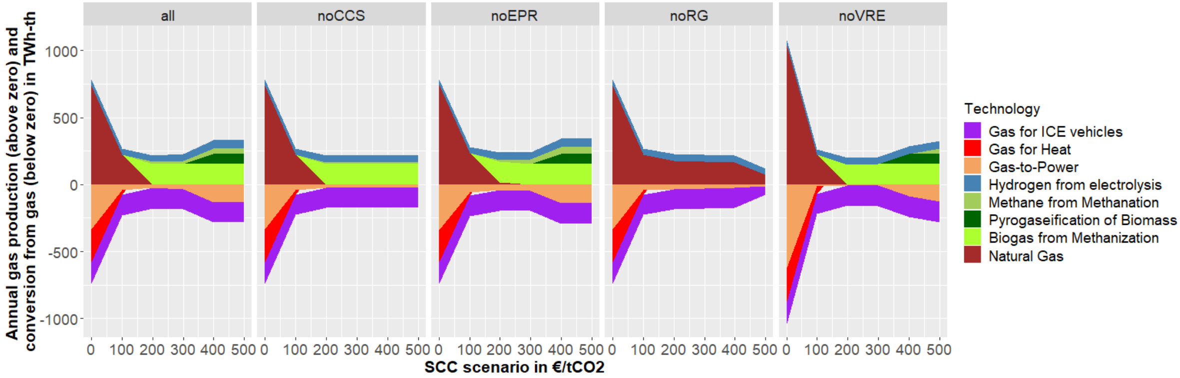

Figure A5.3. Gas production mix for different technology availability scenarios

Figure A5.4 shows the technologies meeting the sectorial demands of heat and transport end-uses. The heat supply technologies remain the same for each availability scenario, following the same pattern as the central scenario: nearly half of the heat is provided from decentralized boilers for zero SCC value, and from the SCC of €100/tCO$_2$ the share of gas-to-heat drops to less than 10% and from €200/tCO$_2$ of SCC on, the heat network is fully electrified, mainly by heat pumps (especially individual heat pumps). Resistive heating has a direct relation with the share of VRE technologies. The efficiency of resistive heating is much lower than heat pumps, but so is its cost. Therefore, for cheap electricity hours where the electricity supply exceeds the demand, storage and power-to-X[1] technologies, resistive heating is considered as a useful option to either satisfy end-use heat demand or to charge the heat storage tanks. Since the increased share of VRE leads to increased share of zero price hours in the power system (chapter 2), there is a positive correlation between the share of VRE technologies in power production and the share of resistive heating in heat production.

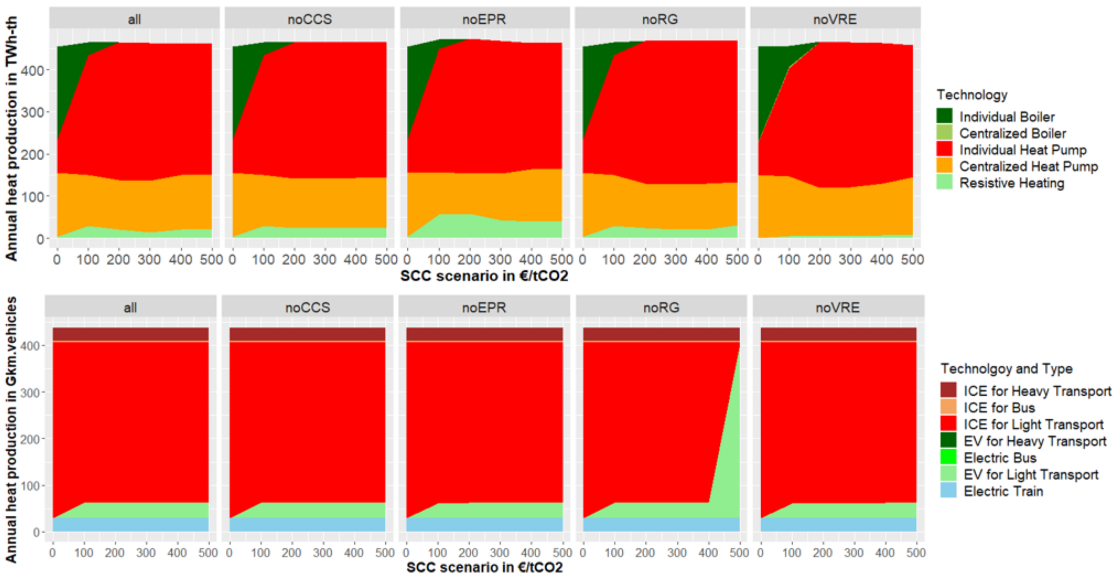

Figure A5.4. Heat and transport demand and the supply technologies for all the availability scenarios and different SCC values

The transport supply technologies' shares for different availability scenarios follow the same pattern as the scenario with the central availability scenario as well. As discussed previously, the transport sector is dominated but ICE vehicles powered by either natural gas for zero SCC or renewable gas for

[1] X stands for gas, heat or transport: power-to-gas, power-to-heat and power-to-transport.

higher SCC values. In case of unavailability of renewable gas, the high cost of fossil gas with the emission tax for very high SCC value of €500/tCO_2 results in replacement of ICE vehicles in light transport by electric vehicles. Therefore, availability of renewable gas is also a key enabler of ICE vehicles' dominance in the transport sector.

Appendix 5.8. Back-of-envelope calculation to compare EV and ICE vehicles

Let's consider 500Gvehicle.km of transport demand. The fuel efficiencies for electric and ICE vehicles are 8km/kWh$_e$ and 3.85km/kWh$_{th}$ respectively. Therefore, to satisfy this light transport demand, 130.21TWh$_{th}$ of gas or 62.5TWh$_e$ of electricity will be necessary. The price projected for natural gas is €23.5/MWh$_{th}$, and the average electricity price is around €48/MWh$_e$. Thus, in case of no carbon tax the variable cost for electric vehicles will be €3b/year while for ICE vehicles it will be €3.06b/year and for an SCC of €500/tCO_2 this variable cost goes up to €18b (I).

Now let's consider the needed investment for charging and storage infrastructures; let's also consider that each electric vehicle user has a charging point worth of average 5kW of charging power. For a fleet of 30M EVs, the charging capacity will be 150GW. Considering an autonomy of 300km per EV a battery energy capacity of 37.5kWh for each EV and an overall energy capacity of 1.125TWh will be needed for the fleet of 30M EVs. Therefore, using the economic parameters in table 5.5, an annual investment cost of €15.88b/year will be needed for this EV fleet. Each gas charging station can charge 400 vehicles per day, considering charging frequency of once each week for each ICE vehicle, 2800 ICE vehicles can be charged by each ICE charging station (costing €300,000 for 15 years of lifetime, therefore an annuity of €28,563/year) each week, therefore 10,714 charging stations will be needed, which would cost €306M/year (II).

From (I) and (II) one can calculate a breakeven point for different SCC values, where it would be preferable for a light vehicle user to choose an electric vehicle instead of an ICE vehicle. Knowing that each GWh of natural gas contains 22.95tCO_2, the breakeven SCC can be calculated from the equality below:

$$15.88+3 = 0.306 + 3.06 + SCC\times22.95\times130.21/100000$$

This break-even point is €519/tCO_2 and for this SCC value, natural gas is already abandoned from the results.

Considering the renewable gas as fuel for ICE vehicles, using the same numbers and reasoning above, we can study the relative economic attractiveness of ICE vehicles fueled with renewable gas and electric vehicles.

According to figure 5.8, the gas price is roughly €25/MWh$_{th}$ (nearly the price of natural gas) for a zero SCC and this price goes up to €68/MWh$_{th}$ for the SCC of €500/tCO_2 because of mobilization of two more expensive gas options (biogas and pyro-gasification of biomass). For the highest SCC value, the cost of a fully EV fleet being equal to €18.88b/year is higher than the cost of the ICE fleet (€8.85b/year) when only battery and charging points and used energy cost are considered. For lower SCC values, the price of gas would be even less, and the ICE vehicle fleet would cost even cheaper.

It can be concluded that ICE vehicles are more interesting from the cost-optimality point of view. The small share of EV in the final transport mix for the light transport is thanks to the zero price hours of electricity (high VRE generation hours where the electricity price is the marginal cost of VRE technologies, in other words; zero.) and limited renewable gas availability.

Appendix 5.9. Sensitivity to heat network coverage limit

In the central scenario, I considered that 52.2% of final heat demand can be satisfied by the heat network (because of urbanization and density limitations of France – Appendix 5.2.1). In case of higher urban population density and higher urbanization assumptions, the value can go up and vice versa. Therefore, to account for a high range of heat network coverage possibilities, I applied a variation of +/-50% in the 52.2% of final heat demand that can be satisfied by heat network (low scenario of 26.1% of heat demand and high scenario of 78.3%).

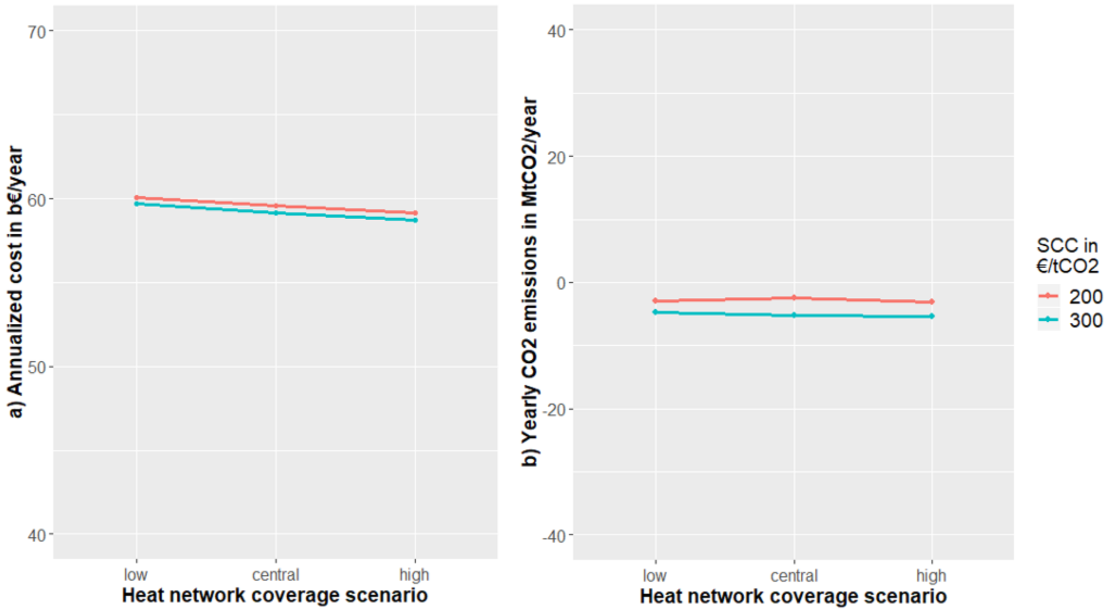

Figure A5.5. Sensitivity of the yearly total cost and emissions of the energy system to the +/-50% variation of the maximal heat network coverage limits

Figure A5.5 summarizes the cost and emission related results of the sensitivity analysis over the heat network coverage for SCC scenarios of €200/tCO_2 and €300/tCO_2.

Heat network coverage limit does not impact the system cost and the yearly emissions for any of the SCC values. The cost variation stays below 2% for a threefold change in the heat network coverage limit, and the emissions stay nearly stable and below zero in any SCC scenario.

Appendix 5.10. Sankey flow diagram for the proposed SCC of 300€/tCO_2

Figure A5.6 shows the Sankey flow diagram for the proposed SCC scenario of 300€/tCO_2. This figure summarizes the whole energy system, technologies and the interactions between different vectors and end-use demands for the proposed robust SCC value.

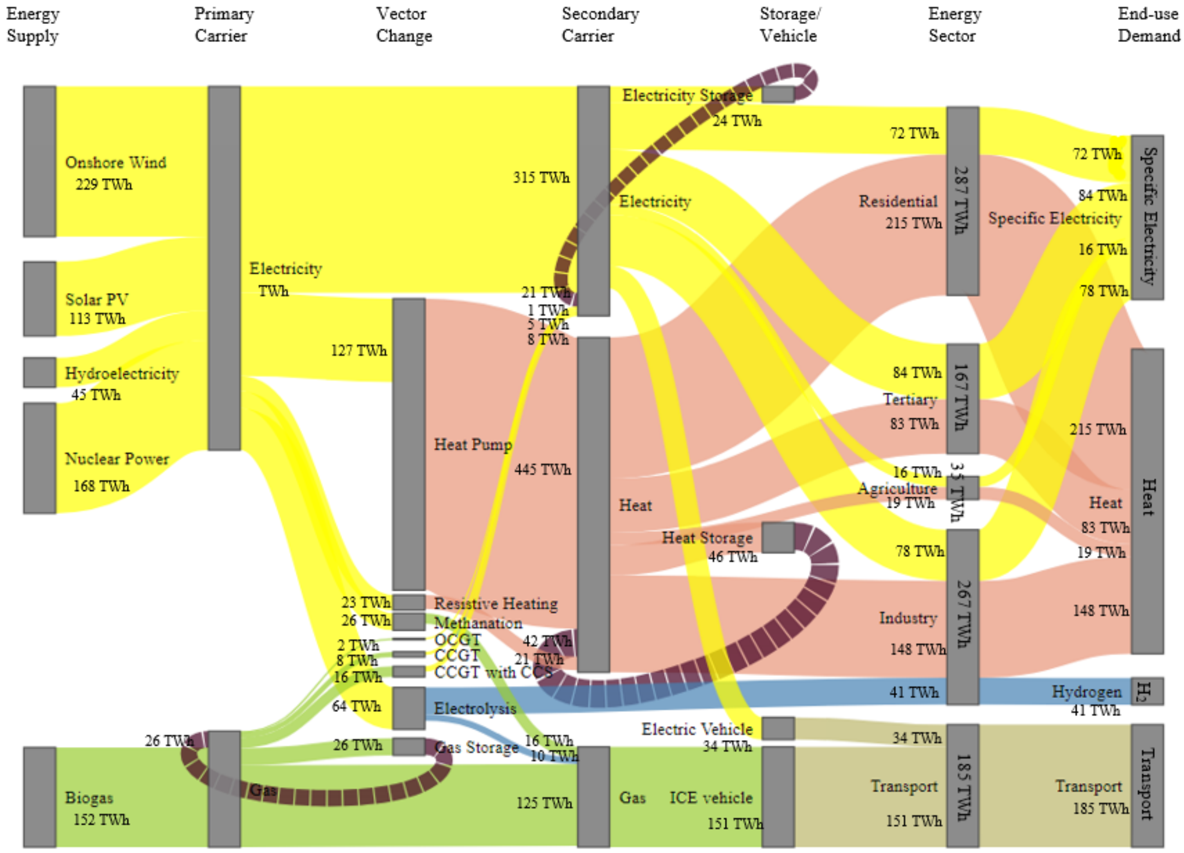

Figure A5.6. Sankey flow diagram for the energy system for the proposed SCC of 300€/tCO2 ; yellow color represents the electricity flow, pink represent heat flow, green represents gas flow, blue represents hydrogen flow and khaki represents transport sector. The purple flows in each of electricity, heat and gas sectors are the energy storage in each of the carriers.

Appendix 5.11. Sankey flow diagram for the proposed SCC of 300€/tCO_2 in the absence of nuclear energy

Figure A5.7 shows the Sankey flow diagram for the case with no nuclear power. As we can see, offshore wind power appears in the optimization results, and power productions from onshore wind and solar PV are much more than the case with nuclear power. Overall electricity production is increased by 54TWhe serving the same electricity, transport and heat demand. Higher energy storage leads to higher storage related loss from electricity (7TWhe vs. 3TWhe) and increased share of VRE technologies leads to an increased curtailed electricity (25TWhe vs. 19TWhe). However, as we discussed previously, the availability of nuclear power has negligible impact on the energy system cost and total CO2 emissions of the system.

