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Analyse et modélisation des impacts du développement des énergies renouvelables intermittentes sur le système électrique Français : Etude du potentiel du stockage de l'électricité et de la complémentarité avec la chaleur

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THÈSE

Pour obtenir le grade de

DOCTEUR DE L'UNIVERSITE GRENOBLE ALPES

Spécialité : MEP : Mécanique des fluides, Energétique, Procédés

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préparée au sein du **Laboratoire CEA Liten**
dans **l'École Doctorale I-MEP2 - Ingénierie - Matériaux, Mécanique,
Environnement, Energétique, Procédés, Production**

**Analyse et modélisation des impacts du développement
des énergies renouvelables intermittentes sur le système
électrique Français : Etude du potentiel du stockage de
l'électricité, et de la complémentarité avec la chaleur.**

**Analysis and modeling of the impacts of the
development of intermittent renewable energies on the
French electricity system: Study of the potential of
electricity storage and the complementarity with heat.**

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RÉSUMÉ

La France affiche une volonté de développer massivement les énergies renouvelables intermittentes — éolien et photovoltaïque — tout en diminuant la part des sources pilotables, ici le nucléaire. Ce changement de paradigme implique de repenser la gestion des systèmes énergétiques. En effet, l'intermittence des renouvelables génère un besoin de flexibilité à différentes échelles de temps, de la journée à l'année. Ne pouvant plus se reposer sur la flexibilité des moyens pilotables, cette thèse questionne le potentiel d'autres moyens pour y répondre : stockage d'électricité, surdimensionnement de la production et réseaux de chaleur.

Face à la nécessité d'une approche système, des modèles simples ont été développés pour affiner la compréhension des interdépendances entre production et stockages. Les indicateurs optimisés sont économiques (€) mais aussi environnementaux : énergie grise et émission de gaz à effet de serre sur l'ensemble du cycle de vie. Les performances des systèmes considérés sont celles d'aujourd'hui et leur développement est limité par les ressources et l'espace disponibles. Sans rentrer dans le détail précis du fonctionnement de chaque technologie, cette approche physique donne les domaines de fonctionnement optimaux des différentes technologies, et les cas difficiles pour lesquels les solutions manquent encore.

Dans un premier temps, le besoin en flexibilité généré pour différents taux de pénétration de l'intermittence est quantifié pour plusieurs échelles de temps. Cela permet de comparer le potentiel de différentes technologies de stockage d'électricité à chacune de ces échelles pour mettre en phase production et consommation. Les résultats montrent que les temps longs, typiquement le stockage saisonnier, sont ceux qui demandent les plus gros investissements pour une faible rentabilité. Ensuite, les mécanismes de compétition entre plusieurs stockages et le surdimensionnement sont analysés pour montrer dans quel cas les optimums utilisent des solutions complémentaires. L'étude aborde alors le potentiel du couplage entre le réseau électrique et le réseau de chaleur comme moyen de flexibilité, notamment pour la gestion des besoins longs termes. Ce travail de thèse se focalise à l'échelle française, bien que la méthodologie soit applicable ailleurs.

Mots clefs : Energies renouvelables; Intermittence; Flexibilité; Stockage; Réseaux de chaleur; Modélisation; Optimisation linéaire; France

ABSTRACT

France aims to massively develop intermittent renewable energies — wind and photovoltaic — whilst reducing the share of dispatchable sources, in this case, nuclear power. This paradigm shift implies rethinking the management of energy systems. Indeed, renewables' variable nature generates a need for flexibility on different time-scales, from day to year. Being no longer able to rely on the flexibility of dispatchables, this thesis questions the potential of other means to meet this need: electricity storage, oversized production and heating networks.

Faced with the need for a systemic approach, we developed simple models to enhance the understanding of the interdependencies between production and storage. The optimized indicators are economic (€), but also environmental: embodied energy and greenhouse gas emissions over the entire life cycle. The performances of the systems considered are those of today and their development is limited by the resources and space available. Without going into the specific detail of how each technology works, this physical approach points out optimal operation areas for the different technologies and the difficult cases for which solutions are still lacking.

First, the need for flexibility generated for different intermittency penetration rates is quantified for several time scales. It enables us to compare the potential of different electricity storage technologies — for each of these scales — to make production and consumption concur. The results show that longer time-scales — typically seasonal storage — require the largest investments for low profitability. The competition mechanisms between various storage options and oversizing are then analyzed, showing how the optimum solutions use complementary flexibility strategies. The study then addresses the potential of coupling between electrical and heating grid as a source of flexibility, particularly for the management of long-term needs. This thesis work focuses on French territory, although the methodology is applicable elsewhere.

Keywords: Renewable energy; Intermittency; Flexibility; Storage; District Heating; Modeling; Linear optimization; France

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BASIC DEFINITIONS

Important notions for the understanding of the study are defined here. They are presented in a logical order to ease their comprehension.

| | |
|-----------------|--|
| Load | Energy consumption. It mostly refers to the electricity demand. |
| Supply | Energy production. |
| Intermittent | Qualifies energy generation sources or consumption. For example, for PV or wind power electricity generation, their production fluctuates because of meteorological constraints; energy is not available on demand. Intermittent production can be partially predicted but not controlled as opposed to dispatchable power plants. |
| Variable | It is used as a synonym with intermittent in the manuscript to qualify Renewable Energy Sources |
| Dispatchable | Qualifies energy generation sources, such as coal, gas or nuclear power plants. It means that the energy production is available on demand. |
| Residual demand | Difference between the electricity consumption and the non-dispatchable electricity production. It represents the excess or shortage of electricity that will have to be handles. |
| Flexibility | The flexibility qualifies the potential of an energy system to modify electricity supply or demand. It can be achieved by different methods, such as energy storage or dispatchable power plants. Said differently, an energy system's flexibility reflects its ability to compensate the discrepancy between electricity production and consumption, named residual demand. |
| Oversizing | Installing a greater energy generation capacity than what would be required to provide on average the annual energy demand. It ensures that production is greater than consumption most of the time. |

| | |
|------------------------|---|
| Curtailment | The action of reducing or discarding the energy production. An excess electricity production can be <i>curtailed</i> rather than stored. |
| Demand-side management | Also known as energy demand management, it consists of modifying consumers' energy demand to adapt it to what is available. |
| Service | It is the sum of all energy provided by flexibility means, such as storage or oversizing, to make sure that at all times electricity production = consumption, when, otherwise, production will not satisfy consumption. |
| Time-scale | Different time-scales variations of the intermittency, such day/night, weekday/week-end, winter/summer. |
| Primary Energy | It is a form of energy found in nature that has not been converted by human engineering. It is for example the case of fossil fuels. |
| Final Energy | It is the carrier of the energy after conversion, such as electricity, heated water. |
| Life Cycle | Analysis of the different stages of the life of the system. It can go from the raw material extraction, construction, to its recycling. |
| Cradle-to-gate | It qualifies the life cycle of a device, starting from the <i>cradle</i> , i.e., the extraction of raw materials, includes its construction and until its gets out from the factory: the <i>gate</i> . |
| Cradle-to-grave | Additionally to the <i>Cradle-to-gate</i> , it involves use phase, decommissioning and recycling. |
| Embodied energy | Primary <i>cradle-to-gate</i> energy required to set up a device. |
| Capacity factor | Ratio between the electrical energy actually produced over a given period of time and the energy that would be produced by operation at maximum power during the same period. For example, in 2019 in France, according to [1], photovoltaics had an average capacity factor of 13.5% and nuclear power plants reached 68.6% (a particularly low value this year for the latter means of production.) |

ACRONYMS & ABBREVIATIONS

| | |
|-------|--|
| ADEME | Agence De l'Environnement et de la Maîtrise de l'Énergie |
| AEC | Alkaline Electrolyzer Cell |
| CAES | Compressed Air Energy Storage |
| CAPEX | CAPital EXPenditure |
| CF | Capacity Factor |
| DH | District Heating |
| ESOI | Energy Stored On energy Invested (electrical/primary), defined page 63 . |
| FFT | Fast Fourier Transform |
| GWP | Global Warming Potential |
| HP | Heat Pump |
| IEA | International Energy Agency |
| IRENA | International Renewable Energy Agency |
| LCA | Life Cycle Analysis |
| LHV | Low Heating Value |
| PEMFC | Proton Exchange Membrane Fuel Cell |
| PHS | Pumped Hydro-electricity Storage |
| PV | Photovoltaic |
| P2P | Power-to-Power |
| RES | Renewable Energy Sources |
| IRES | Intermittent Renewable Energy Sources |
| VRES | Variable Renewable Energy Sources |

| | |
|------|---|
| STES | Seasonal Thermal Energy Storage |
| TS | Thermal Storage |
| TSO | Transmission System Operator |
| UF | Utilization Factor, defined page 53 |

LIST OF SYMBOLS

| | |
|---------------|--|
| η | Round trip efficiency of a storage device |
| ζ | Energy intensity |
| ρ | Density |
| φ_i | Wavelet function of index in time i |
| β_i | Coefficient of wavelet decomposition corresponding to the wavelet φ_i |
| in | Stands for input and concerns energy storage devices. MW_{in} or MWh_{in} are input power or energy |
| out | Stands for output and concerns energy storage devices. MW_{out} or MWh_{out} are output power or energy |
| $prim$ | Primary energy |
| el | Electrical energy |
| th | Thermal energy |
| $stock$ | Energy capacity of a storage |
| $installed$ | Power installed |
| $produced$ | Energy produced |
| $delivered$ | Energy delivered |
| f | Signal function of time |
| \mathcal{D} | Set of wavelets |
| $\ f\ _2$ | L^2 norm |
| A | Wavelet matrix |

GENERAL INTRODUCTION

The development and growth of our modern societies have, since the industrial revolution, entirely rested upon access to cheap and abundant energy sources. This dependence has been the focus of most geopolitical quarrels of the last century. M. Auzanneau in “*Oil, Power, and War: A Dark Story*” [2] depicts the history of the race for oil, gas, and energy in which the world has engaged.

The unlimited use of fossil fuels has brought global warming to a tipping point. Today, it urges the world to change the pace of human activities in order to reduce Greenhouse Gas (GHG) emissions. Every sector is required to determine the potential leverage that will ease its environmental footprint. The economy, as a whole, must adapt.

We are not all up against the same challenges. Developing countries have limited access to energy and are only small contributors to global pollution [3]. In their case, infrastructure first needs to be developed to bring access to energy and raise living standards. Environmental constraints will result in a different economic trajectory from that of developed countries, based on activities less dependent on fossil fuels. Developed countries face different challenges. The current economic system is based on unsustainable activities, from the CO₂ standpoint. Reports such as “*Decarbonize Europe*” from the *Shift Project* [4], highlight that the most efficient options to reduce GHG emissions consist in primary energy consumption reduction — e.g., use of fossil fuels — focusing on high impact sectors such as transportation, building renovation and agriculture.

These activities, so far, depend on an abundant supply of cheap energy. Thus, when it comes to global warming mitigation, energy supply is a cornerstone. Primary energy sources need to be as “*clean*” and decarbonized as possible.

A successful energy transition must find the critical balance between technical issues, social acceptance constraints, economic trajectories and political agendas. The following research studies part of this complex system. We will focus on the technical issues facing the transformation of the French electricity production system.

This thesis is organized into two parts. First, we define the scope and framework of the study, along with the current state of the art. The second part is dedicated to the research methodology and findings.

PART I:

FLEXIBILITY ISSUES: STATE OF THE
ART

Framework, scope and hypothesis of this work

“All models are wrong, but some are useful”

— Attributed to *George Box*

Chapter outlook

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I Context

I.1 A Rising share of Renewable Energy Sources

Today’s trend is to develop intermittent energy sources and to reduce the number of fossil fuel power plants and nuclear facilities. On the international stage, this ambition is driven by prospective scenarios like IRENA’s *Global Energy Transition: A Roadmap to 2050* [5]. In France, the “*Stratégie Nationale Bas-Carbone*” (SNBC) and the energy transition plan, known as PPE [6] mandates that an equivalent of about 25% of the electricity consumption will have to be produced by solar photovoltaic and wind power by 2028.

In this manuscript, we use the adjective *intermittent* to qualify energy sources such as photovoltaic or wind power. It is important to note that some works like Suchet et al. [7] propose different semantics for the definition of *variable* or *intermittent* character. In the context of this thesis, these two terms are used as synonyms.

I.2 Renewable energy sources and intermittency

Electricity generation sources can be divided into two categories: dispatchable and intermittent energy sources. The formers, such as nuclear, coal, or gas power plants, can deliver supply on demand. The second, such as photovoltaic or wind power, are reliant on uncontrollable phenomena like weather cycles.

This manuscript focuses on the study of intermittent sources, especially wind and solar PV. Their production signals are very complex and fluctuate with days, months, and seasons. Likewise, electricity demand is intermittent and fluctuates due to human needs and activity.

The variability of energy systems involves different time scales related to human rhythms and natural cycles: day and night, weekdays and weekends, summer and winter. These different time scales must all be satisfied and addressed respectively to ensure the balance between production and consumption at any given time.

I.3 Residual demand

The residual demand is the difference between electricity demand and intermittent production. In other words, it is the remaining energy to supply when the production is lower than demand.

Satisfying the residual demand involves technical systems, also called flexibility means. Different methods can provide this required flexibility. First, using a dispatchable electricity supply that follows the demand. Electricity consumption can also be adapted to production. It is known as demand-side management. Eventually, storing electricity when there is excess production to deliver it when needed is a supplementary manner to match electricity demand with supply.

II Aim and thesis framework

Nevertheless, the following issue is rarely raised in energy transition discussions. On the one hand, intermittent sources create an enormous need for flexibility — e.g., energy storage — to ensure that electricity supply meets the demand at all times. On the other hand, dispatchable power plants such as gas, nuclear, or hydro-power are by far the cheapest means of flexibility. However, their share tends to be dramatically reduced in the electricity

generation mix.

This conflict is at the heart of our investigations: *how to ensure the required flexibility while reducing dispatchable power plants' use?* We tackle this question from the other end and use *reductio ad absurdum** reasoning. The question addressed is “*To what extent can the electricity demand be met without using at all the flexibility of dispatchable power plants?*”

This concept — *dispatchable power plants do not provide any flexibility* — is a central assumption to the whole study and highlights the potential of other means of flexibility. It amounts to consider the various strategies to match the energy needs, by dealing with the remaining production fluctuations when the dispatchable resources (baseload production) have been subtracted and kept constant.

This work is not based on any pre-existing energy modeling tools. Everything has been developed from scratch for the purpose of the present study. Energy systems are very complex and modeling their behavior in a detailed and exhaustive way would require to take into account a wide variety of parameters, such as the different energy networks, losses, import-export, and many others. To grasp the essential features and stay focus on the main trends of this complex system, we decided to reduce the number of parameters to a minimum while keeping the principal features: the time-scales and main characteristics of the means considered as potential contributors.

Thus, we use simple technological models. We do not consider any threshold or power ramp that would be a more precise representation of a system — gas turbine, for example — but that would distract us from understanding the basic principles.

Additionally, this work is based on the analysis of seven years of existing electricity production and consumption signals. These time-series are fully known in advance, when optimizing the sizing and operation of the energy system.

It is a bias of our model and a source of costs underestimating: a real system would be oversized to account for electricity production and consumption uncertainty.

For these reasons, we carry out comparative and not absolute analyses which aim to provide orders of magnitude. Our objective is to understand the behavior of the energy system and to highlight its key technological issues. Therefore, we will not try to optimize any electricity generation mix. The technologies considered are the existing ones with their current performances. This work is not a prospective study based on “*would be technologies*” but an analysis of the relevance and limits of existing solutions.

In summary, we want to provide keys to understanding the implications of the major parameters on the system and highlight the main trends. By focusing on a selected set of parameters and using models with a low level of details, we seek a better understanding of the impact of each decision on the global system.

III Scope

This work focuses on the French energy system. The conclusions we draw are, therefore, valid for this country only. However, the methodology would remain valid for other case

*Also known as *absurd reasoning*, it is a form of argument that attempt to establish a claim by showing the contradictions of the opposite scenario.

studies and regions of the world, as long as input data are modified accordingly (weather induced, fluctuation of demand and production, etc).

III.1 Scope definition, approach and simplifications

France is modeled as a closed system with no import–export with neighboring countries[†]. We do not assess the flexibility potential of interconnections. It is a different issue that deserves a proper estimate of associated economic investments and land area usage. Besides, relying on interconnections with neighboring countries with their own energy policy is somehow a “*wishful thinking*” when dealing with intermittency as a key issue.

The electricity system is modeled with a “copper-plate” approach (i.e., without any grid losses and power limitations). The complementarity between electricity and heat systems is assessed. However, it has not been extended to fuels or other energy vectors due to time constraint.

We assess the potential of different flexibility means to ensure that the energy supply always meets the demand. This analysis is narrowed to a few technological solutions: storage of heat or electricity, oversizing of the electricity generation system, or a combination of these.

The energy demand is considered as input data that has to be satisfied. The question is not to know whether we can adapt the load to the supply, but how to make sure that the energy supply always accounts for the demand. Demand-side management, which is not included in the study, is a technical issue, but it also relies on sociological and regulations aspects.

The purpose here is not only to reduce the computational burden or to resolve models with greater temporal resolution. We deliberately use simple technological models, strong assumptions, and a reduced number of parameters to highlight their understanding by varying them in a kind of “sensitivity analysis”.

The limitations and scope of this work are summarized in Figure 1.1.

III.2 Analysis standpoint

We define three different *metrics* to compare several technical solutions and estimate the potential of a “*flexibility strategy*”. They are the cost in euros, but also the embodied energy and the Global Warming Potential (GWP).

We alternately use euros and embodied energy to evaluate the cost and overall impact of a solution. However, the comparison with the global warming potential could not be presented in this manuscript due to time constraints. The input data that would allow this analysis to be carried out are, nevertheless, provided in the following technology chapter.

The economic investment cost aims to reflect the actual investment required to set up a technology. It is not a market price, but accounts for the system’s life cycle, from raw materials extraction to its set-up. When relevant, operating costs are also included.

The embodied energy and GWP illustrate the environmental impact of a solution because of their physical meaning. Calculated over a cradle-to-gate cycle, the embodied energy represents the amount of primary energy required to manufacture a system. Similarly, the GWP emphasizes the Greenhouse Gas (GHG) released during the overall

[†]Not being able to control our neighbors’ import/export ability leads us to exclude this strategy from the available flexibility options.

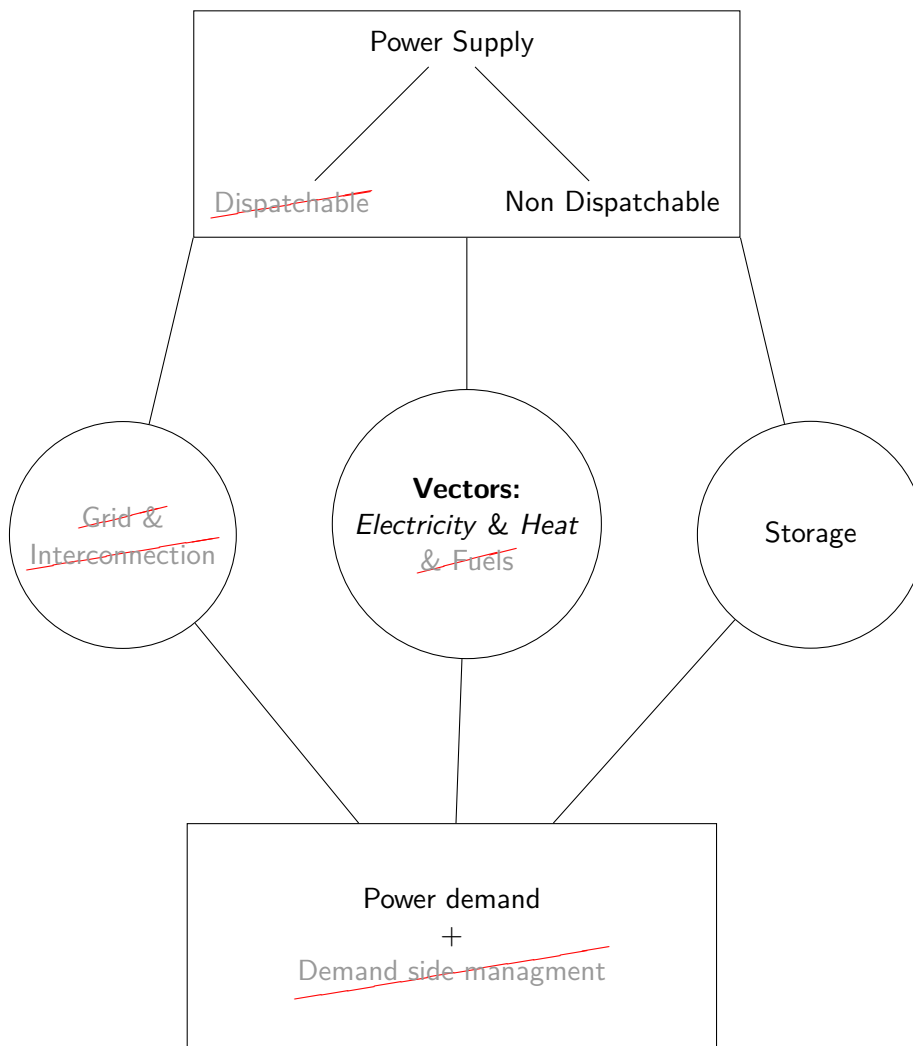


Figure 1.1: Sketch of the energy system considered and its boundaries. The flexibility solutions considered in this work will rely entirely on storage capacity and heat vector complementarity. Interconnections, demand-side management or dispatchable sources will not be considered.

manufacturing process. Gases are weighted relatively to CO_2 (e.g., 1 for CO_2 , larger for CH_4). The impact of a manufacturing process is given as the equivalent of CO_2 released throughout the whole process. We also consider the potential operating cost — e.g., GHG emissions of a gas turbine operation, for instance.

The embodied energy and the GWP are directly related to physical processes such as heating, cooling, and chemical reactions. Conversely to a market price, these value changes are not related to any economic speculation. Changes are related to physical causes such as resource depletion or process improvements.

To summarize, we have chosen to study two aspects. First, economic investments in euros. Second, in order to go beyond changes in technology prices and focusing on the variability of the energy market — which is not correlated to any price signal (see N. Bouleau [8]) — we also study physical flows. We do it in terms of energy or greenhouse gas emissions. In doing so, we can assess the French energy system’s physical behavior and the mere impacts of a technological choice.

Therefore, in this study, costs may refer to, depending on the context, either Euro,

embodied energy or global warming potential. Based on the data available in the literature, we provide costs for each element of the energy system. These data, provided by the literature on Life Cycle Assessment (LCA), are not always exhaustive. This point is discussed in more details in the following technological state of the art Chapter.

III.3 Energy system simplifications – Input data definition

As previously mentioned, technologies are described using simplified models. The next paragraphs define the main parameters of the energy system. Nevertheless, descriptions of all systems, with their own characteristics, are done in the next chapter. What follows only defines the main parameters of our system.

Lifetime: Two physical phenomena can limit the lifetime of a device. It could either be a *calendar limitation* due to physical aging of the components — for instance, concrete structures last 60 years or more whether it is occupied or not. After this given period — the calendar lifetime — the system reaches its life-end.

It could also be a *usage aging*, caused by the operation of a system at its maximum power rate. The life end is considered being reached once a maximum amount of energy has been delivered. This duration is thus defined as the ratio between the maximum energy delivered and the power installed.

For devices like batteries, the usage lifetime is defined by a maximum number of full cycles that can be performed. It is calculated as the ratio between the maximum energy delivered and the battery’s actual energy capacity.

When both calendar and in-use lifetime describe a technology, it is the first of the two to be reached that defines the system’s end-of-life.

Losses: We account for two kinds of losses in energy storage devices.

First, the efficiency, referred to by the Greek letter η . It is the ratio between the output and the input energy. Those losses can be caused by friction for mechanical devices (Pumped Hydroelectricity Storage, for example) or other dissipation processes in electrochemical reactions.

Second, losses do not only occur during cycling. For some devices — thermal storage in particular —, there is also a self-discharge of the stored energy over time. Even if not used, the state of charge decreases over time, as a leakage.

Capacity factor: Electricity power plants are defined by a nominal power install. It is the maximum power that could be produced by the system. However, for meteorological, technical, and energy market reasons, power plants are not working at their full load. We define the *capacity factor* (CF) as the ratio between the total energy produced per year over the total energy it would have produced if it had been working at full load.

$$CF = \frac{\text{Energy produced over a year}}{\text{Maximum energy that could have been produced at full load over a year}}$$

Cost in power A device can be characterized by a cost normalized by a power. It is typically the cost of a power converter, an electricity turbine or a gas burner.

Cost in energy Similarly, a device can also have an investment cost normalized by energy. In the case of energy production, it may be the fuel cost. For storage, it is the cost of the reservoir.

In some cases, this cost must be added to the investment already made to size the system in power — for hydro storage, for example, the cost of the water reservoir (dam) must be added to the investment for the turbine (power).

Concerning electricity consumption and generation time-series, they are provided by RTE, the French Transmission System Operator (TSO)[‡]. We use time-series that last 7 years, from 2012 to 2018, with data recorded every 30 minutes.

IV Questions addressed – Synthesis

To synthesize, this work aims to assess the potential of electricity storage and its complementarity with heat network to handle the variability of PV and wind power deployment. We want to quantify the cost of the service guarantee, i.e. the cost of satisfying the energy demand.

The potential of dispatchable power plants, demand-side management, interconnections as flexibility means, is not evaluated. The electricity or heat grid and their losses are not modeled. We consider the French energy system as a closed system and do not take into account the interconnections and the potential to leverage solar and wind energy in space and time.

V Energy transition scenarios – Case studies

There are many scenarios available in the public domain such as ADEME [9], Negawatt [10], NegaTep [11] and others [12, 13]. Each of them has its said and unsaid technical and ideological assumptions, we have decided not to add one to the list and use them as inputs. Analysis of those scenario can be found in the following references [14, 15]. We aim to define a methodology to address the question of flexibility to match intermittency, and to apply it to a few scenarios. They range from the less intermittent — 0%, the variability is the one of the electricity demand — to extreme cases — 100 % PV and 100 % wind power. Although they do not represent realistic scenarios, these two 100 % renewable case studies highlight typical trends in solar and wind cycles. They should therefore be understood as such. The various mixes analyzed are reminded in Figure 1.2. We refer to the share of total energy produced by VRES as the *Intermittency penetration rate*.

We chose to examine two French energy transition scenarios. The first, known as PPE[§], sets targets to 2028 for the electricity production mix [6]. The second, Ampère [16], has been developed by the French TSO with a 2035 horizon. It is considered as one of the most plausible scenario. They are presented in Table 1.1, along with the other cases studied in the manuscript — 0 % or 100 % VRES.

Objectives of the PPE and the Ampère scenario are on the scale of the French territory. However, they assume electricity imports and exports as well as changes in our energy consumption patterns[¶] — electric vehicles and building thermal renovation, for instance.

[‡]French electricity consumption and generation data are free of charge and available in *eco2mix*: www.rte-france.com/eco2mix

[§]PPE stands for *Programme Pluriannuelle de l'Énergie*

[¶]It is worth noticing that electricity consumption reduction and demand-side management both imply investments outside the electricity system. Besides, electricity consumption reduction might not be compatible with GHG emissions reduction in other sectors consuming fossil fuels, such as mobility and heating.

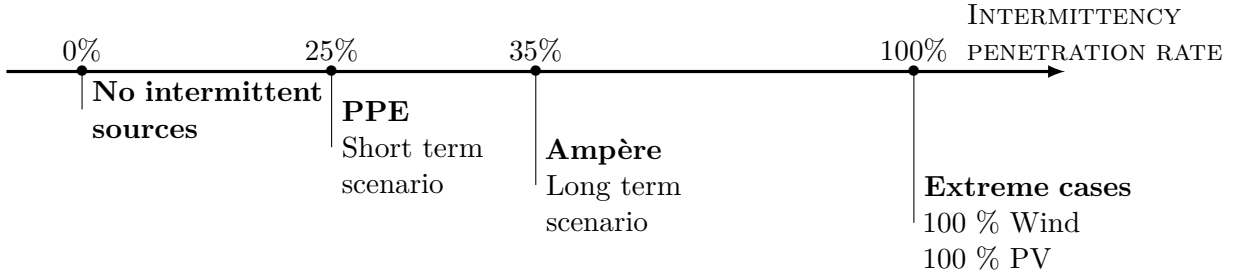


Figure 1.2: Representation of the different scenarios analyzed in this manuscript, from less intermittent to extreme cases, with 100% PV or wind power. The PPE scenario is a French short term objective for the year 2028, while the Ampère scenario, proposed by the French TSO, is for the horizon of 2035.

We are not taking those aspects into account and only want to analyze the potential of the electricity generation mix. To do so, all scenarios are compared on the same basis:

- The average electricity demand is the same for all scenarios. We chose an *average load* of 54 GW. It represents the average French electricity demand over the past years (2014 - 2019)[1].
- PPE and Ampère set targets of power capacity installed for four main energy sources: nuclear, Hydroelectricity, PV, and wind power. Shares of other facilities are neglected.
- Using the power installed and the capacity factors of Nuclear, Hydroelectricity, PV, and wind power — see next chapter for their values — we deduce the energy produced by each production mean and calculate its ratio compared with the total electricity production.

Table 1.1: Share of the different energy sources in PPE and Ampère scenarios.

| Scenario | PV ratio % | Wind ratio % | Nuclear ratio % | Hydro ratio % |
|------------------------|---------------|-----------------|--------------------|------------------|
| No intermittent supply | 0 | 0 | - | - |
| PPE (2028) | 7.7 | 13.9 | 67.4 | 11.1 |
| Ampère (2035) | 10.5 | 24.9 | 53.1 | 11.4 |
| 100 % PV | 100 | 0 | 0 | 0 |
| 100 % Wind | 0 | 100 | 0 | 0 |

VI Research and manuscript organization

In the following chapter 2, we present a technological and methodological state of the art. The research in this thesis is then organized into three distinct phases. Chapters 3 and 4 focus on analyzing the electricity system, whereas Chapter 5 analyzes electricity and heat energy vectors' complementarity.