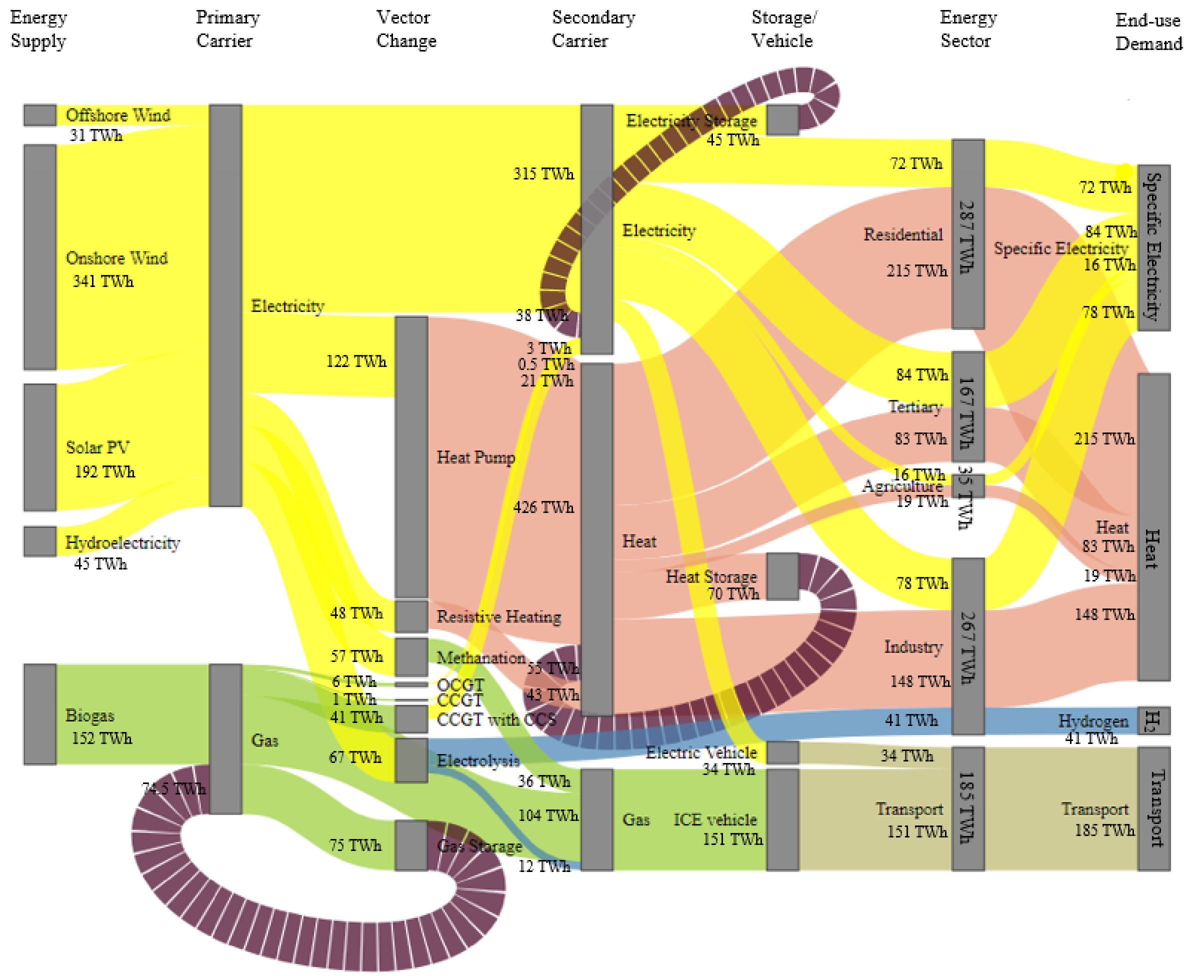

Figure A5.7. Sankey flow diagram for the energy system for the proposed SCC of 300€/tCO2 for the case without nuclear energy; yellow color represents the electricity flow, pink represent heat flow, green represents gas flow, blue represents hydrogen flow and khaki represents transport sector. The purple flows in each of electricity, heat and gas sectors are the energy storage in each of the carriers.

Part III

Technical Studies on Computational Tractability of Energy System Models

Chapter 6

Variable time-step: a method for improving computational tractability for energy system models with long-term storage

6.1. Introduction

Computation of optimized energy system models is very demanding in terms of calculation time and required memory. Hence modelers face a trade-off between, on the one hand, computational tractability and, on the other hand, comprehensiveness of the system modelled, broadness of the sensitivity analyses provided and accuracy of the results. This is especially true for energy systems featuring a high proportion of variable renewables (wind, solar photovoltaics and run-of-river hydropower), for at least three reasons.

First, a coarser-than-hourly temporal resolution lowers the model accuracy due to short-term variations in wind speed and solar irradiation. Hence, most models feature an hourly resolution. This is sufficient for country-level modelling, but a coarser temporal resolution degrades model accuracy (Brown et al, 2018).

Second, inter-annual fluctuations in key weather variables are high (e.g. Collins et al, 2018 and Zeyringer et al, 2018). This is true for wind and for temperature, which drives energy demand for heating and cooling. Optimization over several years is thus useful to check the reliability of an energy mix.

Third, due to annual cycles in wind, solar radiation and temperature, the cost-optimal solution often includes long-term energy storage, typically over several months (Schill and Zerrahn, 2018 and Chapters 2 and 3). Accounting for long-term storage requires the modelling of a continuous, long period of time, rather than defining 'representative' periods which may not ensure continuity of storage facility charge state (Pfenninger, 2017).

Recent progress in energy system modelling includes, inter alia, sector coupling (e.g. Victoria et al, 2019), optimizing the location of renewable facilities over a large number of regions (e.g. Murray et al, 2020 and Bramstoft et al, 2020), and analyzing the impact of climate change (e.g. Seljom et al, 2011 and Ding et al, 2019), which requires optimization over many weather-years. While these developments are useful, they further increase calculation time and required memory. The issue is then to improve computational tractability in order to accommodate these improvements in model comprehensiveness without too great a loss of accuracy.

Some of the methods used to achieve this objective focus on aggregating time series, as in this paper. Hoffmann et al. (2020) provide an up-to-date, comprehensive review of these methods applied to energy system models. They classify the methods into two broad categories: (1) definition of typical periods and (2) resolution variation. Clustering, which belongs to the first category, has gained particular attention in the literature. It consists of grouping together similar periods on the basis of a common characteristic. Clustering can be performed over representative hours as in Blanford et al. (2018) or over days as in Green et al. (2014). While clustering decreases calculation time, it does not maintain chronological order, thus the state of charge and other hourly storage-related profiles cannot be modelled correctly using this method. Nahmmacher et al. (2016) suggest choosing several consecutive days within the representative periods. While this method can improve precision in dimensioning short-term storage technologies, it does not solve the above-mentioned problem of adequately representing long-term storage modelling.

The second method category, resolution variation, does not suffer from this problem since the continuity of time-steps is preserved, but the challenge is to maintain a fine enough resolution so that the specific characteristics of important hours are preserved. This cannot be achieved by uniform down-sampling since, for example, the hour with the highest energy demand would be merged with contiguous hours, which by definition, feature a lower demand.

Another family of resolution variation methods, called “segmentation” by Hoffmann et al. (2020), addresses this issue by varying the time resolution based on features of the supply and/or demand time-series. Mavrotas et al. (2008) use such a feature-based resolution variation algorithm to segment hourly time series to coarser time-steps for 3 seasons and 6 intra-day periods for heating, electricity and cooling loads. Samsatli and Samsatli (2015) and Pineda and Morales (2018) also apply this type of method. The limitation of these methods is that even for a given season and intra-day period (e.g. evenings in winter), there may be a significant heterogeneity, for example in energy demand, which is not accounted for.

The strategy proposed in this chapter, in order to overcome these limitations, is to maintain an hourly temporal resolution for the ‘most important’ hours, while adopting a coarser resolution for the rest of the optimization period. To use the same vocabulary as Hoffmann et al. (2020), a feature-based method is developed to decrease the number of time-steps by hierarchical segmentation: I first define critical periods represented as hourly time-steps, then I apply a daily down-sampling. As in the other resolution variation methods, the chronological order is retained.

This strategy has been inspired by another computationally demanding scientific domain: atmospheric modelling. Many atmosphere models feature a finer spatial definition over the region of interest to modelers, e.g. Europe for many applications of the models developed in this continent (e.g. Hourdin et al, 2013 for LMDZ, the atmospheric part of the IPSL coupled climate model).

The main difficulty is choosing the ‘most important’ hours, hence this chapter proposes a method to achieve this and tests the performance of this ‘variable time-step’ approach in terms of model accuracy and calculation time. This method is applied to two national energy system models, EOLES_elecRES (presented in Chapter 2) and DIETER (Zerrahn and Schill, 2015), which have previously been implemented at an hourly resolution.

The Section 6.2 below introduces the 'variable time-step' method. Section 6.3 describes the two energy system models within their specific cases, to which the method is applied, Section 6.4 presents the results, first for a central cost scenario and second for alternative cost scenarios. Section 6.5 presents the discussion and concludes this chapter.

6.2. The 'variable time-step' method

The proposed 'Variable time-step' method can be defined as follows: all the hours of the considered period (one or several weather-years) are included in the optimization in chronological order but some consecutive hours are grouped into single time-steps, some of which are therefore longer than others. The idea is to maintain an hourly resolution for hours which may matter for dimensioning part of the electricity system (production or storage installations) and to group the other hours into single time-steps.

6.2.1. Definition of critical periods

The hours are selected to be grouped on the basis of residual demand variation. Residual demand is the difference between demand and generation by non-dispatchable technologies (wind, solar and river-based hydro). For example, during a given night, consumption is relatively constant and solar power production is zero, provided that the wind blows relatively constantly, there is little variation in residual demand. These night hours can therefore be grouped into a single time-step without much loss of accuracy. Equation (6.1) shows the mathematical definition of residual demand:

$$d_h^{residual} = d_h - \sum_{vre} G_{vre,h} \tag{6.1}$$

Where $d_h^{residual}$ is the residual demand at hour h, d_h is the electricity demand at hour h and $G_{vre,h}$ is the hourly power production from variable renewable energy source vre (non-dispatchable production).

To set the duration of the critical periods (those which require an hourly resolution) several periods are chosen to cover various difficult situations that must be overcome by the power system. The hours with the highest residual demand are of great importance since the installed capacity should be sufficient to satisfy peak residual demand. Li-Ion batteries for stationary applications in hourly dispatch can be used for both power reliability and power quality, and the intersection between these two applications is a four-hour period (Schmidt et al, 2019); thus, a volume-to-power ratio of four hours (i.e. they can be fully charged and discharged in four hours in nominal power). Therefore, the four-hour period with the highest residual load has been chosen as a second critical period duration.

The longest period should be chosen in such a way that short-term and mid-term storage options (batteries and PHS) are modelled correctly. An analysis on the full discharge time of the pumped hydro storage (mid-term storage) technology is necessary to define the longest period. From Chapter 2 we can deduce that discharge time of PHS plants rarely exceeds four days, therefore, the longest period is considered to be 96 hours. This analysis for the case studied in Chapter 2 is presented in Appendix 6.1.

Since adding a limited number of time-steps does not significantly change the solution time, I added six-hour, twelve-hour, one-day and two-day periods in between the previously mentioned critical periods. The critical periods are found by the Equations (6.2) to (6.8):

$$h_1 \in H = \{1,2,\dots,8760\};$$
$$d_{h_1}^{residual} = \max_{h \in H} d_h^{residual} \tag{6.2}$$

$$H_2 = \{h, h+1, h+2, h+3\} \subset H - h_1 ;$$
$$\sum_{h \in H_2} d_h^{residual} = \max_{H-h_1} \sum_{h \in H_2} d_h^{residual} \tag{6.3}$$

$$H_3 = \{h, h+1, \dots, h+5\} \subset H - H_2 - h_1 ;$$
$$\sum_{h \in H_3} d_h^{residual} = \max_{H-H_2-h_1} \sum_{h \in H_3} d_h^{residual} \tag{6.4}$$

$$H_4 = \{h, h+1, \dots, h+11\} \subset H - H_2 - H_3 - h_1;$$
$$\sum_{h \in H_4} d_h^{residual} = \max_{H-H_2-H_3-h_1} \sum_{h \in H_4} d_h^{residual} \tag{6.5}$$

$$H_5 = \{h, h+1, \dots, h+23\} \subset H - H_2 - H_3 - H_4 - h_1;$$
$$\sum_{h \in H_5} d_h^{residual} = \max_{H-H_2-H_3-H_4-h_1} \sum_{h \in H_5} d_h^{residual} \tag{6.6}$$

$$H_6 = \{h, h+1, \dots, h+47\} \subset H - H_2 - H_3 - H_4 - H_5 - h_1;$$
$$\sum_{h \in H_6} d_h^{residual} = \max_{H-H_2-H_3-H_4-H_5-h_1} \sum_{h \in H_6} d_h^{residual} \tag{6.7}$$

$$H_7 = \{h, h+1, \dots, h+95\} \subset H - H_2 - H_3 - H_4 - H_5 - H_7 - h_1;$$
$$\sum_{h \in H_6} d_h^{residual} = \max_{H-H_2-H_3-H_4-H_5-H_7-h_1} \sum_{h \in H_6} d_h^{residual} \tag{6.8}$$

6.2.2. Daily sub-sampling

The next step is to group the remaining hours in a coherent way. This daily sub-sampling depends on the studied case. Four main daily time-slices are defined, depending on the availability of solar irradiation and daily electricity demand:

a) Morning: a transition period during which non-dispatchable generation rises steeply.
b) Noon: the period with the maximum excess non-dispatchable generation, which determines the required storage volume.
c) Evening: the period with the highest residual demand, resulting in massive use of dispatchable technologies.
d) Night: a period during which residual demand is low, resulting in little use of dispatchable technologies, while storage technologies can be charged during this period.

These four periods can vary among different geographical locations and different lifestyles. For the two case studies in this chapter, these four time-slices are chosen:

a) Morning: 7 am to 10 am.
b) Noon: 10 am to 3 pm.
c) Evening: 3 pm to 10 pm.

d) Night: 10 pm to 7 am of the day after.

6.2.3. Hydro reserve correction

During the evening period, residual demand is high. The model satisfies this demand by using batteries, dispatchable hydraulic power, biogas and gas from methanation. However, a problem with the method described above is that it allows the saturation of hydraulic power to be bypassed when it occurs for only a short time. For example, in the model with a variable time-step, during the period from 3 pm to 10 pm hydraulic power may be saturated, while the peak power demand only lasts from 6 pm to 8 pm that day. To satisfy this peak demand, it would have been necessary to use the batteries, because the hydraulic power available from 6 pm to 8 pm would be insufficient.

To overcome this problem, a supplementary correction equation has been added to prohibit the use of 100% of the hydraulic power for a time-step of several hours, because in reality, the amount of power needed may vary within this time-step. Thus, I implement a reserve when the time-step lasts more than one hour; part of the dispatchable hydropower is reserved for possible rebalancing requirements within the time-step. This correction is formulated in Equation (6.9):

$$E_{hydro,ts} \leq Q_{hydro} \times l_{ts} \times \left(\frac{0.2}{l_{ts}} + 0.8\right) \tag{6.9}$$

Where $E_{hydro,ts}$ is the power production from both dispatchable hydropower technologies (PHS and lake-generated) at time-step ts, Q_{hydro} is the installed capacity of this hydropower technology, and l_{ts} is the length of the time-step ts. The multiplier 0.2 is a calibration coefficient obtained by trial-and-error, in order to minimize the discrepancy with the results of the full model. The variable time-step method is summarized in Figure 6.1:

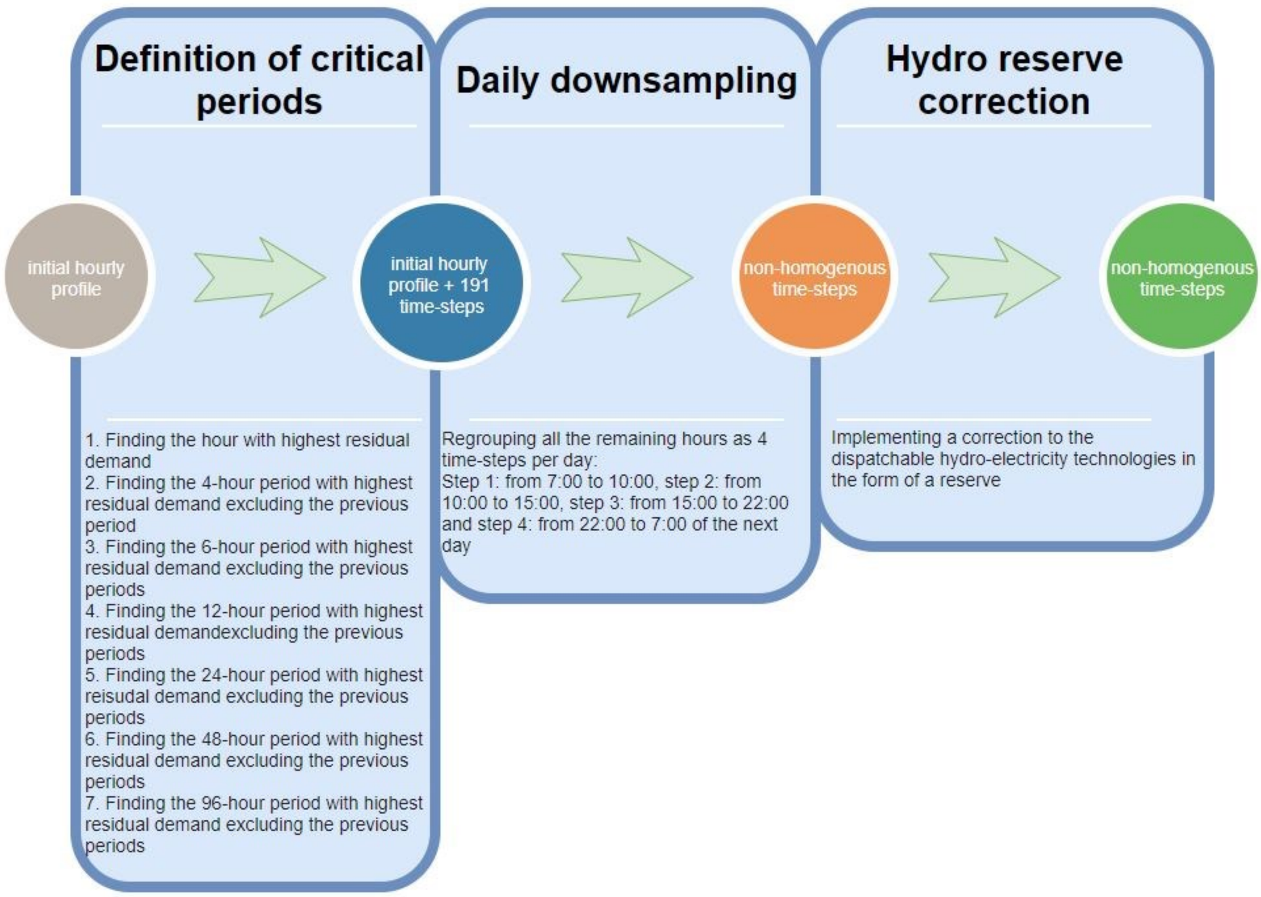

Figure 6.1. The variable time-step method

6.3. Case studies

This proposed 'variable time-step' method is applied to two dispatch and investment models, each one applied to a different country. First, the method is developed for the EOLES_elecRES model applied to continental France, then, I have used it for the DIETER model applied to Germany, to validate this method. I have chosen these models because they are open-access, dispatch and investment models with an hourly temporal resolution, featuring at least three storage categories: short-term (batteries, compressed air storage, etc.), mid-term (e.g. PHS) and long-term storage (hydrogen, methanation etc.). In the following, I briefly describe each model and case study.

6.3.1. The EOLES_elecRES model

EOLES_elecRES is a 100% renewable power system model based on linear optimization. Investment and storage technology capacities and the operation of dispatchable options are simultaneously optimized in order to minimize the annualized system cost. The model is explained in higher detail in Chapter 2. The code and data for EOLES_elecRES model's long version (with fixed, hourly resolution) and the developed compact version (with variable resolution) are available on GitHub[1,2].

[1] https://github.com/BehrangShirizadeh/EOLES_elecRES/blob/master/model/EOLES_elecRES_long.gms
[2] https://github.com/BehrangShirizadeh/EOLES_elecRES_compact

6.3.1.1. Input data

The model is applied to France for the year 2050. The costs, electricity demand and other land-use and resource availability constraints are thus forecasts for that year. All the input data used in this model are the same as Chapter 2.

6.3.2. The DIETER model

I validated the variable time-step method by applying it to the DIETER (Dispatch and Investment Evaluation Tool with Endogenous Renewables) model. Like EOLES_elecRES, DIETER (developed by Zerrahn and Schill, 2015) is a power system greenfield optimization model, simultaneously optimizing dispatch and investment with hourly temporal resolution. It includes run-of-river, nuclear energy, lignite, hard coal, efficient and inefficient open cycle gas turbines, combined cycle gas turbines, biomass, offshore and onshore wind power and solar PV as generation technologies, and seven energy storage technologies: Li-Ion, lead acid, Na-S and redox flow batteries, pumped-hydro storage (PHS), compressed air energy storage (CAES) and power-to-gas. This model contains load curtailment and load shifting as demand-side management (DSM) options, and the primary, secondary and one-minute reserves are represented both as upward and downward reserves. The model ensures hourly supply-demand equilibrium, including the provision and activation of balancing reserves. More information about this model can be found in Zerrahn and Schill (2015). Application of 'variable time-step' method to the DIETER model is presented in Appendix 6.2.

6.3.2.1. Input data

I use the "baseline scenario" data as the input data, where hourly load values are taken from ENTSO-E (2014) for the year 2013 for Germany, hourly reserves called upon from German TSOs for the year 2013 (Regelleistung, 2014), and the hourly capacity factors for variable renewable technologies are calculated by dividing hourly renewable generation by the installed capacity for the year 2013 provided by German TSOs. All technology-specific input parameters reflect a 2050 perspective, especially cost and efficiency of different power plants and other operational parameters that are defined in the operational constraints of the model. The cost data for conventional and biomass power plants as well as VRE generation technologies are taken from medium projections for 2050 of DIW data documentation (Schröder et al, 2013). A 32GW of maximal installable capacity for offshore wind power (Nitsch et al, 2012) and an annual biomass budget of 60TWh (Böhler, 2012) are considered as limiting constraints. The roundtrip efficiency and other operational constraints for storage technologies are taken from Pape et al. (2014). More information about the input data and their sources can be found in Zerrahn and Schill (2015).

6.4. Results

I first ran the complete version of EOLES_elecRES for 19 weather-years (2000 to 2018), followed by the 'compact version', i.e. the model using the variable time-step method. The comparison of the results in Subsection 6.4.1 allows the assessment of the accuracy of the variable time-step method. In Subsection 6.4.2, I present the results of four alternative cost scenarios, changing the cost of battery and methanation each by ±25%, while in Subsection 6.4.3 I present the results with the DIETER model.

6.4.1. Results for the EOLES_elecRES model, central cost scenario

Table 6.1 presents the installed capacities for each of the non-dispatchable technologies and battery storage, and the power production from each of these technologies over the 19 years.

Table 6.1. Installed capacities of endogenous technologies in the complete version of EOLES_elecRES and in its compact version with the corresponding error values. Both models are optimised over a period of 19 weather-years (2000-2018).

Installed capacity (GW)	**Complete version**	**Compact version**	**Error**
Wind power	88.84	89.67	0.93%
Solar PV	111.30	110.64	0.59%
Battery power	19.98	19.59	1.95%
Battery volume (GWh)	67.37	63.74	5.39%
Methanation	34.64	34.97	0.95%
Power generation (TWh)			
Wind power	5252.96	5223.26	0.57%
Solar PV	2986	2968.17	0.60%
Battery	212.43	186.82	12.06%
Methanation	142.60	142.63	0.02%

As shown, the error is below 2% for wind power, solar PV, battery power and methanation. Higher errors occur for battery volume and generation.

Figures 6.2 and 6.3 show the power production and installed capacity by technology. Table 6.2 summarizes the cost and load curtailment observed from the complete model and its compact version. Errors are below 1% for system cost and load curtailment. The compact version underestimates the storage loss by 3% (but by only 0.16 percentage points), presumably due to the lower use of battery storage.

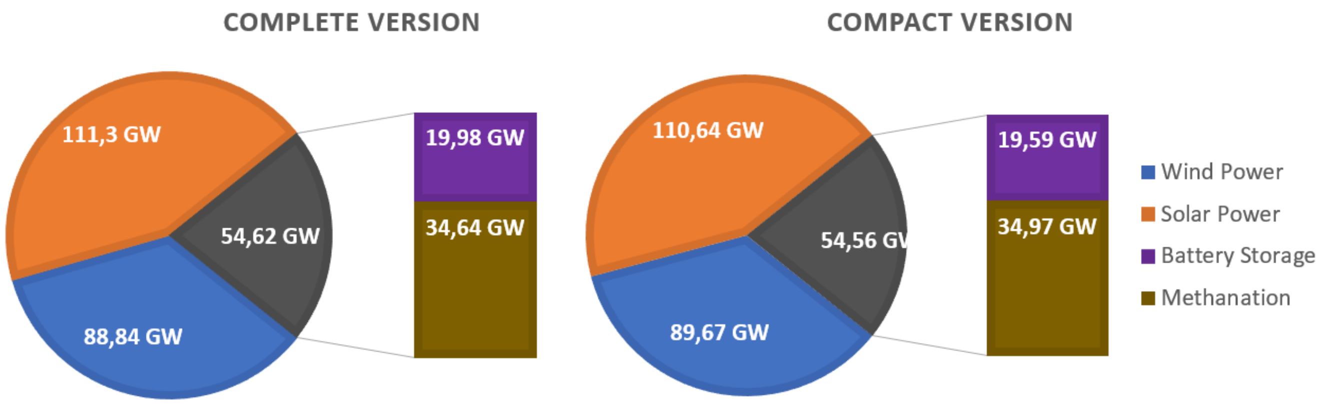

Figure 6.2. Installed capacity of each technology in GW for the complete and compact versions of the EOLES_elecRES model

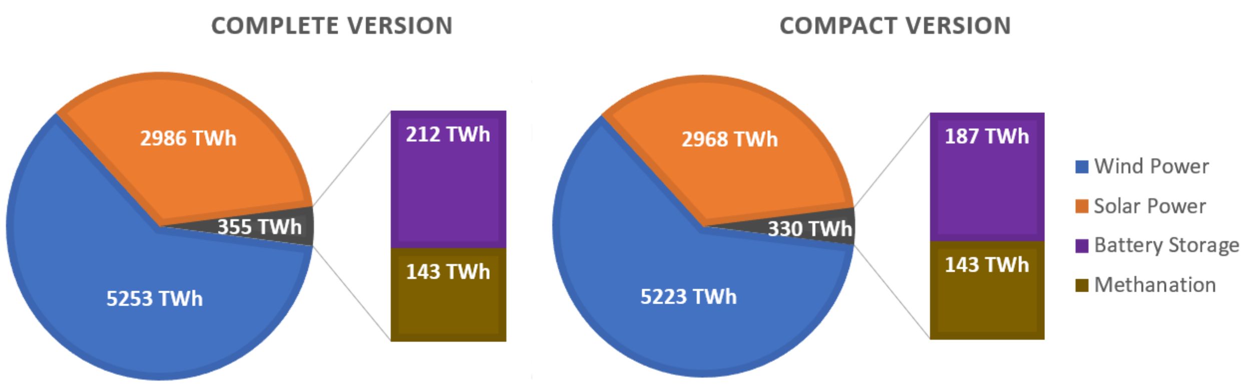

Figure 6.3. Power production for the complete and compact versions of the EOLES_elecRES model

The variable time-step method reduces the number of time-steps from 166,440 to 28,027, i.e. a six-fold decrease in the time-related indices. This six-fold decrease leads to a reduction in calculation time from nearly one week to around one hour for the 19-year optimization. Applying this method to the single-year simulation with 8,760 time-steps, model execution time is reduced from 10 minutes to 10 seconds, i.e. a 60-fold gain in time.

Table 6.2. Annualized cost, average system unit cost, load curtailment and storage related losses for the complete and compact versions of the EOLES_elecRES model

Output	**Complete version**	**Compact version**	**Error**
Annualized cost (b€/year)	20.90	20.77	0.62%
Average system cost (€/MWh)	49.49	49.18	0.62%
Load curtailment %	11.27	11.26	0.09%=0.01 perc. pts
Storage loss %	5.17	5.01	3.09%=0.16 perc. pts

Based on these indicators, one can conclude that the variable time-step method provides a huge gain in optimization time, with very low discrepancies in aggregate variables (cost, load curtailment, storage loss). In the next section I check whether this conclusion stands when the costs of two emerging storage options are varied: batteries and methanation. This sensitivity analysis is applied to the cost of storage, not generation technologies, because the key challenge for the proposed variable times-step method is to correctly reproduce storage technology capacity and operation despite the coarser temporal resolution. I do not change the cost of pumped hydro because its capacity is limited by assumption.

6.4.2. Results for the EOLES_elecRES model, sensitivity analysis

In this subsection, I present the comparison between the complete and compact versions of the EOLES_elecRES model optimized over 19 weather-years for four alternative cost scenarios: battery

25% more expensive, battery 25% cheaper, methanation 25% more expensive and methanation 25% cheaper[1]. The results can be found in Tables A6.1 to A6.4 in Appendix 6.3.

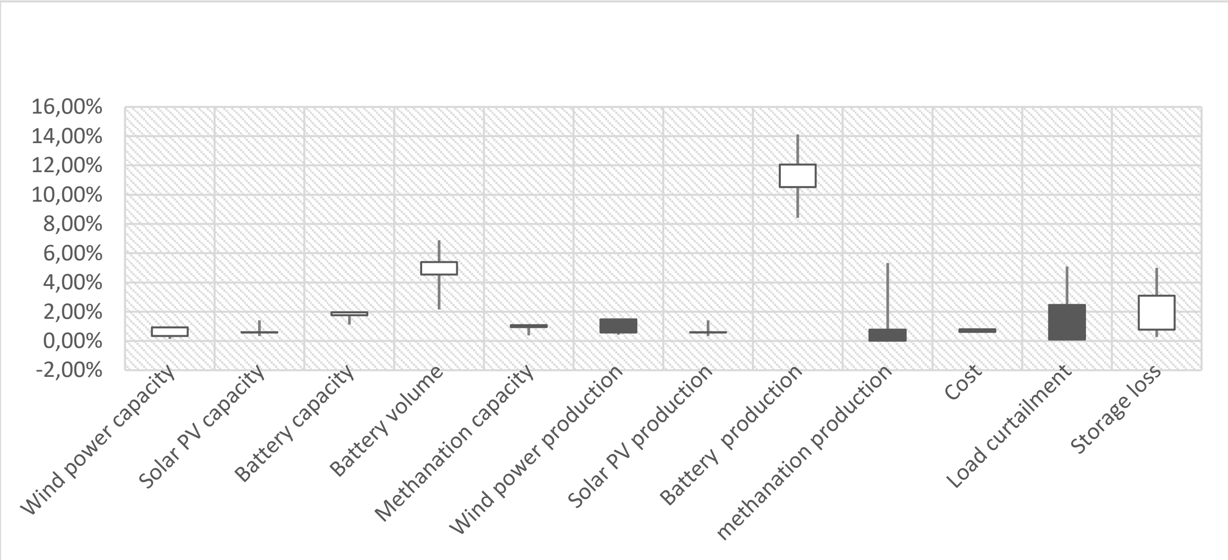

Figure 6.4. Absolute error boxplots for the five cost scenarios

To better understand the absolute error over each important variable, the boxplots of these errors for the five scenarios are presented in Figure 6.4. These boxplots show that the variable time-step method performs very well with respect to installed capacity and power production by technology, as well as to the methanation (long-term) storage option, and the overall system cost. While the installed power capacity of battery storage is estimated with great precision, its volume is underestimated by about 5% and its power generation by around 11%.

Load curtailment and storage loss are generally estimated with an error of less than 2%, but for the case of the cheap power-to-gas scenario the error reaches 5% in both cases. Overall, the main conclusions relating to the reliability of the variable time-step method are robust to uncertainty about storage technology cost.

6.4.3. Results for the DIETER model

As detailed in Subsection 6.3.2 and Appendix 6.2, I ran the DIETER model with renewable technologies alone as generation options and three main storage technologies with no DSM options for the year 2013 for the German power system data (Zerrahn et al, 2015). The complete version of this model has an overall simulation time of 1,310 seconds, of which 202 seconds for the CPLEX solution, while the remainder is for LP generation and data loading. The compact version has an

[1] PEM electrolysers for different dimensions are forecasted to cost between €350/kW and €550/kW in 2050 (ENEA, 2017). The value I chose to represent was 450€/kW, and the boundaries of the projection vary by 22.5%. According to same reference, methanation isothermal reactor is expected to fall from €1000/kW to €700/kW (a 30% cost reduction), and the catalytic methanation process is not a mature process with high uncertainties. Therefore, all together representing methanation, I defined an uncertainty range of ±25%.

Battery storage energy volume capex is estimated at USD150/kWh (€125/kWh at the current market exchange rate) by Cole and Frazier (2019) in 2050, while BNEF (2017) projects a more optimistic cost: €75/kWh (both for 2035 and 2050). The central cost scenario I chose (Schmidt et al, 2019) projects €100/kWh for battery storage in the stationary utility-level use. Therefore, I consider a 25% variation in the cost of batteries as well.

overall simulation time of 25 seconds, with 10 seconds of CPLEX time and 12 seconds of LP generation and data loading. Therefore, this method leads to a 52-fold reduction in the solution time for a one-year simulation, a result close to that obtained with the EOLES_elecRES model.

Figures 6.5 and 6.6 show power production and installed capacity by technology for both the complete and compact versions of DIETER. The installed capacity and power production errors are presented in Appendix 6.4. As for EOLES_elecRES, the errors in the installed generation capacities are below 2%, while they are higher (up to 17%) for storage technologies, especially batteries. The annualized cost for the complete version is €48.05bn/year while the annualized cost for the compact version is €48.66bn/year, an over-estimation of only 1.25%.

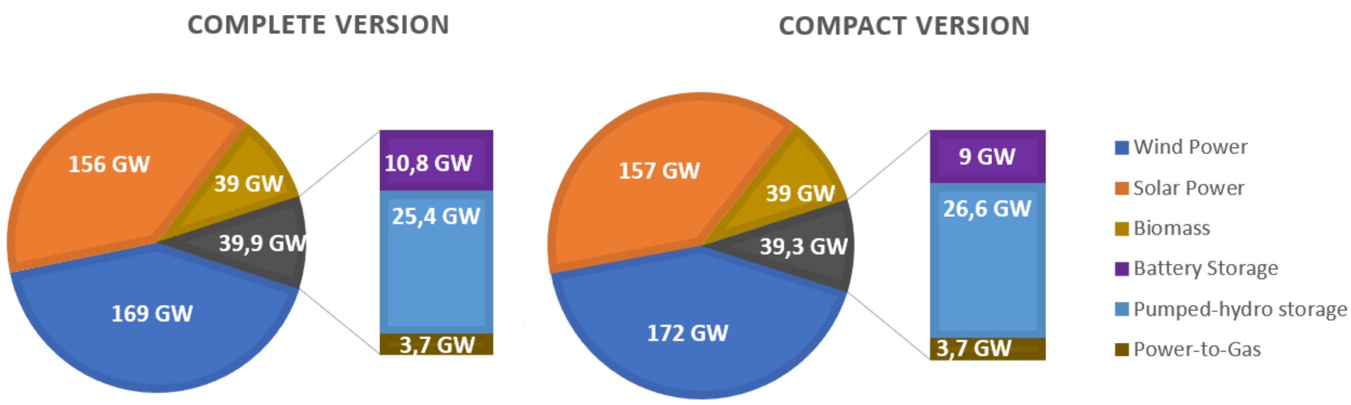

Figure 6.5. Installed capacity of each technology in GW for the complete and compact versions of DIETER

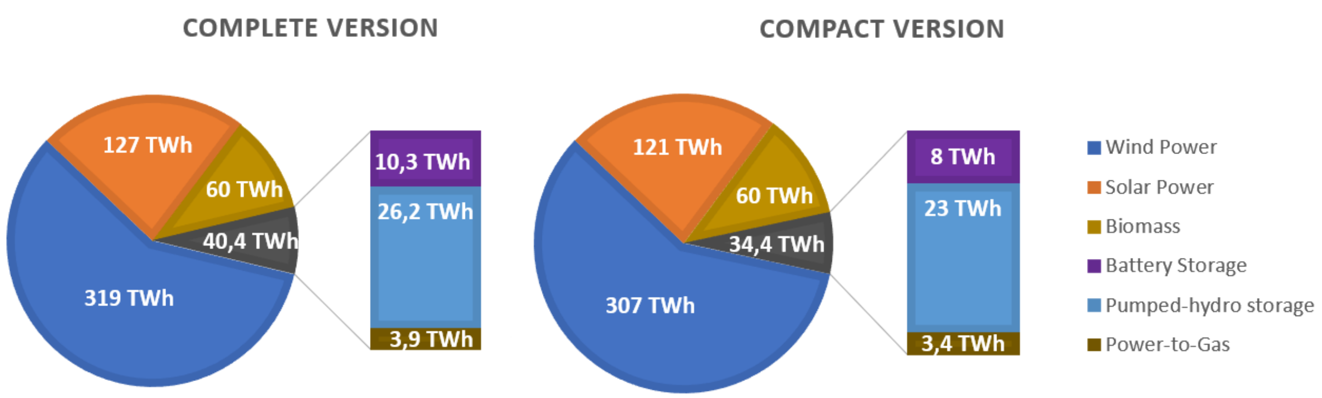

Figure 6.6. Power production for the complete and compact versions of DIETER

These results confirm the initial findings of the variable time-step method as applied to the EOLES_elecRES model, i.e. we observe a huge gain in computation time with very small errors in the most important variables: system cost and power generation mix.