Chapter 3, Storage options and intermittency: Which storage for which time-scale? This chapter introduces the notion of *time-scale* of the intermittency, a central concept throughout the manuscript. We develop a mathematical methodology based on a *wavelet decomposition*, that allows a quantitative description of the intermittency. We quantify the need for flexibility for each time-scale, ranging from an hour to a year.

Depending on the intermittency of electricity production, we evaluate the potential of electricity storage to make production and consumption concur without dispatchable power plants.

Chapter 4, Complementarity of storage systems: How do storages work together? Quantifying the flexibility need time scales per time scales does not provide the big picture. We need to understand their interactions and, for example, whether a storage installed to handle long term fluctuations can also support a shorter variability.

Thus, we analyze the inter-dependencies between time-scales to show how different technologies storage can work in conjunction.

Chapter 5, Beyond electricity: assessing the potential of heat energy vector. Finally, we evaluate the complementarity between electricity and heat. We want to understand what flexibility could be brought by a thermal energy system, in particular to manage long times scales.

Energy modeling for decision making — State of the Art

This *state of the art* chapter is divided into two parts:

- We first present and detail the different technologies analyzed in this study.
- Then, we present different approaches to energy modeling and position our work among the different existing methodologies.

Chapter outlook

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This chapter is organized into two parts. The first one focuses on the different technologies considered in our analysis. The principles of their operation, their main characteristics and the values used are presented. The second part is an overview of approaches used in the energy modeling community and the questions commonly addressed. We present different methods usually used to model energy systems. The purpose of this last section is not to provide an exhaustive description of all methodologies. We aim to highlight this research work's specificities and give keys to understanding the stakes of other works.

I Technological state of the art

The different technologies considered in the present work are detailed here. We first introduce their basic features and then provide technical characteristics. The parameters used for each technology are each time summarized in a table. Each characteristic, the capacity factor, for example, corresponds to the French territory and considers its own specificities such as climate or energy generation mix.

Investment costs of technology are given with three metrics:

1. Economical cost in Euros (€), noted I .
2. Embodied energy (MJ_{prim}), noted ζ .
3. Global Warming Potential (CO_2eq), noted GWP .

These bibliographical searches were only done for the components of the electrical system. Due to lack of time, we could not perform any additional analysis on the thermal system. Consequently, we will only provide economic data for the heating system.

Costs indexed with the letter E or P , respectively refer to a cost normalized by energy — produced or storage size — or power installed. All costs include the life cycle of the technology, from raw material extraction to installation. When relevant, we also provide the operating cost. There is a lack of data available in the literature for some technologies. It will be specified if necessary.

Wherever possible, all characteristics are cross-referenced and we select values in the middle of the range.

Regarding the cost of energy, some are provided by the Levelized Cost of Energy (LCOE) analysis. This methodology is correctly detailed in the introductory section of ADEME's report [17]. The main drawback of this analysis is that calculations are based on assumptions about the discounting rate. Wherever possible, we have chosen energy cost with a discount rate close to zero. It means that the value of money will not change much over the coming decades.

I.1 Electricity generation sources

We first detail the different electricity generation sources considered in this study: solar photovoltaic, wind, hydroelectric and nuclear. For these four sources, the operating cost — i.e., fuel — is negligible compared to the initial CAPEX. The investment expenditures of the system are given in one of the two forms. It can be a cost per unit of installed capacity. It can also be an average cost per unit of energy produced, distributing the investment over the system's life. When the capacity factor is well established — for example, for photovoltaic and wind power — the cost per unit of energy produced can be estimated

from the cost per unit of power.

The Ph.D. work carried by C. François [18] makes a broad review of raw materials and embodied energy required to construct energy generation sources. Data presented here are all compared with his values.

For Global Warming Potential of power sources, most data are provided by the 2014 IPCC report [19]. This report is an extensive review of the literature, where all data were cross-referenced. Those values were also cross-checked with more recent studies, especially for PV and wind power. More details about GWP calculation are available in their methodological annex [20].

I.1.1 Solar power

There are three main exploitable technologies to convert solar radiations into energy: thermal panels, photovoltaic panels, and Concentrated Solar Power (CSP).

The IEA's 2020 *Global Energy Review* [21] indicates that photovoltaic is the fastest growing renewable energy source for three years in terms of installed capacity: plus 33 %, 22 %, and 16 % from 2018 to 2020.

PV technologies market There are mainly five different PV technologies, divided into two families: silicium based ones and thin films, as shown in Figure 2.1. In 2013, 91% of the PV market was held by crystalline silicon. According to the *Photovoltaic Report* of Fraunhofer Institute [22], it reached 95% of the production share in 2020. Costs and details provided in the thesis refer to crystalline Silicon technology.

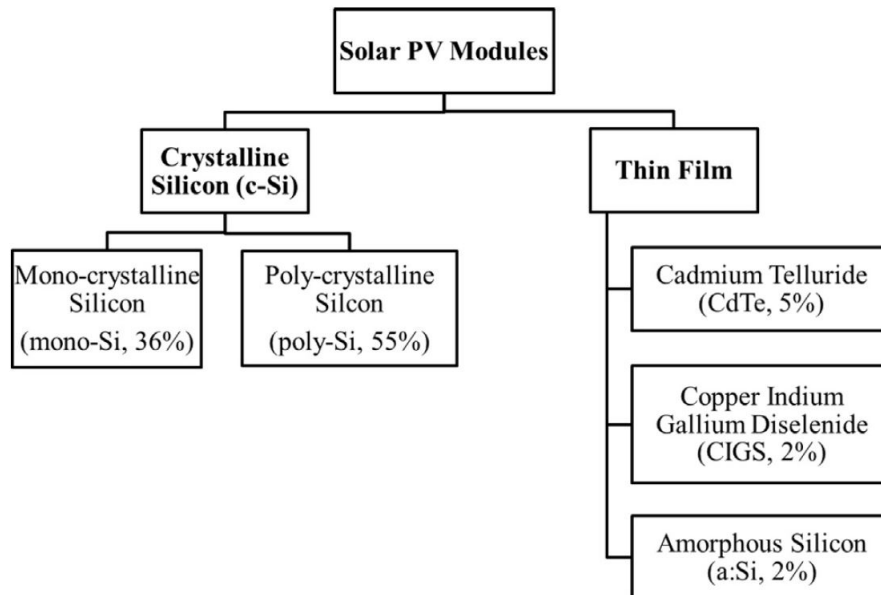


Figure 2.1: Source: [23]. The different PV technologies and their estimated percentage of market share, calculated in 2013.

Capacity factor According to RTE [1], photovoltaics had an average annual capacity factor of 14% in France between 2012 and 2019. We will keep this value to depict solar PV.

Costs Table 2.1 summarizes costs and characteristics of photovoltaic solar panels. In terms of euros per unit of power installed, cost has significantly decreased over the past few years. We picked values from the most recent literature Gulagi et al. [24] and reviews from IEA [25, 26], IRENA [27] or ADEME* [17]. Energy costs are also compared with the energy cost provided by the French “*Commission de Régulation de l’Energie*” (CRE) [28]. This organism defines a market price by issuing invitations to develop RES.

The latest Life Cycle Analysis [22] from 2020 reports that PV embodied energy is similar from 2013 – 2018 studies [18, 23, 29, 30].

Table 2.1: Characteristics and costs of large scale photovoltaic power generation source.

| Component | Symbol | Quantity | Value | Unit | Ref |
|--------------|----------------|---|------------------|--------------------------------------|----------------------|
| Photovoltaic | CF | Capacity factor | 14 | % | |
| | $T_{life,cal}$ | Calendar life time | 30 | years | |
| | I_E | € per unit of energy produced | 55 | € $(MWh_{el,produced})^{-1}$ | [17, 25–28] |
| | ζ_P | Energy intensity in energy | 25×10^6 | $MJ_{prim}(MW_{el,installed})^{-1}$ | [18, 22, 23, 29, 30] |
| | $GWPE$ | $CO_{2,eq}$ per unit of energy produced | 45 | $kgCO_{2eq}(MWh_{el,produced})^{-1}$ | [19, 20, 29, 31] |

Solar photovoltaic potential in France: To grasp the issues of PV deployment potential and land use, we proceed here with a simple order of magnitude calculation. This is a simplified approach that aims to make the manipulated quantities concrete. More detailed analyses such as those of the ADEME [32] or the JRC [33] already exist on this subject.

The French annual average irradiation is about $120W/m^2$, according to V. Smil [34]. To estimate the potential of solar PV, we rely on the methodology that MacKay [35] used for the United Kingdom:

Order of magnitude

We consider widespread solar panels with an efficiency of 20 %. Each household ($30 \cdot 10^6$ in France) can invest in $10 m^2$ of south-facing solar panels on roof. This optimistic hypothesis leads to an average electrical power available of

$$120 \times 0.2 \times 10 \times 30 \cdot 10^6 = 7.2 GW_{el}$$

It would represent an annual energy production of

$$7.2 GW \times 8760 \text{ hours/year} = 63 TWh_{produced}/\text{year}$$

This estimation must be compared with ADEME’s evaluation [32] of PV potential in artificialized, wilderness areas and parking lots. They found a maximum power installed of $53 GW_{inst}$, which implies $\underbrace{0.14}_{CF} \times 53 = 7.4 GW_{el}$ of electric power available in average over the year.

In addition, this same institute [32] accounts for a potential of $364 GW_{inst}$ for PV installed on roof.

*IEA: “*International Energy Agency*”; IRENA: “*International Renewable Energy Agency*”; ADEME: “*Agence de l’environnement et de la maîtrise de l’énergie*”

I.1.2 Wind power

A fraction of the solar irradiation reaching the earth creates a temperature gradient that fosters atmospheric circulation. As a consequence, the exploitable potential of wind power is to be smaller than the planetary irradiance.

Wind turbines tend to be larger and larger to reach more stable and laminar wind cycles. However, there is a limit that cannot be exceeded: the turbine efficiency. Fluid mechanics provides an upper bound to turbine efficiency. Betz's law limits the ratio between incoming airflow and the outgoing mechanical energy. It sets the maximum efficiency to $\eta_{max} = \frac{16}{27} = 0.59$.

Values correspond to the largest wind turbines analyzed in the literature. We distinguish two cases, onshore and offshore wind power. Offshore turbines tend to have a greater capacity factor but require more significant investment costs.

Capacity factor From 2012 to 2019, the French onshore wind power generation showed an average annual capacity factor of 22% [1]. Energy transition scenario Ampère[†], from the French TSO, assumes a 25% capacity factor in 2035. To remain consistent and stick with actual measures and not with predictions or future targets, we chose a 22% capacity factor.

For offshore turbines, there is currently no feedback available from farms in France. We estimate the offshore capacity factors based on two assumptions:

- Compared with neighboring countries [21], France is in the low end of the onshore wind capacity factor range. Consequently, we also chose a low value for offshore: 30 %.
- The French TSO's energy transition scenarios [36] foresee capacity factors between 33 and 36%. A value of 30% may be pessimistic but still consistent with these forecasts.

For the rest of the study, we assume a capacity factor of 30 %.

Lifetime Most studies refer to a calendar lifetime of 20 to 25 years for both onshore and offshore wind turbines. It seems to be very dependent on maintenance and environmental factors. We chose 20 years, the most commonly reported lifetime.

Investment costs Data are more abundant in the literature for onshore than offshore systems. Studies point out that offshore machines require a greater investment than onshore ones. Most economic data are still provided by reports from IEA, IRENA and ADEME.

[†]Ampère scenario is detailed in section V, Chapter 4.

Table 2.2: Characteristics and costs of wind power generation source

| Component | Symbol | Quantity | Value | Unit | Ref |
|---------------|----------------|--------------------------------|------------------|--|------------------|
| Onshore wind | CF | Capacity factor | 23 | % | |
| | $T_{life,cal}$ | Calendar life time | 20 | years | |
| | I_E | € per unit of energy | 55 | €($MWh_{el,produced}$) ⁻¹ | [17, 25, 26, 37] |
| | ζ_P | Energy intensity in energy | 10×10^6 | $MJ_{prim}(MW_{el,installed})^{-1}$ | [18, 30, 38–42] |
| | $GWPE$ | CO_2eq per unit of energy | 11 | $kgCO_2eq(MWh_{el,produced})^{-1}$ | [19, 20, 31, 43] |
| Offshore wind | CF | Capacity factor | 30 | % | |
| | $T_{life,cal}$ | Calendar life time | 20 | years | |
| | I_E | € per unit of energy | 90 | €($MWh_{el,produced}$) ⁻¹ | [26, 44] |
| | ζ_P | Energy intensity in energy | – | $MJ_{prim}(MW_{el,installed})^{-1}$ | |
| | $GWPE$ | $CO_{2,eq}$ per unit of energy | 12 | $kgCO_2eq(MWh_{el,produced})^{-1}$ | [19, 20, 43] |

Wind power potential in France V. Smil [34] reviews and estimates an average power density over the year that lies between $0.60 - 0.75 W_{el}/m^2$.

Order of magnitude

A short calculation helps to grasp the potential energy that could be produced by wind turbines. Let's assume that wind turbines are installed on 10 % of the French territory^a. Without oversea departments, France has a space area of $551.7 \times 10^3 km^2$ ^b.

Using a power density of $0.7 W_{el}/m^2$ we reach an annual average electrical power available of

$$0.7 \times 0.1 \times 551 \cdot 10^9 = 39 GW_{el}$$

This implies a total electricity production of

$$39 \times 8760 \text{ hours/year} = 337 TWh_{produced}/year$$

It is, obviously, an order of magnitude calculation; many parameters are over and underestimated. Furthermore, it is not within this work scope to determine how much land should be available to wind turbines. The Espresso database from the JRC [33] reports a potential for onshore of $614 TWh_{produced}/year$ with high land use restrictions.

This order of magnitude indicates the energy produced by onshore wind turbines, depending on the surface area we are willing to allocate. Note that it does not include the potential of offshore wind power.

^aThe JRC ENPRESSO database[33] reports that about 30 % of the French territory could be potentially used to install onshore wind turbines.

^bIn France, cities occupy 18 % of the country, 13.5 % are protected areas and forests cover 31 % .

I.1.3 Hydroelectricity

The technical characteristics presented here describe hydroelectric dams. Other sources of generation, such as run-of-river plants, are not included in this work.

However, for the sake of simplicity, we have not distinguished between the production from different sources (dams, PHS, run-of-river, and others) in the calculation of the

capacity factor of dams. This could influence a few points on this value, but the result remains valid as an order of magnitude.

Capacity factor French energy transition scenarios from RTE [16] foresee an average capacity factor of about 28 %. It is a global value that includes production from dams but also run-of-river, PHS and others. This value is consistent and stable with last years' production (2012 – 2019) [1].

Although this capacity factor does not take into account only the use of dams, it does depict the overall behavior of the French system. We have therefore used this value of the capacity factor for all our studies.

Hydroelectricity in France According to RTE [1], hydroelectricity in France generates, on average, 60 TWh per year. The Figure 2.2 shows the filling level of lake dams in France. At first order, we consider that hydroelectric dams are used during winter. It is at this time that reservoirs reach their minimum level. The dams are then filled during spring and summer. The difference between the minimum and maximum reservoir level is 2 TWh. This amount of energy represents a flexible seasonal average of the French electricity system.

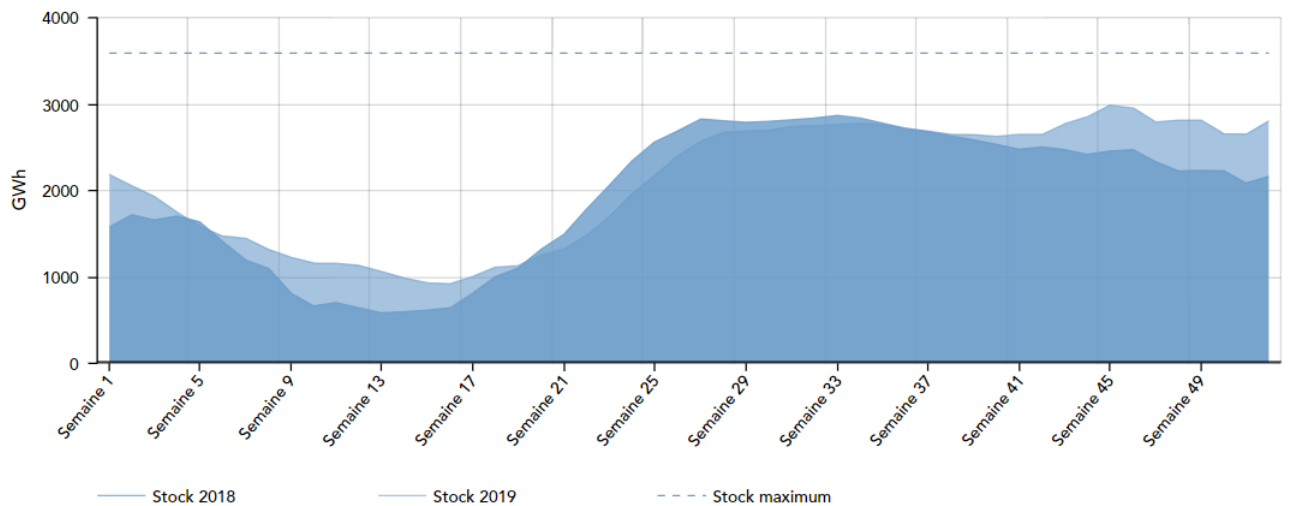


Figure 2.2: Source: RTE, French TSO [1]. Weekly hydraulic stock in lake reservoirs in France. From 2019 to 2018.

Lifetime Most studies reviewed for hydroelectricity dams and Pumped-Hydro-Storage [45] agree on an average life time of 60 years. The life expectation could even reach 100 years [18] for some facilities. We consider a value of 60 years.

Investment costs The European Commission's LCOE [46] refers to a cost of electricity ranging from 30 to 60 €/MWh for hydroelectric dams. These calculations are based on discount rate assumptions which have a strong influence on the result. These values are supported by a wide review made in the Handbook of Energy [47], chapter Hydropower. For large plants (> 10 MW_{out}), they review LCOE ranging between 20 and 100 \$/MWh_{produced}. We will choose a value of 40 €/MWh for our study for lack of better terms and to account for the low cost of hydroelectric.

Table 2.3: Characteristics and costs of hydroelectricity power generation

| Component | Symbol | Quantity | Value | Unit | Ref |
|------------------------|----------------|--------------------------------|------------------|---------------------------------------|--------------|
| Hydroelectricity – Dam | CF | Capacity factor | 28 | % | |
| | $T_{life,cal}$ | Calendar life time | 60 | years | |
| | I_E | € per unit of energy | 40 | $€(MWh_{el,produced})^{-1}$ | |
| | ζ_P | Energy intensity in energy | 15×10^6 | $MJ_{prim}(MW_{el,installed})^{-1}$ | [18, 48, 49] |
| | GWP_E | $CO_{2,eq}$ per unit of energy | 20 | $kgCO_{2,eq}(MWh_{el,produced})^{-1}$ | [19, 20, 31] |

I.1.4 Nuclear power plants

By the end of 2020, there were 61.4 GW of nuclear installed capacity in France, according to [1, 50].

Capacity factor The French nuclear fleet capacity factor had an average of 74.2 % from 2012 to 2015 [51] and reached a minimum of 68.9 % in 2019, according to the French TSO [1]. We consider for the whole study a value of 70 %.

Costs We consider in this work the cost of the existing nuclear power plants. However, it should be noted that the construction cost of new reactors in France and Europe is significantly higher. According to the MIT report, [52], there are two main reasons for this. First, the “*cost of learning*” due to a loss of knowledge when no reactor has been built in a generation. Second, as the report explains, “[...]recent project experience in the United States and Europe has demonstrated repeated failures of construction management practices [...]”. Note that costs presented here represent already existing reactors.

Data available for France estimates an economic cost that ranges from 40 to 60 €/MWh_{produced}. On the one hand, the French energy regulation organism (CRE) [53] set a price of 42 €/MWh. On the other hand, the *Court of Audit*[‡] and EDF [54] claim that the production cost was 50 €/MWh in 2010 and 60 €/MWh in 2013. IEA [25] refers to a cost of life extended nuclear of 43 €/MWh. We arbitrated between these different sources and chose a value of 50 €/MWh.

Table 2.4: Characteristics and costs of nuclear power generation

| Component | Symbol | Quantity | Value | Unit | Ref |
|-----------|----------------|--------------------------------|------------------|---------------------------------------|--------------|
| Nuclear | CF | Capacity factor | 70 | % | |
| | $T_{life,cal}$ | Calendar life time | 60 | years | |
| | I_E | € per unit of energy | 50 | $€(MWh_{el,produced})^{-1}$ | [25, 53, 54] |
| | ζ_P | Energy intensity in energy | 15×10^6 | $MJ_{prim}(MW_{el,installed})^{-1}$ | [18, 48, 49] |
| | GWP_E | $CO_{2,eq}$ per unit of energy | 12 | $kgCO_{2,eq}(MWh_{el,produced})^{-1}$ | [19, 20, 31] |

Seasonal flexibility of French nuclear Nuclear power plants are not operated at their full load factor in France. When compared with other countries [55], some achieve capacity factors of 90 % — USA, for instance. The non-operation at 100 % of the maximum capacity

[‡] *Court des Comptes*, in French

may be due to several reasons, including the following two. First, the facilities follow the load trend during the day and modulate their power to reach so.

Second, plants are shut for scheduled maintenance in summer, during periods of low electricity demand. This ability provides seasonal flexibility to the system. The electricity supply is reduced when less needed (summer) and increased when requested (winter). This phenomenon is particularly noticeable in Figure 2.3, extracted from the French TSO [56]. This graph shows the daily availability of French nuclear power plants over the year. We see that there are about 15 additional GW available in December and January compared to May and June.

In this document, the French TSO note that 85 % of the nuclear power plant are available on average because of this scheduled maintenance.

Order of magnitude:

We consider a nuclear power installed of 60 GW with a 85 % availability rate. We estimate the seasonal flexibility provided by scheduled maintenance such that

$$\text{Flexibility} = 60 \text{ GW} \times 8760/2 \text{ hours/year} \times 15 \% \approx 40 \text{ TWh/year}$$

Thus, we will consider that in France, nuclear power plants provide a seasonal flexibility of about 40 TWh/year.

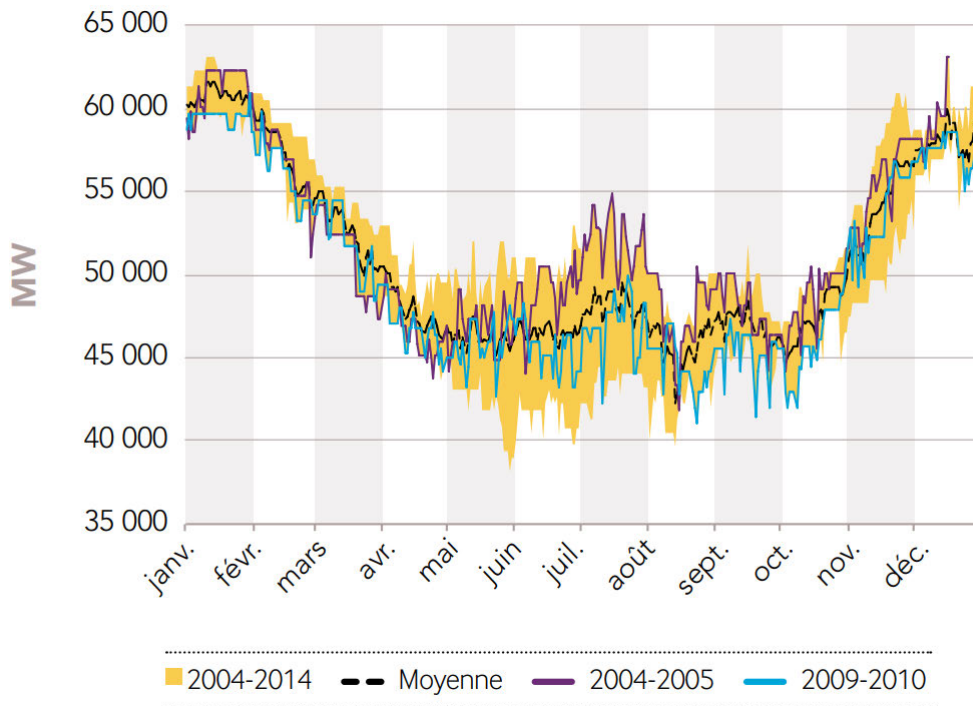


Figure 2.3: Source: RTE, French TSO [56]. Daily availability history of the French nuclear power plants over the period 2004-2014.

I.2 Energy storage

We present in this section storages technologies which have been considered in our analysis. As presented in the previous chapter, note that a device lifetime can either be calendar

or in usage. It would be specified for each technology in the corresponding section. For the specific case of batteries, the usage lifetime is given as a maximum number of charge–discharge cycles that can be performed.

Lifetime, efficiency and cost in € are compared with a 2020 review on energy storage costs from PNNL [57].

Energy storage capacity is denoted by the index $stock$.

I.2.1 Pumped Hydroelectricity Storage

Pumped Hydroelectricity Storage (PHS) is the most developed electricity storage worldwide in energy and power capacity installed. Consequently, there is abundant literature on this topic, and its technical characteristics are correctly assessed. Denholm and Kulcinski [45] reviewed Life Cycle Assessment analyses of ten different facilities and highlights this system’s main features, such as lifetime and efficiency. While these values are typical for most systems, the investment required may vary depending on the system’s terrain and topography. We use costs corresponding to the most common organization of reservoirs and penstocks. Details about world PHS facilities — such as reservoir sizes, land footprint — can be found with many details in the *Hydropower* chapter of Handbook of Energy [47].

Costs The different costs were cross-checked among reviews [45, 57–59].

Two costs describe PHS: one in energy that corresponds to the reservoir, and another cost normalized in power corresponding to the penstocks. Nevertheless, both costs were only available in the literature for investments in euros.

Concerning the embodied energy, both investments ζ_E and ζ_P represent the full system (reservoir + power components). In this case, the cost is calculated with biggest contribution in energy or power. This calculation methodology is detailed in Chapter 3.

For the GWP, an overall cost normalized by energy representing both reservoir and powerhouse was found.

Capacity installed in France. According to EDF[§] [60] there is 100 GWh capacity of PHS installed today in France.

Table 2.5: Characteristics and costs of Pumped Hydroelectricity Storage

| Component | Symbol | Quantity | Value | Unit | Ref |
|-----------|-------------------|-------------------------------------|--------------------|----------------------------------|---------|
| PHS | η | Efficiency | 80 | % | [45] |
| | $T_{life,cal}$ | Calendar life time | 60 | years | [45] |
| | I_P^* | € per unit of power installed | 2.6×10^6 | $\text{€}(MW_{el,out})^{-1}$ | [57–59] |
| | I_E^* | € per unit of energy (storage size) | 1.65×10^5 | $\text{€}(MWh_{el,stock})^{-1}$ | |
| | ζ_P^\dagger | Energy intensity in energy | 20×10^6 | $MJ_{prim}(MW_{el,out})^{-1}$ | [18] |
| | ζ_E^\dagger | Energy intensity in energy | 3.7×10^5 | $MJ_{prim}(MWh_{el,stock})^{-1}$ | [18] |
| | GWP_E^\ddagger | $CO_{2,eq}$ per unit of energy | 35×10^3 | $kgCO_2(MWh_{el,stock})^{-1}$ | [45] |

[§]EDF stands for *Electricité de France*, is the biggest French electricity producer

* I_E is the economic investment for the reservoir, I_P for the power components.

[†]Both *energy intensity* in energy (ζ_E) and power (ζ_P) each represent the investment made for the complete system, including the reservoir and power components.

[‡]GWP in energy (GWP_E) represents the investment made for the complete system, including the reservoir and power components.

I.2.2 Batteries

Batteries are expected to be a cornerstone of the energy transition, either being used in electric vehicles or for stationary storage. Figure 2.4 from Avicenne Energy [61] shows the battery market evolution from 1990 to 2019. We observe that Li-ion batteries are undergoing the fastest growth of all technologies. The capacity installed more than tripled in eight years.

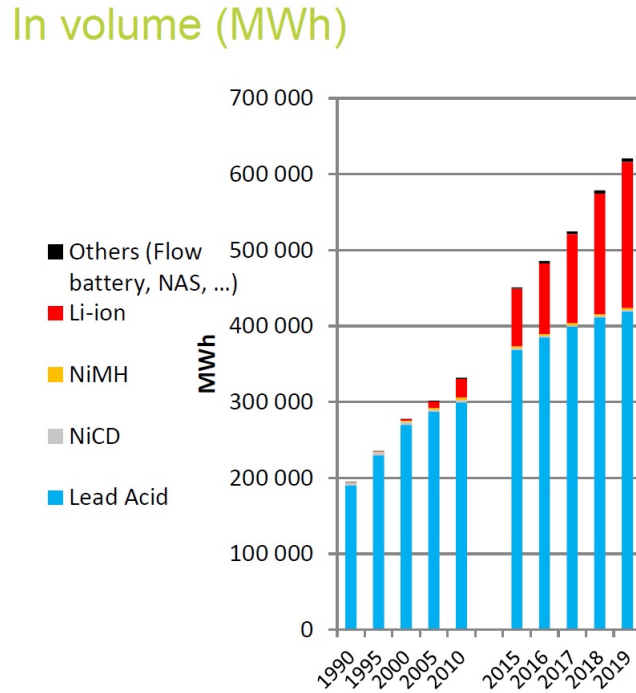


Figure 2.4: Source: C. Pillot, Avicenne Energy [61]. The worldwide battery market from 1990 to 2018, in volume.

Li-ion batteries are expected to be the most widely used and developed because of their high energy density and long life, according to [61]. There are two leading Li-ion technologies used, those of *LFP* and *NMC*. As a first approximation, the figures given can be applied to both chemistries.

Costs Because of their fast development for electric vehicles, Li-ion battery economical cost benefits from a scale effect and decreases fast. We chose an economic cost that reflects the 2020 trend, even though they are expected to keep on decreasing.

Battery manufacturing includes energy-consuming processes that require electricity. Hence, the battery's GWP depends on the factory location and *electricity's CO₂ footprint*. The life cycle analysis of batteries for electric vehicles Kim et al. [62], based on data from 2014, shows a *cradle-to-gate CO₂* of 140 *kg/kWh* of energy capacity. Based on data from 2017, Dai et al. [63] gives a *CO₂* footprint of 70 *kg/kWh*. However, it assumes that electricity was fully decarbonized. Therefore, we consider a Global Warming Potential of 100 *kg/kWh* for the French case study.