6.5. Discussion and conclusion

In this chapter a new method (the 'variable time-step' method) has been developed to reduce the optimization time of energy system models and I applied it to the dispatch and investment optimization models EOLES_elecRES (Chapter 2) and DIETER (Zerrahn and Schill, 2015). The variable time-step method allows calculation time to be reduced by a factor of 50 to 60.

The price to pay in terms of accuracy is small: for both models and for contrasted cost scenarios, the error in system cost is around 1%. For the generation capacity in wind, solar PV and biomass, the error remains below 2%. For curtailment and storage loss, it remains below half a percentage point. The only sizable error concerns battery volume and generation, but it remains below 20% in the worst case (the DIETER model for battery power capacity). This method underestimates the required electricity generation from, and capacity of, batteries. Battery storage technology can be fully charged and discharged in less than 4 hours (energy volume to power capacity ratio), while in this method, daily sub-sampling leads to time-slices of 5 hours and even more. This may explain the relatively low precision in battery modelling. As a reserve constraint is defined for the hydro-reserve correction, similar correction constraints for battery storage could be defined but to do so, a deeper analysis of the battery charge and discharge dynamics is required. Further work is required to fully understand and correct this discrepancy.

The method proposed in this chapter brings greater accuracy and much faster optimization than if one uses a constant temporal resolution coarser than one hour. For instance, running EOLES_elecRES with time-steps of 6 hours speeds up the calculation by a factor of only 36 (compared with ca. 60 for this method) but underestimates the system cost by 3%, overestimates the solar PV capacity by 17% and underestimates the battery volume by 18%. This method should be useful for any large-scale model featuring long-term storage, including other technologies than those considered here, such as power-to-heat with storage (Bloess et al, 2018). For models applied at a subnational local level, the definition of critical periods would be more difficult because ideally it should be based not only on the residual load, but also on imports and exports of electricity. In any case, I consider that this method might contribute to the improvement in computational tractability that is required to cope with the increasing complexity of energy system models, thus making further research into the method worthwhile.

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Appendices 6

Appendix 6.1. Definition of critical periods and daily sub-sampling for EOLES_elecRES

To set the duration of the critical periods (those which require an hourly resolution) several periods have been chosen to cover various difficult situations that must be overcome by the power system. The hours with the highest residual demand are of great importance since the installed capacity should be sufficient to satisfy peak residual demand. Batteries can be fully discharged in less than four hours; I therefore chose the four-hour period with the highest residual load as a second critical period duration. The longest period should be chosen in such a way that short-term and mid-term storage options (batteries and PHS) are modelled correctly. This is achieved by identifying the periods during which the state of charge of these two storage options declines from the maximum to zero and tracing them using histograms (Figure A6.1).

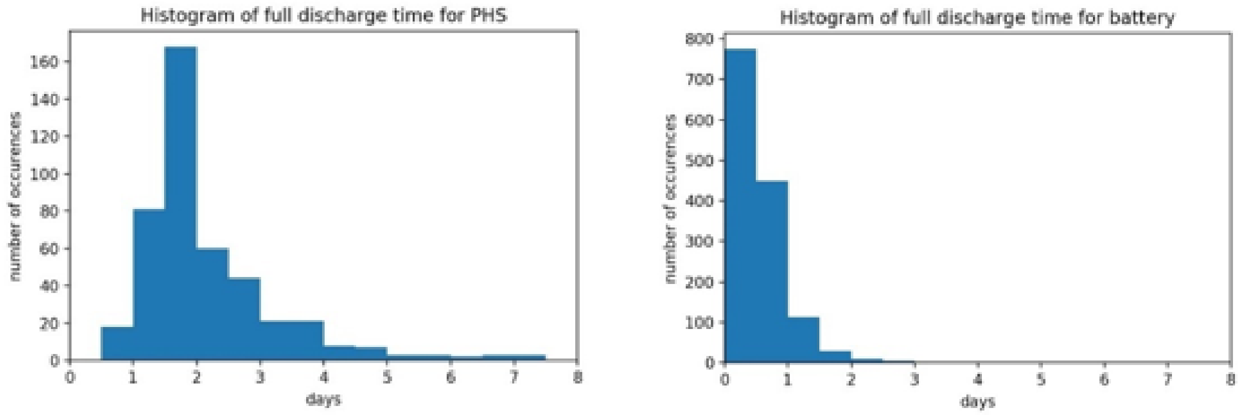

Figure A6.1. Histograms of discharge time for PHS and battery storage

As we can observe, the PHS discharge time rarely exceeds four days, therefore the 96-hour period with the highest residual demand is chosen as the longest critical period, within which every hour is represented as a single time-step. Since adding a limited number of time-steps does not significantly change the solution time, I added six-hour, twelve-hour, one-day and two-day periods in between the previously mentioned critical periods.

The next step is to group the remaining hours in a coherent way. I prepared a daily power production and consumption profile by taking an average over each day of the 18-year period for which I calculated the results in Chapter 2. Figure A.2 shows this typical day including all technologies (left) and including only dispatchable technologies (right).

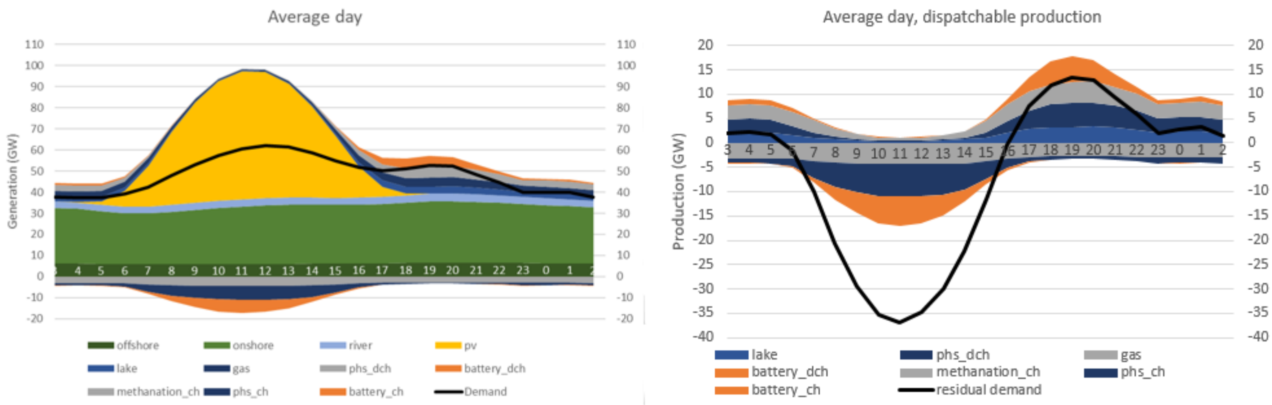

Figure A6.2. Average typical day for the 18-year period simulation, with (left) and without (right) non-dispatchable technologies

Using the power production profiles and focusing on the dispatchable technologies, the typical day can be divided into four time-steps:

1. Morning, from 7 am to 10 am, a transition period during which non-dispatchable generation rises steeply.
2. Noon, 10 am to 3 pm, the period with the maximum excess non-dispatchable generation, which determines required storage volume.
3. Evening, 3 pm to 10 pm, the period with the highest residual demand, resulting in massive use of dispatchable technologies.
4. Night, 10 pm to 7 am, a period during which residual demand is low, resulting in little use being made of dispatchable technologies, but storage technologies can be charged during this period.

Appendix 6.2. Application of 'variable time-step' method to DIETER model

To apply the variable time-step method to DIETER, I first set the installed capacities of all non-renewable generation technologies to zero. Therefore, the only electricity production technologies studied are offshore and onshore wind power, solar power, run-of-river and biomass. Similarly, to keep the same storage technologies as in the EOLES_elecRES model, I fixed the installed power and energy capacities of Na-S, lead acid and redox flow batteries and CAES to zero. Li-ion batteries, pumped-hydro storage and power-to-gas are the only storage technologies considered, as in Zerrahn and Schill's (2015) 'baseline' scenario. Demand-side management options are all set to zero, so that the main flexibility providers are storage options and biomass. To allow curtailment of excess renewable power generation, I modified the supply-demand balance equation (Equation 4 in Zerrahn and Schill, 2015), from equality to inequality, and removed the DSM components, hence this equation becomes:

$$d_h + \sum_{sto} S^{in}_{sto,h} \leq \sum_{con}(G^{l}_{con,h} + \beta_{con,h}) + \sum_{res} G_{res,h} + \sum_{sto} S^{out}_{sto,h} \quad \text{(A6.1)}$$

Where d_h is hourly inelastic demand, $S^{in}_{sto,h}$ is the charging of storage technology sto at hour h, $G^{l}_{con,h}$ is the hourly generation level of conventional technology con, $\beta_{con,h}$ is the reserve provision from the conventional technology con at hour h, $G_{res,h}$ is the hourly generation from renewable technology res and $S^{out}_{sto,h}$ is the discharging of storage technology sto at hour h.

In addition to the above changes, the compact version of the DIETER model includes corrections of time-step length in the equations relating the installed capacity to power production and reserve provisions. Similarly, I added the hydro-reservoir correction (Equation 6.9) to the maximum inflow and outflow equations for pumped-hydro storage technology. The codes and input data for the compact version can be found on GitHub[1].

I apply the variable time-step method as discussed previously. The critical periods are defined as those with the highest residual demands and hourly time-steps are introduced for their whole duration. The average daily power production and storage profile for the year 2013 is presented in Figure A6.3. For non-critical periods, I applied the same daily down-sampling as with EOLES_elecRES. Critical period definition and daily down-sampling resulted in 1,626 time-steps.

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

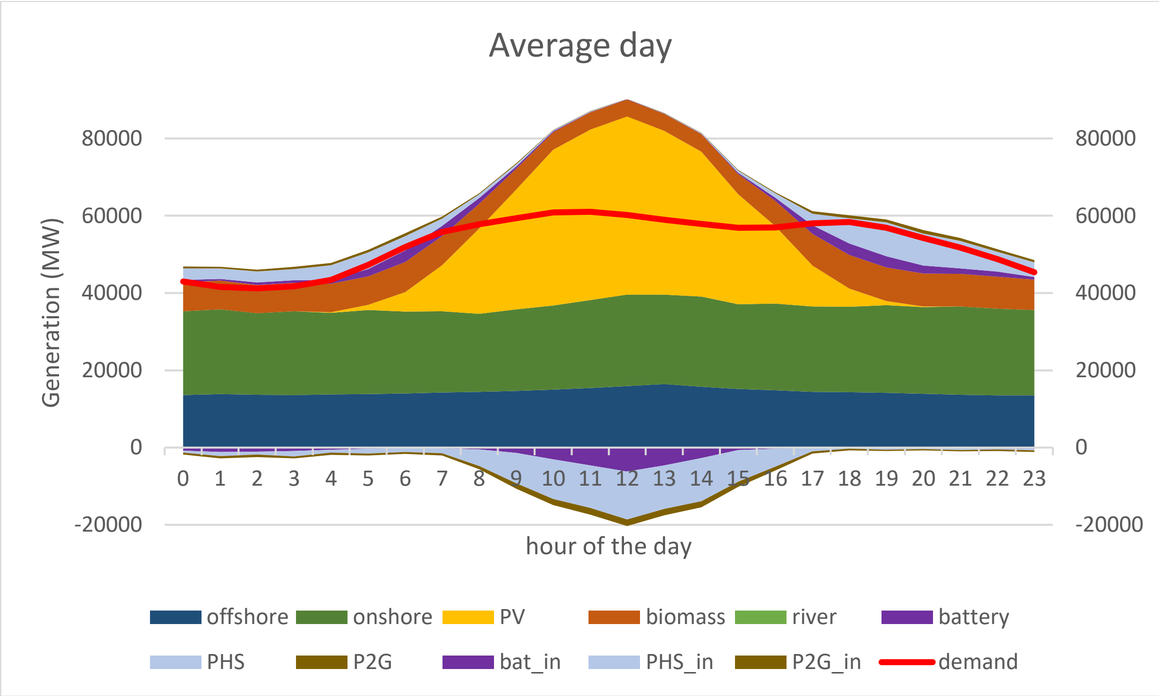

Figure A6.3. Average day for 2013 with the DIETER model for Germany

Appendix 6.3. Sensitivity of the variable time-step method to cost scenarios

Tables A6.1 to A6.4 summarize the results of the sensitivity analysis that is applied to the 19 year-long version of EOLES_elecRES model and the compact version developed using variable time-step method. The varying parameters are battery storage cost (+/-25%) and methanation cost (+/-25%).

Table A6.1. Results for the expensive battery scenario.

Installed capacity (GW)	**Complete version**	**Compact version**	**Error**
Wind power	101.23	100.89	0.34%
Solar PV	104.24	104.83	0.57%
Battery power	17.63	17.32	1.76%
Battery volume (GWh)	48.47	46.27	4.54%
Methanation	35.95	36.34	1.08%
Power generation (TWh)	**Complete version**	**Compact version**	**Error**
Wind power	5547.21	5465.32	1.48%
Solar PV	2796.70	2812.52	0.57%
Battery	153.23	137.09	10.53%
Methanation	144.17	148.64	0.78%
Output	**Complete version**	**Compact version**	**Error**
Annualized cost (b€/year)	21.23	21.06	0.80%
Average system cost (€/MWh)	50.27	49.87	0.80%
Load curtailment %	12.22	11.92	2.45%=0.3 perc. pts

Table A6.2. Results for the cheap battery scenario

Installed capacity (GW)	**Complete version**	**Compact version**	**Error**
Wind power	82.57	82.84	0.33%
Solar PV	123.25	121.51	1.41%
Battery power	23.19	22.82	1.60%
Battery volume (GWh)	133.08	130.20	2.16%
Methanation	32.35	32.65	0.93%
Power generation (TWh)	**Complete version**	**Compact version**	**Error**
Wind power	4856.76	4836.15	0.42%
Solar PV	3306.65	3259.88	1.41%
Battery	355.99	326.04	8.41%
Methanation	134.91	135.61	0.52%
Output	**Complete version**	**Compact version**	**Error**
Annualized cost (b€/year)	20.41	20.27	0.69%
Average system cost (€/MWh)	48.32	48.00	0.66%
Load curtailment %	10.46	10.28	1.72%=0.18 perc. pts

Table A6.3. Results for the cheap power-to-gas scenario

Installed capacity (GW)	Complete version	Compact version	Error
Wind power	90.21	90.53	0.35%
Solar PV	107.88	108.25	0.34%
Battery power	18.80	18.59	1.12%
Battery volume (GWh)	57.65	54.89	4.79%
Methanation	35.65	35.87	0.62%
Power generation (TWh)	**Complete version**	**Compact version**	**Error**
Wind power	5145.71	5109.58	0.70%
Solar PV	2894.28	2904.17	0.34%
Battery	210.08	184.79	12.04%
Methanation	207.64	201.18	3.11%
Output	**Complete version**	**Compact version**	**Error**
Annualized cost (b€/year)	20.37	20.24	0.66%
Average system cost (€/MWh)	48.23	47.91	0.66%
Load curtailment %	7.48	7.86	5.08%=0.38 perc. pts
Storage loss %	7.19	6.83	5.01%=0.36 perc. pts

Table A6.4. Results for the expensive power-to-gas scenario

Installed capacity (GW)	Complete version	Compact version	Error
Wind power	92.43	92.31	0.13%
Solar PV	112.70	111.34	1.21%
Battery power	20.45	20.04	2%
Battery volume (GWh)	74.03	68.94	6.88%
Methanation	33.97	34.10	0.38%
Power generation (TWh)			
Wind power	5436.17	5398.98	0.68%
Solar PV	3023.43	2987.16	1.20%
Battery	188.18	161.60	14.12%
Methanation	88.62	93.34	5.33%
Output			
Annualized cost (b€/year)	21.23	21.08	0.70%
Average system cost (€/MWh)	50.26	49.91	0.70%
Load curtailment %	14.75	14.33	2.85%=0.42 perc. pts
Storage loss %	3.53	3.52	0.28%=0.01 perc. pts

Appendix 6.4. Results for DIETER model

Table A6.5. Results of the complete and compact versions for DIETER model, and the precision of the compact model

	Complete model	**Compact model**	**Ratio (x)**
overall time (s)	1310	25	52.4
load time (s)	1090.14	12	90.845
CPLEX time (s)	202	10.22	19.7651663
	Complete model	**Compact model**	**Error (%)**
cost (b€/an)	48.05	48.66	1.25%
battery_power (GW)	10.89	9.02	17.17%
battery_volume (GWh)	34.66	35.98	3.67%
PHS_power (GW)	25.43	26.61	4.43%
PHS_volume (GWh)	300	300	0.00%
P2G_power (GW)	3.65	3.72	1.88%
P2G_volume (GWh)	154.06	140.37	8.89%
Offshore_power (GW)	32	32	0.00%
Offshore_energy (TWh/an)	126.254	125.26	0.79%
Onshore_power (GW)	137.05	139.75	1.93%
onshore_energy (TWh/an)	192.914	181.37	5.98%
Wind_power_aggregated	169.05	171.75	1.57%
Wind_energy_aggregated	319.168	306.63	3.93%
PV_power (GW)	155.93	157.33	0.89%
PV_energy (TWh/an)	126.706	120.5	4.90%
Biomass_power (GW)	38.65	39.36	1.80%
Biomass_energy (TWh/an)	60	60	0.00%

Chapter 7

Time series aggregation in multi-sector energy systems modelling

7.1. Introduction

As highlighted in Chapter 5, a rigorous energy policy must be based on an energy system modelling including most of the main energy sectors and allowing optimal allocation of different energy sources and carriers to meet the end-use demands of each main sector. The high coverage of different energy sectors can avoid overestimation in energy storage need (Blanco and Faai, 2018). Moreover, the real optimal policy is the policy resulting from sector-coupling (Lund et al, 2017): endogenous modelling of several energy sources, carriers, energy conversion and storage options to enable them to meet the end-use demand in each sector optimally.

A highly integrated dispatch and investment model that meets all the highlighted conditions for an efficient energy policy decision is developed and presented in Chapter 5: a multi-sectorial optimization that considers the key energy supply, carrier, conversion and storage options in an endogenous way, with high temporal resolution where the positive and negative emissions are both internalized. Although this model performs well and shows the gains of sector-coupling in a systematic approach, the optimization is computationally demanding. Not only the needed active memory is very high, but also the calculation time is very long (The optimization for a single scenario needs more than 60 hours).

The literature highlights the importance of high temporal precision (hourly) to account for a correct dimensioning of short-term storage options over a long period of time in power systems modelling (Brown et al, 2018, Pfenninger, 2017 and Chapter 6). Therefore, neither resolution variation, nor representative period selection can result in correct dimensioning of storage options in electricity systems. However, sector-coupling can lead to lower storage needs thanks to flexibility gains from other-than-electricity energy sectors (Victoria et al, 2019). Moreover, the findings of Chapter 5 show that the required short-term storage for a multi-energy system with sector-coupling is much less than the required storage capacity when the power system is modelled in isolation. Therefore, the required precision in temporal resolution may be less than in the case with only the power sector.

Hoffmann et al. (2020) classify the time-series aggregation methods into two main categories: (1) resolution variation and (2) definition of representative periods. Each of these two categories perform better in taking into account a particular type of variability of intermittent energy sources and energy demand; representative period selection methods capture the inter-hourly variability, however the long-term variability (especially the required long-term storage options) are not represented correctly. Contrarily, resolution variation methods which vary the temporal resolution of used time-series are normally defined over continuous periods, therefore, they take into account the inter-seasonal and long-term variability of intermittent energy production and energy demand. However, considering coarser-than-hourly time-slices in resolution variation methods leads to a smoother representation of short-term variability of energy production and demand, leading to underestimation of required short-term storage options and peak power plants. Therefore, each of these categories of time-series aggregation methods have their own strength and weaknesses and both should be evaluated.

Although fewer studies in multi-energy system modelling apply resolution variation methods, the representative period selection is very popular among the energy system modelling community. For instance, all the TIMES models are based on representative days and weeks (Doudard, 2018, Postic et al, 2016, Kang et al, 2017 etc.). The selection of representative periods keeping high temporal resolution, but over discrete short periods would account for short-term variability in the energy demand and intermittent energy supply technologies (such as variable renewables), however, the inter-seasonal weather and demand variability might be underestimated.

This chapter aims to study the importance of the temporal resolution in a multi-sectorial coupled energy system: EOLES_mv. To this end, I develop different versions of the EOLES_mv model in terms of temporal precision (2-hour, 4-hour, 6-hour and 8-hour long time-steps) in a continuous period and discrete representative weeks (over one month, two months and three months) for a full year. Using the findings of these different versions of EOLES_mv model, I study first the trade-off between the calculation time and the precision of each time-series aggregation method, and second the relative performance of these two main time-series aggregation methods: resolution variation and representative period selection.

The remainder of this chapter is organized as follows. Section 7.2 presents the methods: different versions of the EOLES_mv model and the input data, Section 7.3 presents the results and Section 7.4 presents the discussion and concludes this chapter.

7.2. Methods

7.2.1. The model

In this chapter I use the EOLES_mv model that is presented in complete detail previously in Chapter 5. As a reminder, EOLES_mv is an integrated dispatch and investment model allowing for sector-coupling covering all the major energy sectors, internalizing social cost of carbon and keeping an hourly temporal resolution for a full year. I study both types of time-series aggregation: a) resolution variation and b) representative periods. All the variant versions of EOLES_mv model and their input data are available on GitHub[1].

7.2.2. Resolution variation

To account for the importance of temporal resolution, I developed several versions of the model regarding their temporal resolutions: 2-hour, 4-hour and 8-hour resolutions. Therefore, each of these variant versions reduce number of time-steps from 8760 to 4380, 2190, 1460 and 1095 time-

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

steps respectively. To adapt the EOLES_mv model to each of these time-steps, Equations (A5.1), (A5.12), (A5.16), (A5.19), (A5.20), (A5.21), (A5.25), (A5.27), (A5.29), (A5.32) and (A5.34) in Chapter 5 have been modified respectively (Equations 7.1 to 7.11).

$$COST = \left(\sum_{tec}[(Q_{tec} - q_{tec}^{ex}) \times annuity_{tec}] + \sum_{str}(VOLUME_{str} \times annuity_{str}^{en}) + \sum_{tec}(Q_{tec} \times fO\&M_{tec}) + \sum_{tec}\sum_{ts}(G_{tec,ts} \times l_{res}^{ts} \times (vO\&M_{tec} + e_{tec}SCC_{CO_2}))\right)/1000 \quad (7.1)$$

$$lake_m \geq \sum_{ts\in m} G_{lake,ts} \times l_{res}^{ts} \quad (7.2)$$

$$\sum_{ts\in w} CHARGE_{transport,ts} \times l_{res}^{ts} \leq RESERVOIR_{transport} \quad (7.3)$$

$$\sum_{ts} G_{ocgt,ts} \times l_{res}^{ts} \leq Q_{ocgt} \times cf_{ocgt} \times 8760 \quad (7.4)$$

$$\sum_{ts} G_{ccgt,ts} \times l_{res}^{ts} \leq Q_{ccgt} \times cf_{ccgt} \times 8760 \quad (7.5)$$

$$\sum_{ts} G_{ccgt-ccs,ts} \times l_{res}^{ts} \leq Q_{ccgt-ccs} \times cf_{ccgt-ccs} \times 8760 \quad (7.6)$$

$$G_{nuc,ts+1} + RSV_{nuc,ts+1} \leq G_{nuc,ts} + r_{nuc}^{up} \times Q_{nuc} \times l_{res}^{ts} \quad (7.7)$$

$$\sum_{ts} G_{nuc,ts} \times l_{res}^{ts} \leq Q_{nuc} \times cf_{nuc} \times 8760 \quad (7.8)$$

$$SOC_{str,ts} \times l_{res}^{ts} \leq VOLUME_{str} \quad (7.9)$$

$$\varphi_{CO_2}^{max} \geq \sum_{h} G_{ccgt-ccs,h} \times \tau_{ccgt-ccs} \times e_{ccgt} \times l_{res}^{ts} \quad (7.10)$$

$$\sum_{ts} G_{biogas,ts} \times l_{res}^{ts} \leq g_{biogas}^{max} \quad (7.11)$$

Where l_{res}^{ts} is the length of the time-slice for each resolution (2,4,6 and 8) and ts is the number (order) of the time-slice that replaces h. All the other symbols are the same as in Chapter 5. Equation (A5.26) is an operational constraint that limits the downward ramping of nuclear power. Since the smallest time-slice length (least coarse resolution) is two hours, and the ramping rate of nuclear power is 50%, this constraint does not limit any operation since in two hours nuclear power can be fully shut-down. Therefore, I deleted this constraint equation.

7.2.2.1. Input data

All the input data used are the same as in Chapter 5. For the variant versions of EOLES_mv, the input profiles are prepared by taking an average over the hourly data that are in the considered time-step. Therefore, for a time-step of 4-hour length from 5 to 8, an average of hourly values from 5 to 8 are taken to prepare the value of the profiles on the considered time-step.

7.2.3. Representative periods

Representative periods can take several forms to account for different variations. Doudard (2018) considers 576 time-slices per year, by considering one weekday and one weekend day for each month. Samsatli et al. (2016) use one weekday and one weekend day for each season, resulting in

192 time-slices for each year. Although weekday and weekend classification can account for the difference between a working day and weekend, it doesn't represent the differences between the weekdays or two days of the weekend. To overcome this issue, Perrier (2018) chose a representative week over 2 months. In this section, I follow the same method, by choosing a representative week for a month, for two months and for three months. Thus, each day of the week is repeated identically each time it appears in the month. Considering one representative week per month, one representative week per two months and one representative week per three months reduces the number of time-slices from 8760 to 2016, 1008 and 672 respectively. To adapt the EOLES_mv model to these new more compact versions, I defined two different storage types: short and mid-term storage options which can be fully charged and discharge in one week, and long-term storage options which can be fully charged and discharged in one month, two months or three months. In a continuous period, the storage options operate endogenously depending on their economic characteristics: a storage option with high energy capacity cost and low power capacity cost will operate as short-term storage option (such as batteries), while a technology with low energy capacity cost and high power capacity cost will operate as a long-term storage option (such as methanation storage). However, in a model with non-continuous periods the charging and discharging cycles must be defined exogenously because from a modelling perspective one must know if the operation of a storage technology will be repeated during each week of the chosen period to be represented or if it will be added up during the whole chosen period to be represented. For instance, the state of charge of a short-term storage option at the end of one representative week is equal to the state of charge of that storage options in the beginning of the next representative week, but the state of charge of a long-term storage option at the beginning of a representative week is its state of charge at the end of the previous representative week multiplied by the number of weeks in the considered period to be represented by a week. To apply this condition, Equation (A5.8) in Chapter 5 is modified and divided into three equations:

$$SOC_{str\_short,h+1} = SOC_{str\_short,h} + (STORAGE_{str\_short,h} \times \eta_{str\_short}^{in}) - (\frac{G_{str\_short,h}}{\eta_{str\_short}^{out}}) \tag{7.12}$$

$$\forall \begin{cases} h \in w \\ h+1 \in w \end{cases};$$

$$SOC_{str\_long,h+1} = SOC_{str\_long,h} + (STORAGE_{str\_long,h} \times \eta_{str\_long}^{in}) - (\frac{G_{str\_long,h}}{\eta_{str\_long}^{out}}) \tag{7.13}$$

$$\forall \begin{cases} h \in w \\ h+1 \notin w \end{cases};$$

$$SOC_{str\_long,h+1} = SOC_{str\_long,h} \times l_w^p + (STORAGE_{str\_long,h} \times \eta_{str\_long}^{in}) - (\frac{G_{str\_long,h}}{\eta_{str\_long}^{out}}) \tag{7.14}$$

Where $SOC_{str,h}$ is the state of charge of the storage option str at hour h, $STORAGE_{str,h}$ is the hourly energy entering to the storage option str at hour h, $G_{str\_long,h}$ is the energy generation (discharging) of the storage option str at hour h, while $\eta_{str}^{in} \in [0,1]$ and $\eta_{str}^{out} \in [0,1]$ are the charging and discharging efficiencies. str_short represents the short-term storage technologies (Li-Ion batteries, PHS and individual thermal energy storage), str_long represents long-term energy storage options (gas storage and central thermal energy storage). w represents the week and l_w^p is the relative length of the chosen period to the representing week, which is equal to number of the hours in the chosen period divided by number of the hours in a week (168).

Equations (A5.1), (A5.12), (A5.19), (A5.20), (A5.21), (A5.27), (A5.29), (A5.32) and (A5.34) in Chapter 5 have been modified respectively as in the previous subsection;

$$COST = \left(\sum_{tec}[(Q_{tec} - q_{tec}^{ex}) \times annuity_{tec}] + \sum_{str}(VOLUME_{str} \times annuity_{str}^{en}) + \sum_{tec}(Q_{tec} \times fO\&M_{tec}) + \sum_{tec}\sum_{h}(G_{tec,h} \times l_{ratio}^{p} \times (vO\&M_{tec} + e_{tec}SCC_{CO_2}))\right)/1000 \tag{7.15}$$

$$lake_m \geq \sum_{h\in m} G_{lake,h} \times l_w^p \tag{7.16}$$

$$\sum_w \sum_{h\in w} G_{ocgt,h} \times l_w^p \leq Q_{ocgt} \times cf_{ocgt} \times 8760 \tag{7.17}$$

$$\sum_w \sum_{h\in w} G_{ccgt,h} \times l_w^p \leq Q_{ccgt} \times cf_{ccgt} \times 8760 \tag{7.18}$$

$$\sum_w \sum_{h\in w} G_{ccgt-ccs,h} \times l_w^p \leq Q_{ccgt-ccs} \times cf_{ccgt-ccs} \times 8760 \tag{7.19}$$

$$\forall \begin{cases} h \in w \\ h+1 \in w \end{cases}; \ G_{nuc,h+1} + RSV_{nuc,h+1} \leq G_{nuc,h} + r_{nuc}^{up} \times Q_{nuc} \tag{7.20}$$

$$\forall \begin{cases} h \in w \\ h+1 \in w \end{cases}; \ G_{nuc,h+1} \geq G_{nuc,h}(1 - r_{nuc}^{down}) \tag{7.21}$$

$$\sum_w \sum_{h\in w} G_{nuc,h} \times l_w^p \leq Q_{nuc} \times cf_{nuc} \times 8760 \tag{7.22}$$

$$\varphi_{CO_2}^{max} \geq \sum_w \sum_{h\in w} G_{ccgt-ccs,h} \times \tau_{ccgt-ccs} \times e_{ccgt} \times l_w^p \tag{7.23}$$

$$\sum_w \sum_{h\in w} G_{biogas,h} \times l_w^p \leq g_{biogas}^{max} \tag{7.24}$$

Where l_{ratio}^{p} is the ratio of the real length of a whole year to the represented fraction of the year which is equal to 8760/2016 for a week over one month, 8760/1008 for a week over two months and 8760/672 for one representative week over three months.

7.2.3.1. Input data

All the input data are the same as in Chapter 5. To prepare the input data, first each day of each week has been categorized as day 1 to 7, later, hourly profiles of each input data series have been considered by taking an average over the days of the same category in a month. Therefore, the hourly profiles of each typical day for the representative week for a considered period are the average of all the days with the same category in that period (one month, two months or three months).

7.3. Results

In Chapter 5, we saw that an integrated energy system with full sector coupling can reach carbon-neutrality for an SCC of €200/tCO_2. Therefore, all the results presented are for this SCC value.

7.3.1. Primary energy production

In this section, the primary energy production resulting from the optimization with the basic EOLES_mv model with hourly resolution and the different versions of this model with different temporal resolutions and representative periods are presented. As explained previously in chapter 5, The primary energy is considered to be the main form of the initial energy produced: offshore and onshore wind, solar PV, run-of-river, dams & reservoirs and nuclear energy[1] are the primary electricity generation technologies and natural (fossil) gas, methanization and pyro-gasification of biomass (and energy wood) are the primary gas supply technologies. These primary energy vectors then can be either used directly to satisfy the final energy demand, or converted to other energy forms (heat, gas, electricity and hydrogen) to form the secondary energy vectors. For both primary and secondary energy vectors, storage possibilities can also allow the energy to be stored for later use.

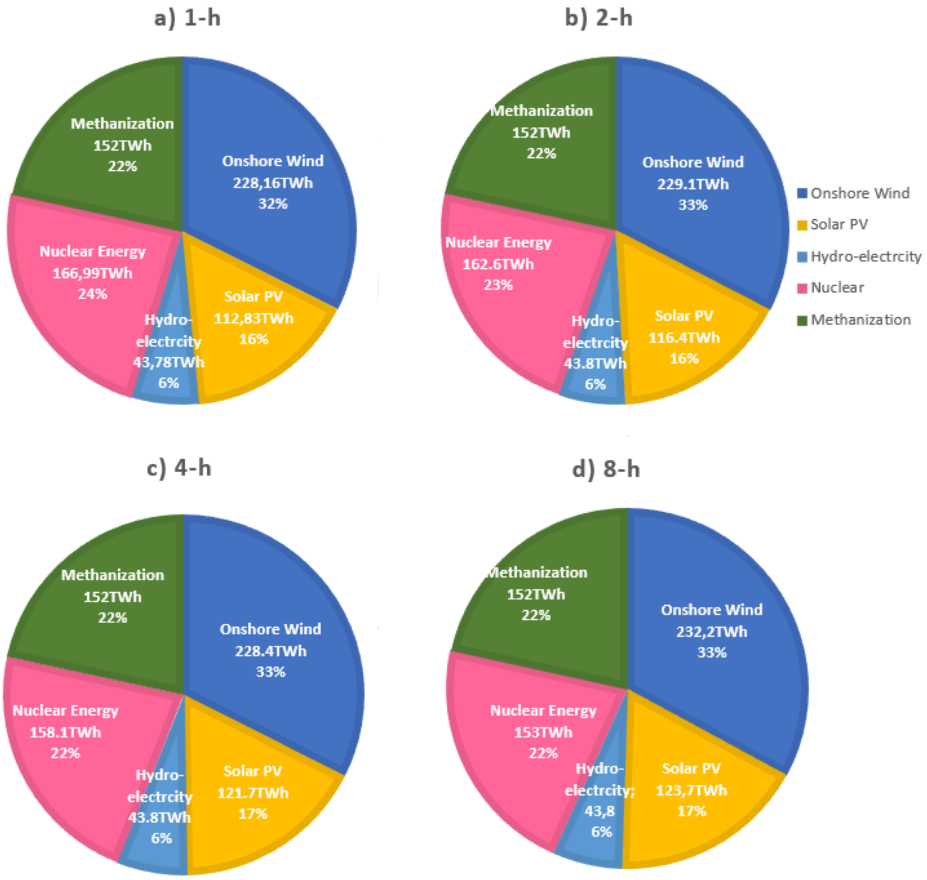

Figure 7.1. Annual energy supply from each primary supply technology for different temporal resolutions

Figures 7.1 and 7.2 show the primary energy mix for used times series aggregation methods: resolution variation (hourly, two-hourly, four-hourly and eight-hourly temporal resolutions) and representative periods (hourly continuous case and the compact versions with representative weeks over one month, two months and three months).