Conversely to PHS, it is the same device that provides both energy and power. Thus, the total cost is calculated as the maximum (and not the sum) of both energy and power contributions. Note that the GWP is only normalized by an energy.

Table 2.6: Characteristics of Li-ion batteries.

| Component | Symbol | Quantity | Value | Unit | Ref |
|------------------|----------------|-------------------------------------|-----------------|--------------------------------|-----------------|
| Li-ion batteries | η | Efficiency | 80 | % | |
| | $T_{life,cal}$ | Calendar life time | 15 | years | |
| | N_{max} | Max number of cycles | 5000 | | |
| | I_E | € per unit of energy (storage size) | 3×10^5 | $\text{€} (MWh_{el,in})^{-1}$ | [24, 57–59, 64] |
| | ζ_E | Energy intensity in energy | 2×10^6 | $MJ_{prim} (MWh_{el,in})^{-1}$ | [65–70] |
| | GWP_E | $CO_{2,eq}$ per unit of energy | 10^5 | $kgCO_2 (MWh_{el,in})^{-1}$ | [62, 63] |

I.2.3 Hydrogen

Hydrogen can be a vector for electricity storage, also known as Power-to-gas-to-Power, or simply Power-to-Power (P2P). Different electrolyzer and fuel cell technologies can perform the conversion from and to electricity. We chose to use an Alkaline electrolyzer (AEC) and PEM fuel cell (PEMFC), as described in Figure 2.5.

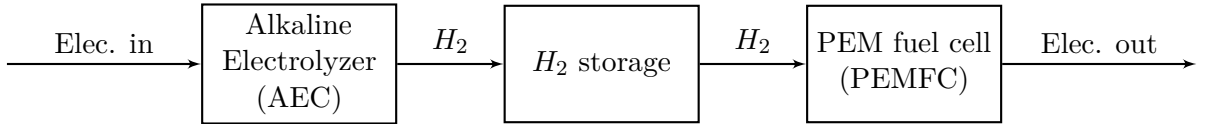


Figure 2.5: Description of the Power-to-gas-to-Power system considered. We use Alkaline electrolyzer and PEM fuel cells.

After water electrolysis and H_2 production, we consider two ways of storing hydrogen:

1. **Steel containers** are commonly used for hydrogen storage. This storage mode is the *reference case* of the study. However, this is not the most suitable solution to store massive amounts of energy (e.g., seasonal energy demand). The number of containers — and therefore, steel — would skyrocket with the cost of gas storage.
2. **Underground storage:** We evaluate the potential of storing large amount of hydrogen in underground storage. In 1979 Foh et al. [71] already presented the state of the art of underground gas storage, especially hydrogen, in depleted gas fields, excavation caverns, aquifer and salt caverns. Besides, recent reviews such as [72–74] agree that this technology is far from mature. It also raises other strong technological issues for hydrogen transportation [75]. There are, however, existing demonstrators. The *Chevron Phillips Clemens Terminal* in Texas is storing H_2 since the 1980s. In 2016, Air Liquide commissioned the largest hydrogen storage facility, an underground cavern in Beaumont, Texas.

Nevertheless, salt caverns would be much cheaper storage for large volumes of hydrogen. A study from PNNL [57] assumes very low costs of storage in salt caverns[¶]. To account for this technology and the potential of a cheaper way of storing large quantity of hydrogen, we carry sensitivity analyses on the storage cost. We prescribe a zero cost for underground hydrogen storage.

In chapter 3, we consider an additional step to the Power-to-Power conversion chain. After the electrolysis, hydrogen has to be compressed. This analysis is made only from the

[¶]The study does not directly provide the cost of underground hydrogen storage. The cost of storing compressed air in salt caverns is given at a $2\$/kWh$ value. Knowing that hydrogen’s energy density is about 100 times higher than the one of compressed air, one can assume the order of magnitude of the cost of storing hydrogen in salt caverns.

Table 2.7: Parameters of the various power-to-gas-to-power components.

| Component | Symbol | Quantity | Value | Unit | Ref |
|-----------------------|----------------------|--|---------------------|---------------------------------|------------------|
| Alkaline Electrolyzer | $T_{life,use,AEC}$ | Lifetime in continuous use | 10^5 | hours | [65, 76–78] |
| | η_{AEC} | Efficiency ($LHV_{H_2}/Electricity_{in}$) | 65 | % | [65, 76, 79, 80] |
| | I_P | € per unit of power | 7.25×10^5 | $\text{€}(MW_{el,in})^{-1}$ | [81–83] |
| | $\zeta_{P,AEC}$ | Energy intensity | $2.4 \cdot 10^6$ | $MJ_{prim}(MW_{el,in})^{-1}$ | [65] |
| | GWP_P | $CO_{2,eq}$ per unit of power | – | $kgCO_{2eq}(MW_{el,in})^{-1}$ | |
| PEM Fuel Cell | $T_{life,use,PEMFC}$ | life-time in continuous use | 10^4 | hours | [65, 84] |
| | η_{PEMFC} | Efficiency ($Electricity_{out}/LHV_{H_2}$) | 45 | % | [84–86] |
| | I_P | € per unit of power | 5.785×10^6 | $\text{€}(MW_{el,out})^{-1}$ | [81–83] |
| | $\zeta_{P,FC}$ | Energy intensity | $1,14 \cdot 10^6$ | $MJ_{prim}(MW_{el,out})^{-1}$ | [65, 87] |
| | GWP_P | $CO_{2,eq}$ per unit of power | 86×10^3 | $kgCO_{2eq}(MW_{el,out})^{-1}$ | [87] |
| H_2 storage | $T_{life,cal,stor}$ | Calendar life-time | 20 | years | Assumption |
| | I_E | € per unit of energy | 2.9 | $\text{€}(MJ_{LHV,H_2})^{-1}$ | [81–83] |
| | ζ_E | Energy intensity | 27 | $MJ_{prim}(MJ_{LHV,H_2})^{-1}$ | [65] |
| | GWP_E | $CO_{2,eq}$ per unit of energy | 1.6 | $kgCO_{2eq}(MJ_{LHV,H_2})^{-1}$ | |
| Compressor | $\zeta_{P,comp}$ | Energy intensity | 2.3×10^5 | $MJ_{prim}(MW_{el,out})^{-1}$ | [65] |
| | η_{comp,H_2} | H_2 compressing efficiency | 90 | % | [85] [86] |
| | $T_{life,use,comp}$ | Life time in continuous use | 10 | years | Assumption |

return on energy investment standpoint only. Other costs (intensity and GWP) are not provided.

Costs We have selected values from the literature that reflect hydrogen’s technical characteristics for stationary storage purposes. Studies show that the electrolyzer and fuel cell maintenance is not negligible in front of the investment cost. The values provided here take this into account.

As hydrogen cost is a controversial issue, we cross-referenced the literature with reports such as ADEME [80], IRENA [83, 88], USA Department of Energy [82] and FCHJU [81].

In this case, contributions of electrolyzer, fuel cell and H_2 storage must be added to calculate the total investment cost. Characteristics are presented in Table 2.7.

I.2.4 CAES

We consider compressed air energy storage based on two existing demonstrators (McIntosh, *Alabama* and Huntorf, *Germany*), with the following process:

$$\text{Electricity} \xrightarrow{\text{compressor}} \text{compressed air} \xrightarrow{\text{air turbine}} \text{Electricity}$$

The air passes through a compressor of up to 13 bar and reaches about 600 °C. Then, it is cooled before being injected into a geological cavern. When energy is required, the compressed air is warmed by a gas heater and sent to a turbine. This storage cannot achieve a high efficiency due to energy losses during the cooling and heating process.

Details about the two demonstrators are provided in [89]. McIntosh, installed in 1978, has a storage capacity of 1160 MWh and an average efficiency of 29 %. Since 1991, Huntorf

|| Calculation made with the following assumptions: 1) 41.5 L can be stored in L50 bottle that weights 56 kg of steel. 2): GWP of steel is $2 kgCO_2/kg steel$. We use the H_2 volumetric mass density at 300 K and 200 bar $\rho_{H_2} = 0.0144 kg/L$ and its Low Heating Value $LHV_{H_2} = 119.96 MJ_{LHV}/kg_{H_2}$.

$$GWP_{stock,steel,H_2} = \frac{GWP_{steel} \cdot mass_{steel}}{Volume_{stock} \cdot \rho_{H_2} \cdot LHV_{H_2}} = 1.56 kgCO_2/MJ_{LHV,H_2}$$

has a capacity of 2640 MWh and a round trip efficiency of 36 %.

New technologies like Adiabatic-CAES are under development and are expecting higher round trip efficiency. They are, however, not yet mature to be set up at a large scale. We consider in the document cost and characteristics of the existing system.

Costs Values provided in Table 2.8 are mainly based on assessment of the two existing demonstrators. Like PHS, Compressed Air systems consist of the energy capacity and a power system. The energy and power contributions are only given for the investment in Euros. They must be added. The energy intensity and the GWP are represented by a normalized global energy cost that considers both energy and power components.

Table 2.8: Characteristics and costs of Compressed Air Energy Storage.

| Component | Symbol | Quantity | Value | Unit | Ref |
|-----------|----------------|-------------------------------------|-------------------|---------------------------------|------|
| CAES | η | Efficiency | 35 | % | |
| | $T_{life,cal}$ | Calendar life time | 40 | years | |
| | I_P | € per unit of power installed | 10^6 | $\text{€}(MWh_{el,out})^{-1}$ | [57] |
| | I_E | € per unit of energy (storage size) | 3×10^6 | $\text{€}(MWh_{el,in})^{-1}$ | |
| | ζ_E | Energy intensity in energy | 2.6×10^5 | $MJ_{prim}(MWh_{el,in})^{-1}$ | [45] |
| | GWP_E | $CO_{2,eq}$ per unit of energy | 19×10^3 | $kgCO_{2,eq}(MWh_{el,in})^{-1}$ | [45] |

I.3 District Heating

District Heating (DH) networks are thermal systems pooling energy infrastructures, particularly production sources, to achieve economies of scale. A heat network distributes hot water to buildings for space heating and other water heating purposes. Heat networks can also be connected to thermal storage facilities.

DH has several advantages over individual heating. It makes it possible to use local fuels such as biomass or waste or take advantage of thermal resources such as industry's waste heat. However, heating networks are only relevant in dense urban areas with high heat demand close to production sources.

The following section briefly introduces some background information to situate heating networks. We will then present the different components considered in the modeling of coupling between heat and electricity networks.

I.3.1 Introduction to District Heating

France does not have a highly developed DH network when compared with other European countries, as reported in ADELE's report [90]. In 2019, 7 % of the French heat demand was supplied by this mean, according to [91]. However, these are likely to be developed, as illustrated by the series of studies carried out by *Heat Road Map Europe* [92], and the French ambitions of the PPE [93]. Besides, Connolly et al. [94] underlines that heating networks have a strong potential to reduce primary energy consumption and CO_2 emissions in Europe.

Historically, the first generations of DH networks operated at high temperatures, above 200 °C. Subsequent generations have reduced their temperature level. The 2nd generation was operated on average above 100 °C, the 4th generation is now running around 70 °C.

Currently, research focuses on the potential for even lower temperatures, the 5th generation. A review of the existing 5th DH generation is carried out by Buffa et al. [95] and presents pros and cons.

I.3.2 Waste heat recovery in France

Nowadays, heat generation from waste incineration represents about $7 \text{ TWh}_{th}/\text{yr}$, according to the French National Union of District Heating and urban air-conditioning (SNCU) [96]. With the PPE [93], France has set targets by 2030 to produce $7.5 \text{ TWh}_{th}/\text{yr}$ from waste incineration and recover $2 \text{ TWh}_{th}/\text{yr}$ of wasted heat.

ADEME [97] assesses a potential of $8.4 \text{ TWh}_{th}/\text{yr}$ available from waste incineration, data centers and sewage treatment to support these figures. Besides, they amount for an additional $109.5 \text{ TWh}_{th}/\text{yr}$ released by the industry, $52.9 \text{ TWh}_{th}/\text{yr}$ at more than 100°C .

Overall, waste heat recovery has a strong potential and could be more extensively developed in France, along with district heating. We use for this work a reference value of $7 \text{ TWh}_{th}/\text{yr}$.

I.3.3 Heat generation

Three different heat production sources are considered: gas boiler, biomass boiler, and waste incineration. The systems considered correspond to collective ones, rather than individual means of production.

Gas boiler For district heating systems, gas boilers run on natural gas, with a capacity ranging between 1 and 20 MW thermal. As these systems rely on fossil fuels, a carbon tax on CO_2 emissions is a potential lever to influence its competitiveness.

Biomass boiler For DH systems, biomass boilers are mostly operated with wood pellets or straw. Their capacity generally varies between 0.5 and 25 MW thermal. Unlike natural gas, biomass is considered clean energy. In the future, its cost could benefit from taxes on fossil fuels.

Costs Economic costs are based on a 2019 study from ADEME [17]. These are overall cost from LCOE, including both operation cost (fuel) and the initial investment.

Table 2.9: Costs of heat generation power plants

| Facility | Economic investment $\text{€}(\text{MWh}_{th,out})^{-1}$ | Ref |
|--------------------|---|------|
| Waste incineration | 20 | [17] |
| Biomass boiler | 70 | [17] |
| Gas boiler | 60 | [17] |

Heat pumps come to complement these heat generation systems. It is presented below.

I.3.4 Heat pump

Heat pumps are energy conversion systems that can produce both heat and cold from input electricity. In our case, only heat production is considered. There are two heat pump technologies, *compression* and *absorption*. The first uses an electrical source to compress the cooling medium and raise the temperature. The second is a tri-thermal heat machine

that will not be considered. Only compression heat pumps are modeled.

For DH, the capacity of the compression heat pump is typically between 3 and 5 MW thermal.

The installation cost of a heat pump per unit of energy installed (CAPEX) is very sensitive to the system size. According to a 2017 IRENA report [88], there is up to a factor of 5 between 50 kW and 1 MW plants. Study [98] reviews large scale HP facilities (>MW) installed for district heating in Sweden. Its feedback helps to understand the aging and other technological stakes of large heat pump facilities. According to this review and the literature analyzed [99–101], a heat pumps' calendar lifetime is on average 20 years.

German and Danish studies [99, 100] provide feedback on existing facilities and show that maintenance represents about 1%/yr of the initial investment cost. With lifetime of 20 years, maintenance reaches 20 % of the initial investment and would be considered.

Heat pumps are characterized by a *Coefficient of Performance* (COP) which is the ratio between the output heat supply and the electrical input work. It is defined such that

$$COP = \frac{E_{th,out}}{E_{el,in}} \quad (2.1)$$

A 2020 IEA report [101] indicates that COP reaches values greater than 5. However, we use an average value of 3.

Table 2.10: Characteristics and costs of heat pump

| Component | Symbol | Quantity | Value | Unit | Ref |
|-----------|----------------|-------------------------------|-----------------|---|----------------|
| Heat pump | COP | Coefficient of performance | 3 | | |
| | $T_{life,cal}$ | Calendar life time | 20 | years | |
| | I_P | € per unit of power installed | 1×10^6 | € · (MW _{th,out}) ⁻¹ | [99, 102, 103] |

I.3.5 Seasonal Thermal Energy Storage

In addition to electricity storage technologies, we are also considering Seasonal Thermal Energy Storage (STES), which would store large amounts of energy. Long-term Thermal Storages (TS) are detailed in reviews [104, 105]. We consider technologies based on heated water, either in tanks or in underground reservoirs. Over a season, the charge – discharge efficiency of such system is about 60 %. This efficiency comes from self-discharge losses. However, thermal storages are modeled in this manuscript only as seasonal storages, so self-discharge is not a necessary input to the study. The characteristics used for this technology are reminded in Table 2.11.

The thermal energy is stored as heated water between 27 °C and 80 °C, which allows its direct use for district heating. Today, there are already operational storages installed on a large scale: 19 GWh in Mastra, Denmark; 90 GWh in Kungälv, Sweden.

Table 2.11: Characteristics and costs of Seasonal Thermal Energy Storage.

| Component | Symbol | Quantity | Value | Unit | Ref |
|---------------------------------|----------------|-------------------------------------|---------|----------------------------------|------------|
| Seasonal Thermal Energy Storage | η | Seasonal efficiency [§] | 60 | % | [104, 105] |
| | $T_{life,cal}$ | Calendar life time | 40 | years | Assumption |
| | | Water heat capacity [¶] | 60 – 80 | $kWh \cdot m^{-3}$ | |
| | I_E | € per unit of energy (storage size) | 10^3 | $\text{€}(MWh_{th,stored})^{-1}$ | [104] |

I.3.6 Heat networks

We present here the characteristics of the district heating distribution system. The distribution network is composed in particular of *pipes* for hot water transportation and *substations*, which ensure water pumping and heat exchange between network and building. The values provided reflect the French district heating system. They are mainly based on the 2019 report from ADEME [90] and personal communications with R. Bavière [106] from CEA Liten, who closely works with French DH system operators.

We characterize the heating network by their cost and losses. It is described in the next points.

Cost We choose to describe the cost of the network using a top-bottom approach. The purpose of this work, we do not need to distinguish all the different components. ADEME in [90] reported that the median cost for heating distribution in France was $19\text{€}/MWh_{th,delivered}$. This value is representative of networks currently being built in the most favorable situations. On average in France, this figure might be higher. However, we will use this median and chose $20\text{€}/MWh_{th,delivered}$.

Losses: Heat losses in the network is the ratio between the yearly energy injected in the network and the energy delivered. According to Gudmundsson et al. [107], modern DHs have 10 % losses. This value, however, depends on the density of the grid. It varies from 5 % for very dense systems to 25 % for more spread ones. There are also energy losses during pumping in the substations. Gudmundsson et al. [107] assess that they are negligible when compared with heat losses. We will consider the average value of 10 %.

Values are summarized in Table 2.12.

Table 2.12: Characteristics of heating networks: distribution grid and substations.

| Component | Symbol | Quantity | Value | Unit | Ref |
|--------------|--------|--------------------------|-------|-------------------------------------|------------|
| Heat network | η | Global annual losses | 10 | % | [106, 107] |
| | I_E | Energy distribution cost | 20 | $\text{€}(MWh_{th,delivered})^{-1}$ | [90, 106] |

I.4 Features of the French energy system

I.4.1 Electricity demand and production

Because of its temperate climate and technological choices, the French energy system has specific patterns that must be detailed before starting its analysis. We represent in Figure 2.6 the 2012 time series of electricity consumption, wind energy, and solar photovoltaic

[§]This value is calculated from the self-discharge of the thermal storage. As this technology is only used seasonally in our models, the self-discharge value does not need to be provided and can be calculated from the seasonal efficiency.

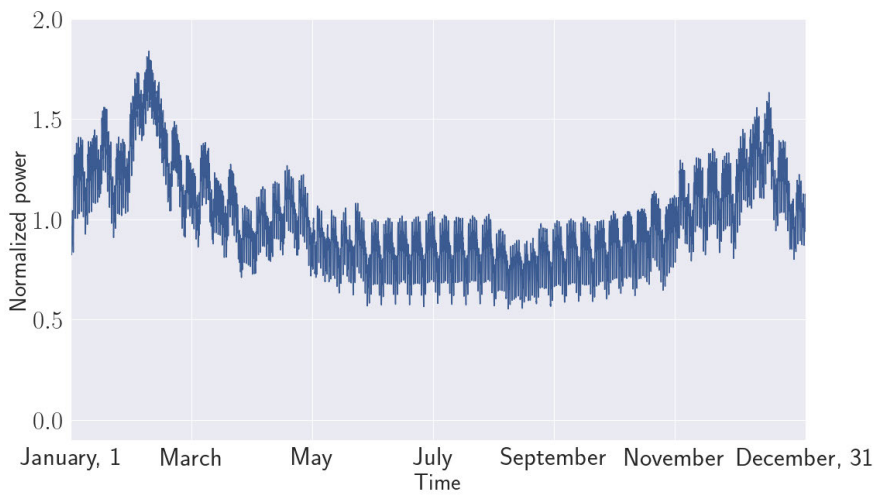
[¶]Provided for information purposes only.

production. All signals are normalized to an average power of 1 to allow comparison between minimum and maximum.

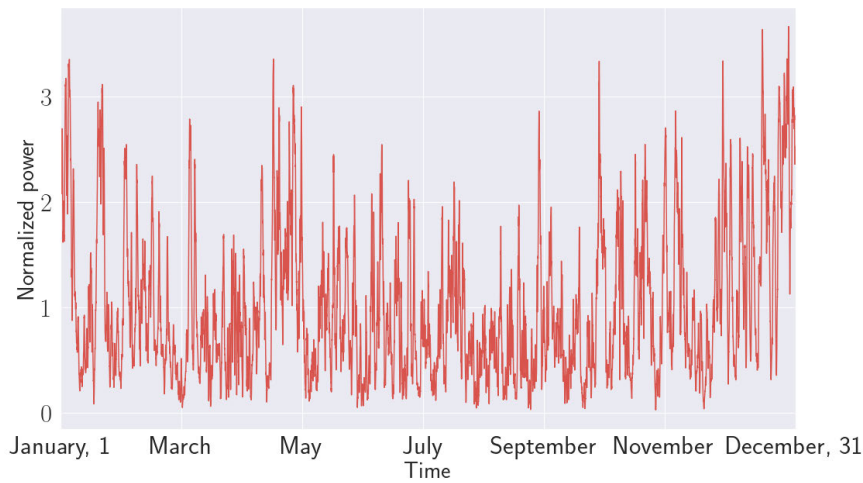
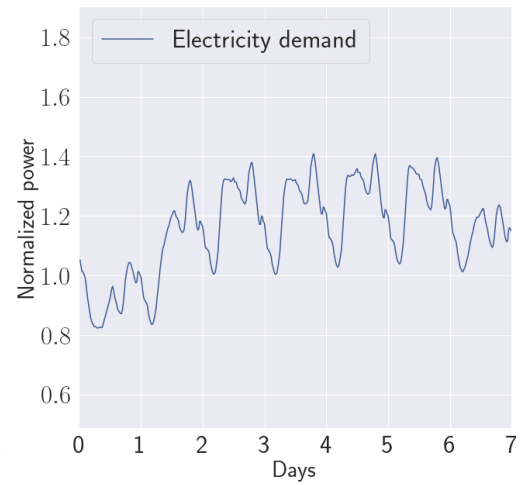
French electricity consumption, illustrated in Figure 2.6a, has a particularly high seasonal variability, mainly because residential and tertiary heating comes from convection heaters. Wind patterns in France — as in the rest of Europe — have a stronger amplitude in winter than in summer, as shown in Figure 2.6b. However, this variation is not as marked as PV production between summer and winter (figure 2.6c). Figure 2.6 highlights that wind generation is in phase with the seasonal electricity demand. It is in contrast to solar PV, which produces when electricity demand is the lowest.

One can also notice that photovoltaic intermittency fluctuates at shorter time-scales than wind power. The latter can remain at low production levels for weeks.

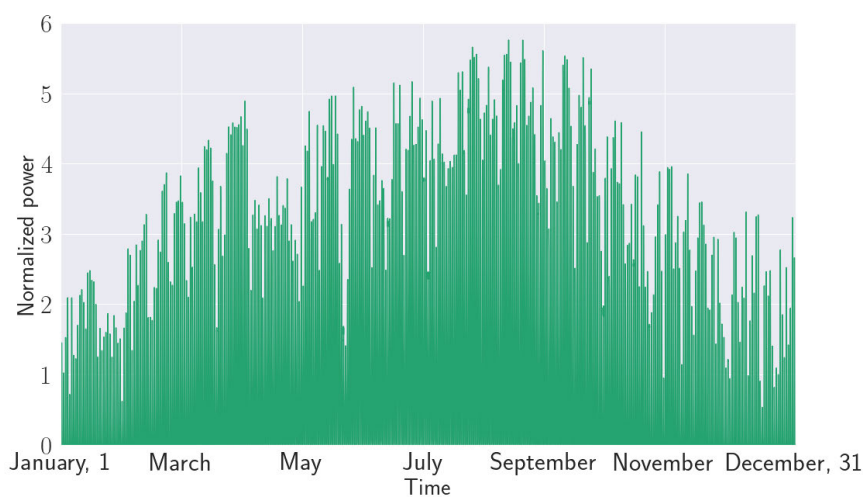
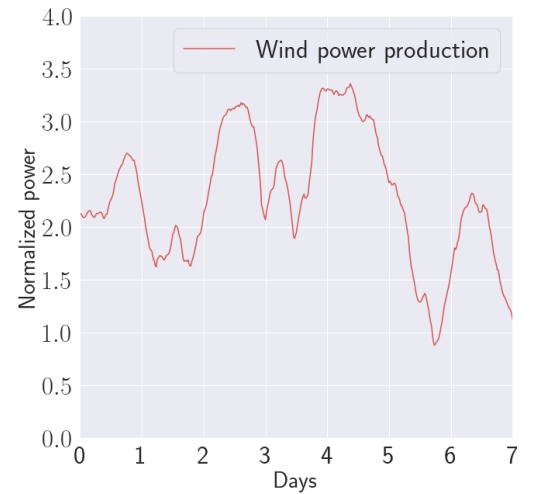
Figure 2.7 divides the annual consumption according to electricity uses: cooking, lighting, and others. The upper blue bump represents the annual heating requirement. It may vary slightly from one year to the next, but represented 14 % of annual consumption in 2015, that is to say, 66 TWh.



(a) Electricity consumption



(b) Wind power



(c) Photovoltaic

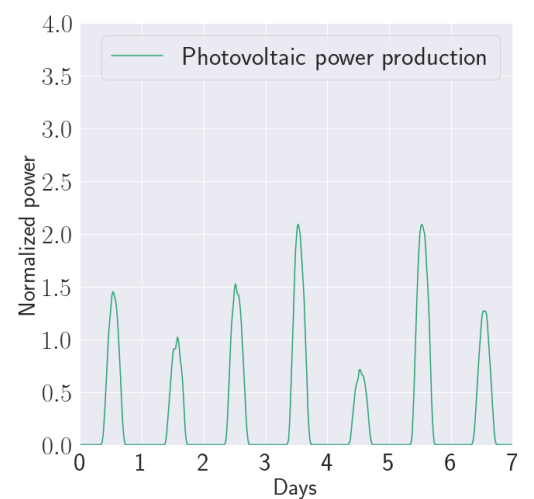


Figure 2.6: One year of electricity consumption in France (a), wind energy production (b) and photovoltaic production (c). All signals are normalized by their average power. Time-series correspond to the year 2012. The figures on the right are a zoom of the first week of the year.

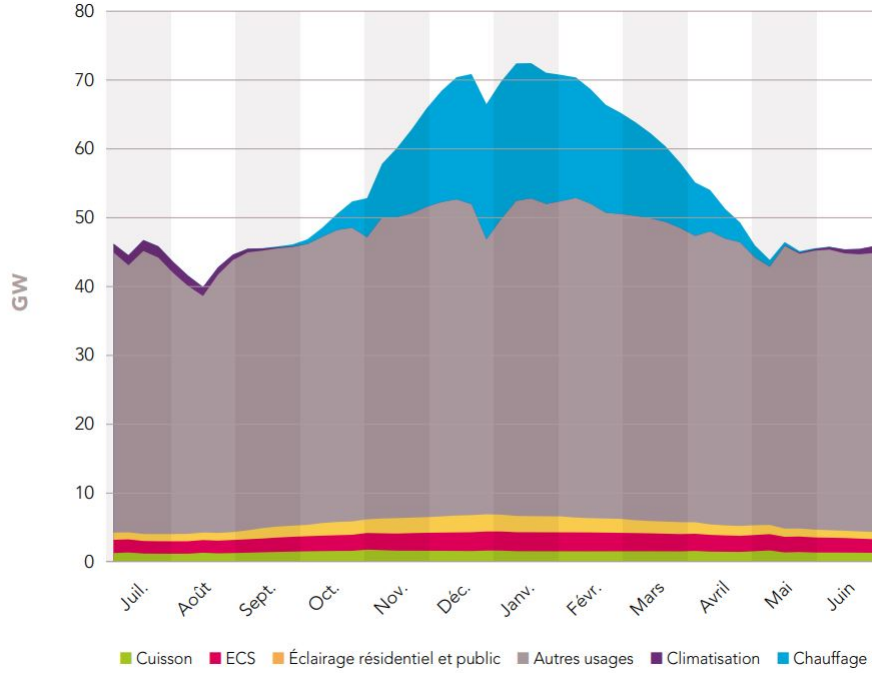


Figure 2.7: Source: [13]. 2015 French electricity consumption, power called per uses. The upper blue part is the electricity used for heating and it corresponds to 14 % of total electricity demand, i.e., 14 TWh in 2015. From bottom to top, we observe *cooking, domestic water heating, lighting, others, Air conditioning* and *heating*.

I.4.2 Heating demand

We provide in Table 2.13 heating demand of the French territory, based on data from 2018, provided by national statistical studies [108, 109]. We only present consumption of tertiary and residential sectors. Industrial needs are assumed to be met by other means than the heating district network. in particular because the temperature level used is different.

Figures are given in terms of thermal energy consumed per year. These values can be

Table 2.13: 2018 French heat demand for residential and tertiary sectors

| TWh_{th}/yr | Residential | Tertiary | Total |
|--------------------|--------------|--------------|--------------|
| Heating | 281.6 | 102.7 | 384.4 |
| Sanitary Hot Water | 47.6 | 22.4 | 70.1 |
| Total | 329.2 | 125.1 | 454.5 |

compared with the energy delivered by district heating in France. In 2017 ADEME [90] reported that it represented 25 TWh_{th} .

II Modeling energy systems: different approaches

After defining the various components of an energy system and their characteristics, we now present a state of the art of energy system modeling.

The energy system modeling community is very diverse, and its tools are numerous. In the following, we propose a classification of this modeling world to underline this work’s motivations.

We first present a general classification of different strategies that can be used to solve a technical problem. Then, we detail the most commonly used tools for energy modeling.

Finally, we illustrate this classification on issues currently being addressed by the energy modeling community.

II.1 Tackling a technical issue

Depending on the intention and need, a problem can be modeled with different levels of complexity. For example, if the objective is to compare two technical solutions quickly, a low-detailed model should be enough. In contrast, when it comes to designing a system that will be implemented on a large scale — a nuclear power plant for example — accurate modeling and analysis is required.