[1] Nuclear plants convert thermal energy of its combustible (mainly isotopes of Uranium) to electricity, with an efficiency of ~35%. Here we consider the produced electricity as the primary energy.

A very big proportion of the primary energy is in the form of electricity (78% for all temporal resolutions) and this electricity is mainly from renewable sources (54% to 56% of the primary energy supply). The only primary energy supply technology providing energy in gas vector is methanization (anaerobic digestion of organic waste). However, for representative periods, from the first representative period choice of one week over one month, a very big deviation from the base case with continuous representation of a year can be observed in the primary energy mix.

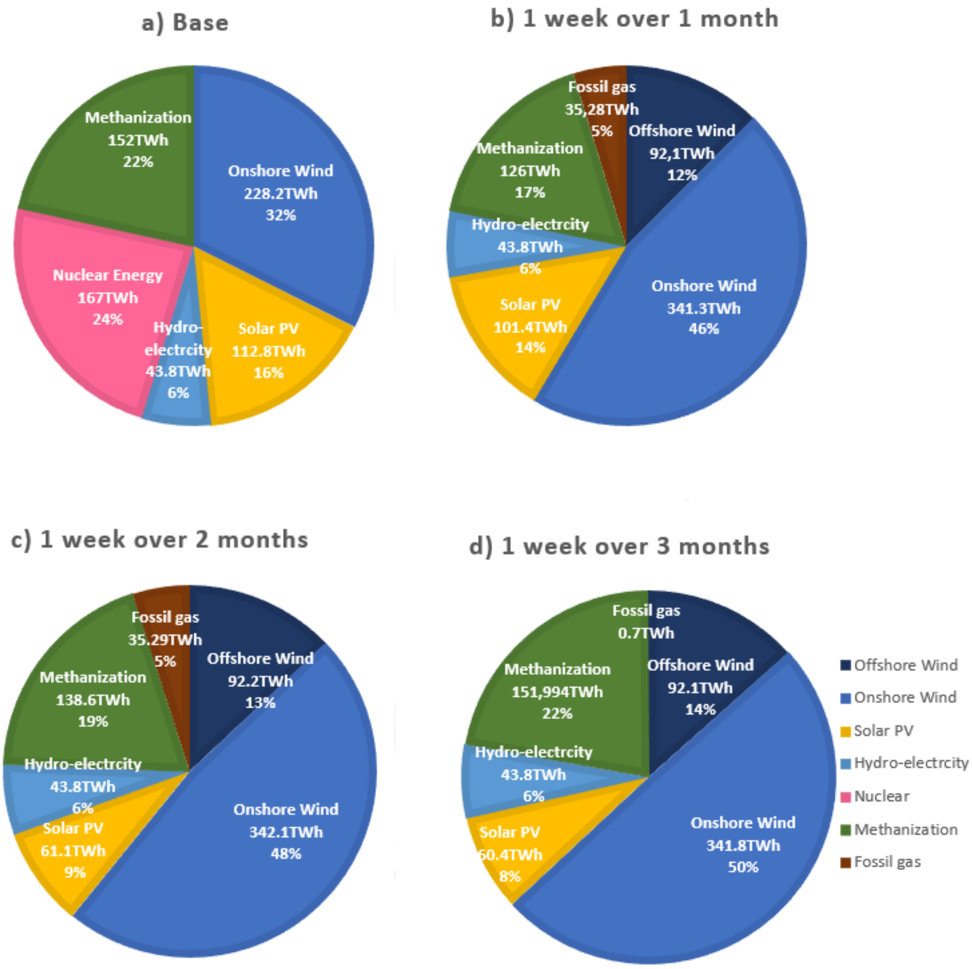

Figure 7.2. Annual energy supply from each primary supply technology for different representative period selections

By decreasing the temporal resolution from hourly to eight-hourly precision, the energy mix remains nearly identical to the optimization with hourly temporal resolution. The share of renewables increases slightly, replacing 14TWh$_e$/year of the nuclear energy supply. This increase is mainly led by Solar PV since its variability decreases by decreasing the temporal resolution of the model. However, the energy mix for eight-hourly temporal resolution remains very similar to the energy mix with one-hourly temporal resolution. The energy production from methanization is the same for all the temporal resolutions, and it is the upper bound of energy that can be produced from this technology (152TWh$_{th}$/year). But representative weeks are associated with much higher differences in energy mix: nuclear power disappears completely from the energy supply side (initially 24% of primary energy supply), and initially non-existing offshore wind power and fossil gas result from optimization (12% to 13% and up to 5% of primary energy supply respectively). Onshore wind energy's share in primary energy supply increases from 32% in the base case to up to 49% for the case with one representative week over three months. Representative week selection decreases long-term variability of energy system, which therefore increases the share of offshore and onshore wind power technologies. Nuclear power as a technology that can produce energy stably non-regarding the season is replaced by these wind energy technologies.

To compare the error caused by each time series aggregation method, I calculated the mean absolute percentage error (MAPE) which represents the overall errors when several variables are considered together (Figure 7.3). Here the mean absolute percentage error of annual primary energy production from offshore and onshore wind, solar PV, nuclear power, methanization, hydroelectricity, pyro-gasification of biomass and fossil gas is considered, and it is calculated by summing the normalized absolute differences[1] and dividing it by number of the technologies considered:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_i - x^*{}_i}{x^*{}_i}\right| \tag{7.25}$$

Where x_i is the annual energy production of each technology i for each temporal resolution and $x^*{}_i$ is the annual energy production of that technology for the case with hourly temporal resolution and n is the number of technologies considered.

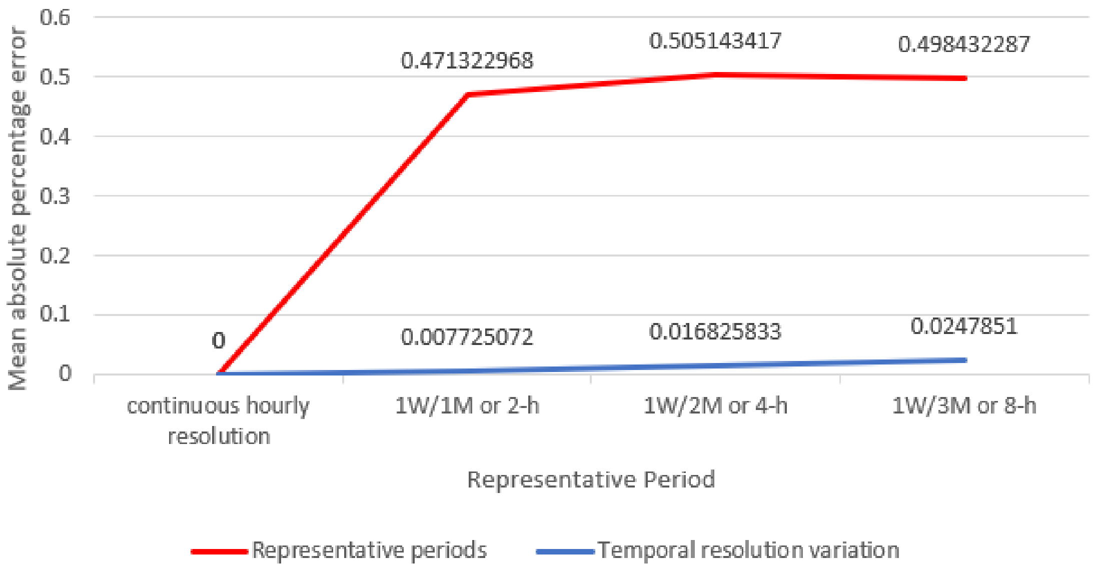

Figure 7.3. Mean absolute percentage errors of the installed capacity for each time series aggregation method with respect to the base case with continuous hourly temporal resolution over a full year

The MAPE for any of the studied coarser-than-hourly temporal resolutions is negligible compared to that of the representative weeks. This value increasing from 0.0077 for the two-hourly resolution to 0.0248 for the eight-hourly resolution, has an order of magnitude difference with the representative periods' MAPE which is around 0.5 for all three representative week selection periods.

[1] The installed capacity of hydroelectricity is fixed and pyro-gasification of biomass never in the optimal mix in the considered social cost of carbon.

7.3.2. Electricity mix

Since the literature highlights mainly the importance of temporal resolution in power system modelling, it is worth studying the electricity mix besides the whole energy system. Figures 7.4 and 7.5 show the electricity mix and its role in satisfying final energy demand for different sectors, for each of the studied time series aggregation methods.

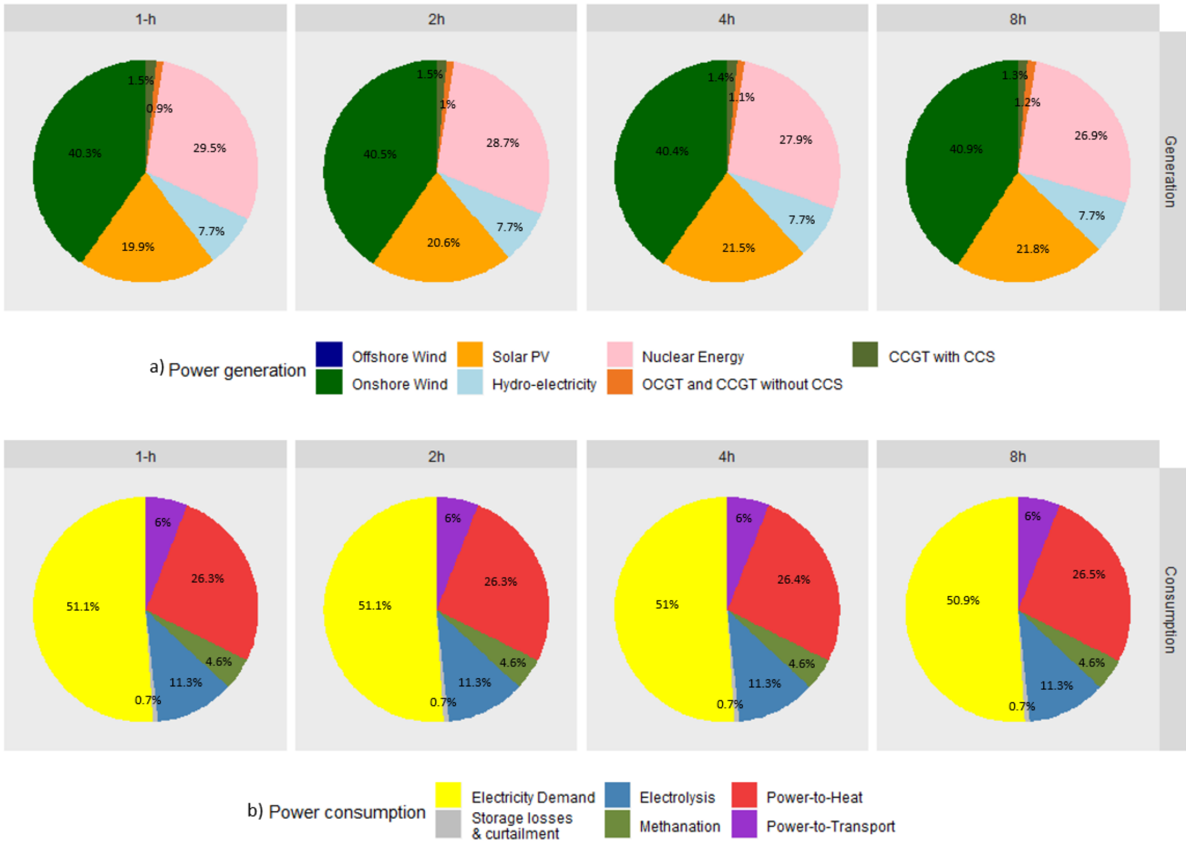

Figure 7.4. Annual electricity supply and consumption mix for different temporal resolutions

Considering the base case with hourly temporal resolution over the continuous period of a full year, nearly 80% of the primary energy supply is from electricity generating technologies. The electricity supply is mainly from renewable sources with 67.9% of electricity production from renewables electricity sources and 2.4% from renewable gas sent to open and combined cycled gas turbines with and without carbon capture and storage.

The electricity supply and consumption mix remain nearly stable across modelling with different temporal resolutions. As this temporal resolution decreases, nuclear power's share in electricity supply decreases from 29.5% to 26.9%, and it is partially replaced by solar PV and onshore wind power (19.9% to 21.8% and 40.3% to 40.9% respectively). Although the electricity consumption for different temporal resolutions in resolution variation methods remains very similar to the base case with hourly temporal resolution, the electricity supply and demand for different representative weeks is very different than continuous base case. For representative week modelling, nuclear power is eliminated and both onshore and offshore wind power technologies reach their maximal installation limits (120GW and 20GW) and they provide a very big majority of electricity supply (from

73.6% to 80.7%). Increasing the length of the represented period reduces the share of solar power in the electricity supply from 19.9% in the base case to 10.7% in the case with one representative week over three months. Therefore, nuclear energy and solar PV are replaced by offshore and onshore wind power technologies. On the other hand, as the share of solar power becomes less in the electricity supply, the need for dispatchable OCGT and CCGT (with and without CCS) becomes less. From the base case with continuous time series to the case with one representative week over three months, the share of these gas turbines decreases from 2.5% to 0.4% in the electricity supply side.

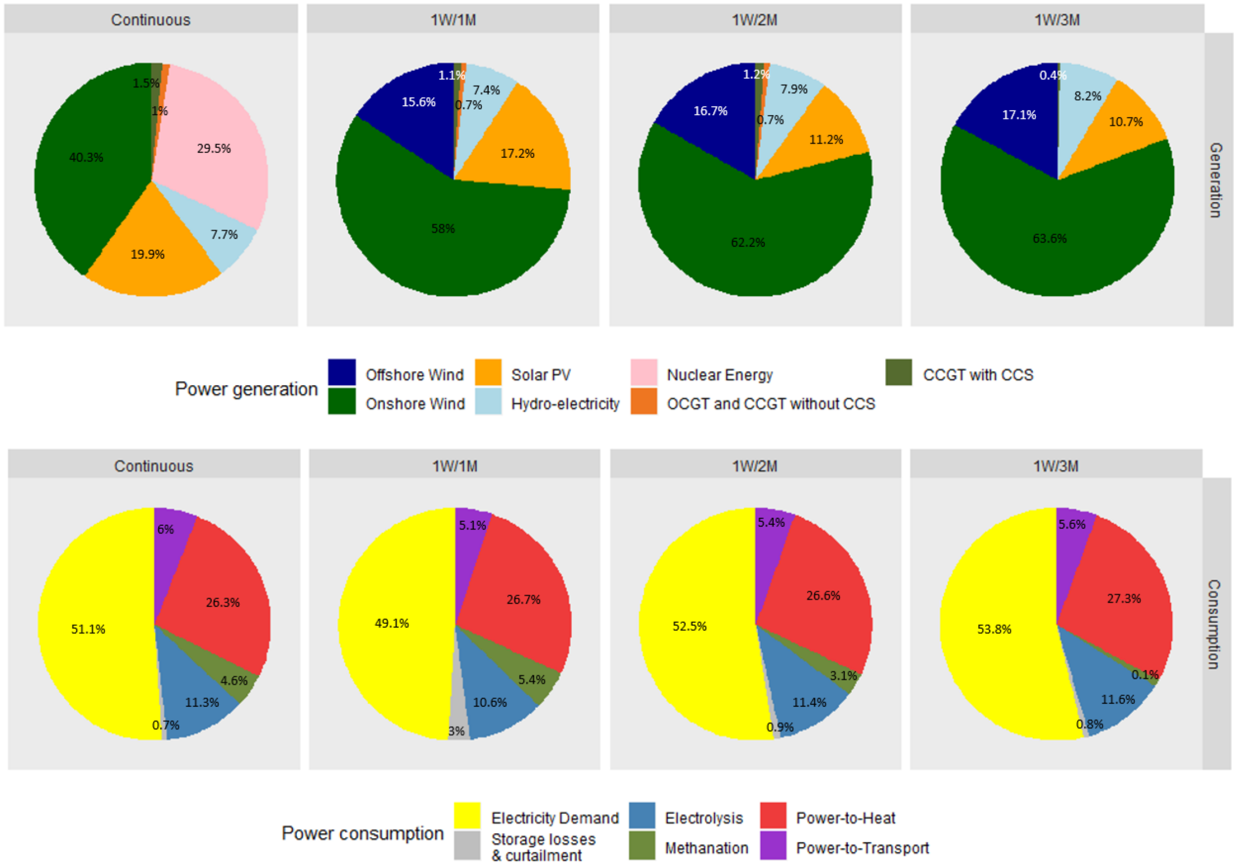

Figure 7.5. Annual electricity supply and consumption for different representative periods

The electricity consumption side remains nearly the same as the case with hourly resolution for different temporal resolutions, even for a case with very low temporal precision such as eight-hourly resolution. For representative periods, the difference is bolder: the very small share of electric vehicles in the light transport demand disappears as the represented period grows and the only usage of electricity in transport sector is for the rail transport (30TWh$_e$/an). The overall electricity production decreases from the base case (551.78TWh$_e$/year) to the case with one representative week over three months (535.34TWh$_e$/year), except for the case of one representative week over one month (578.32TWh$_e$/year). This excessive power stems from higher share of solar power in the electricity mix, which is also the reason why load curtailment is higher for this case compared to other cases (3% vs. ~0.8%). To sum up, the choice of representative periods not only changes the whole energy mix, but also the electricity mix both in supply and consumption sides.

7.3.3. Cost and emission

Table 7.1 shows the cost of the energy system, CO_2 emissions from the energy system and the computation time of the EOLES_mv model for different temporal resolutions, and their differences from the case with hourly temporal resolution.

Table 7.1. Simulation time, cost and the CO_2 emissions for different temporal resolutions and their error (difference) from (with) the base case of hourly resolution

	Temporal Resolution						
Main characteristics	**1-h**	**2-h**	**Error***	**4-h**	**Error***	**8-h**	**Error***
Total simulation time (s)	216254	19974	90.8%	3180	98.5%	339	99.8%
LP generation time (s)	210	84	60%	8	96.2%	2	99.1%
CPLEX solution time (s)	216044	19890	90.8%	3172	98.5%	337	99.8%
Annual cost (b€/year)	59.55	59.51	0.07%	59.43	0.20%	59.39	0.27%
Annual CO_2 emissions ($MtCO_2$/year)	-2.51	-2.43	3.19%	-2.37	5.58%	-2.19	12.75%

*For the time related data, it is the difference in calculation time.

Changing the temporal resolution from one hour to two hours leads to a nearly 11-fold decrease in calculation time, with less than 0.1% of error in system cost. As this temporal resolution becomes coarser, the computation times becomes even smaller (640-fold reduction in calculation time for the case with eight-hour temporal resolution), and the cost related error increases to up to 0.27%, which is a very slight error taking into account the gain in the computational tractability. On the other hand, decreasing the precision of temporal resolution leads to a slight underestimation of negative CO_2 emissions (up to 12.75%). The increase of the error in system cost and emissions by decreasing the temporal resolution is presented in Figure 7.6.

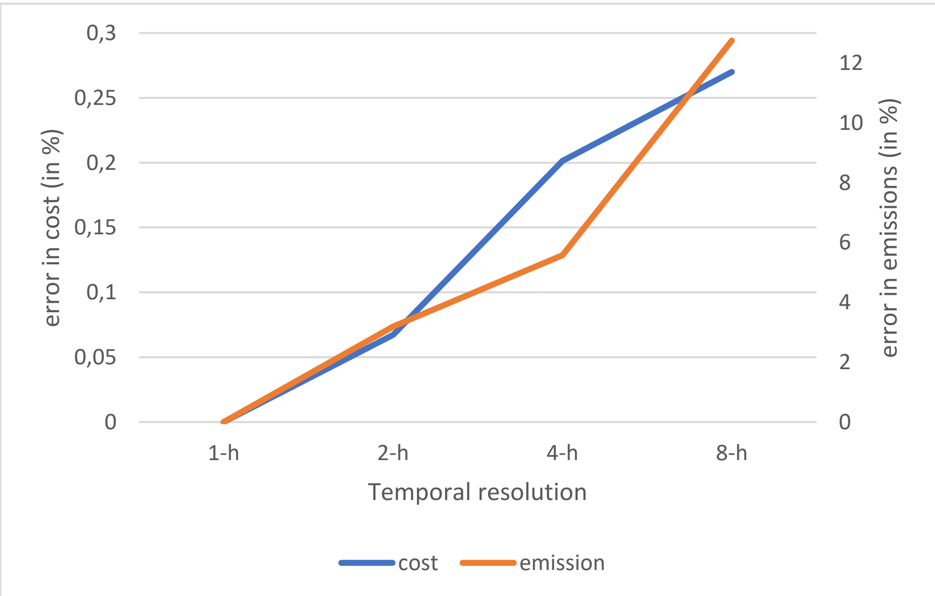

Figure 7.6. Error in system cost and CO2 emissions for coarser-than-hourly temporal resolutions

Representative period selection provides a huge reduction in calculation time; one representative week over one month leads to a nearly 250-fold reduction in the overall simulation time (Table 7.2). However, the difference in cost and emissions is not negligible. The error in the estimation of the energy system cost is much higher than the resolution variation methods, varying from 4.7% to

10.1% by increasing the duration of represented period by a week. Because of the share of natural gas in the primary energy supply, emissions become positive for the cases of one week over one and two months with a more than four time increase in emissions.

Table 7.2. Simulation time, cost and the CO_2 emissions for different represented periods and their error (difference) from (with) the base case of hourly resolution on continuous period of one year

		Representative periods					
Main characteristics	**Base**	**1W/1M**	**Error***	**1W/2M**	**Error***	**1W/3M**	**Error***
Total simulation time (s)	216254	869.5	99.6%	161.4	99.93%	61	99.97%
LP generation time (s)	210	8.3	96.05%	2.3	98.9%	1.4	99.33%
CPLEX solution time (s)	216044	861.2	99.6%	159.1	99.93%	59.6	99.97%
Annual cost (b€/year)	59.55	56.76	4.69%	55.665	6.52%	53.565	10.05%
Annual CO_2 emissions ($MtCO_2$/year)	-2.51	6.25	349.00%	6.198	346.93%	-0.401	84.02%

*For the time related data, it is the difference in calculation time.

Figure 7.7 shows the error in annual energy system cost and CO_2 emissions for different representative periods.

Figure 7.7. Error in system cost and CO2 emissions for different representative periods

7.3.4. The extra cost of coarse temporal resolutions

In the previous subsections, we saw that the error values of the modelling with coarser time-slices are negligible, but the gains in the computational tractability are very high. On the contrary, modelling by choosing representative periods is associated with big error values regarding all the important variables (energy mix, system cost and CO_2 emissions). Energy system planning based on modelling with coarser temporal resolutions provides an attractive trade-off between the precision and calculation time. However, energy planning based on low temporal resolution would lead to extra cost since the energy mix differs from the optimal case with hourly temporal resolution, and since it is cheaper, it might lead to shortages in energy supply. This section aims to present the extra cost of planning an energy system based on coarser-than-hourly temporal resolutions, and to analyze the penalty caused by the erroneous planning of energy system. Since the representative period selection method is associated with very high errors, I do not consider it as a valid method to base the future energy planning on. Thus, I limit my analysis to coarser-than-hourly temporal resolutions. The main question to answer is: What if the energy system is based on a planning with low temporal precision, what would be the extra cost compared to the planning with an hourly temporal resolution?

To answer this question, I ran the hourly model with the installed capacities of all the energy supply, conversion and storage technologies of the values obtained by the optimizations with coarse temporal resolutions, and I defined a value of lost load of €10,000/MWh$_e$ for electricity supply as in Chapter 4. We saw previously that in case of introduction of an SCC of €200/tCO_2 the natural gas is eliminated from the optimal mix, however, to limit the extra cost from the lost load, I left the natural gas exchange as a free variable. Therefore, imports of natural gas are still enabled. The cost, the emissions and the lost electric load are presented in Table 7.3:

Table 7.3. Social and technical costs, lost load and CO_2 emissions of the planning with the optimal installed capacities of coarse temporal resolution with natural gas trade possibility

	1-h	2-h		4-h		8-h	
Social cost (b€/year)	59.55	59.57	+0.03%	59.88	+0.55%	59.70	+0.25%
Technical cost (b€/year)	60.05	60.05	+0%	59.61	-0.73%	60.03	-0.03%
Lost Load (GWh$_e$/year)	0	0		3.77		10.03	
Lost load (percentage of all electric load)	0	0		0.0007%		0.0019%	
Natural gas consumption (TWh$_{th}$/year)	0	0.101		15.9		2.72	
CO_2 emissions (MtCO_2/year)	-2.51	-2.42		1.33		-1.68	

Although the extra cost of planification of the energy system with these non-optimal installed capacities is very limited (between €0.02bn/year and €0.15bn/year), the CO_2 emissions are different for erroneous planning of the energy system, and a small share of the primary energy is provided by natural gas for coarser-than-hourly temporal resolutions: 101GWh$_{th}$/year for two-hourly temporal resolution, 15.9TWh$_{th}$/year for four-hourly temporal resolution and 2.72TWh$_{th}$/year for eight-hourly temporal resolution. Therefore, although the extra cost is limited, a slight increase in CO_2 emissions can be associated with coarser temporal resolutions. However, the lost load is very small for erroneous planning based on resolution variation methods varying between 3.77GWh$_e$/year and 10.03GWh$_e$/year respectively for four-hourly and eight-hourly temporal resolutions (0.0007% and 0.0019% of the electric load respectively).

The share of fossil gas in erroneous planning based on coarser-than-hourly temporal resolutions is the reason why the CO_2 emissions can slightly differ from hourly temporal resolution case. Keeping the emissions below zero would require limiting the capacity of fossil gas to its value resulting from the optimization with hourly temporal resolution (null). Thus, fixing also the capacity of natural gas to zero would disable natural gas importations. Table 7.4 shows the same results of Table 7.3, but for the case with no natural gas importation possibility.

Table 7.4. Social and technical costs, lost load and CO2 emissions of the planning with the optimal installed capacities of coarse temporal resolution with no natural gas trade possibility

	1-h	2-h	4-h	8-h
Social cost (b€/year)	59.55	59.57	60.97	59.79
Technical cost (b€/year)	60.05	60.05	61.46	60.23

Lost Load (GWh_e/year)	0	0	3.77	10.03
Lost load (in percentage of all electric load)	0	0	0.0007%	0.0019%
CO_2 emissions ($MtCO_2$/year)	-2.51	-2.43	-2.44	-2.19

Planning the energy system based on 2-hourly temporal resolution leads to €0.02bn/year of extra cost (less than 0.03%), and this extra cost increases as the planning is based on coarser temporal resolutions. A €0.24bn increase of the social cost of the energy system for the erroneous decision based on the optimal energy mix for eight-hourly temporal resolution is observed. The maximal value is observed for the planning based on a four-hourly temporal resolution with an extra cost of €1.42bn/year (2.4% increase). Thus, by limiting the natural gas importations, energy system's CO_2 emissions remain below zero and very close to the case with planification based on modelling with hourly temporal resolution, and the extra cost of energy system stays very low (≤ 2.4%).

7.4. Discussion and conclusion

7.4.1. The relative performance of time series aggregation methods

The findings of Sections 7.3.1 and 7.3.2 show that, although time series aggregation based on representative weeks can lead to high gains regarding computational tractability (up to 3,500-fold reduction in simulation time), the error associated with this method is very high. On the contrary, resolution variation methods perform very well in preserving the main characteristics of the energy system.

The sensitivity of the electricity mix to the temporal resolution has been highlighted in the literature. This literature mainly focuses on power system. The findings of Chapter 6 also highlight the importance of hourly temporal resolution or variable time-step method as a new proposed segmentation method. However, including the whole energy system with its major sectors nearly eliminates the need for short-term electricity storage (Li-Ion batteries) as we saw in Chapter 5. Therefore, sector-coupling decreases variation of residual demand by adding flexibility to the intra-hourly 'variability' of VRE production and energy demand. Findings of Sections 7.3.1 and 7.3.2 show that in such an energy system, modelling with coarser-than-hourly temporal resolution keeps very high precision in the energy mix, energy system cost, emissions and load curtailment. Even for a very coarse temporal resolution containing eight consecutive hours in one time-slice, the electricity mix is nearly identical to the one resulting from optimization with one-hourly temporal resolution. Similarly, considering the whole energy system, the optimal energy mixes for both coarser-than-hourly temporal resolutions and hourly temporal resolution are nearly identical, with a maximal mean absolute percentage error of less than 2.5%.

From the cost point of view, resolution variation methods perform better than the representative period selection methods as well. For any of the studied coarser-than-hourly temporal resolutions (two-hourly, four-hourly and eight-hourly time-steps), the cost of the energy system is underestimated by less than 0.3%. However, for representative period selection methods, this cost underestimation can exceed 10%.

The findings of this chapter are consistent with the findings of Alimou et al. (2020) to some extent. Alimou et al. (2020) by coupling the TIMES-FR model (optimization of dispatch and investment with representative weeks) with ANTARES (a dispatch model developed by RTE, French transmission network operator, with high temporal resolution considering stochastic scenarios) show that the former underestimates the system cost by 28% and the capacity mix derived from TIMES-FR does not meet the supply/demand adequacy requirements of the French public authorities (i.e. annual loss of load of no more than three hours) .

Coarser-than-hourly temporal resolutions lead to slight underestimation of negative emissions (-2.52MtCO_2/year vs. -2.43MtCO_2/year to -2.19MtCO_2/year). This slight underestimation in negative CO_2 emissions stems from the slight decrease in power generation from CCGT power plants combined with CCS units (5.72TWh_e/year vs. 5.52TWh_e/year to 4.99TWh_e/year – Appendix 7.1). However, representative period selection method leads to 6.25MtCO_2/year of positive emissions (an error of 350%). This overestimation of CO_2 emissions stems from the presence of fossil gas in the primary energy supply of these methods.

The findings of the ex-post extra cost of planning based on coarse temporal resolutions show that not only the planning based on modelling with a temporal resolution as coarse as eight hours estimates the energy mix and the main characteristics of the energy system with very high precision, but also an energy system based on these results would operate with minimal extra cost. These findings confirm the high performance observed for resolution variation methods in modelling energy systems with sector-coupling.

7.4.2. Conclusion

In Chapter 5, based on the power system modelling literature, I considered an hourly temporal resolution for the EOLES_mv model. However, the results of modelling with hourly temporal resolution with sector-coupling reduces the required battery storage capacity (both power and energy volume capacities) drastically. The reason being the flexibility gains from other-than-electricity sectors, in this chapter I analyzed the importance of the temporal precision of a multi-energy model. A very big proportion of the popular energy system models (ex. the TIMES models) use representative periods (particularly representative weeks and days) over longer periods such as months and seasons.

This chapter first compares two main categories of time series aggregation methods in energy systems modelling: resolution variation methods and representative period selection methods by applying different coarser-than-hourly temporal resolutions and represented periods by one week in an energy system with sector-coupling. To study if time series aggregation methods can give an accurate representation of the energy system, I developed several versions of the EOLES_mv model (presented in Chapter 5) with (1) coarser-than-hourly temporal resolutions (two-hourly, four-hourly and eight-hourly) and (2) discrete representative weeks over varying periods (one week over one month, over two months and over three months).

Comparison of the results of modelling with coarser-than-hourly time-steps with the basic hourly modelling shows that reducing temporal precision leads to very high gains in calculation time, keeping high precision in energy mix, energy system cost, CO_2 emissions and load curtailment. A less than 2.5% of mean absolute percentage error for the primary energy mix and less than 0.3%

variation in the energy system cost is followed by nearly 640-fold reduction in calculation time using eight-hour long time-slices.

Courser-than-hourly temporal precision would allow the future modelling studies to increase their computational tractability, keeping the needed precision in calculations with much faster solution time. Thus, some other aspects of energy systems modelling can be developed, such as better technical representation of different technologies, inclusion of a higher number of options in the modelling and application of detailed sensitivity and robustness studies that require wide ranges of scenarios to account for the uncertainties regarding the energy demand, future cost, resource availability and weather variability.

The representative week choice in this chapter is based on preparation of an average week for each month, without considering other grouping characteristics of different periods. One interesting extension of this work can be the choice of representative periods based on similar weather and demand characteristics, which might improve the performance of representative period selection, such as seasonal representative periods. Similarly, the coarser-than-hourly time-slices are based one simple division of 24 hours of a day to two-hour, four-hour and eight-hour long time-steps with no particular consideration of variable time-step choice for a day as in Chapter 6. The performance of the resolution variation methods also can be improved by a more intelligent sub-sampling of daily time-steps, however, even without variable time-step choice, this method performs very well with negligible error from the modelling with hourly temporal resolution.

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Appendices 7

Appendix 7.1. Installed capacities and annual energy production for simulation with coarse temporal resolutions

In order to better visualize the accuracy of each variant case, the energy mix and the associated errors must be studied. Tables 7A.1 and 7A.2 show the installed capacity and the annual energy production for the base case with hourly temporal resolution and for each variant case with coarser temporal resolution and the error associated with it.