Three chronological phases can be distinguished for tackling a technical problem. It starts with a *screening* of all solutions, followed by a *selection* process. Once the most appropriate solution has been chosen, it finally leads to the final phase, *optimal design*.

These three steps are detailed in the following paragraphs. To give them concrete meaning and easy understanding, each is accompanied by an example in a footnote.

Step 1: Screening — Rough solutions sorting

The first step is to eliminate potential solutions that are not appropriate, using simple calculations and common sense. This is the *screening step*.*

For energy systems, this is typically the approach of D. MacKay or J.-M. Jancovici [110]. Their studies provide meaningful orders of magnitude to evaluate the potential of technologies. In the preface of his book, *Sustainable Energy — without the hot air*[35] D. MacKay clearly states his objective: “*This is a straight talking book about numbers. The aim is to guide the reader around the claptrap to actions that really make a difference*”.

It eliminates infeasible solutions with a rough level of detail. However, it cannot pick up the optimal solution. This phase provides a set of solutions that seem reasonable. In some cases, it may be sufficient. However, in others, more detailed analysis is needed to select the best set of solutions.

Step 2: Selection — Decision aid for system design

Then, the physical feasibility of each solution is assessed in a selection process. Each solution is modeled and compared through a more detailed analysis[†].

This Ph.D. thesis is carried out at this level of detail. We do not want to create an energy transition scenario, or dimension an energy system. The objective is to select the most appropriate solutions and to transfer this knowledge to modelers who conduct more detailed analyses.

*To make easier the understanding these different steps, we use for each a simple and intuitive common example. We consider the following case study: “*Many people want to cross a several km wide river*”.

The screening phase makes the inventory of the possibilities: crossing on foot, taking a plane, a boat or building a bridge. Elements of common sense enable to exclude swimming and taking a plane.

[†]The level of detail here is pushed further to see if the solution is physically acceptable. It is now necessary to carry out calculations to know if it is possible to build a bridge wide enough, is it possible to build a ferry that will accommodate enough cars?

Step 3: Optimal design — Analysis of the different solutions

Third, the system must be precisely sized and designed[‡]. In the context of energy systems, this would correspond to the detailed design of transition scenarios. It would specify the investments such as production capacities, flexibility means, and others.

The scientific literature is rich on this subject: optimizing the dimensioning and operation of micro-grid systems, heat networks, managing the stability of the electricity grid.

II.2 Mathematical toolbox

This section details the different methods commonly used in the energy system modeling field. All problems can be formulated in the same way: in the form of an *Optimization Problem*.

After the problem statement — i.e., after the strategy choice, as presented in section II.1 —, a resolution methodology must be chosen. We distinguish two main families, heuristic-based and optimal methodology. The more precise and detailed the solution needs to be, the more likely the method will rely on optimization. This is detailed in the following points.

1. There are methods based on **heuristics**. It is said of an approach that provides a solution without any guarantee of being optimal or perfect. Nevertheless, it can be sufficient.

Heuristics are common-sense strategies to move intelligently through the solution space to obtain an approximate solution within a reasonable time. It implies, for example, the use of expert rules and simplifications to get closer to the result of a problem.

2. Other methodologies provide the **optimal solution** to the *Optimization Problem*. However, these approaches can be much more time-consuming.

We detail these two points in the following paragraphs.

Heuristic-based methods

Heuristics-based methods may be preferred to optimization methods to reduce the computational burden, or to obtain a quick solution, even if it is an approximation. Those methodologies do not guarantee that the result is optimum.

Heuristic gathers methodologies from the most simples — *the rule of thumb*, for example — to more complex ones such as *system dynamics* with ruled-based models or *Neurals network*. For instance, reports from *Club de Rome* [111, 112], are based on heuristic models of system dynamics.

Optimization methods

Mathematical optimization, also known as **Mathematical Programming**, groups various optimal problem-solving methods. Conversely to heuristics, this approach might be more time-consuming in computation time, but provides an optimal solution to a stated

[‡]Let us assume that building a bridge is the selected solution. It is then necessary to go into the details of its construction and sizing. What type of concrete should be used, what should be the design of the beams, etc?

Optimization Problem.

Depending on the detail level of equations, a resolution method is said linear (LP), linear with integer variables (MILP) or non-linear (NLP). LP and MILP are the most commonly used in the field. However, NLP and even more precise methods can also be found. Those main methods are detailed here:

Linear programming (LP): This method qualifies a problem whose requirements are represented by linear relationships. The *objective function* is a linear function of variables, under constraints that are also linear functions of these same variables.

Mixed Integer Linear Programming (MILP): In addition to a linear programming problem, this type of problem integrates binary decision variables: equal to 0 or 1. This formulation allows accounting for *if statements*.

Non-Linear Programming (NLP): When a problem cannot be described with linear equations and *if statements*, it can be solved using NLP. Nevertheless, algorithms are more processor-intensive and, in general, do not guarantee to find the optimum.

Overall, the more complex the problem is, the more computational time is needed to reach the optimal solution. We need an energy model able to performing numerous simulations. Our problem is described using only linear equations, so that calculations can be done in a reasonable time frame.

II.3 Different problems addressed by the energy modeling communities

We can distinguish different issues addressed by the energy modeling community according to the time scales analyzed.

First, there are the very short-term fluctuations in the power grid, where problems are analyzed through the prism of the *grid stability*. Time-scales at stake are the milliseconds. This stability function is ensured by the inertia of the rotating masses of generation machines, sets connected to the grid.

Second, at the minute scale comes the *frequency relation* questions. To ensure that frequency remains close enough to its nominal value at all times — 50 Hz for the European grid.

Last, at longer time-scales, it is the *balance between electricity supply and demand* which is at stake.

In the context of the energy transition, several questions arise at every time-scale:

- *How to ensure grid stability?* Reducing traditional dispatchable means such as gas, coal, or nuclear power plants diminishes the number of rotating generators. These machines are connected to the same grid and rotate in phase. In case of an accidental shut-down of a machine, the enormous mechanical inertia buffer the shortage and gives time to launch complementary means of production to balance the deficit.

Replacing dispatchable power plants with renewable energies, reduces the grid inertia. New systems will therefore have to be set up to compensate for the loss of inertia.

- *How to develop local and autonomous energy systems?* Small and partially independent energy systems are called micro-grids. Their development requires managing

issues ranging from very short times — the current and voltage control of the different systems — to longer ones, such as managing energy storage stocks.

- *How to operate the network under uncertainty?* Due to partly unpredictable electricity production and electricity market price volatility, the energy system’s operation under uncertainties is critical for integrating RES. This specific point has been, for example, recently addressed in the Ph.D. work of I. Blanco [113].
- *How to plan the development of an energy system along with its investments?* *Energy planning* is the research area we can relate to the most, particularly in terms of the objectives and tools used. Here we briefly present this community’s work and highlight our study’s place among the different approaches.

The general question addressed is the following:

Which component shall be installed to develop an energy system in order to reach an objective — for example, a lower cost — while fulfilling constraints — such as CO₂ emission limitation?

This question is approached in two steps:

1. **A deterministic frame:** decisions are taken knowing all parameters and their evolution in the future: market price, energy demand, weather, etc.
2. **A stochastic frame:** future is unknown, the realization of variables is unknown. It is rising a second issue: “*How to decide for the future with uncertainty?*” This last question is one of the central issues of planning and an ongoing research topic, such as Ph.D. work from S. Moret [114] and A. Nadal [115].

They are many existing tools developed for energy planning, as reviewed in the appendix of Limpens et al. [116]. Additionally, a dynamic planning community aims to develop and share open-source models, known as OpenMod Initiative [117].

Developed since the 1980s, TIMES-MARKAL models [118] represent the evolution over usually 20 to 50 or 100 years of a specific energy-environment system at the global, multi-regional, national, state/province, or community level.

Today, the review from Koltsaklis and Dagoumas [119] shows that most planning models are based on MILP.

To relate to the *strategies* defined above in section II.1, Energy Planning is carried at different levels of detail. Some like S. Moret [114] assessed the potential of different technologies: it is the *selection strategy*. Others would go into more detail and create transition scenarios.

II.4 Position of our work with respect to the state of the art

At first glance, our study might appear very much related to the issues addressed by Energy Planning models. It is, however, quite different. Our main objective is to depict the behavior of the energy system rather than optimizing its sizing and operation.

We address this issue by performing multiple parametric analyses. To avoid computational burden, we have developed models that run fast. Technological models are simply described, we only take into account the main technical trends. Because of the incomplete description of the energy system, we do not know where the complete problem’s overall

optimum lies. We must then explore the whole parameter space. It enables to highlight operation modes of the system, which would not have been detected without the hindsight provided by parametric studies.

II.5 Summary – Energy modeling state of the art

This section’s purpose was not to provide a complete picture of all the energy modeling community’s issues and methodologies. Instead, we have illustrated their diversity and proposed classification to order them to one another.

The number of issues addressed by this community is extremely diverse. They offer various aspects according to the level of detail desired, the geographical scale — from micro-grid to national or even global models — the time scale — from frequency regulation to supply-demand equilibrium or long-term investment planning.

For each of these issues, we have seen that there are many tools available. Their choice depends on the accuracy of the desired modeling.

We have schematized this classification in Figure 2.8.

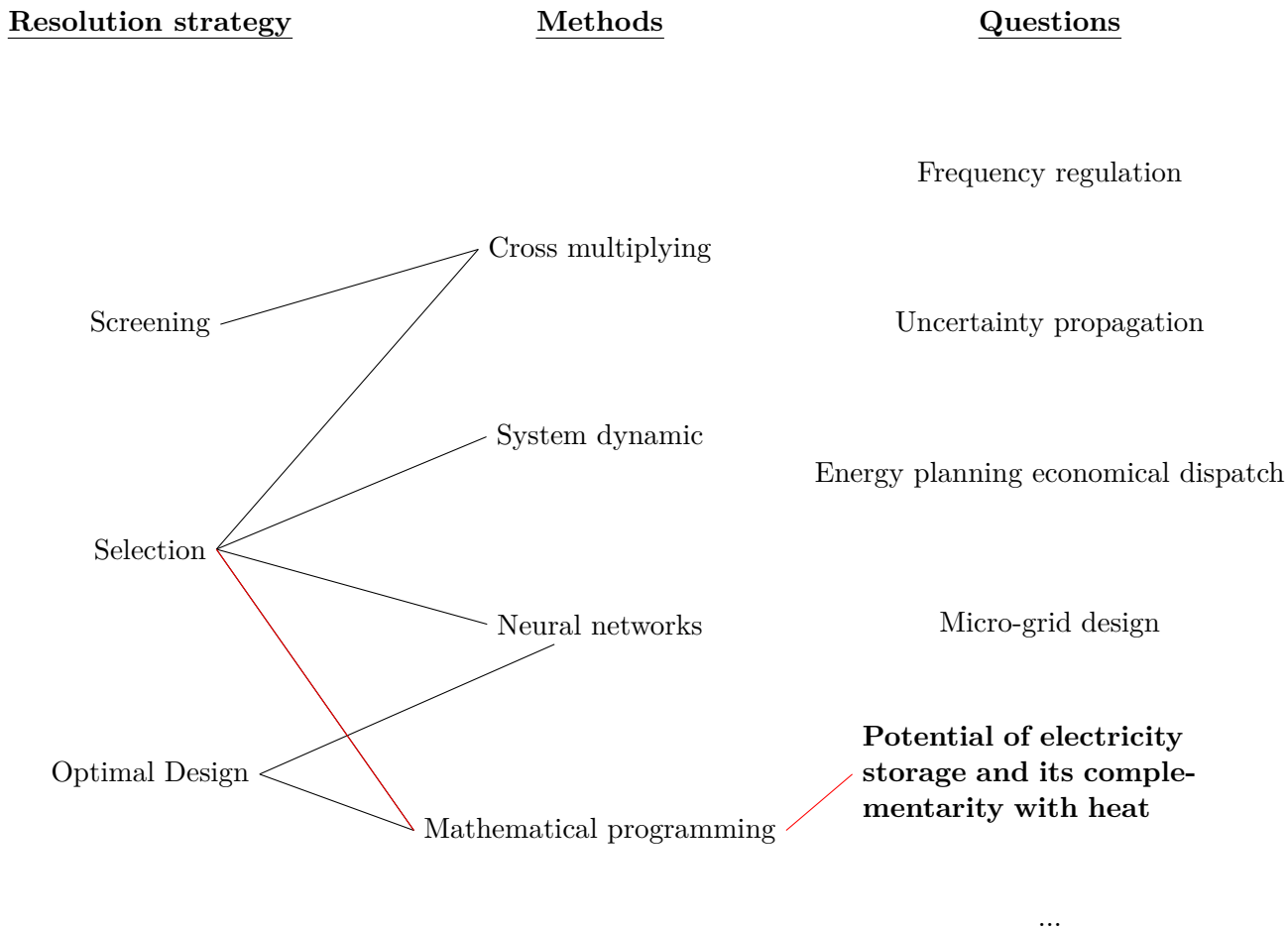


Figure 2.8: Sketch of the classification of different approaches, methods and problems in energy systems modeling. For example, a given question (right column) can be resolved using one of the center’s methodology, with one of the three resolution strategies. This thesis project follows the red line: in the framework of the selection strategy, we use mathematical programming tools to assess electricity storage’s potential and its complementarity with thermal energy as flexibility means. Note that each problem can be treated using different methods, depending on the approach taken. For the sake of clarity, not all paths are represented.

PART II:

DEALING WITH INTERMITTENCY: RESULTS

We present in this part the three chapters of results. They are built in the same way. Starting with a reminder of the questions addressed, we define the study's framework and specify limitations that are not general to the whole thesis. At the end of the chapter, the conclusion will lead to a *Take home message* that summarizes the main ideas.

Storage options and intermittency: Which storage for which time-scale?

This chapter develops a methodology to quantify the intermittency of a signal — e.g., electricity demand, solar photovoltaic and wind power. Here is a short chapter overview:

- Analyses per time-scale of intermittent signals.
- Comparison of the potential of various electricity storage options.
- Analysis from the standpoint of energy return on investment.

This is an extended and more detailed version of Clerjon et al, 2019 [120].

Chapter outlook

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I Questions addressed

The question of electricity storage as a flexible solution has only been addressed recently by the energy modeling community. Hass et al. [121] highlighted in 2017 that “*only the last [7] years research efforts have been put in [expansion planning for energy storage]*”.

Based on the analysis of intermittent electricity production and consumption time-series, this chapter first analyzes the need for flexibility of different power generation mixes. In the context of a large deployment of photovoltaic and wind power, we quantify this need for different time-scales. For example, we size electricity storage capacity to handle daily or seasonal fluctuations.

Once the need for flexibility is quantified, we determine the most suitable solutions to fulfill it. The focus is on electricity storage’s potential to match variable supply and production, excluding any other means. These results are also compared with increasing the electricity generation facilities to ensure that production is on average greater than consumption.

The very core of this chapter is the analysis of the intermittency in terms of time-scales. The potential of each technology is then assessed from the standpoint of energy return on investment*.

II Framework and additional assumptions

In the introductory Chapter 1, we mentioned that this study is dealing with the French situation. Based on actual electricity production and demand signals provided by the French TSO, we create and analyze electricity production time series for any mix generation through a linear combination of solar photovoltaic and wind power. Those signals stem from 2012 to 2018 with data being registered every 30 minutes.

In addition to already stated assumptions, in this chapter only the electric power system is modeled.

Chapter outlook

We start the core of this chapter with a mathematical preamble that provides details about our wavelet decomposition. Next, we develop a twofold approach that addresses the following points:

- *Step 1:* Through the wavelet decomposition of photovoltaic power (PV), wind power and electricity demand time series, we study and **characterize the intermittency at different time scales**.
- *Step 2:* Each storage technology is then evaluated for each time scale from an energy return on investment (EROI) standpoint.

III The wavelet decomposition: mathematical presentation

This section presents a mathematical tool, the wavelet decomposition, which is the cornerstone of our intermittency analysis by time scale. We detail here how this decomposition is applied to the specificities of electricity production and consumption time-series.

*Interactions and dependencies among time-scales or between different storage options — for example between seasonal and daily needs — are not modeled here. This point is discussed in the next chapter.

III.1 Introduction

Theoretical background

A *Wavelet Tour Of Signal Processing* [122] provides clear and detailed explanations to better understand the mathematics of *wavelet decomposition*. We provide here a simplified and practical approach.

This transformation goes from time to time-frequency domain. Figure 3.1 depicts the differences between Fourier and wavelet transformations. Fourier decomposes a signal as a sum of infinite sines. The amplitude of the sine function only returns information averaged in time. However, when it comes to energy-related issues, it is clear that it is crucial to meet demand at each time and that providing an average response is not enough. Let us explain this point with an example. To size daily storage, it matters to know whether there are ten big cycles to perform at some point of the year and nothing at other times, or instead if it would be 365 short cycles. The Fourier transform does not provide this information, but wavelet decomposition does.

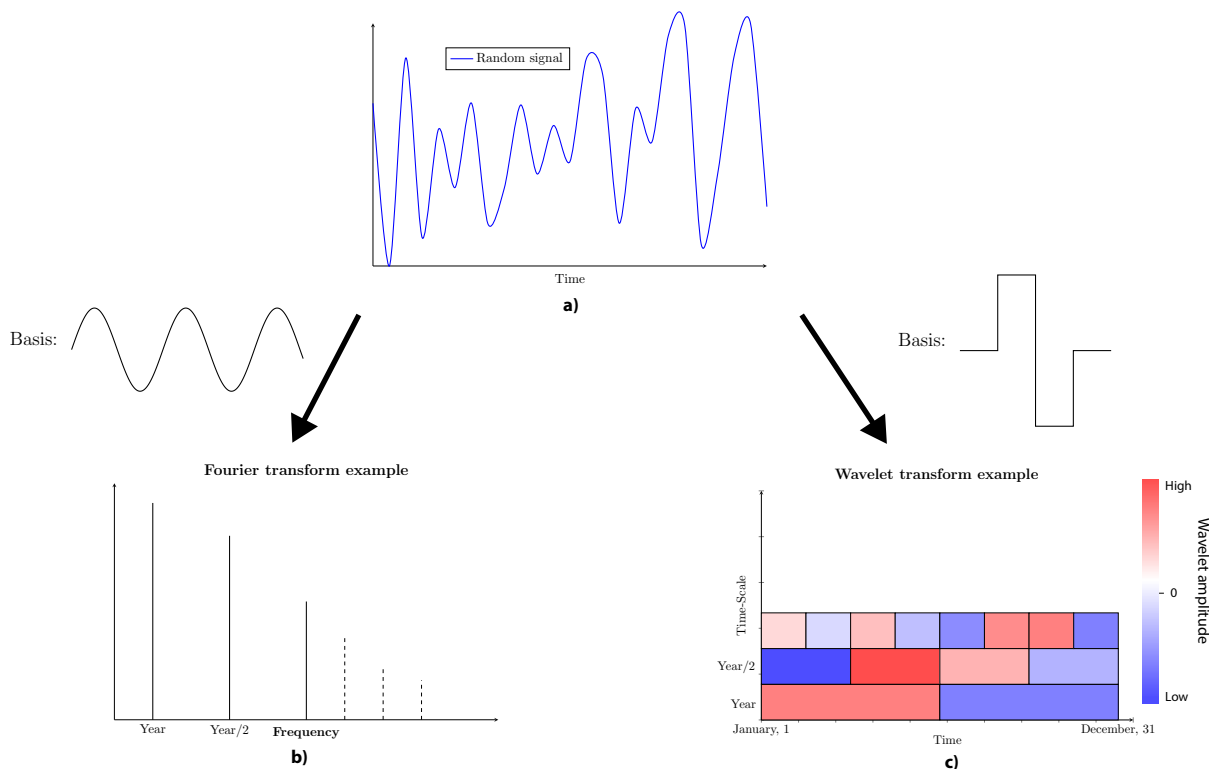


Figure 3.1: Illustration of the differences between Fourier transform and wavelet decomposition. A random signal a) is decomposed into both *Fourier series* b) and *wavelets* c). The Fourier transform decomposes the signal as a sum of infinite sines of different frequencies. It does not enable to localize in time *when and how often* event happens, conversely to wavelet decomposition. Example c) shows a wavelet decomposition with 3 different periods: year, year/2, year/4. The wavelet amplitude is represented as a colormap, red for the positive values, blue for the negative. **How to read this example: The bottom row depicts the seasonal fluctuation: amplitude of the signal is greater over the first half of the year. The second row indicates the fluctuations amplitude of the two 6-months wavelets. It shows that the first 6 months have a greater amplitude fluctuations than the last ones.**

It is necessary to keep the temporal localization and that is what wavelet decomposition does.

S. Mallat [122, chap.1] provides a comprehensive and physical understanding of this distinction:

“Wavelet bases, like Fourier bases, reveal the signal regularity through the amplitude of coefficients, and their structure leads to a fast computational algorithm. However, wavelets are well localized and few coefficients are needed to represent local transient structures. **As opposed to a Fourier basis, a wavelet basis defines a sparse representation of piecewise regular signals**, which may include transients and singularities.”

Let’s explain it with a concrete example. The Fourier transform of a bump, such as a Gaussian, will return many coefficients and not only the central frequency. In the extreme, the Fourier transform of a Dirac will produce a constant. Conversely, wavelet decomposition of such event will be localized in time and frequency.

Practical implementation

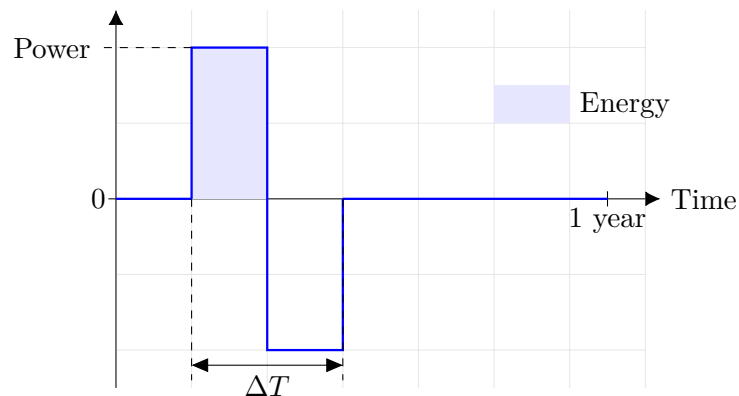


Figure 3.2: An example of a Haar wavelet with its three characteristics: *Energy*, *Power*, and charge-discharge duration *time-scale* ΔT .

We seek here to provide a physical context of this decomposition, because this is the main reason that lead us to employ it.

We mainly worked with Haar wavelets (see Figure 3.2) for their shape close to a charge-discharge signal of an energy storage system — batteries for instance. This decomposition was first introduced by Haar in 1910 [123] for geophysical purposes. From such wavelets, we can define *Power* and *Energy*, as shows the legends of Figure 3.2. In addition to a Fourier transform, a wavelet has beginning and end, characterized by its time-scale ΔT . Thus, it describes at what time power was consumed or produced, unlike Fourier transform where this information is averaged over the signal duration.

The Figure 3.3 shows an approximation of a signal with a set of wavelets of four different time-scales ΔT : 12h, 24h, week/4 and week/2. By using a wavelet base of 15 different time scales pas approximate : we perfectly reproduce the initial signal.

State of the art: wavelet usages for energy modeling

To our knowledge, wavelet decomposition in the field of energy modeling has been mainly used for one purpose: to analyze the temporal pattern of intermittent renewable energy sources. Pérez Ciria et al. [124], analyze the complementary between hydro and solar power along an alpine transect. Similarly, Alam et al. [125] investigates the “*inherent nature of*

wind speed using wavelets and FFT".

The use made in this thesis of wavelet analysis diverges slightly from these studies. The methodology developed not only allows the characterization of the intermittency of renewable sources. It also enables to quantify the need for flexibility due to an intermittent power generation mix at different time-scales, from hour to year.

This methodology is detailed in the following section.

III.2 Method

First, we define a set of wavelets \mathcal{D} : The set is built with time-scales that relate to human rhythms and natural cycles:

1. There are three *mother functions*: wavelets with time scale of
 - A year
 - One week
 - One day
2. Each mother wavelet of time scale ΔT gives two *daughter wavelets* of time scale $\Delta T/2$.
3. We iterate the process on daughter wavelets. Time scales are respectively going from 1 year to a 1/32 of year ; from 1 week to a 1/4 of week, from one day to a 1/32 of day (=45 minutes).
4. We optimise the position of the three mother wavelets upon the signal: yearly wavelets are in phase with the alternation summer/winter. Weekly ones fit to the alternation of working days and week-ends. Daily ones account for the cycle day/night.

Thus, wavelets are defined on time scales ΔT going from 45 minutes to one year.*

Second, the signal f is decomposed such that $f = A\beta$ over the linearly dependent spanning set \mathcal{D} : We define A the wavelet matrix such that

$$A = \begin{bmatrix} \varphi_{11} & \varphi_{12} & \varphi_{13} & \cdots & \varphi_{1n} \\ \varphi_{21} & \varphi_{22} & \varphi_{23} & \cdots & \varphi_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \varphi_{d1} & \varphi_{d2} & \varphi_{d3} & \cdots & \varphi_{dn} \end{bmatrix}_{d>n}$$

with φ_i the wavelets, n the number of wavelets, d the number of data per year. $d > n$.

For mathematical purposes — making sure that the set of wavelets is as much orthogonal as possible — the signals are extrapolated from 48 to 64 data per day. Thus, there is $d = 365 \times 64 = 23360$ points per year and $n = 2^6 + 52 \times 2^3 + 365 \times 2^6 = 23840$ wavelets in the set \mathcal{D} . The number of wavelets is greater than the number of points, which implies \mathcal{D} is not a linearly dependent set of vectors. $23840 - 23360 = 480$ wavelets are a linear combination of the others.

In other words, the set \mathcal{D} is not a proper base but a linearly dependent set.

*For mathematical reasons, wavelets have to be as much as possible orthogonal with one another. It is why cycle length ΔT of daughter wavelets are sub-multiples of the mother cycle length.

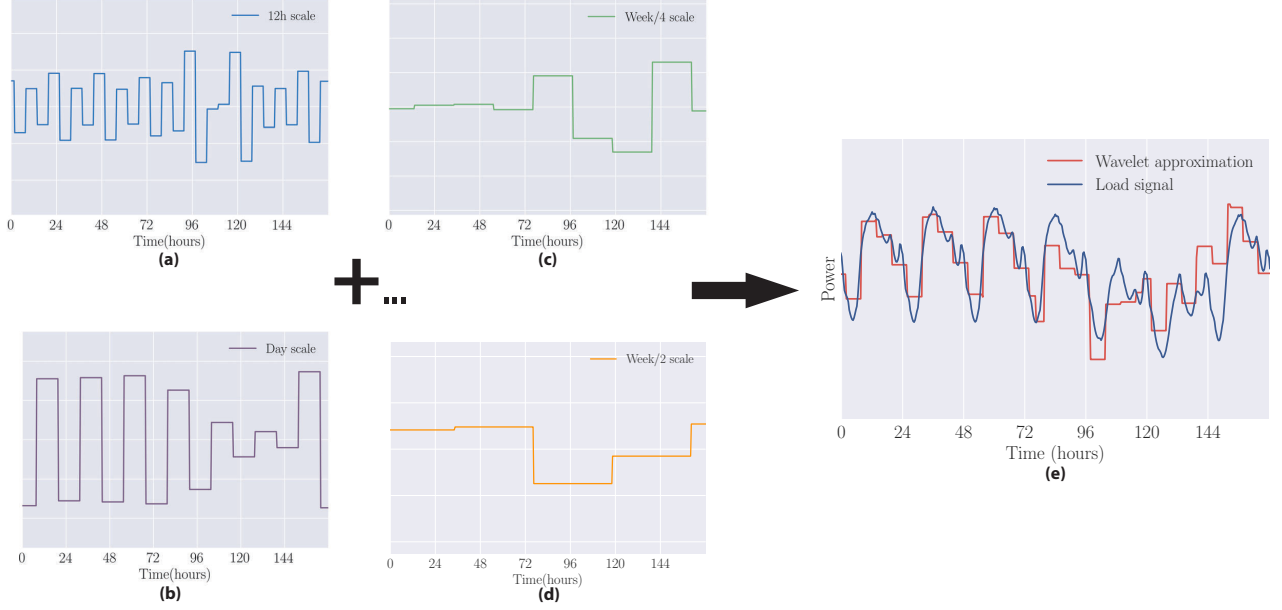


Figure 3.3: Illustration of the wavelet decomposition. Wavelet signals of time-scales $\Delta T = 12$ hours (a), 1 day (b), week/4 (c) and week/2 (d) are summed and placed on top of the original signal (e). Shorter time scales are omitted here to show an imperfect approximation.

Given an input signal f , the wavelet decomposition is the solution to the equation

$$f = A\beta \quad (3.1)$$

However, as pointed out previously, A is not invertible (or even square). With $\text{rank}(A) = n$, we have $\dim(\ker A) = d-n$.

Thus, for any β solution of equation 3.1 and $x \in \ker A$, we have $f = A(\beta + x)$. $\beta + x$ are both solutions of equation 3.1.

To ensure the uniqueness of the decomposition, we have to use an additional constraint on the norm of β . Using the *least-square* algorithm, we provide β , the unique solution to equation 3.1 that minimize $\|\beta\|_2$.

Note that equation 3.1 is equivalent to

$$f = \sum_{i=1}^n \beta_i \varphi_i \quad (3.2)$$

where β_i is the i -th coefficients of the decomposition corresponding to the wavelet φ_i .

Overall, this wavelet decomposition defined by the set \mathcal{D} , enables to transform any input signal f into a unique vector β . This linear application is used to characterize the intermittency of energy signals. The next section presents the decomposition results applied to electricity consumption, wind and solar power time-series.