Table 7A.1. Installed capacities of energy production, conversion and storage technologies for different temporal resolutions and their error from the base case of hourly resolution

	Temporal Resolution						
Technology Installed Capacity (GW)	**1-h**	**2-h**	**error**	**4-h**	**error**	**8-h**	**error**
Energy Production							
Offshore wind	0.0	0.0	0.00%	0.0	0.00%	0.0	0.00%
Onshore Wind	80.21	80.53	0.40%	80.35	0.17%	81.62	1.76%
Solar PV	79.35	81.84	3.14%	85.59	7.86%	86.96	9.59%
Hydroelectricity	20.4	20.4	0.00%	20.4	0.00%	20.4	0.00%
Nuclear energy	22.6	22.26	1.50%	21.77	3.67%	21.21	6.15%
Fossil Gas	0.0	0.0	0.00%	0.0	0.00%	0.0	0.00%
Methanization	17.35	17.35	0.00%	17.35	0.00%	17.35	0.00%
Pyro-gasification of Biomass	0.0	0.0	0.00%	0.0	0.00%	0.0	0.00%
Energy Conversion							
OCGT	2.14	2.15	0.47%	1.88	12.15%	2.2	2.80%
CCGT	5.03	5.22	3.78%	5.88	16.90%	6.36	26.44%
CCGT-CCS	5.72	5.52	3.50%	5.35	6.47%	4.99	12.76%
Electrolysis	6.37	6.35	0.31%	6.37	0.00%	6.37	0.00%
Methanation	3.48	3.48	0.00%	3.47	0.29%	3.46	0.57%
Central heat pump	26.42	26.67	0.95%	27.45	3.90%	27.82	5.30%
Individual heat pump	41.84	41.60	0.57%	41.23	1.46%	40.92	2.20%
Resistive heating	17.78	17.96	1.01%	17.50	1.57%	17.92	0.79%
Central gas boiler	0.0	0.0	0.00%	0.0	0.00%	0.0	0.00%
Individual gas boiler	0.0	0.0	0.00%	0.0	0.00%	0.0	0.00%
Energy Storage							
Battery storage	4.72	5.11	8.26%	5.19	9.96%	5.46	15.68%
Battery storage (GWh)	0.0	0.0	0.00%	0.0	0.00%	0.0	0.00%
Gas Storage	24.61	24.55	0.24%	24.66	0.20%	25.48	3.54%
Gas Storage (TWh)	134.6	134.6	0.00%	134.6	0.00%	134.6	0.00%
Individual thermal energy storage	35.8	18.15	49.30%	9.23	74.22%	3.57	90.03%
Individual thermal energy storage (GWh)	44.31	36.30	18.08%	36.93	16.66%	28.558	35.55%
Central thermal energy storage	46.25	46.76	1.10%	46.99	1.60%	47.689	3.11%
Central thermal energy storage (TWh)	31.58	31.28	0.95%	30.26	4.17%	29.644	6.12%
Heat Network	46.25	46.76	1.10%	46.99	1.60%	47.69	3.11%

Table 7A.2. Annual energy production from energy production, conversion and storage technologies for different temporal resolutions and their error from the base case of hourly resolution

	Temporal Resolution						
Technology Energy Supply (TWh/year)	**1-h**	**2-h**	**error**	**4-h**	**error**	**8-h**	**error**
Energy Production							
Offshore wind	0.0	0.0	0.00%	0.0	0.00%	0.0	0.00%
Onshore Wind	228.16	229.07	0.40%	228.55	0.17%	232.15	1.75%
Solar PV	112.83	116.38	3.15%	121.71	7.87%	123.66	9.60%
Hydroelectricity	43.8	43.8	0.00%	43.8	0.00%	43.8	0.00%
Nuclear energy	166.99	162.59	2.63%	157.94	5.42%	153.02	8.37%
Fossil Gas	0.0	0.0	0.00%	0.0	0.00%	0.0	0.00%
Methanization	152.0	152.0	0.00%	152.0	0.00%	152.0	0.00%
Pyro-gasification of Biomass	0.0	0.0	0.00%	0.0	0.00%	0.0	0.00%
Energy Conversion							
OCGT	1.04	1.05	0.96%	0.86	17.31%	1	3.85%
CCGT	4.54	4.78	5.29%	5.33	17.40%	5.81	27.97%
CCGT-CCS	8.59	8.33	3.03%	8.10	5.70%	7.51	12.57%
Electrolysis	51.21	51.18	0.06%	51.17	0.08%	51.18	0.06%
Methanation	16.57	16.51	0.36%	16.58	0.06%	16.5	0.42%
Central heat pump	117.13	117.34	0.18%	118.38	1.07%	118.47	1.14%
Individual heat pump	329.49	328.76	0.22%	326.90	0.79%	325.59	1.18%
Resistive heating	19.18	19.48	1.56%	19.89	3.70%	20.86	8.76%
Central gas boiler	0.0	0.0	0.00%	0.0	0.00%	0.0	0.00%
Individual gas boiler	0.0	0.0	0.00%	0.0	0.00%	0.0	0.00%
Energy Storage							
Battery storage	0.0	0.0	0.00%	0.0	0.00%	0.0	0.00%
Gas Storage	25.61	25.53	0.31%	25.59	0.08%	25.55	0.23%
Individual thermal energy storage	7.93	6.56	17.28%	5.90	25.60%	4.02	49.31%
Central thermal energy storage	34.06	33.85	0.62%	32.81	3.67%	32.72	3.93%
Heat Network	151.19	151.19	0.00%	151.19	0.00%	151.19	0.00%
EV train	30	30	0.00%	30	0.00%	30	0.00%
EV light	3.98	3.97	0.25%	3.96	0.50%	3.97	0.25%
EV heavy	0.0	0.0	0.00%	0.0	0.00%	0.0	0.00%
EV bus	0.0	0.0	0.00%	0.0	0.00%	0.0	0.00%
ICE light	89.64	89.66	0.02%	89.68	0.04%	89.69	0.06%
ICE heavy	56.97	56.97	0.00%	56.97	0.00%	56.97	0.00%
ICE bus	6.47	6.47	0.00%	6.47	0.00%	6.47	0.00%

Appendix 7.2. Installed capacities and annual energy production for representative period selection methods

Tables 7A.3 and 7A.4 show the installed capacity and the annual energy production of each technology for the base case with hourly temporal resolution over the continuous period of a whole year and for each of the representative period precisions.

Table 7A.3. Installed capacities of energy production, conversion and storage technologies for different periods represented by a week (1 month, two months and three months) and their error from the base case

	Represented period by one week						
Technology Installed Capacity (GW)	**base**	**1M**	**error**	**2M**	**error**	**3M**	**error**
Energy Production							
Offshore wind	0.0	20	100%	20	100%	20	100%
Onshore Wind	80.21	120	49.61%	120	49.61%	120	49.61%
Solar PV	79.35	70.89	10.66%	43.39	45.31%	40.52	48.94%
Hydroelectricity	20.4	20.4	0%	20.4	0 %	20.4	0%
Nuclear energy	22.6	0	100%	0	100%	0	100%
Fossil Gas	0.0	39.6	100%	44.84	100%	20.43	100%
Methanization	17.35	16.01	7.72%	16.86	2.81%	18.03	3.94%
Pyro-gasification of Biomass	0.0	0.0	0%	0.0	0%	0.0	0%
Energy Conversion							
OCGT	2.14	0	100%	0	100%	0	100%
CCGT	5.03	3.92	22.07%	4.094	18.61%	0	100%
CCGT-CCS	5.72	4.19	26.75%	4.97	13.11%	1.336	76.64%
Electrolysis	6.37	6.24	2.04%	6.245	1.96%	6.227	2.24%
Methanation	3.48	4.54	30.46%	2.059	40.83%	0.632	81.84%
Central heat pump	26.42	39.51	49.55%	31.183	18.03%	31.266	18.34%
Individual heat pump	41.84	33.41	20.15%	36.586	12.56%	41.071	1.84%
Resistive heating	17.78	14.77	16.93%	10.738	39.61%	12.36	30.48%
Central gas boiler	0.0	0.0	0%	0.0	0%	0.0	0%
Individual gas boiler	0.0	12.42	100%	13.791	100%	0.0	0%
Energy Storage							
Battery storage	4.72	0.0	100%	0.0	100%	0.0	100 %
Battery storage (GWh)	0.0	0.0	0%	0.0	0%	0.0	0%
Gas Storage	24.61	24.88	1.10%	29.31	19.10%	20.045	18.55%
Gas Storage (TWh)	134.6	134.6	0%	134.6	0%	134.6	0%
Individual thermal energy storage	35.8	41.52	15.98%	0.0	100%	0.0	100%
Individual thermal energy storage (GWh)	44.311	82.16	85.42%	0.0	100%	0.0	100%
Central thermal energy storage	46.25	39.86	13.82%	37.47	18.98%	40.88	11.61%
Central thermal energy storage (TWh)	31.58	0.23	99.27%	3.16	90.00%	4.87	84.53%
Heat Network	46.25	39.86	13.82%	37.47	18.98%	40.88	11.61%

Table 7A.4. Annual energy production from energy production, conversion and storage technologies for different representative week precisions and their error from the base case

		Represented period by one week					
Technology Energy Supply (TWh/year)	**base**	**1M**	**error**	**2M**	**error**	**3M**	**error**
Energy Production							
Offshore wind	0.0	92.07	100%	92.181	100%	92.138	100%
Onshore Wind	228.16	341.31	49.59%	342.097	49.94%	341.79	49.80%
Solar PV	112.83	101.14	10.36%	61.647	45.36%	57.612	48.94%
Hydroelectricity	43.8	43.8	0%	43.8	0%	43.8	0%
Nuclear energy	166.99	0	100%	0	100%	0	100%
Fossil Gas	0.0	35.28	100%	35.293	100%	0.696	100%
Methanization	152.0	126	17.11%	138.602	8.81%	151.994	0%
Pyro-gasification of Biomass	0.0	0.0	0%	0.0	0%	0.0	0%
Energy Conversion							
OCGT	1.04	0.0	100%	0.0	100%	0.0	100%
CCGT	4.54	4.04	11.01%	4.149	8.61%	0.0	100%
CCGT-CCS	8.59	6.34	26.19%	6.513	24.18%	1.919	77.66%
Electrolysis	51.21	50.07	2.23%	50.121	2.13%	49.709	2.93%
Methanation	16.57	20.34	22.75%	10.992	33.66%	3.364	79.70%
Central heat pump	117.13	148.25	26.57%	132.915	13.48%	131.976	12.67%
Individual heat pump	329.49	261.74	20.56%	292.48	11.23%	309.242	6.15%
Resistive heating	19.18	36.27	89.10%	22.261	16.06%	18.62	2.92%
Central gas boiler	0.0	0.0	0%	0.0	0%	0.0	0%
Individual gas boiler	0.0	10.06	100%	12.582	100%	0.0	0%
Energy Storage							
Battery storage	0.0	0	0%	0.0	0%	0.0	0%
Gas Storage	25.61	7.87	69.27%	8.39	67.24%	7.86	69.30%
Individual thermal energy storage	7.93	17.52	120.93 %	0.0	100%	0.0	100%
Central thermal energy storage	34.06	2.38	93.01%	17.907	47.43%	18.88	44.57%
Heat Network	151.19	150.63	0.37%	150.82	0.24%	150.86	0.22%
EV train	30	30	0%	30	0%	30	0%
EV light	3.98	0.0	100%	0.0	100%	0.0	100%
EV heavy	0.0	0.0	0%	0.0	0%	0.0	0%
EV bus	0.0	0.0	0%	0.0	0%	0.0	0%
ICE light	89.64	97.92	9.24%	97.92	9.24%	97.92	9.24%
ICE heavy	56.97	56.97	0%	56.97	0%	56.97	0%
ICE bus	6.47	6.47	0%	6.47	0%	6.47	0%

Chapter 8

Conclusion

This thesis aims to study the French energy transition and show optimal and robust investment strategies for a carbon-neutral national energy system by 2050. To this end I developed a family of optimization of dispatch and investment models (EOLES – Energy Optimization for Low Emission Systems) to simulate the optimal energy system for France. The EOLES models are developed to answer five main questions regarding the French energy transition:

1. What is the relative role of different energy carriers in a carbon-neutral energy system?
2. What is the impact of the main uncertainties in the future cost of key technologies?
3. What is the importance of the weather-variability in designing future electricity system with high shares of variable renewable energy sources?
4. What are the relative roles of three main low-carbon options; renewables, nuclear energy and carbon capture and storage regarding the cost optimality and emission reductions?
5. How to minimize the investment risk associated with variability of renewables to attract private investments in variable renewable energy sources?

First, I developed the EOLES_elecRES model, which considers only the French power sector and only renewables in the supply side. Using this model and robust decision-making technic, I studied the second and the third questions highlighted above. Using the results of this model over different weather years and using risk aversion technics, I studied the sixth question.

Second, I developed the EOLES_elec model, which considers French power system, this time adding nuclear power and natural gas with carbon capture and storage and biogas/biomethane with carbon capture and storage as other low-carbon and negative emission technologies. Using EOLES_elec, I studied the fourth and fifth questions identified above.

Finally, developing the EOLES_mv (mv stands for multi-vector) model, I integrated the main energy sectors (residential and tertiary buildings, industry, agriculture and transport) in a single dispatch and investment model, enabling full sector-coupling between different energy supply, carrier, storage and end-use demands. Using this multi-sector dispatch and investment model, I studied the first question integrating the answers for the fourth and the fifth questions not only considering the power sector but also the whole energy sector.

First, I study the economics of the electricity system and I show that renewables will be the cornerstone of the energy transition in power sector, by a share of at least 75% in the electricity mix. Even a fully renewable power system will cost similar to the current electricity cost, with very small impact of the technology cost related uncertainties in the overall electricity system cost. While the cost of storage technologies is brought up as an important disadvantage for renewables in public debate, the findings of this dissertation show that storage technologies account for a small proportion of the cost of the energy system, even when a fully renewable electricity system is considered (less than 15%). However, even though renewables can be competitive in the coming years, the risks stemming from the intermittence of variable renewables is a strong barrier to private investments in these technologies.

Second, I study the whole energy system and I find that not only renewable electricity, but also renewable gas is one of the key and non-replaceable elements of reaching carbon-neutrality at the lowest cost. A very important element in the correct evaluation of future low-carbon energy strategy is the internalization of CO_2 emissions, which I do by introducing social cost of carbon. While the existing literature for France is concentrated on the debate of 'renewables' or 'nuclear', by internalizing the CO_2 emissions I highlight the importance of carbon capture and storage especially when it is coupled with bio-energies that provides negative emissions (up to 21MtCO_2/year). An energy system where the CO_2 emissions are internalized, comes up with a carbon market that can be worth up to 1/6 of the whole energy market size (more than €10bn/year).

One of the main contributions of this thesis to the existing public debate in the French energy transition is as follows: Although the future energy system must be highly electrified, the role of the gas network in the energy transition shouldn't be underestimated. While electricity can provide the end-use demand of most of the major energy sectors, in an idealized cost-optimal energy system, the transport sector is dominated by internal combustion engines fueled with renewable gas.

The construction of new nuclear power plants in Europe (in the UK, France and Finland) takes much longer time than expected and it costs much more than predicted. For instance, the French Flamanville 3 project was initially estimated to cost €3.8bn and to operate by 2012. However, the latest cost estimation for this project amounts to at least €12.4bn (without the estimated financial cost of at least €6.7bn), moreover, this power plant is not expected to be operational before 2023[1]. Even if (very optimistically) new nuclear power plants experience highly positive learning rates and rapid reduction in their construction time, their share never exceeds 25% of the energy supply of a cost-optimal low-carbon energy system. Therefore, if we are to prioritize investments (as it is highlighted in the French public debate on energy transition), renewable electricity and gas technologies are of utmost importance, while nuclear power has negligible economic and climate benefits, even considering very optimistic developments in the latter.

From a social planner's point of view, renewables are the most cost-optimal solutions. However, in an energy-only highly renewable market, the risk for investors is high. It is possible that only a few very big companies can bare the risks associated with investments in renewables, leading to a highly concentrated energy market and consequently, high market power for few big companies. Therefore, a non-concentrated and competitive energy market requires new market structures rather than the classical liberalized energy markets with merit-order mechanism and marginal pricing.

This thesis provides several frameworks to analyze the energy transition strategy from the economic point of view, by developing several open access models and evaluation methodologies. These models have all their limitations, such as inelastic energy demand, deterministic optimization, full information and copper-plate assumption. Each of these assumptions induces limitations that can lead the optimization results to diverge from the real-world. One very interesting extension of this thesis can be introduction of elastic demand, both including the temporal elasticity of energy

[1] https://www.ccomptes.fr/fr/publications/la-filiere-epr

consumption (such as load-shifting) and modification of the energy demand based on the efforts that can be made (thermal isolation of buildings, modal shift in transport sector etc.). Although the importance of spatial optimization is studied in some extent, a highly renewable future energy system will be based on decentralized energy production, increasing the need for advanced transmission and distribution networks. Thus, economic evaluation of energy transmission and distribution networks parallel with the integration of renewable energy sources can give wider insight about the real cost of the energy transition.

In this thesis I consider a full year with hourly time-slices to account for the short-term (inter-hourly), mid-term (inter-daily) and long-term (inter-seasonal) variability of the variable energy sources and energy demand. On the one hand, dynamic modelling of the energy system with a transition trajectory is computationally demanding using such models. On the other hand, correct introduction of the consequences of investment in a technology with a long lifetime (such as nuclear and hydroelectric power plants) in a dynamic model allowing the investments at different time horizons is a challenging mission, since each investment made in a specific technology in a given year will be a part of the energy system for its whole lifetime (up to 60 years for nuclear power and 80 years for hydroelectricity). This means that allowing investment in nuclear power plants in 2050 requires a modelling horizon of at least until 2110, a year that is unimaginable currently. Finding alternative methods to represent the impact of investment in such technologies correctly for the modeled horizon can be another extension of this work.

In the last part (Part III) of this thesis, I introduce the variable time-step method to increase the computational tractability of power system models, and by coupling other energy sectors with electricity sector, I show that coarser-than-hourly temporal resolutions can reduce calculation time of energy system optimization models, keeping high precision in the optimization results. Therefore, future works in power and energy systems modelling can include variable time-step method for the former and can be based on coarser-than-hourly temporal resolutions for the latter, which would increase the computational tractability of these models. Increasing the computational tractability of energy system models can allow modelers to increase the technological coverage and technical details of their models. In such models, the limitations of my thesis such as inelastic demand and low spatial resolution can be overcome.