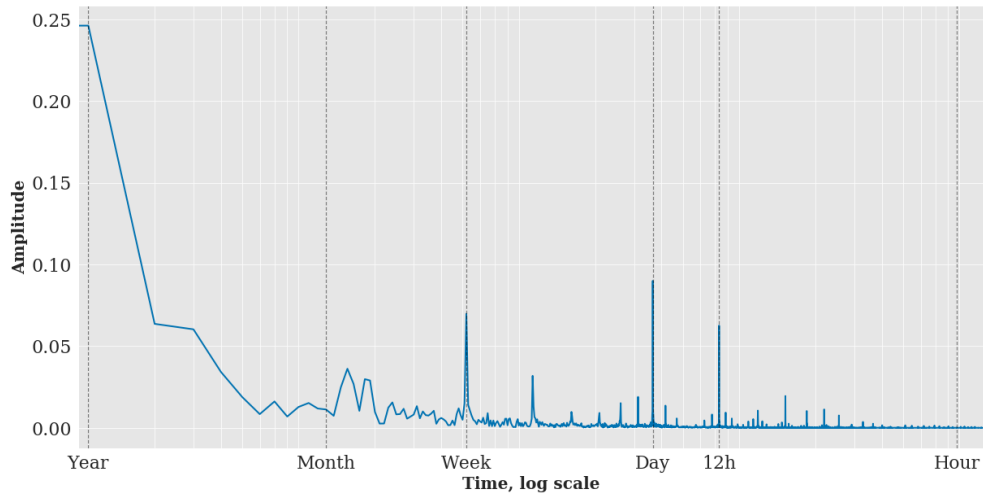
III.3 Results and discussion

Python source codes that enabled to proceed to the following analysis are available on GitHub[†].

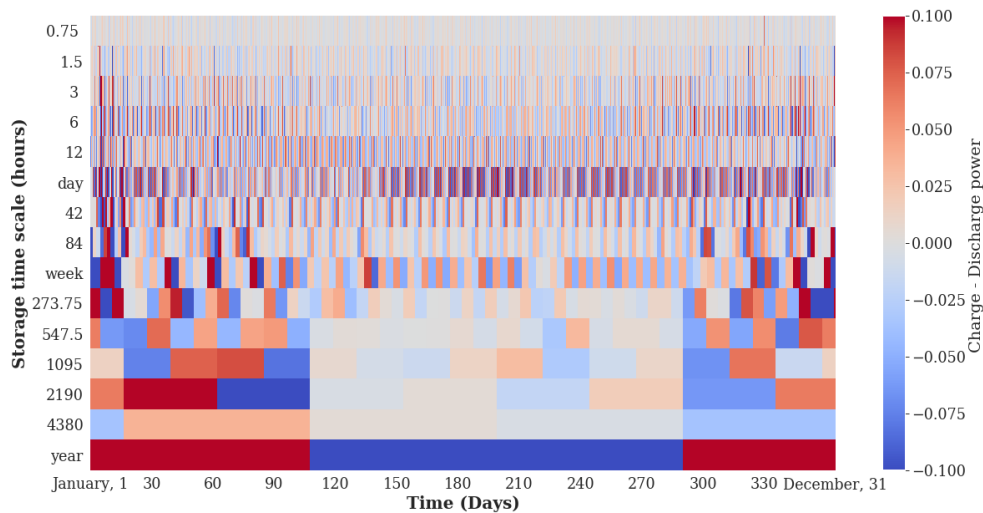
[†]It can be accessed, along with a tutorial, in following link: www.github.com/ArthurClerjon/wavelet_decomposition

As illustrated in Figure 3.1, the wavelet decomposition preserves temporal information from the signal. Results of this transformation are presented in Figures 3.4 and 3.5. They are displayed in the form of a heat map, where colors represent the amplitude of the variability, according to their duration (ordinate) and the time of their occurrence (abscissa). They are compared with a Fast Fourier Transform of the same input signal where the period (occurrence per year) is abscissa. The Fourier *frequency* in abscissa has to be compared with the wavelet *time-scale*, ordinate.

Signals used relate to the year 2018. Figure 3.4 corresponds to the French electricity consumption, Figure 3.5 depicts both the solar PV and wind power generation.



(a) Fast Fourier Transform



(b) Wavelet decomposition

Figure 3.4: FFT (a) versus wavelet decomposition (b) of the French electricity consumption in 2018.

Analysis of the electricity demand is shown in Figure 3.4. To clarify the understanding of the results, the main trends are detailed here:

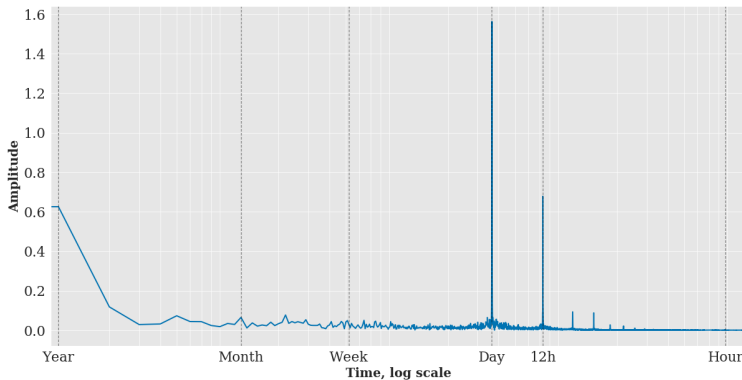
- The variability is the strongest at the year, week and daily scale.
- The *week* row of Figure 3.4b shows that in 2018, the largest fluctuations between weekdays and weekends are observed in December and January. A similar pattern is

observed in the other years, recorded, from 2012 to 2019.

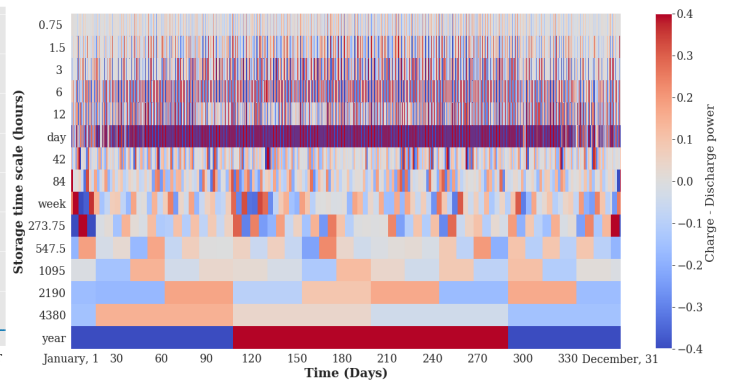
- Figure 3.4b does show that the daily variations in electricity consumption are greater in winter than in summer.

The same exercise can be conducted on photovoltaic and wind power generation of Figure 3.5. These are the main trends and patterns that can be identified:

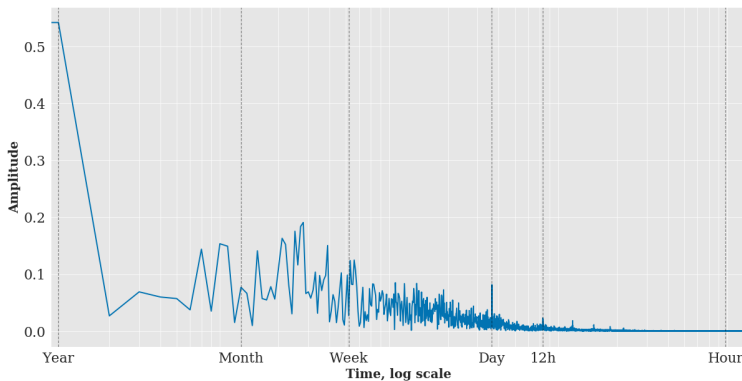
- Unsurprisingly, the intermittency of photovoltaics is highest on a year-round and daily basis.
- On the contrary, wind cycles vary from a few days to few weeks. Wind energy production is higher in winter than in summer, in contrast to PV and on phase with the demand.



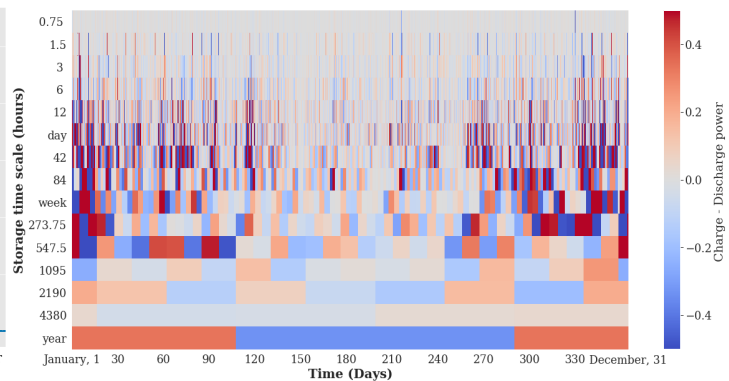
(a) FFT of solar PV signal



(b) Wavelet decomposition of solar PV signal



(c) Fast Fourier Transform of wind power signal



(d) Wavelet decomposition of wind power signal

Figure 3.5: FFT (left) versus wavelet decomposition (right) of two French power generation signals in 2018: PV signals are at the top, wind power generation at the bottom.

Wavelet decomposition reveals patterns and mains trends of intermittent signals. In addition to the Fourier transform, it not only provides the amplitude of the largest fluctuations but also locates these fluctuations over time. We can now answer questions such as "What are the most power-consuming days?" or "What are the windiest weeks of the year?".

The characteristics provided by the wavelet decomposition enable to quantify the necessary flexibility means to match intermittent supply and demand, and so for each time scale. This point is presented in the next section.

IV Step 1: Assessing the required flexibility

After this introduction of wavelet decomposition, we will now use this mathematical tool to analyze time series of consumption and production — PV and wind power.

This section presents a methodology to quantify the need for flexibility generated by a given power generation mix. In other words, we quantify for each time scales the electricity storage capacity required because production is sometimes less than consumption.

IV.1 Methodology: characterizing the flexibility need — a signal analysis

We define the *residual demand* as the difference between the electricity demand and the non-dispatchable production — photovoltaic or wind power for example. From a physical point of view, this represents the power that is not controllable but must be met at all times by flexibility means. It is this quantity that we analyse here by a wavelet decomposition. The methodology is as follows:

1. Decomposition of the seven years of residual demand data as a sum of Haar wavelets.
2. Analysis of the need for flexibility to meet the residual demand. For this purpose we define new indicators in the section [IV.1.1](#).

The results and methodology of this chapter could be extrapolated to the flexibility provided by various means such as dispatchable power plants, demand side management. However, we focus on the analysis of the potential of electricity storage technologies only.

IV.1.1 Definitions: characterizing a storage need with Energy, Power, Number of cycles per year

We characterized a storage need by:

- The amount of *energy* to be stored and delivered **E**
- The maximum power to be delivered **P**
- The *number of charge/discharge* cycles **N** performed during a year

Those three parameters are computed for a given time scale ΔT (daily storage for instance) and are sufficient to characterize a storage need and determine its life time. To simplify the notations, ΔT will be omitted in the text.

Energy (E): The maximal size of an electricity storage that must be installed to handle the variability of a given duration ΔT .

Power (P): The power is computed as $P = \frac{E}{\Delta T/2}$, as shown in [Figure 3.2](#).

Number of cycles / year (N): Numbers of full cycles per year storage sized with an *Energy* E and a *Power* P must perform to handle the variability at time scale ΔT . For example, two cycles that only empty half of a storage equal a full cycle.

As drawn in [Figure 3.6](#), β is the wavelet maximum and ΔT the oscillation duration. It could also be seen as the charge - discharge time of a storage device. The wavelet decomposition previously detailed enables to compute the parameters E , P , N such that

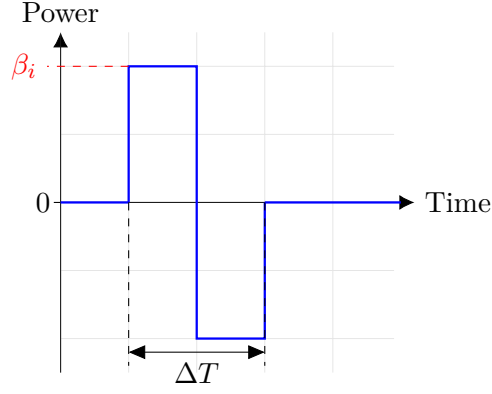


Figure 3.6: Square wavelet indexed by i in time, of time scale ΔT . We refer to its amplitude by β_i .

$$\left\{ \begin{array}{l} P_{\Delta T} = \max_i(|\beta_i|) \\ E_{\Delta T} = P_{\Delta T} \cdot \Delta T / 2 \\ N_{\Delta T} = \frac{\sum_i |\beta_i|}{\max_i(|\beta_i|)} \end{array} \right. \quad (3.3)$$

With i the wavelet index of a wavelet φ_i having a time scale ΔT .

Satisfaction rate: We define a *satisfaction* rate as the time fraction during which the storage can satisfy the residual demand and ensure the balance between load and supply. For example, a rate of 100 % means that the storage is dimensioned to ensure that demand and supply are equal at all times. A rate of 95 % implies that the storage will not provide the required need for 5 % of the time.

This approach makes it possible not to size a system for exceptional occurrences, but for most cases. The 5 % of most significant amplitude events, for example, days of high electricity consumption in winter, can be managed by peak power plants.

The satisfaction rate requires redefining equation 3.3 accordingly:

Let $X \in [0, 100]$ be the satisfaction rate.

For a given time scale ΔT there are M coefficients β_i , $i \in [1; M]$.

We define β_X as the smallest positive real such that

$$\#\{i, |\beta_i| \leq \beta_X\} \geq \frac{X}{100} \times M$$

Where $\#$ is the cardinal.

Said differently, β_X is the X^{th} percentile among the $|\beta_i|$, $i \in [1, M]$.

Therefore, $E_{\Delta T}$, $P_{\Delta T}$ and $N_{\Delta T}$ are calculated such that

$$\left\{ \begin{array}{l} P_{\Delta T} = \beta_X \\ E_{\Delta T} = P_{\Delta T} \cdot \Delta T / 2 \\ N_{\Delta T} = \frac{\sum_i \min(|\beta_i|, \beta_X)}{P_{\Delta T}} \end{array} \right. \quad (3.4)$$

IV.1.2 Definition of additional indicators

The previous characteristics *Energy*, *Power* and *Number of cycles* enable to characterize the storage need for each time scale ΔT . Based on this decomposition per time scale, we define two additional indicators: *Service* and *Utilization factor*. For the sake of readability, the subscript ΔT no longer appears. They are defined here.

Service is the total energy dispatched to the grid over a year, by a storage device and for a given time scale.

$$Service = E \cdot N \quad (3.5)$$

Utilization factor (UF) is the ratio between the energy delivered by a storage throughout a year ($E \cdot N$) and the maximum energy it could have delivered if running at full power all year long ($E \cdot \frac{1}{\Delta T}$). It goes from 0 to 100 %.

Hence

$$UF = N \cdot \Delta T \quad (3.6)$$

The utilization factor is a distinctive feature of the wavelet transform. A Fourier decomposition would have involved a permanent use of the storage and an utilization factor equal to 100 %. UF allows to see if a storage is used regularly, or on the contrary for large and rare events.

IV.1.3 Residual demand definition – Four different case studies

The wavelet decomposition presented above is applied to seven years of French electricity production and consumption data, from 2012 to 2018.

Each additional year provides a statistical insight for each time scale. For example, we take into account for seven different annual fluctuations between summer and winter with a seven-year signal.

To quantify the flexibility need of a production mix, we perform the wavelet decomposition to its residual demand. In this chapter, we compare the four following scenarios:

1. Fully photovoltaic power
2. Fully wind power
3. A hybrid-mix, the French PPE 2028 targets. It is a moderate VRES penetration scenario with 9.1 % of PV, 16.4 % of wind power. More details are provided in chapter 1.
4. No intermittent electricity generation. Production is assumed constant and the only variability comes from the consumption signal.

Based on the different ratios of photovoltaic (PV_{ratio}) and wind power ($Wind_{ratio}$) in the generation mix, ranging between 0 and 1, we create a residual demand time-series such that:

- The average values of production and consumption are equal and amount to 54 GW. This is the average French power consumption used in this thesis work.
- Except for PV and wind power, production of other means (e.g., nuclear and hydropower) is assumed constant. To ease equations readability, we add the time subscript t to the time series variables. $Supply_t$, the electricity production is equal to

$$Supply_t = Average\ load \times [PV_{ratio} \times PV\ signal_t + Wind_{ratio} \times Wind\ signal_t + (1 - PV_{ratio} - Wind_{ratio})] \quad (3.7)$$

With $PV\ signal_t$ and $Wind\ signal_t$ normalized to 1.

We recall that the residual demand is defined as the difference between consumption and non-dispatchable production, in this case $Supply$.

The results presented correspond to the wavelet decomposition of the four scenarios above.

IV.2 Results & Discussion: Main features of the wavelet decomposition

Results of the wavelet decomposition are presented in Figure 3.7. For each scenario — i.e. each line — we calculate three different indicators (y-axis) as a function of the time scale (x-axis). Figure (a) represents the *Energy*, (b) the *Utilization factor* and (c) the *Service*.

These calculations are performed for a 95 % satisfaction rate, see the section IV.1.1 for its definition. This means that, for each time scale, the residual demand is satisfied at all times except for 5 % of the events, when the largest amplitudes occur.

The system is therefore not sized to meet fully the demand. Extreme events can be managed by other means, such as peak power plants.

Sensitivity to satisfaction rate

We analyzed the sensitivity to the *satisfaction rate* for the PPE scenario in Figure 3.8. The same way, we calculate the three indicators presented in section IV.1.2 — Energy, Utilizationfactor, Service — for different satisfaction rate: 80 %, 95 %, 99 % and 100 %.

Figures 3.7 and 3.8 are analyzed and compared in the next paragraph.

Results analysis

Energy, Utilization factor and Service both enable to quantify and characterize the flexibility need of the different scenarios. We analyze here each of these parameters and compare each scenario with one another.

This need for flexibility is presented here as a need for storage capacity.

Energy to be installed (Figures 3.7a and 3.8a) is an increasing function of the storage duration: It goes from GWh to tens of TWh for yearly storage.

The PPE scenario proposes to install 9.1 % of PV and 16.4 % of wind power (see Figure 3.13a). In this case of moderate VRES penetration, the storage energy that must be deployed remains close at long time scale to what is needed for the load

signal alone. However, even if the flexibility need remains close to the actual one, there are less dispatchable power plants providing the required flexibility. All this implies an increased need for new means of flexibility, such as electricity storage.

It is meaningful to compare this energy with the actual flexible capacity available in France. This comparison is presented in Figure 3.9 and Table 3.1. Additional details about the French flexible capacity can be found in chapter 2. This comparison shows that PHS can handle up to one day of the current flexibility need. Dams enables to reach time scales up to a few weeks. However, there remain several orders of magnitude to deal with yearly fluctuations. This is hardly done thanks to the seasonal flexibility of nuclear power plants. It emphasizes that today, seasonal variability is a central issue that cannot be addressed without dispatchable power plants.

Analysis of different scenarios for 95 % satisfaction

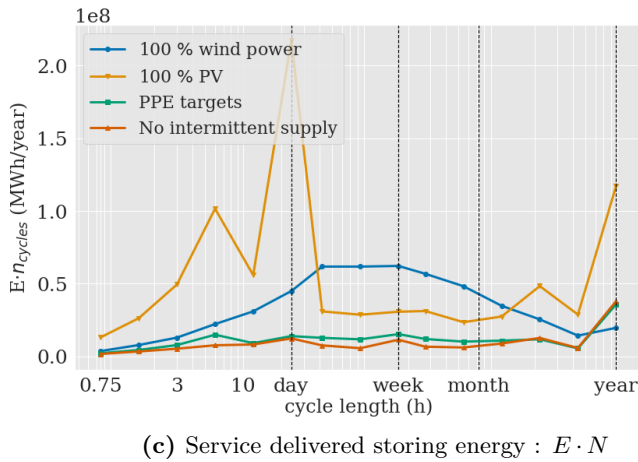
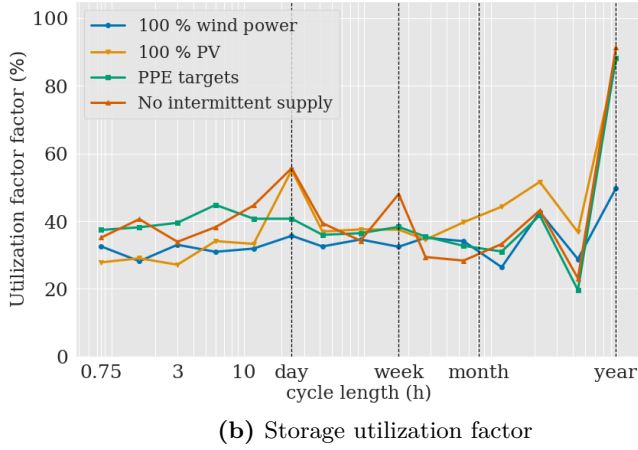
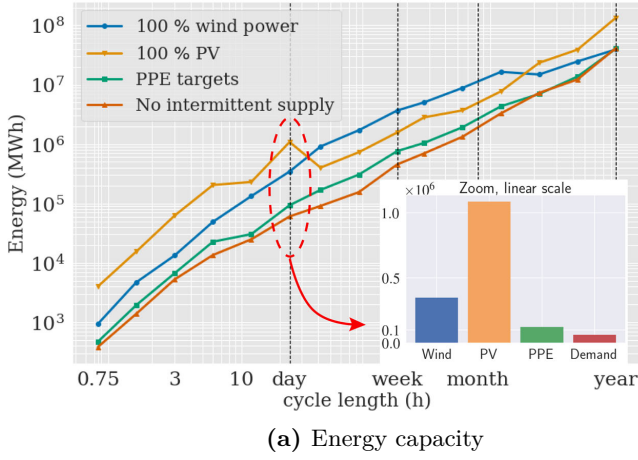


Figure 3.7: Decomposition of the residual demand of several electricity generation mixes: 100 % Photovoltaic, 100 % wind power, and the intermittent mix from PPE 2028 targets: 9.1 % PV, 16.4 % wind Power. Those results can be compared with the intermittency generated by the load signal. Satisfaction rate, as defined in section IV.1.1, is 95 %. (a) shows E , the energy capacity that would have to be stored for each time scale. (b) shows the storage utilization factor, (c) the total energy stored per year.

Influence of satisfaction for PPE scenario.

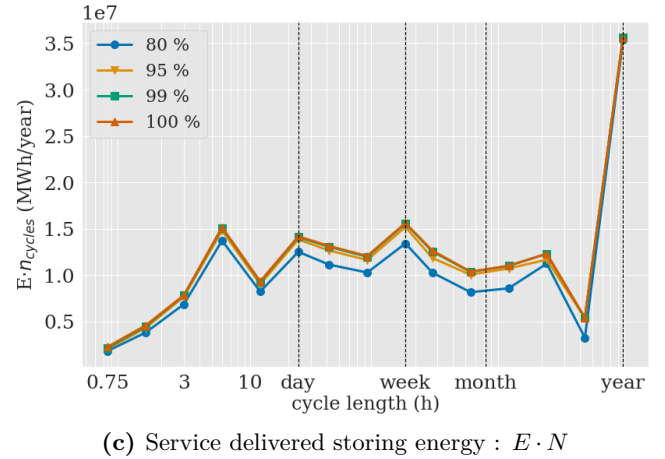
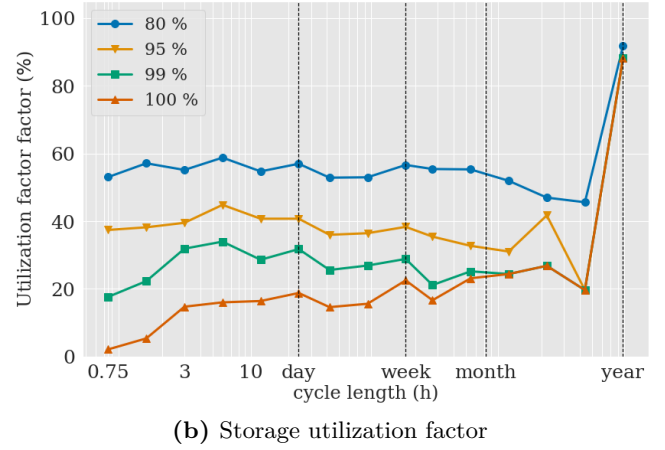
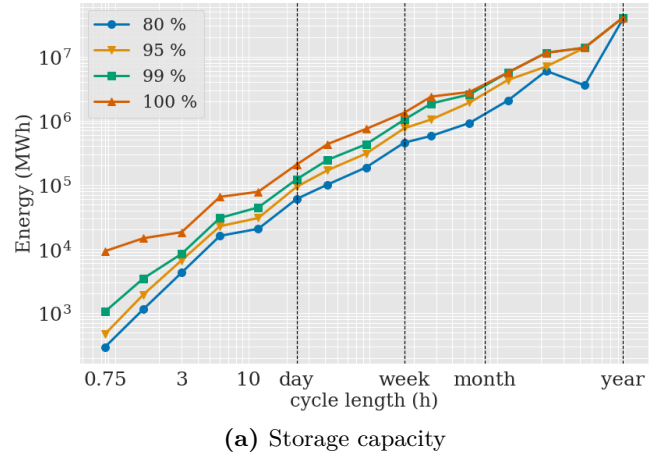


Figure 3.8: Decomposition of the residual demand for the 2028 PPE target energy mix for various satisfaction rates, from 80 % to 100 %. (c) shows that the service provided is not very different from 90 % to 100 % satisfaction rate. However, the installed energy increases by an order of magnitude (a), while the utilization factor of the storage degrades by the same amount (b), leading to much less profitable storage.

Utilization Factor Figure 3.8b stresses that 100 % satisfaction will result in storage devices which are not profitable as will be little used (have a low utilisation factor). It raises the question of the installation of dispatchable production means for the highest consumption periods: storage can be sized to provide most of the service, when exceptional events would be handled by peak generation means. In other words, the storage would satisfy the consumption at all time except when exceptional events occur. In this case the exceptional event energy demands — the last percent — would have to be covered by peak generation means.

Service is the total energy that would have to be discharged over a year, for a given time scale (Figures 3.7c and 3.8c). This quantity highlights the specific features of each residual demand:

- Photovoltaic has two maxima, at the day and year scales. It accounts for the day/night and the summer/winter cycles for solar input.
- Wind power intermittency is the highest between one day and one month. It results from the typical length of wind systems and their dynamics.
- The load is also an intermittent signal. We observe three higher peaks, at the day, week and year scale. It is a pattern of the electricity French consumption.
- The PPE scenario has a moderate penetration rate of variable renewable electricity (27 %). When compared with the consumption only, we notice that the service is not strongly modified. It is even lower at the year scale, thanks to the higher production of wind power during winter, when demand is at its highest. In other words, PV, wind power, load are not in-phase, so their intermittencies do not add up.
- A last point must be noted from analysis of Figures 3.7c. The *Service* shows that intermittency is not additive. In other words, *Service* of PPE targets is different *Service*. It is also true for the other indicators, Energy and Utilization factor.

Satisfaction Figure 3.8a reveals that at short time scales there is an energy gap greater than one order of magnitude between 95 % and 100 % of satisfaction. At 100 % it is the exceptional events which set the size of the capacity. Fulfilling the last 5 – 10 percent of satisfaction requires a strong investment in terms of installed storage capacity — up to a factor 10 — for a small additional service. It may be more relevant to have "additional production" active only when those rare events occur.

Table 3.1: Flexibility capacity available in France in 2020. See chapter 2 for more details and references.

| Flexibility mean | Capacity (GWh/year) |
|--------------------------------------|---------------------|
| Shut down of nuclear for maintenance | 40×10^3 |
| Hydroelectricity dams | 2×10^3 |
| PHS | 100 |

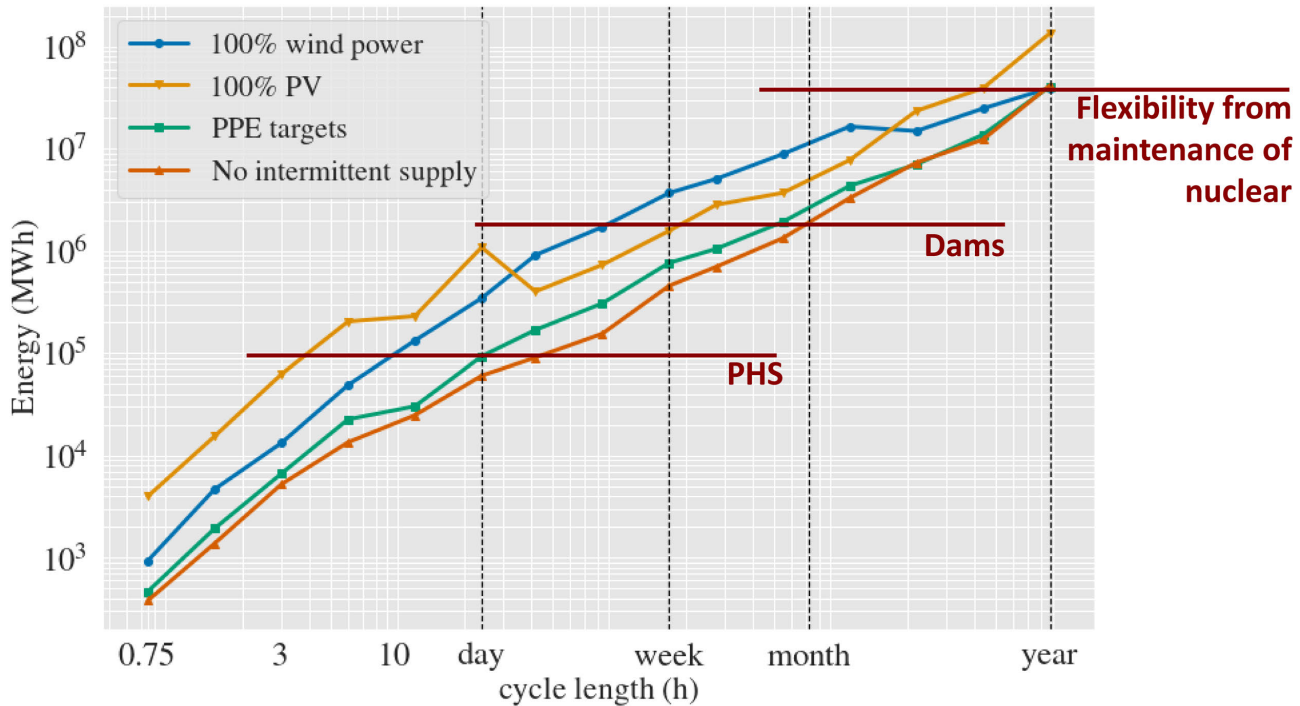


Figure 3.9: Zoom of Figure 3.7a. It shows the flexibility requirements in terms of energy capacity (y-axis) of 4 power generation scenarios, calculated for each time scale (x-axis), going from 45 minutes (left) to one year (right). The need for flexibility is compared to the French flexible means: PHS, hydroelectricity dams. We also add the flexibility provided by deliberate nuclear shutdowns for maintenance. More details on these flexible means are available in Table 3.1 and chapter 3.

Main conclusions

Among these results, the following are particularly noteworthy:

- The more intermittent the production, the greater the need for flexibility.
- The need for flexibility increases even more strongly with the time scale considered. There are 3 to 4 orders of magnitude between short-term and seasonal needs. Compared to the existing flexible capacity, the seasonal variability of electricity consumption is a crucial element. Today, the shift in consumption between summer and winter can only be managed with dispatchable power plants.
- Finally, we have seen a real interest in not sizing a storage system to satisfy 100 % of demand. Indeed, this implies oversizing the storage to ensure that it can handle rare events of high amplitude. For example, to satisfy daily needs, storage is sized to go through days when consumption is highest, in winter. The rest of the time, it is not used to its full capacity. It may be appropriate not to size the storage for these rare events, and for example, to handle them with peaking power plants.

V Step 2: Assessing the sustainability of storage solutions

In the previous section, we analyzed the variability of electricity production and consumption time-series. It enables quantified the flexibility required by different electricity production scenarios for time scales ranging from 45 minutes to one year.

This work emphasized the importance of distinguishing different time-scales of intermittency. Daily, weekly and seasonal fluctuations indeed represent very different needs, particularly in terms of energy capacity, and must therefore be treated differently.

In this second section, we will compare for each time-scale the potential of different electricity flexible means.

V.1 Input data: Technical characteristics of storage and production devices

All technologies used in this analysis have already been presented and characterized in the chapter 2. In this chapter, our analysis are carried from the stand point of energy return on investment. Costs refer to ζ , the energy intensity of a system.

We start by presenting the technological framework of this analysis and summarize the different technological characteristics used.

V.1.1 Storage devices

Five different electricity storage devices are considered: Li-ion batteries, Pumped Hydroelectricity Storage, Compressed Air Energy Storage and Power-to-Power through hydrogen.

For this latest, we consider two manners of storing hydrogen, in steel containers and geological caverns.

These five storages are eventually compared with an additional flexible solution: oversizing the electricity production to ensure that supply is always greater than demand. The excess electricity is then curtailed. We refer to this solution as *curtailment* or *oversizing*. Curtailment is modeled as a storage with a null cost and a null efficiency.

Storage characteristics are reminded in Table 3.2. Parameters for H_2 storage are them detailed in Table 3.3.

Table 3.2: Parameters of storage devices except power-to-gas-to-power.

| Component | Symbol | Quantity | Value | Unit |
|------------------|----------------|----------------------------|------------------|----------------------------------|
| Li-ion batteries | ζ_E | Energy intensity in energy | $2 \cdot 10^6$ | $MJ_{prim}(MWh_{el,stock})^{-1}$ |
| | η | Efficiency | 80 | % |
| | $T_{life,cal}$ | Calendar life time | 15 | years |
| | N_{max} | Max number of cycles | 5000 | |
| CAES | ζ_E | Energy intensity in energy | $2,6 \cdot 10^5$ | $MJ_{prim}(MWh_{el,stock})^{-1}$ |
| | η | Efficiency | 35 | % |
| | $T_{life,cal}$ | Calendar lifetime | 40 | years |
| PHS | ζ_E | Energy intensity in energy | $3,7 \cdot 10^5$ | $MJ_{prim}(MWh_{el,stock})^{-1}$ |
| | ζ_P | Energy intensity in power | $20 \cdot 10^6$ | $MJ_{prim}(MW_{el,out})^{-1}$ |
| | η | Efficiency | 80 | % |
| | $T_{life,cal}$ | Calendar lifetime | 60 | years |

Table 3.3: Parameters of the various power-to-gas-to-power components.

| Component | Symbol | Quantity | Value | Unit |
|-----------------------|------------------------------|---|-------------------|--------------------------------|
| Alkaline Electrolyzer | $\zeta_{P,AEC}$ | Energy intensity | $2.4 \cdot 10^6$ | $MJ_{prim}(MW_{el,in})^{-1}$ |
| | $T_{life,use,AEC}$ | Lifetime in continuous use | 10^5 | hours |
| | η_{AEC} | Efficiency ($LHV_{H_2}/Electricity_{in}$) | 65 | % |
| Compressor | $\zeta_{P,comp}$ | Energy intensity | $2,3 \cdot 10^5$ | $MJ_{prim}(MW_{el,in})$ |
| | η_{comp,H_2} | H_2 compressing efficiency | 90,5 | % |
| | $T_{life,use,comp}$ | Lifetime in continuous use | 10 | years |
| PEM Fuel Cell | $\zeta_{P,FC}$ | Energy intensity | $1,14 \cdot 10^6$ | $MJ_{prim}(MW_{el,out})^{-1}$ |
| | $T_{life,use,PEMFC}$ | Lifetime in continuous use | 10^4 | hours |
| | η_{PEMFC} | Efficiency ($Electricity_{out}/LHV_{H_2}$) | 45 | % |
| H_2 storage | $\zeta_{steel\ storage,H_2}$ | Energy intensity of steel bottles for H_2 storage | 27 | $MJ_{prim}(MJ_{LHV,H_2})^{-1}$ |
| | $\zeta_{H_2\ storage,geol}$ | Energy intensity of geological cavities | 0 | $MJ_{prim}(MJ_{LHV,H_2})^{-1}$ |
| | $T_{life,cal,stor}$ | Calendar lifetime | 20 | years |

Energy production facilities

Costs and characteristics of electricity generation devices are also reminded from the bibliographical chapter in table 3.4.

Table 3.4: Parameters used for power generation devices.

| Facility | ζ_P $MJ_{prim}(MW_{el,out})^{-1}$ | $T_{life,cal}$ year | Capacity Factor % |
|-------------------|--|------------------------|----------------------|
| Wind power | $10 \cdot 10^6$ | 20 | 23 % |
| Photovoltaic | $25 \cdot 10^6$ | 30 | 14 % |
| Nuclear Power | $20 \cdot 10^6$ | 60 | 75 % |
| Hydro-electricity | $15 \cdot 10^6$ | 60 | 28 % |

V.2 Methodology: Total embodied energy calculation

We present the methodology for calculating the embodied energy invested in a system to manage a given time scale variability. This primary energy is then compared to the flexible energy supplied, i.e., the energy to displace to ensure the balance between production and consumption

We use an energy return on investment indicator, the ESOI (Energy Stored On Invested). It was, to our knowledge, first introduced by Barnhart et al. [69]. It is defined such that

$$ESOI = \frac{[\text{Energy dispatched to the grid over life time}]_{electricity}}{[\text{Energy required for manufacturing}]_{primary}} \quad (3.8)$$

V.2.1 Energy cost calculation

Investments needed to handle the intermittency are double. There is a direct cost, which corresponds to the cost of the device itself (battery, PHS...). Nevertheless, storage efficiency is lower than 1. Delivering a given power after storage requires oversized electricity production, leading to an indirect cost. This is illustrated in Figure 3.10.

Storage cost: We assign a cost per year to each storage device. The calculation changes depending on the definition of the lifetime, whether it is calendar, continuous use, or

maximum number of cycles. We calculate the cost of a device (numerator) as the maximum investment in energy (ζ_E) or power (ζ_P), when data are available. When a system is composed of several parts, such as power-to-power, the devices' cost must be added (electrolyzer, H_2 storage and fuel cell).

When a device is characterized by its *continuous use lifetime*, cost is computed such that

$$Cost/yr = \frac{\max(E \cdot \zeta_E; P \cdot \zeta_P)}{T_{life,use} \cdot \frac{P}{E \cdot N}} \quad (3.9)$$

It is how electrolyzer and fuel cell annual cost are calculated.

When a device is limited by a *calendar lifetime*:

$$Cost/yr = \frac{\max(E \cdot \zeta_E; P \cdot \zeta_P)}{T_{life,cal}} \quad (3.10)$$

This calculation method is used for compressed air and pumped hydroelectricity storage. CAES is characterized by an average energy investment, representing both the investment for the reservoir (energy) and the electrical system.

PHS is described by both an energy and a power intensity. Each value represents the global system, both reservoir and power components. Thus, the cost is calculated as the maximum value of energy and power contributions.

The cost of the hydrogen tank is also calculated in this way.

For *batteries*, which are both characterized by a maximum number of cycles they can reach and a calendar lifetime:

$$Cost_{batterie}/yr = \frac{E \times \zeta_E}{\min(\frac{N_{max}}{N}; T_{life,cal})} \quad (3.11)$$

Production cost: Storage cost does not involve the efficiency η . When $\eta < 1$ more energy is charged than discharged. To account for it we consider that the whole electrical generation system has to be oversized to compensate for the non-perfect efficiency. The *additional* embodied energy for the electrical generation system has to be accounted for. (Figure 3.10).

The electricity system installed can be oversized by a factor α to ensure that average production is greater than consumption. The power installed goes from P to $(1 + \alpha)P$.

We detail in the following the method to compute this oversizing factor α :

Let $\langle . \rangle$ be the mean value over a year of a given quantity.

Before oversizing, the equation $\langle \text{production} \rangle = \langle \text{consumption} \rangle = P$ must be fulfilled.

Considering a single wavelet φ of the decomposition, β_i^p and β_i^c are respectively the components of the production and the consumption on this vector.* Index i refers to a given time position over a given time scale ΔT .

Before oversizing, $\langle \text{production} \rangle = \langle \text{consumption} \rangle = P$. After oversizing, $\langle \text{production} \rangle = (1 + \alpha) \times P$ and its wavelet decomposition component becomes $(1 + \alpha) \cdot \beta^p$.

*For the sake of simplicity we assume in this section that $\forall i, \beta_i^p > 0$ and $\beta_i^c > 0$. At the end of the demonstration we generalize the expression of α .

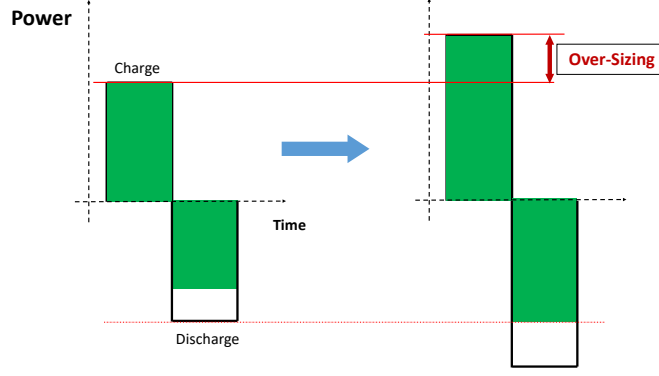


Figure 3.10: When the round trip efficiency η of a storage device is <1 , the production has to be oversized by a factor α . It enables to charge more energy in order to discharge as much as needed.

The device is charged on the first half of ΔT . The power of charge is

$$P_{charge,i} = (P + \beta_i^p)(1 + \alpha_i) - P - \beta_i^c$$

Discharge power on the second half of the time step is

$$P_{discharge,i} = \eta \cdot P_{charge,i} = ((P + \beta_i^p)(1 + \alpha_i) - P - \beta_i^c) \cdot \eta$$

Discharge power plus production should be at least equal to the consumption at all time i . It can be written as

$$\forall i, \quad P_{discharge,i} + P_{production,i} \geq P_{consumption,i}$$

i.e.

$$P_{discharge,i} + (1 + \alpha_i)(P - \beta_i^p) \geq P - \beta_i^c$$

\Leftrightarrow

$$\alpha_i \geq \frac{-\beta_i^p + \beta_i^c}{\frac{\eta+1}{\eta-1}P + \beta_i^p}$$

As β^p and β^c could be positive or negative, several cases arise which lead to the following result:

$$\alpha = \max_i \left(\frac{-\beta_i^p + \beta_i^c}{\pm \frac{\eta+1}{\eta-1}P + \beta_i^p} \right) \quad (3.12)$$

As the electricity mix is an input of the problem, we use the same α to oversize each element of the electricity generation system. For each production device k , we denote by P_k the average power generated by this element. For example for the photovoltaic, $P_{PV} = P \times PV_{ratio}$. CF_k its capacity factor. Therefore

$\frac{P_k}{CF_k}$ is the power which is actually installed.

$\zeta_{P,k}$ is the energy intensity of the production device normalized by its power. Thus

$\frac{P_k \cdot \zeta_{P,k}}{CF_k}$ is the embodied energy invested to set up the electricity production system.

Thus the additional annual cost due to the oversizing can be calculated as:

$$Cost_{oversizing/yr,k} = \frac{\alpha \cdot P_k \cdot \zeta_{P,k}}{T_{life,cal,k} \cdot CF_k} \quad (3.13)$$

If the production system is made of several electricity generation devices such as for the PPE scenario, we sum the costs associated with each technology.

V.2.2 The "Service/Costs" ratio: a global ESOI

We calculate the ratio *service/costs* for each time scale and technology, as

$$\frac{Service}{Cost_{storage} + Cost_{oversizing}}$$

This is a global ESOI because it accounts for the total embodied energy attributable to the storage: the embodied energy of the storage itself and of the production oversizing due to the storage efficiency lower than 100 %. *Service* is the total output energy, as defined in section IV.1.2.

Both *Service* and *Costs* are yearly produced or consumed energy. Service is expressed in term of *electrical energy*, costs in terms of *primary energy*.

V.3 Results: an energy return on investment analysis

The results presented here are also performed using time-series that last 7 years. We first assess the potential of storage technologies and oversizing for the 100 % RES and PPE scenario. Then, we conduct a sensitivity analysis of costs and performances of storage technologies for the PPE scenario.

V.3.1 Assessing the sustainability

ESOI ratios are shown in Figure 3.11. They are calculated at each time-scale for each of the storage technologies. Those results are compared to an additional strategy, consisting of only oversizing the production and curtailing excess electricity.

A high ratio ($\gg 1$) means that the storage device will store and return much more electricity throughout its life than the primary embodied energy required for its fabrication and the production system's oversizing. High ESOI areas on heatmaps give trends of relevance for the use of each system. In a strategy of sustainable development, only solutions with $ESOI \gg 1$ are relevant. $ESOI \ll 1$ would mean that the energy spent in implementing the means of flexibility is greater than the service provided by this same system.

The three heatmaps of Figure 3.11 show that the field of relevance of each technology follows similar patterns, independently of the electricity generation mix.

We observe that Li-ion batteries are relevant, in the energy return on invested sense, for storage time scales going from the hour to two days. PHS covers a broader range, which goes from the hour to the month. CAES might be relevant for similar time scales as PHS, but is more sensitive to high VRES penetration rates. Power-to-Power could be the only potential technology able to handle seasonal storage if hydrogen were stored in geological cavities.

On the contrary, storing H_2 in steel bottles lowers the long time scale ESOI and makes hydrogen ESOI profitable only up to the month. These values are strongly lowered by high VRES penetration. We notice that ESOI of long time scales — except free H_2 storage

— are lower than those obtained with electricity curtailment. This latest is modeled as a free storage with an efficiency equal to zero. Therefore, low-investment, low-efficiency technologies such as P2P with free H_2 storage can be seen as an improved curtailment. We notice that for long term storage they are the only solutions with $ESOI > 1$.

Besides, we see that ESOI values decrease with the penetration rate of renewables, and even faster if the storage efficiency is low (CAES, P2P, and of course for curtailment). This effect is visible for PV production at the daily time scale: as the production vanishes during nights, oversizing has no effect and low efficiency storages have low ESOI values. It can be noted that PV has a stronger variability than wind power.

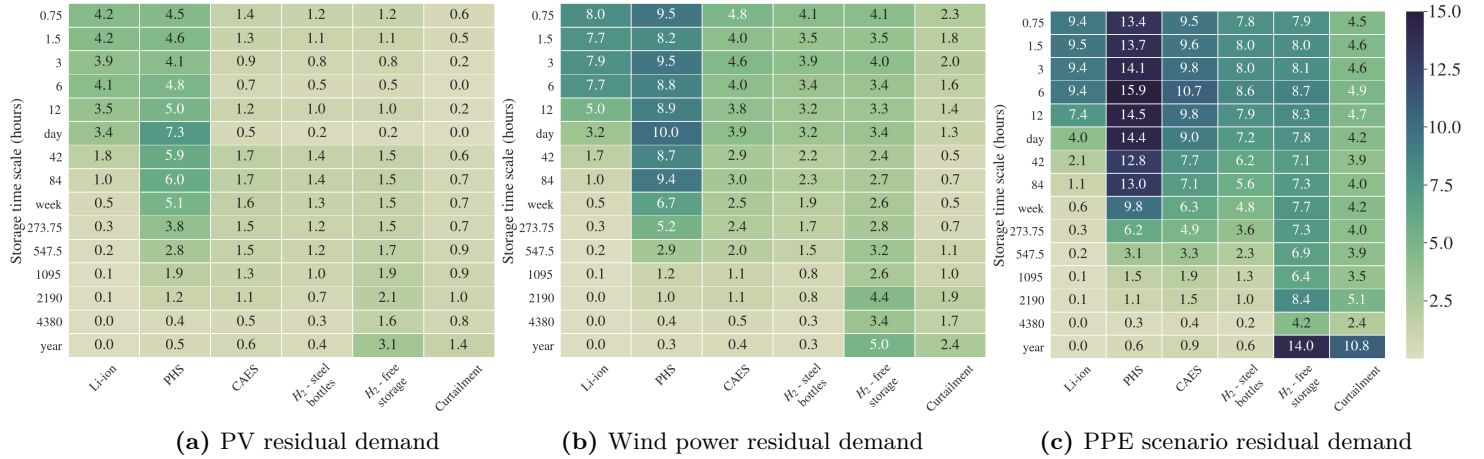


Figure 3.11: ESOI ratio (Service / cost) plotted for three different residual demands. This ratio is function of the storage time scale and depends of the storage device. The higher and the darker, the more relevant it is to use the device. Thus, the light areas stress the functions for which the use of a storage device is unsuitable. Results are computed for a satisfaction rate of 95 % as drawn on Figure 3.7.

V.3.2 Sensitivity analysis

We proceed to a sensitivity analysis, to evaluate the impacts of potential technological improvements. It is applied to each scenario and compared to the nominal case of Figure 3.11 described above. Results for scenario PPE are shown on Figure 3.12. The technological characteristics are modified as follows:

Li-ion batteries: As embodied energy is the major cost factor for Li-ion batteries, it was divided by two [63]. One could expect such an improvement by a more efficient use of innovative materials for electrodes and electrolytes, and an improvement in energy intensive process steps such as electrode drying.

$$\zeta_E = 2 \cdot 10^6 \quad \rightarrow \quad 10^6 \text{ MJ}_{prim}/\text{MWh}_{elec}$$

With those parameters Li-ion remains profitable on twice longer time scales: $ESOI > 1$ up to 4 days instead of 2. Besides, ESOI reaches values of 15, when the previous maximum was of 9.

Compressed Air Energy Storage (CAES): We raised the efficiency of the device up to a typical value targeted by Advanced Adiabatic CAES [89, 126].

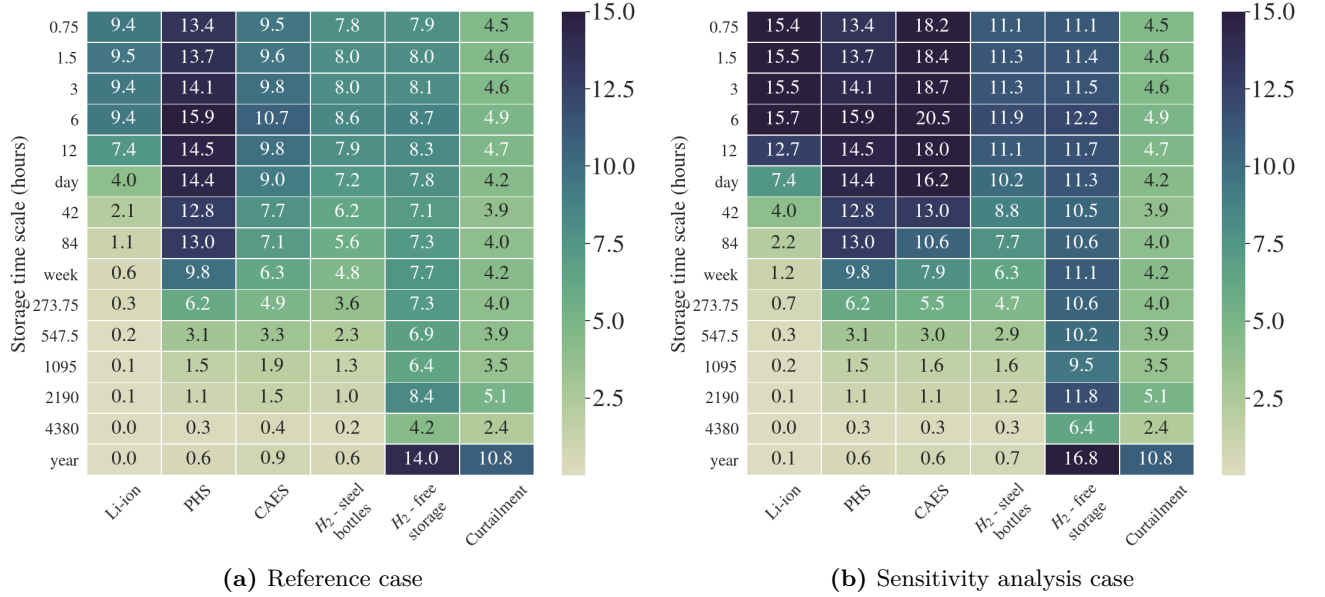


Figure 3.12: Sensibility analysis realized on PPE scenario. Figure (a) represents the reference case and (b) the sensitivity analysis. Energy intensity ζ of Li-ion batteries was divided by 2. Efficiency η of CAES and P2P was respectively raised to 60 % and 50 %. The ESOI ratio (service/cost) is a function of the storage time scale and depends on the storage device. The higher and the darker, the more relevant it is to use the device. Thus, the light areas stress the functions for which the use of a storage device is unsuitable. Results are computed for a satisfaction rate of 95 % as drawn on Figure 3.7.

$$\eta_{CAES} = 35\% \rightarrow 60\%$$

Compressed air energy storage thus remains relevant for the same time scale range with an ESOI ratio closer to the PHS's one. However, one should take care that higher efficiency will probably come with higher embodied energy, especially from the thermal storage.

Power-to-gas-to-Power (P2P): As the oversizing of the production system is the major cost factor for P2P, we raised the efficiency of the device.

$$\eta_{P2P} = 30\% \rightarrow 50\%$$

With this efficiency P2P with H_2 storage in geological cavities shows higher ESOI in this low variability scenario. It remains relevant for every time scale. However when hydrogen is assumed to be stored in steel bottles, the ESOI is degraded to values lower than 1 at time scales longer than months.

Overall, we observe trends similar to ones of Figure 3.11, with higher ESOI.

V.4 Discussion

To summarize, we show above that Li-ion batteries have higher ESOI at time scales shorter than two days. It could be understood in this way: batteries are energy efficient (80 %) and have a high embodied energy compared with other devices. Hence the battery has to perform many cycles to discharge more energy than what was embodied. They can afford to cycle a lot because of the good efficiency. For these short times, they are preferred to

P2P because of their good efficiency.

In contrast, as long as the embodied energy of H_2 storage is not included, the ESOI of P2P does not degrade with time scale, and the technology became relevant for seasonal storage. It would be the case if H_2 were stored in geological caverns. We remind here that, despite the fact that underground hydrogen storage has not been demonstrated yet, the number of sites available would also limit its deployment. The low efficiency of Power-to-Power implies that the production oversizing is a dominant cost. Consequently, it is less suited to higher VRES penetration rates, which imply higher and more costly oversizing.

Concerning the Pumped Hydro-electricity Storage, it covers a wide range of time scales, from hour to weeks, with very good ESOI. However, its deployment is bounded by the site's availability. Compressed Air Energy Storage covers the same range of time scales with lower ESOI ratios. The sensibility analysis reflects the potential of Advanced Adiabatic CAES, which has higher ESOI. However, the latter is meant to be used on a daily scale due to technological constraints. CAES deployment will also be very limited by the geological caverns availability, a parameter that is not included in this study. Additionally, compressed air takes 100 times the volume of hydrogen for the same stored energy. This energy density competition might be an additional limitation to the CAES development.

Comparing Figures 3.11a and 3.11b with figures 3.12a stresses that the higher the VRES penetration rate is, the smaller is the field of relevance of every technology. It is partly because the energetic investment of PV and wind power is greater than nuclear and hydropower. Symmetrically, when there is a lack of production, the minimum power produced decreases with a growing share of VRES. Thus, the required oversizing increases with the share of VRES, and particularly for low-efficiency technologies such as CAES and P2P. On the contrary, a moderate penetration rate such as for the PPE scenario makes those solutions more profitable.

V.4.1 Towards a better understanding – an example:

As explained in V.2.1, $ESOI = \frac{Service}{Costs}$. Costs are two fold, the storage one and the production oversizing participation.

In order to understand the meaning of those results, we focus here on a specific value of the PPE scenario (see Figure 3.12a). For a yearly storage, with power-to-power storage, $ESOI = 14^\dagger$. We present here different characteristics of this point:

$$\left\{ \begin{array}{l} Service \\ \eta_{P2P} \\ \alpha \text{ (oversizing factor)} \end{array} \right. = \begin{array}{l} 35.6 \text{ TWh/yr} \\ 30\% \\ 9, 2\% \end{array}$$

An investment of $2.08 \text{ TWh}_{prim} \text{ year}^{-1}$ primary embodied energy is involved to set up the production means. The storage cost is $0.79 \text{ TWh}_{prim}/\text{yr}$.

[†]Indeed, for long time scales, the cost of hydrogen storage becomes dominant over all costs and does not allow to distinguish the contribution of each element.

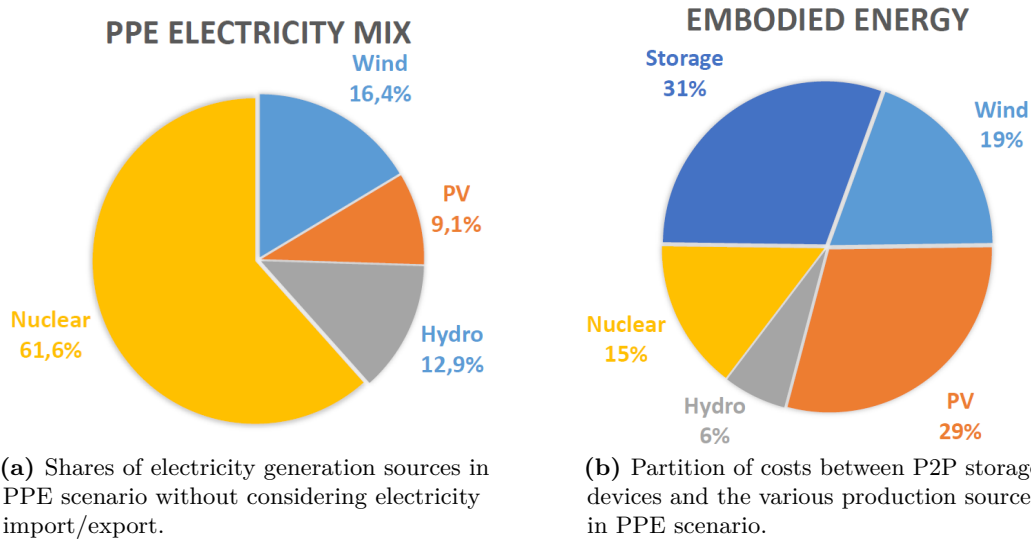


Figure 3.13: Details of the embodied energy investments repartition for a yearly storage with P2P storage device — H_2 stored in geological cavities, not in steel containers — (3.13b) in the PPE scenario. It includes the energy invested for storage and to *oversize* the electricity generation sources. Figure 3.13a shows production sources shares of PPE scenario.

Finally

$$ESOI = \frac{\overbrace{13.7 \text{ TWh}_{elec}/yr}^{\text{Storage}} + \overbrace{21.9 \text{ TWh}_{elec}/yr}^{\text{Production oversizing}}}{\underbrace{0.77 \text{ TWh}_{prim}/yr}_{\text{Storage}} + \underbrace{1.77 \text{ TWh}_{prim}/yr}_{\text{Production oversizing}}} = 14 \quad (3.14)$$

Two inherent features of low efficiency storage are worth being highlighted. First, a large part of the service (more than two thirds here) is provided by the production oversizing, which delivers electricity directly to fulfill the demand without charging and discharging the storage. Second, the cost is also dominated by the energetic investment required to oversize the production. The pie charts in Figure 3.13 stress the share of the production cost. Even if VRES only represent 36 % of the generation mix, they account for more than 50 % of the total energetic cost (storage + over-production).

VI Conclusion

The methodology we propose enables the quantification of flexibility and determination of relevance for possible energy storage choices according to their ESOI index. Applied to different power generation mixes in France, with different intermittency penetration rates, it highlights the differences between photovoltaic and wind power generation modes.

The former requires a high storage capacity at a daily and yearly level. It accounts for the cycles of days and seasons. In comparison, wind power has a stronger variability from the day to week scales. Wind patterns are not as consistent as the PV ones. They are more spread out and last much longer.

The example of a moderate penetration of variable renewable electricity scenario — the French energy transition targets, 27 % of RES — shows that intermittency is not additive. Wind power and PV are not running in phase and do not have the same dynamics. Therefore, using different VRES in an electrical mix lowers the variability that has to be

handled, at certain time scales.

The methodology — based on the energetic return on investment (EROI) — highlights the usage field of relevance of commonly used storage devices. Li-ion batteries — with high investment and high efficiency — are well suited for storage time scales up to days, while Pumped Hydro-electricity Storage (PHS) is relevant up to weeks. Compressed Air Energy Storage (CAES) is also able to ensure storage up to the week scale, but with lower return on investment than PHS. The performance of Power-to-gas-to-Power is very dependent upon the hydrogen storage means. If hydrogen storage is nearly free (geological cavities), seasonal storage is possible. Otherwise, the energy investment necessary to manufacture the bottles precludes its use for durations longer than one month. The share of Variable Renewable Energy Sources in the electricity mix has also a strong impact : the higher it is, the less relevant are storage technologies with low energy efficiency (P2P, CAES).

Finally, oversizing the production system and curtailing the excess electricity becomes an interesting option at long time scales for moderate VRES shares. To go a step further, a low-investment, low-efficiency storage such as P2P with free hydrogen storage can be seen as an improvement over this curtailing strategy, lowering the necessary oversizing.

The present study also points out that ensuring the load and supply balance at any time via electricity storage requires a much bigger energetic investment than allowing a mismatch for a short period of time. Hence, it would make sense for energy storage devices to go hand in hand with dispatchable generation means and demand-side management in order not to size the system based on the extreme events.

The present study focuses on the French scenario. However, it could be applied to other countries by adapting hypotheses such as the input signals and the capacity factors. Indeed, electricity consumption habits could vary from a country to the other, as well as the patterns of wind and sunshine. The methodology presented here could also be used to look at other indicators such as equivalent CO_2 or euros instead of the embodied energy. Those results are not presented here but each indicator has similar trends and patterns.

VII Limits of the methodology

The work presented here analyzed time-scales of the intermittency independently one from another.

This methodology does not enable to deduce potential complementarities between storages and time-scales. For example, we cannot determine from this analysis if a storage installed to handle weekly fluctuations — PHS, for instance — can also support part of the daily variability, since it is already installed.

In the next chapter, this point is analyzed. Using mathematical programming tools, we investigate in detail the behavior of an electricity system and the complementarities between flexibility means.

VIII Chapter's highlights

In this chapter a new methodology to quantify the flexibility need was developed. We introduce here the concept of *time-scale* and evaluate the potential of electricity storage technologies for each of them. We summarize here the main trends of this approach.

Take home message

First, the quantification of the flexibility need shows:

- Flexibility need linearly grows with the time-scale considered. There are four orders of magnitude between the short (hour) and long (season) fluctuations.
- The higher the penetration rate of VRES, the higher the flexibility need.
- Contrary to photovoltaic, wind generation is stronger in winter, when electricity consumption is also the highest. As a result, it lowers the seasonal flexibility need.

The sustainability assessment of electricity storage solutions shows that:

- Suitable solutions are available for short time scales, but none of the mature solutions considered are suitable to handle seasonal variability.
- Oversizing electricity production and curtailing excess might be more relevant than storage for long time-scales.

Complementarity of storage systems: How do storages work together?

This chapter provides further details on the mechanism of flexibility means. We investigate how electricity demand is satisfied, and what are the contribution of each means to handle daily, weekly, seasonal variability of the energy system. Here is a short chapter overview:

- Presentation of a Linear Programming (LP) model.
- Analysis of complementarity between electrical flexibility means, e.g., multiple electrical storages and oversizing.
- Calculation of trade-offs between the energy system's cost and parameters to determine which are the most appropriate flexibility strategy to handle a given variability.
- Analysis from the economic investment cost standpoint.

This is an extended and more detailed version of the conference paper [127]

Chapter outlook

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I Questions addressed

In the previous chapter, we assessed the potential of different electricity storage for different time scales. We aimed to quantify the potential of storages and oversizing for each need — e.g. time scale variability.

We now investigate the interdependencies between time-scales and the complementary mechanisms between flexibility means — storage technologies and oversizing of the electricity supply.

This methodology provides *figures of merit* and a basis for understanding trade-offs between investment cost and storage efficiency. In particular, it provides insights into the following questions:

- How does storage compete with production over-sizing and excess electricity curtailment?
- Which is the optimal storage for a given time-scale?
- Will optimal storage for long term also handle shorter time-scales?

II Framework and assumptions

II.1 Assumptions

To depict the trade-off between electricity storage efficiency and the investments costs of all the energy system components, assumptions of our model remain the same than previously:

1. *Energy consumption is 100% satisfied:* This is made possible through electricity storage, electricity generation over-sizing and curtailment.
2. *Copper plate approach:* Only the electricity vector is modeled. We do not consider grid losses and assume a perfect match between production and consumption, wherever electricity is produced.

In this chapter, the *optimization criteria* are the total cost in € of the energy system. We simplify electricity generation and storage technologies:

3. *Electricity storages characteristics:* Storages are defined by a charge efficiency η , a calendar lifetime T_{life} and an investment cost. We do not consider self-discharge, aging or response time.
4. *Electricity generation characteristics:* We consider a global electricity cost in € per unit of energy produced that accounts for CAPEX and OPEX.

II.2 Input data

The technological parameters used in this chapter are reminded in Table 4.1, and more extensive detail in the state of the art Chapter 2. It includes Li-ion batteries, Power-to-Gas-to-Power through the hydrogen vector — using a steel container for H_2 storage* — and Pumped Hydro-electricity storage. For hydrogen gas storage, we consider a tank reservoir for stationary purposes.

For the energy production system, we assume an overall cost of the energy produced, representing the French power generation system. Based on an analysis presented in chapter 2, we choose an energy cost of $60 \text{€}/MWh_{\text{produced}}$. In the following methodological description, we will refer to this cost as γ_3 .

Table 4.1: Electricity storage characteristics. Input data used for the simulations.

| Component | Investment cost | | T_{life} (year) | Efficiency η (%) | γ_E $\text{€} \cdot (MWh_{stock} \cdot yr)^{-1}$ | γ_P $\text{€} \cdot (MW_{out} \cdot yr)^{-1}$ |
|--------------|---------------------------|---------------------|----------------------|--------------------------|--|---|
| | $\text{€}/kWh_{el,stock}$ | $\text{€}/kWh_{el}$ | | | | |
| Li-ion | 300 | 300 | 15 | 85 | 2.0×10^4 | 0^\dagger |
| PHS | 165 | 2600 | 60 | 80 | 2.7×10^3 | 4.2×10^4 |
| Hydrogen | | | | 30 | 1.2×10^3 | 3.7×10^5 |
| H_2 tank | 10.5 | – | 20 | 1 | | |
| Electrolyzer | – | 725 | 1.14^\ddagger | 65 | | |
| Fuel cell | – | 5785 | 11.4^\ddagger | 45 | | |

Power time series are provided by the French Transmission System Operator. We use 7 years of data, ranging from 2012 to 2018.

II.3 Computational tools

The energy system considered all over the study includes two electricity storage devices. We prescribe an electricity load and supply. The electricity is either stored, curtailed, or directly consumed. The supply can be over-sized (i.e., total yearly supply is larger than total yearly load), only its shape is determined — we denote the over-sizing factor by α . It is depicted in Figure 4.1.

The energy system is modeled with linear equations and the optimization problem described in the following.

The states of charges E_1 and E_2 of respectively storage 1 and 2 are calculated such that

$$\begin{cases} \frac{dE_1(t)}{dt} = P_{charge,1}(t) \cdot \eta_1 - P_{disch,1}(t) \\ \frac{dE_2(t)}{dt} = P_{charge,2}(t) \cdot \eta_2 - P_{disch,2}(t) \end{cases} \quad (4.1)$$

With the following nodal law:

$$P_{in} - P_{out} = P_{charge,1} + P_{charge,2} - P_{disch,1} - P_{disch,2} + P_{curt} \quad (4.2)$$

In order to simplify the understanding of the equations we will refer to storage 1 or 2 with the index i .

*The potential of underground hydrogen storage is evaluated through a sensitivity analysis in the last part of this work.

[†]Batteries both have an energy and a power capacity. Once the investment is made to size the device in energy, the investment for the power share is 0.

[‡]Electrolyzer and fuel cells are defined with a usage lifetime. Other lifetimes are calendar.

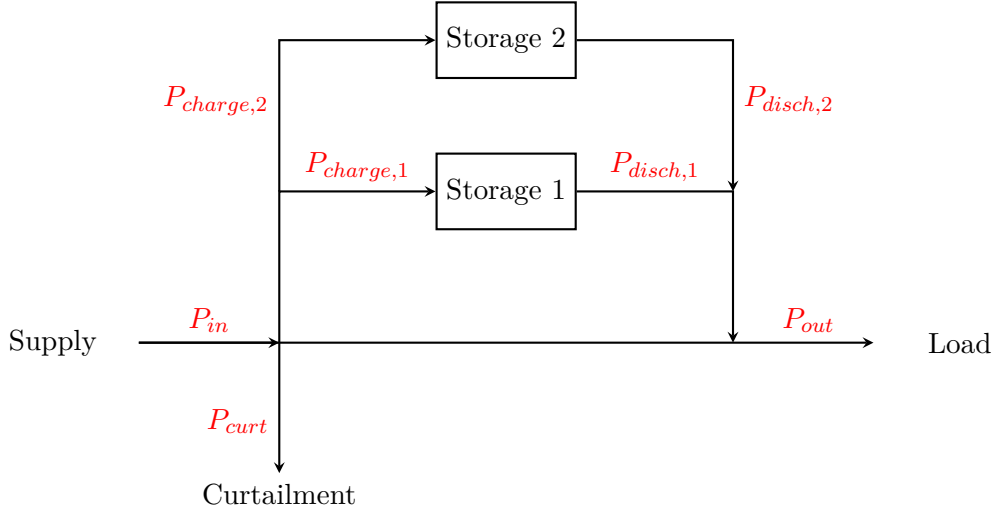


Figure 4.1: Representation of the energy system. Electricity supply can either be directly consumed, stored or curtailed.

The input P_{in} is the power supply after oversizing of by a factor α . Thus, if we name $P_{in,0}$ the power supply which is the input data of the optimization problem, $P_{in} = (1 + \alpha) \times P_{in,0}$.

The storage system is sized in energy and power by respectively $E_{max,i}$ and $P_{max,i}$.

$$E_i(t) \leq E_{max,i} \quad (4.3)$$

$$P_{i,disch}(t) \leq P_{max,i} \quad (4.4)$$

We also define a periodic constraint on the state of charge to ensure that its level is equal at the beginning and end of the time frame considered:

$$E_i(t_0) = E_i(t_{end}) \quad (4.5)$$

The objective function *Cost* of this model is

$$Cost = Production\ cost + Storage\ cost\ 1 + Storage\ cost\ 2 \quad (4.6)$$

The calculation of the cost of storage and electricity production is detailed in the next section III.

This optimization problem is solved by two manners. First, for a very simple case study, we resolve “by hand” the Simplex algorithm and provide parametric equations to the problem. However, this approach is limited to problems described by few parameters. More complex cases are thus resolved using both the software GAMS and a solver. An example of the GAMS code is released in the Appendix E.

II.4 Global framework

We investigate further the interdependencies of the variability time-scales. To get an intuitive grasp of the main trends, we first consider “toy models” with single and dual time-scale, and then the real situation with entire signals. This chapter is therefore divided into three main steps:

1. The electricity production varies over a single time-scale. It could depict a winter–summer photovoltaic production. This model is details in section III.
2. Then a second time-scale is added, representing daily and yearly variations — see section IV.
3. Eventually, the previous results are compared with the analysis of real intermittent signals, presented in section V.

The first two models are idealized descriptions for a deeper understanding of the fundamental phenomena.

III Part 1: Single time-scale

III.1 Method

We consider a constant electricity load ($= 1$), whereas the input supply has a *charge-discharge shape*, as depicted on Figure 4.2. Average value of electricity production and demand are equal before oversizing of the production by a factor α .

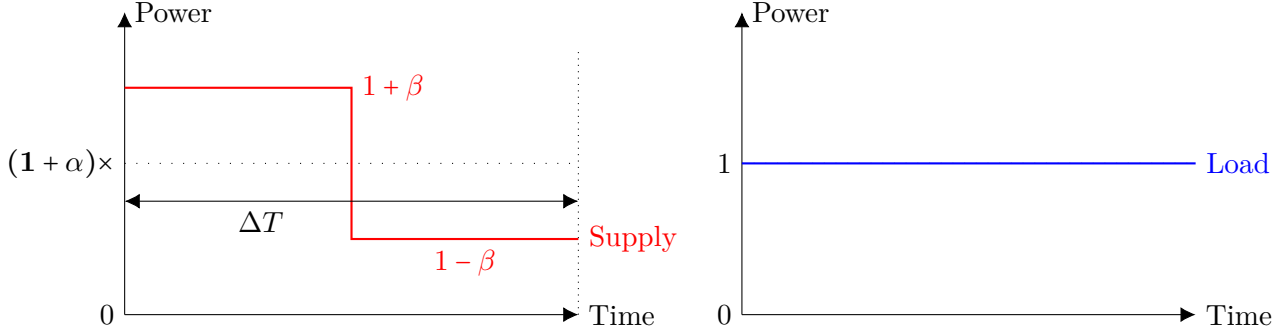


Figure 4.2: Input signals of the simulation with a single characteristic time-scale.

The energy model includes two electricity storages. We define their annual investment cost per unit of energy and power as $\gamma_{i,E}$ and $\gamma_{i,P}$, such that storage cost is

$$Cost_{storage,i} = \gamma_{i,P}P_i + \gamma_{i,E}P_i \frac{\Delta T}{2} \quad (4.7)$$

with P_i the discharge power of storage i .

We generalize this definition and introduce a global γ_i such that

$$\gamma_i = \gamma_{i,P} + \gamma_{i,E} \frac{\Delta T}{2} \quad (4.8)$$

Regarding the electricity generation cost:

$$Cost_{production} = \alpha\gamma_3\bar{\mathbf{P}} \quad (4.9)$$

where γ_3 is the cost of electricity generation per unit of energy produced. $\bar{\mathbf{P}}$ is the average value of the electricity load. Here $\bar{\mathbf{P}} = 1$ MW.

The Objective Function can be written therefore such that

$$Cost = \gamma_1P_1 \frac{\Delta T}{2} + \gamma_2P_2 \frac{\Delta T}{2} + \alpha\gamma_3\bar{\mathbf{P}} \quad (4.10)$$

Storage characteristics and γ_i are listed in Table 4.1.

III.2 Results and discussion

We calculate analytic conditions — detailed in the Appendix B — to determine which is the optimal solution. However, the solution depends on β , the level of variability. As the general case is complex, we only provide results for the extreme cases, $\beta \rightarrow 1$ and $\beta \rightarrow 0$.

1. $\beta \rightarrow 1$: Strong variability of the production signal. Power is null half of the time.

The optimal solution never implies curtailment, only the storage with the smallest figure of merit is used:

$$\text{Storage 2 is used} \iff \underbrace{\gamma_1 \frac{\Delta T}{2} + \frac{\gamma_3}{2\eta_1}}_{\text{Storage1}} \geq \underbrace{\gamma_2 \frac{\Delta T}{2} + \frac{\gamma_3}{2\eta_2}}_{\text{Storage2}} \quad (4.11)$$

This is the figure of merit of storage use. In this particular case of a strong variable signal, electricity curtailment cannot be a solution. In fact, electricity production is null half of the time. Electricity consumption could not be satisfied without using electricity storage.

2. $\beta \rightarrow 0$: Small variability of the production signal

When $\beta \rightarrow 0$, over-sizing the production by a factor α and curtailing the excess electricity can be relevant in certain cases, while storing it is preferred in others.

$$\text{Electricity is stored} \iff \begin{cases} \gamma_1 \frac{\Delta T}{2} \leq \gamma_3 \\ \text{or} \\ \gamma_2 \frac{\Delta T}{2} \leq \gamma_3 \end{cases} \quad (4.12)$$

In that case, a single storage is used:

$$\text{Storage 2 is used} \iff \frac{1}{\eta_1 + 1} \left(\eta_1 \gamma_1 \frac{\Delta T}{2} + \gamma_3 \right) \geq \frac{1}{\eta_2 + 1} \left(\eta_2 \gamma_2 \frac{\Delta T}{2} + \gamma_3 \right) \quad (4.13)$$

We can extract from Equation 4.11 and 4.13 valuable comparisons between two storages.

In particular, we calculate ΔT_{eq} , the time-scale of charge-discharge from which both storages have the same figure of merit. One storage will be preferred for shorter time scales, and the other storage for longer ones.

For this calculation, we introduce $\gamma_{i,E}$ and $\gamma_{i,P}$ such that

$$\gamma_i = \gamma_{i,E} + \frac{2\gamma_{i,P}}{\Delta T}$$

where ΔT is the time-scale displayed on Figure 4.2.

$$\begin{cases} \Delta T_{eq,\beta \rightarrow 1} = \frac{\gamma_3 \left(\frac{1}{\eta_2} - \frac{1}{\eta_1} \right) + 2(\gamma_{2,P} - \gamma_{1,P})}{\gamma_{1,E} - \gamma_{2,E}} \\ \Delta T_{eq,\beta \rightarrow 0} = \frac{2\gamma_3 \left[\frac{1}{1+\eta_2} - \frac{1}{1+\eta_1} \right] + 2 \left[\gamma_{2,P} \left(\frac{\eta_2}{1+\eta_2} \right) - \gamma_{1,P} \left(\frac{\eta_1}{1+\eta_1} \right) \right]}{\gamma_{1,E} \left(\frac{\eta_1}{1+\eta_1} \right) - \gamma_{2,E} \left(\frac{\eta_2}{1+\eta_2} \right)} \end{cases} \quad (4.14)$$

Equation 4.12 shows when over-sizing the energy generation and curtailing excess electricity is more relevant than using electricity storage. We denote this specific time scale by $\Delta T_{\beta \rightarrow 0, curt}$.

$$\Delta T_{\beta \rightarrow 0, curt} = 2 \cdot \frac{\gamma_3 - \gamma_P}{\gamma_E} \quad (4.15)$$

To conclude, these figures of merit provide an analytical formulation of the trade-off between cost and efficiency. In particular, it emphasizes that this trade-off depends on intermittency level: at higher intermittency, low efficiency is more detrimental.

Numerical application of Equation 4.14 and 4.15: Li-ion batteries are compared with hydrogen storage: the former has a high investment cost in energy, the latter a high *power* investment cost because of the electrolyzer and the fuel cell.

Results are summarized in Figure 4.3. In particular, we observe that using Li-ion is preferable for up to 2–4 days. In the case of a small variability, it would be more relevant to oversize the electricity production for longer durations. In the case of a strong variability, where electricity production can be null, hydrogen is preferable for long time-scales^{||}.

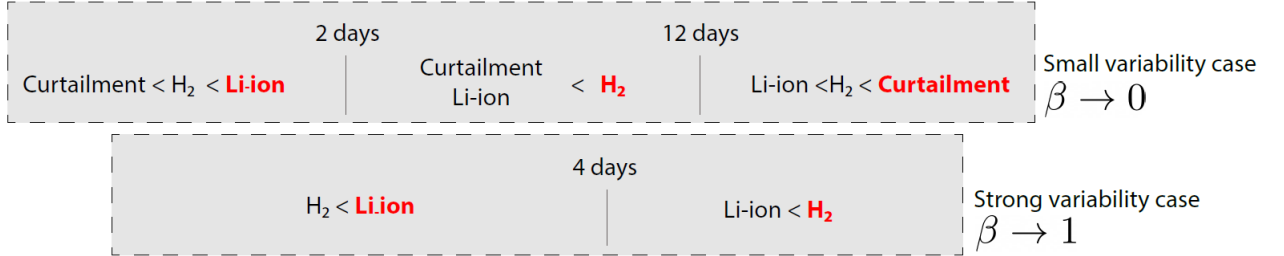


Figure 4.3: Calculation of ΔT_{eq} between the use of Li-ion, hydrogen or oversizing. Those results corresponds to the framework “*Single time-scale*”. It shows which is the most relevant technology to be used, depending of the time-scale usage. Warning note: the cost of the optimal technological solution does not appear. It skyrockets for long time-scales and strong variability.

These conclusions can be generalized into two principal points:

- The lower the variability, the more electricity production will be oversized. Conversely, the greater the variability, the more electricity storage with a low efficiency will be penalized.
- Depending on the storage duration, long term or short term, electricity storage does not require the same characteristics. Equation 4.11 shows that there is a trade-off between investment cost and efficiency. For short-term storage, the investment cost dominates the total cost. Conversely, for the long-term, it is the investment cost that prevails. It explains why Li-ion batteries are preferred for short-term storage, whereas hydrogen goes for longer durations.

IV Part 2: Dual time-scale

IV.1 Method

The previous section shows that for a single time-scale intermittent signal, only one storage technology is used. Here we investigate the co-existing domain of two technologies. To this

^{||}An interactive tool has been created on <https://fabienperdu.github.io/ElecStorageCost> for users to play with the features of their own storage technology. Besides, it compares the cost of storage with the one of electricity generation.

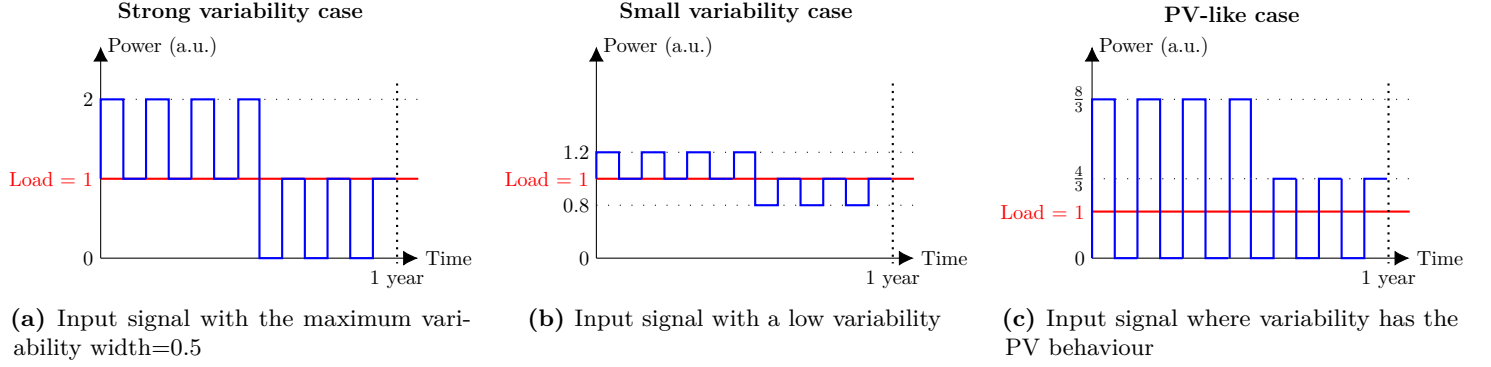


Figure 4.4: Input signals of the dual time-scales simulation described in IV. For readability concerns, we display only 7 days among the 365 of the signal. Electricity supply is the pseudo-periodic blue signal, Load signal is the constant value red value.

end, we now consider a variable production with two time-scales, as drawn on Figure 4.4: seasonal and a daily time-scale. We refer to the short term fluctuations as *day and night*, long term ones as *summer and winter*.

This time, the problem is too complicated to be solved analytically. We now use a solver to perform a parametric analysis on three parameters, as defined in the new paragraph. Simultaneously, simulations are performed with three different input signals, shown in Figure 4.4. It accounts for different penetration rates of variability in the power generation.

We consider two hypothetical storage devices: one with a high efficiency, compared with another one with a low investment cost. To do so, we assign an efficiency of 80 % to the storage 1. It accounts for high efficiency devices such as Li-ion batteries or PHS. η_2, γ_1 and γ_2 are varying parameters such that

$$\begin{cases} \eta_2 \in [0, 100\%] \\ \frac{\gamma_1}{\gamma_3} \in [10^{-1}, 10^7] \text{ (year}^{-1}\text{)} \\ \frac{\gamma_2}{\gamma_3} \in [10^{-1}, 10^7] \text{ (year}^{-1}\text{)} \end{cases}$$

For the sake of simplicity we assign $\gamma_P = 0$, since we cannot easily display results in a 5-dimension space.

The calculations return the following results:

- α , the *oversizing factor* of the electricity generation means.
- $P_{charge,i}$ and $P_{discharge,i}$, the charge and discharge power time-series of storage i .
- P_{curt} , the curtailed electricity power time-series.

IV.2 Results and discussion

We represent in Figure 4.5 the results of the parametric analysis for the *small variability case*. This behavior is typical of the two other cases. This figure shows the set of parameters $(\eta_2, \gamma_1, \gamma_2)$ for which both or no storages are used to fulfill the electricity consumption.

Obviously, as long as $\eta_2 < 80\%$, the optimal solution when $\gamma_2 \geq \gamma_1$ is not storage 2.

In particular, we observe that a single storage can operate the total intermittency on its own. However, two storages can be used in conjunction with a large range of parameters: it is depicted by the green area in Figure 4.5. When costs are too high, it became more relevant not to use storage but oversize the production to make sure that it is greater than the consumption at all times. It is represented by the rectangular cuboid in the corner of the figure.

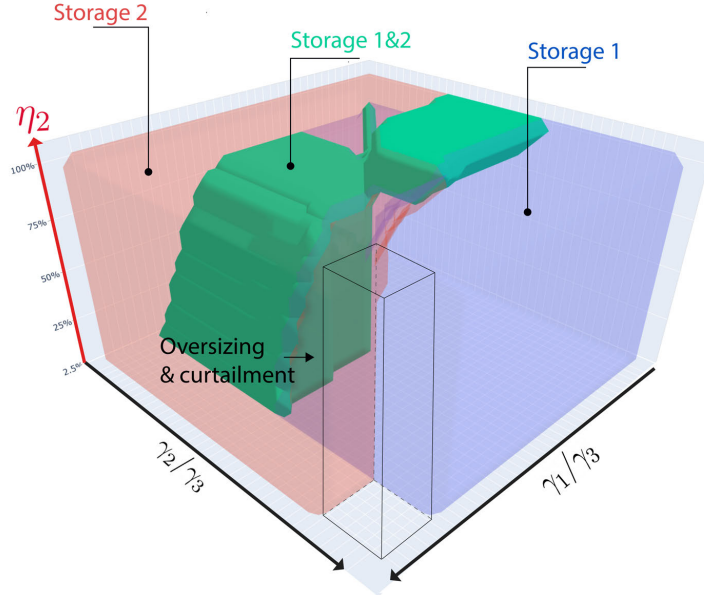


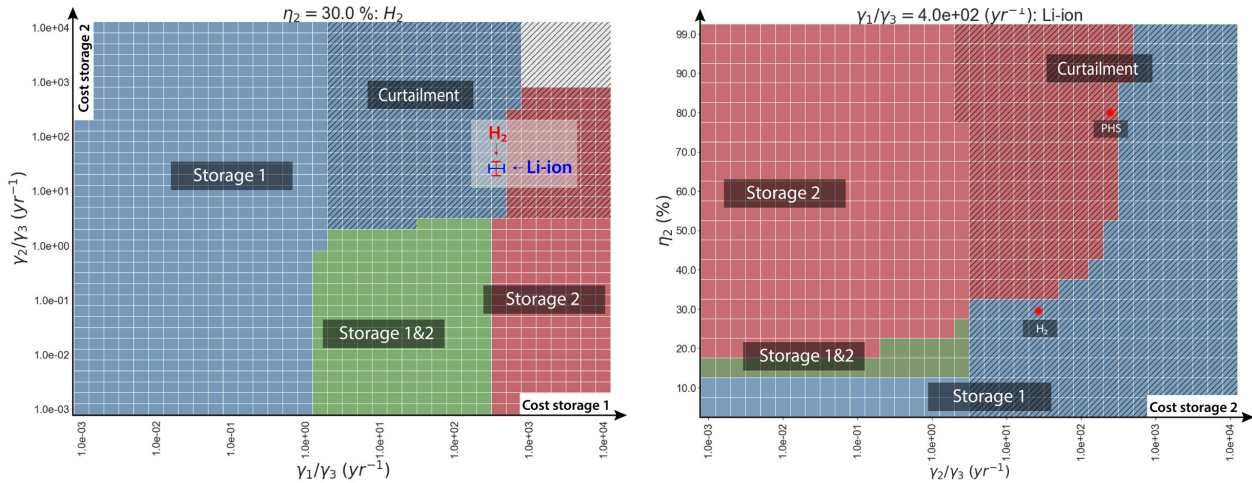
Figure 4.5: Mapping of the flexibility means used by the optimal solutions for the *small variability case*, depending on the relative costs of the storages, and storage 2 efficiency. The red area corresponds to storage 2, the blue to storage 1. Where the space is green, both storages are used in combination. Where there is no color, *Service* is entirely provided by the over-sizing.

Figure 4.5 is sliced along two axes. First, in Figure 4.6a, with a constant efficiency of storage 2 $\eta_2 = 30\%$. It corresponds to the efficiency of hydrogen storage.

Second, Figure 4.6b depicts a slice with a constant investment cost of storage 1, corresponding to the Li-ion batteries investment.

For example, Figure 4.6a shows that, in this configuration, Li-ion must be a little more expensive so that hydrogen became used. However, lowering the overall cost of hydrogen would not be the most efficient strategy for becoming profitable. Its cost would almost have to be divided by a factor of 10. Figure 4.6b shows that it is more interesting to improve hydrogen efficiency. By switching this efficiency from 30 to 35 %, hydrogen would be competitive with Li-ion for this usage.

We investigate now further the area where both storages 1 and 2 are used in combination (green area). When both storages are used in conjunction, no electricity is curtailed. In fact, low efficiency storage, when sufficiently low cost, behaves as an improved version of oversizing and curtailment. Among the three different cases, we observe two clusters of behavior, represented in Figure 4.7:

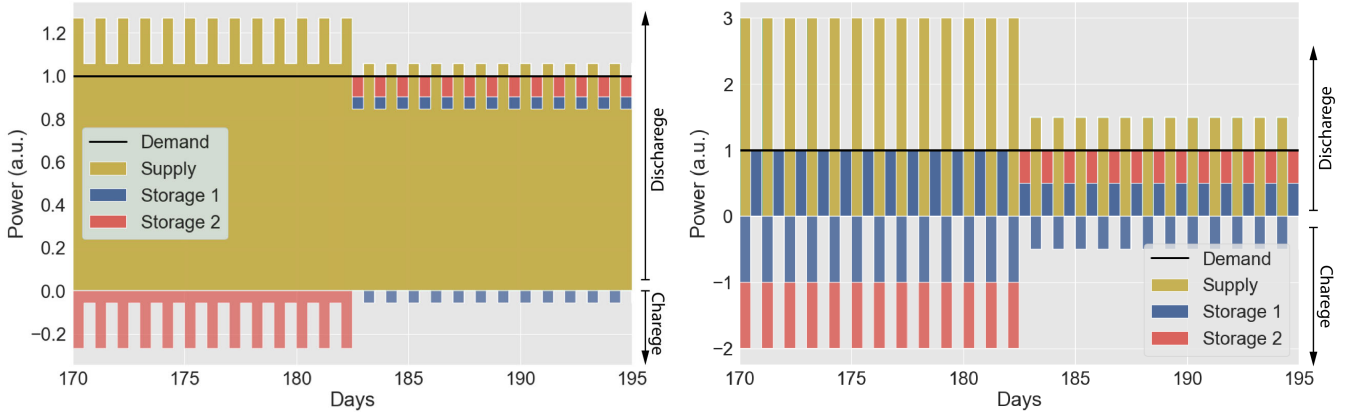


(a) Slice with constant $\eta_2 = 30\%$, the efficiency of Power-to-gas-to-Power

(b) Slice with constant ratio $\gamma_1/\gamma_3 = 4 \times 10^2 yr^{-1}$. It is the average cost ratio of Li-ion batteries

Figure 4.6: Slices of the volume presented in Figure 4.5. It shows the domains where **only storage 1, storage 2 or both are used**. One also notices in (a) that for expensive storages, the electricity consumption is only satisfied thanks to the power generation over-sizing. This area is denoted by *curtailment*. Energy is also curtailed in the hashed area.

- **Figure 4.7a:** Low cost storage 2 is charged mainly during summer days and discharged during winter nights, while storage 1 is only cycling in winter. As such, storage 2 contributes to the service at both at daily and seasonal time scales. This behavior has only been observed with the input signals of Figures 4.4a and 4.4b, the strong and small variability cases.
- **Figure 4.7b:** Storage 2 behaves similarly as in Figure 4.7a. But this time, storage 1 is cycling everyday, all year long. It can be observed for the *PV-like case* described on Figure 4.4c.



(a) For input signals such as the ones drawn on Figure 4.4a and 4.4b

(b) For the input signal drawn in Figure 4.4c

Figure 4.7: The two typical charge–discharge operating modes, when the optimal solution requires to use the two storages, are presented here. The figures are centered on the summer/winter season change and do not show the complete year.

V Part 3: Real signals analysis

V.1 Method

We eventually simulate the behavior of the energy system with two storages using 7 years (2012-2018) of real *demand* and *supply* electricity time-series as input data. This analysis is carried in four steps, as illustrated by the Figure 4.8.

1. We create input signals based on electricity production and consumption time series as already presented in section IV.1.3, Chapter 3.
2. Energy system with two electricity storages is optimized. We then proceed to steps 3 and 4 to understand the behavior of the optimized system at different time scales.
3. Output signals are decomposed over 15 different time-scales using the wavelet methodology described in the previous chapter.
4. Eventually those results are analyzed to determine which system — from storage 1, storage 2, oversizing of the electricity production — provides the required flexibility for each time scale.

Let the *Service* be the total amount of energy provided by the storage and the production oversizing when initial production is lower than consumption. It is described on the Equation 4.16.

One share of the *Service* is provided by storages and named *useful discharge*. The other share comes from oversizing of the production. We refer to it as *useful oversizing*.

$$\begin{aligned}
 Service &= \int_{P_{Load} > P_{Supply}} (P_{load}(t) - P_{supply}(t)) \cdot dt \\
 &= \sum_i \int_{Load > Supply} (P_{discharge,i}(t) - P_{charge,i}(t)) (dt) + \int_{P_{Load} > P_{Supply}} (\alpha P_{supply}(t) - P_{curt}(t)) dt
 \end{aligned} \tag{4.16}$$

For each of the 15 time scales, the *Service* distribution between storage and oversizing is calculated. Small corrections need to be made to this calculation. Indeed,

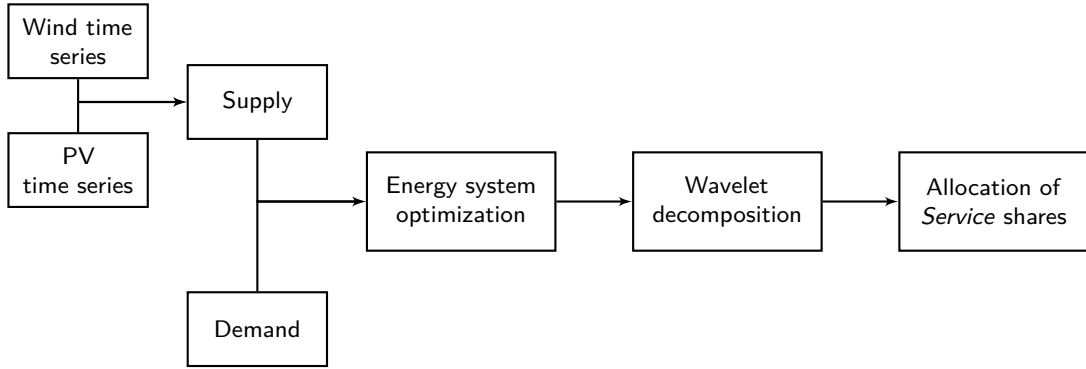


Figure 4.8: Description of the methodology in four steps of the simulation carried with real time series. First, the power generation signal is created. Second, with this input data, the energy system is optimized. Third, the output time series of the optimization are decomposed using the wavelet methodology. Finally, we analyzed which flexible mean provides the required *Service* that matches electricity demand and supply: storage 1, 2 or oversizing.

after the wavelet decomposition, one of the three terms — useful oversizing, useful discharge 1 & 2 — can be negative.

Thus we have to correct of their calculation, as explained in appendix VI page 153. We made sure that those corrections do not change much the results.

Note that the *Service* calculated on the entire signal is not equal to the sum of all 15 *Services* calculated for each time-scale. This non-linearity is explained by the *Service* integration domain: when consumption greater than production.

However, the *Service* decomposition in 15 time-scales remains relevant to depict the behavior of flexibility means.

Three different electricity generation mixes are compared here: two extreme cases, one fully photovoltaic and another one fully wind power. We additionnaly consider an hybrid-mix, the Ampere-like scenario. It includes 25% of wind power and 10.5 % PV. It is more details in the bibliography V. For all cases we choose the same average load such that

$$\text{Average load} = 54 \text{ GW}$$

V.2 Results and discussion

Figure 4.9 shows results calculated for each residual demand of the three scenarios: 100 % PV, 100 % Wind and Ampere scenario. Two electricity storages are compared here, *Li-ion batteries* — the expensive and efficient storage — and power-to-gas-to-Power through *hydrogen* — the less expensive and less efficient one. Results are compared for hydrogen stored in steel containers (Figure 4.9) and for free, e.g., geological caverns (Figure 4.10).

The analysis of Figure 4.9 shows how *Service* is allocated between Li-ion batteries, hydrogen, and oversizing. On the right-hand side of each subfigure is represented the total *Service* repartition. Then, the left-hand side figures represent the decomposition of the *Service*.

We start to analyze to right-hand side figures, the total *Service*. It shows that:

- The more intermittent the production, the more storage is developed. For example, in Ampère scenario, Figure 4.9c we see that most of the flexibility comes from the oversizing.

- When compared with the results of two previous models, the share of oversizing is here even greater, storage is less used.

Then, the Service decomposition analysis (left figures), can be done in two phases.

First, the general shape of the Service, the green dotted line. This analysis has already been done in the previous chapter for Figure 3.7. It highlights the main trends of the intermittent sources.

Second, we can analyze the Service allocation between Oversizing, Li-ion batteries and Hydrogen.

- The comparison between Figures 4.9a, 4.9b and Figure 4.9c shows that, the more intermittent the electricity production, the more efficient storages are developed. Conversely, the less intermittent the production, the more oversizing will be sufficient to provide the required flexibility.
- The optimal solution combines the use of both storages at various time-scales. The two mechanisms presented on Figures 4.7a and 4.7b are at stake here.
- Additionally, we see that hydrogen, the low cost and low efficiency storage prevails for the longer time-scales, whereas Li-ion is to be preferred for the shorter ones.

This simulation confirms the main trends that have been observed with the previous two models. However, 15 different time-scales are mixed here, which makes the analysis more complex, additional interactions between time-scales being now at stake.

V.2.1 Sensitivity analysis

Today, hydrogen is a research track for long-term energy storage. In the previous chapter, we have shown that massive hydrogen storage is dramatically penalized from a few weeks duration because of the cost of gas containers. Research has been investigating the potential of geological cavities to store massive quantities of hydrogen. It is far from being mature and today raise many technical and economic problems. This is more discussed in the state of the art Chapter 2, section I.2.3.

However, we evaluate the potential for possible progress in H_2 storage field by comparing the previous results with hydrogen storage that would be free. These results are presented in the Figure 4.10.

Analysis and comparison of the Figures 4.10 and 4.9 show the differences when H_2 is stored in steel bottles or for free:

- We observe that the free storage of H_2 replaces part of the Service previously provided by the oversizing.
- We can still notice that the less intermittent the production, the less storage is used. Here, even if storing H_2 is free, we observe that oversizing contribution remains high, particularly for Ampère scenario, where intermittency is low.
- For example, in the case of limited penetration of renewable energy sources — like Ampère scenario — most of the Service is provided by the oversizing, as observed on Figure 4.10c.
- With a lower H_2 storage cost, we would observe a more important use of this electricity storage means around the month, in line with what was observed with the previous *two-time scale* model.

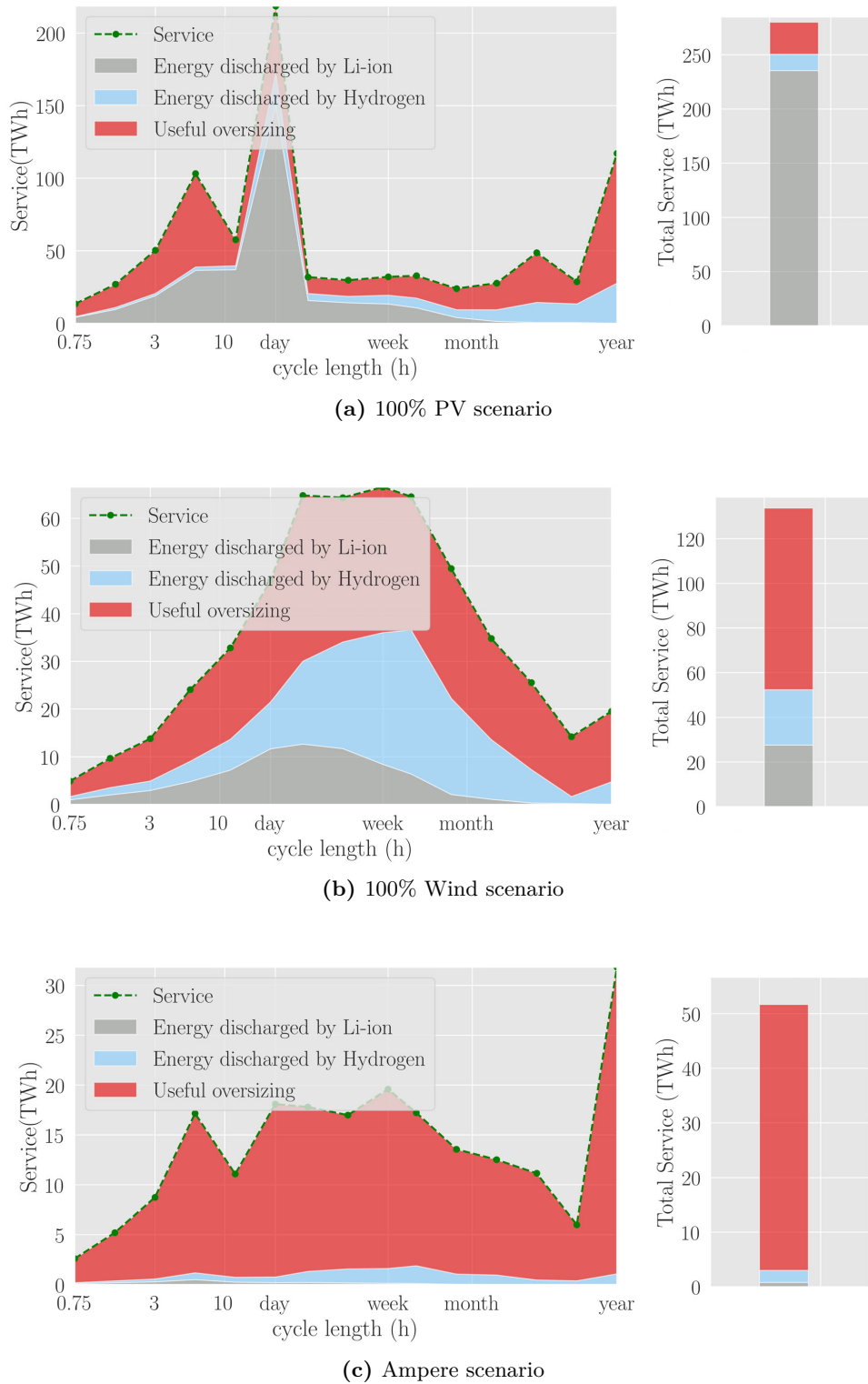
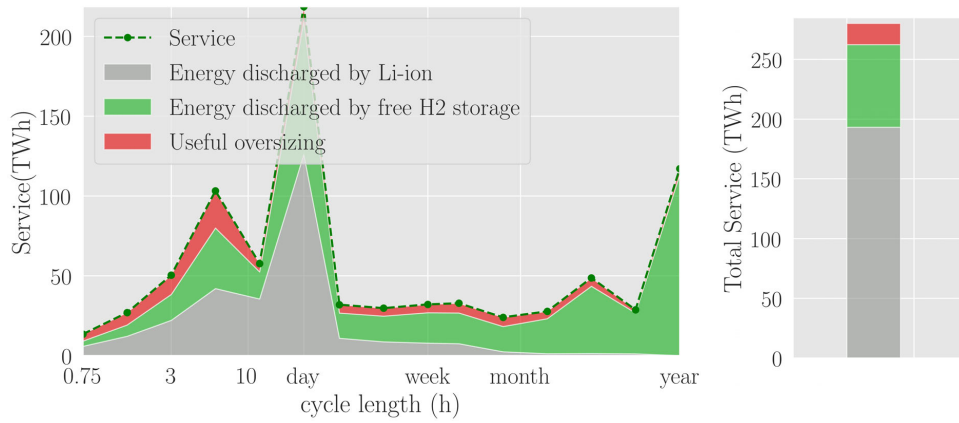
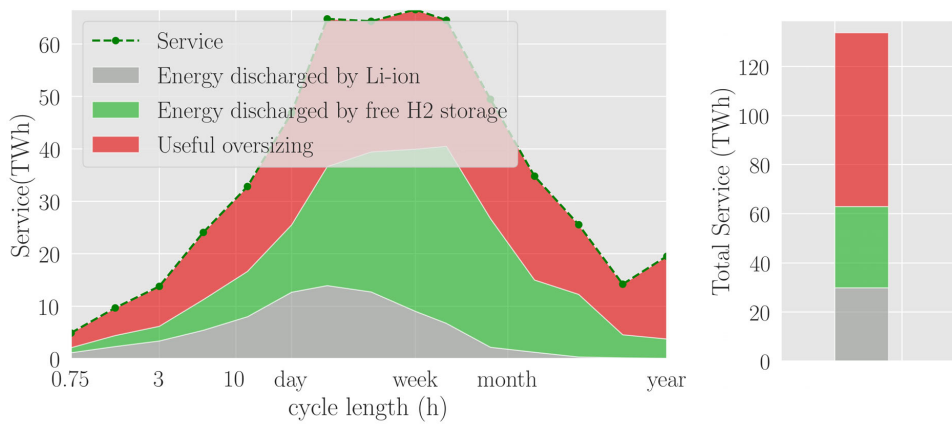


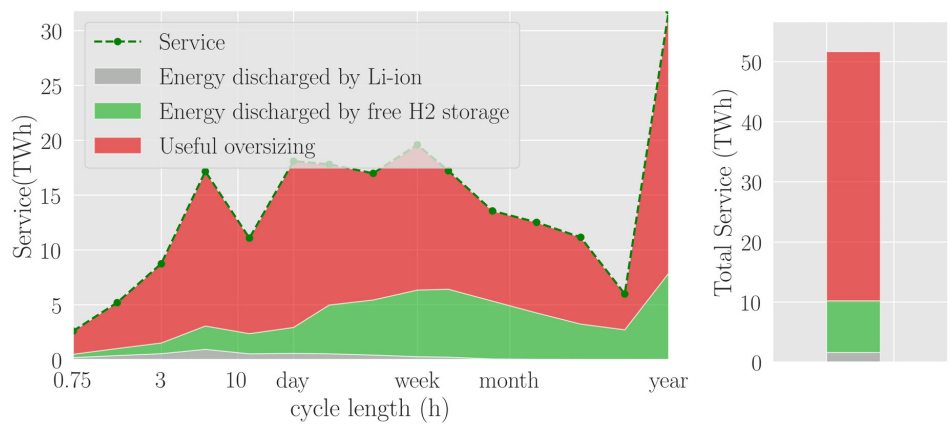
Figure 4.9: *Service* allocation between oversizing, Li-ion and Power-to-Power with hydrogen stored in steel bottles. *Service* is calculated for three different scenarios: 100 % PV (a), 100 % wind power (b) and the Ampère electricity generation mix (c) that includes 25 % of wind power and 10.5 % of photovoltaic. Left-hand figures depict *Service* decomposition over the 15 time-scales, right-hand figures the total *Service*, all time scales combined.



(a) 100% PV scenario



(b) 100% Wind scenario



(c) Ampere scenario

Figure 4.10: Service allocation between oversizing, Li-ion and Power-to-Power with hydrogen stored for free. Service calculated for three different scenarios: 100 % PV (a), 100 % wind power (b) and the Ampere electricity generation mix (c) that includes 25 % of wind power and 10.5 % of photovoltaic. Left-hand figures depict Service decomposition over the 15 time-scales, right-hand figures the total Service, all time scales combined.

V.2.2 Cost analysis

The service allocation presented in Figures 4.9 and 4.10 shows optimal solutions if the flexibility should only be provided by electricity storage and production oversizing. However, the cost of this flexibility is not visible in these figures but sharply rising with the penetration of intermittency.

To account for it, we summarize in Table 4.2 the cost of the flexibility and electricity for each scenarios.

Table 4.2: Total cost of flexibility and oversizing factor for all three scenarios. The cost of flexibility must be added and compared to the cost of the electricity produced of 60 €/MWh. The first half corresponds to simulations when H_2 is stored in steel bottles, as shown on Figure 4.9. The second half refers to the simulation where H_2 is stored for free, as depicted on Figure 4.10.

| | Scenario | Flexibility cost €/MWh _{service} | Electricity cost €/MWh _{delivered} | Oversizing factor α |
|-------------------------|----------|--|--|----------------------------|
| H_2 stored in bottles | PV | 440 | 320 | +254 % |
| | Wind | 434 | 182 | + 97 % |
| | Ampère | 389 | 103 | + 60 % |
| Free H_2 storage | PV | 295 | 220 | +87 % |
| | Wind | 382 | 143 | + 76 % |
| | Ampère | 320 | 95 | + 38 % |

Note: *Flexibility cost* represents the investments for electricity storage and production oversizing divided by the Service provided to match demand and supply. It is calculated such that

$$\text{Flexibility cost} = \frac{\text{Cost storages} + \text{Cost production oversizing}}{\text{Service provided}} \quad (4.17)$$

It represents the cost of a flexible unit of energy, available to fill a shortage whenever needed.

On the other hand, *cost of electricity* is calculated such that

$$\text{Electricity cost} = \frac{\text{Cost storages} + \text{Cost total electricity production.}}{\text{Total energy consumed}} \quad (4.18)$$

This cost analysis highlights that:

- The more intermittent the electricity production, the more expensive the delivered electricity. There is indeed a factor of 3 in the cost of electricity between a 35 % VRES and 100 % PV scenarios, for the same initial electricity production cost.
- In particular, even for a low intermittency, *delivered* electricity cost remains much greater than the *production* cost — 60 €/MWh. Its cost is 1.6 times greater than the one of electricity produced for Ampère scenario, even with free H_2 storage.
- Free H_2 storage would enable to reduce the cost of available electricity from 8 to 30 %, which does not change the above conclusions.
- In comparison, the cost of the flexibility provided by dispatchable power plants is significantly lower.

Non-provision of electricity demand

The electricity costs presented in Table 4.2 show that ensuring the entire flexibility requirement with storage and oversizing represents huge investments. These values should be compared to the cost of distributable electricity, which is intrinsically flexible.

To evaluate the cost of satisfying the last few percents of the Service, we conducted a sensitivity analysis on the *unmet load*: *What is the cost of meeting X % of the annual electricity demand?*

Calculations are made for the Ampère scenario over the year 2012, using Li-ion batteries and H_2 stored in steel cylinders. With this scenario, when electricity production is on average equal to the consumption, 88.2 % of the electricity demand is already satisfied. Oversizing the production and using electricity storage enables to switch from 88.2 to 100 % of satisfaction. Results are presented on Figure 4.11.

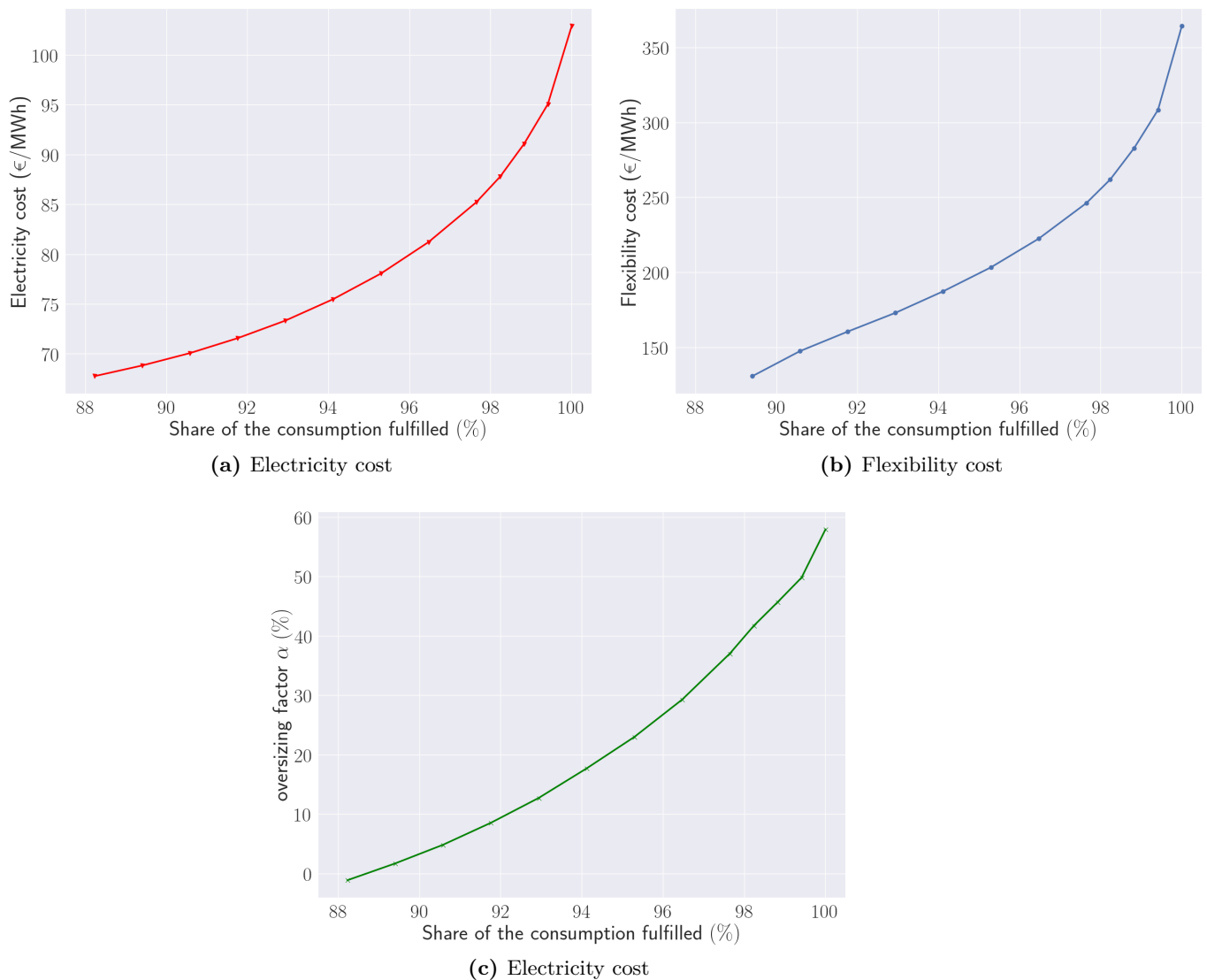


Figure 4.11: Sensitivity analysis for the Ampère scenario with Li-ion and H_2 stored in bottles. Figure (a) shows the electricity cost as a function of the share of the electricity demand satisfied. With the same x-axis, (b) shows the cost of flexibility and (c) the oversizing factor α .

The first Figure 4.11a) shows that 88.2 % of electricity demand is already satisfied

without oversizing or storage, only because average production and consumption are equal. Part of the electricity produced is curtailed when greater than consumption, which leads to an electricity cost of 68 €/MWh. Then, satisfying the last 11.8 % of consumption, electricity cost jumps from 68 to 103 €/MWh.

Figure 4.11b shows the cost of flexibility as a function of the consumption fulfilled. This cost also sharply decreases with the first percent of unmet consumption. Note that the last point, when consumption is satisfied an 88.2 % is *NaN* because the denominator (Service provided) is equal to zero.

Figure 4.11c shows similar trends for the oversizing factor α . When no Service is provided to the system — i.e., consumption is fulfilled at 88.2 % — the production is not oversized.

VI Discussion and Conclusion

In line with the objectives described in Chapter 1, this study provides an *understanding* of electricity storage integration within the context of a variable electricity generation.

We investigate how electricity storage can handle the intermittency generated by a strong deployment of variable Renewable Energy Sources. Starting from a very simplified model of intermittency — involving a single time scale —, we have provided figures of merit for electricity storage and curtailment. We prolonged those analytical solutions by optimizing a more complex model, including both daily and seasonal fluctuations. That enables to study how two storages can work in conjunction. Eventually, results are compared with the analysis of 7-year real time-series over three energy generation scenarios: two extreme cases, 100 % PV and 100 % wind power mixes, and Ampere, a scenario with 35 % of intermittent energy sources.

We emphasize the complementarity of those three models: the first two toy-models provide guidelines and an intuitive grasp of the phenomena. Results are then confirmed by this last more detailed modelling, using real time-series.

This methodology provides a better understanding, especially with analytical expressions, of the *trade-off between storage efficiency and its investment cost*. Moreover, those different approaches enable a better foundation of the results.

In particular, we note that *intermittency level* of electricity generation has a key role in the behavior of flexible systems. We observe that the lower the variability, the more interesting it is to oversize production and curtail the surplus. It is especially true for long times scales that can mostly be handled by oversizing the production. On the contrary, the stronger the intermittency, the more electricity storage is used.

Besides, the level of intermittency has a significant impact on the cost of electricity. The higher the variability, the greater the cost of electricity. In particular, for strong variability, handling the long term fluctuations with electricity storage has a dramatic cost, regardless of the technology. Nevertheless, intermittency is not the only central parameter of the system behavior.

Depending on cost and efficiency of storage, the technology will be more likely to be used for a given usage. An expensive technology with a good efficiency — like Li-ion batteries — will be dedicated to handle the short-term intermittency (up to a few days). Indeed, when a device performs many cycles, its investment cost becomes less important. Then, it is its performance that becomes discriminating.

On the other hand, technologies with a low investment cost and a low efficiency will be preferred for more extended time scales. It is because investment cost will penalize a

system that cycles little.

However, time-scales are not independent and storages can be used in conjunction. When electricity production and consumption mix several time scales, several storages may be involved and operate jointly. In particular, storage installed to handle long-term fluctuations — hydrogen for example — can also support Li-ion batteries that were installed to cope with shorter fluctuations. However, the reverse is not possible, short term cannot support the long term.

This analysis is performed using economic costs. However, apart from numerical applications, the three models are generic and the methodology can be applied at any other indicators, not only costs in terms of euros.

VII New elements of understanding compared to the previous chapter

The previous Chapter 3 has shown that, except for hydrogen stored for free, the cost of storage increased sharply with the time scale, and it was more relevant to oversize electricity production than use storages for long time scales. This chapter has highlighted similar patterns. Besides, the analysis of the complementarity between the time scales provided additional insights.

A closer look on the results, compared to the previous chapter, shows that oversizing is even more preferred when time scales are mixed. Indeed, once the system is oversized, all other time scales benefit from it, contrary to the analysis where the time scales are taken independently and the oversizing must be paid for each one.

VIII Going further

This study highlights the limited interest of handling intermittency of a system only using electrical flexible means — storage and production oversizing. It is especially true for long time scales. We saw that there is no appropriate strategy that can handle the seasonal variability of electricity consumption. In every case, the cost of electricity is multiplied by a factor of three.

It points out that other flexibility solutions must be investigated. In this work, the potential of dispatchable power plants is not evaluated. However, the complementarity between storages and dispatchable power plants is a research topic that should be conducted. It would answer questions such that “*With how many storage facilities and intermittent units can I replace a dispatchable unit?*”. *Pareto front* could be drawn between intermittent and dispatchable sources.

Long term flexibility could also be provided by other energy vectors such as gas or heat. In the following chapter, we investigate the potential of coupling heating and electricity networks. Indeed, two main reasons lead us to consider that this solution has great potential to handle seasonal variability. First, as detailed in Chapter 2, the difference in electricity consumption between summer and winter is mostly related to a demand for heating. This usage could be reported on the heating network.

Second, thermal storage has greater efficiency than hydrogen and a lower investment cost. Therefore it has real potential for long-term storage.

IX Chapter's highlights

In this chapter, we develop two simplified intermittency models to grasp the electricity system's main trends. Those analyses provide an intuitive understanding of energy storage behavior and how they can work in combination. A more realistic model finally confirms these results. The major conclusions of this study are listed below.

Take home message

- **Low cost** & **low efficiency** storage suits long-term electricity storage.
- **High cost** & **high efficiency** storage suits short-term electricity storage.
- Two storages can be used in conjunction over a large range of technology characteristics.
- Long-term energy storage can meet short-term needs. The reverse is impossible.
- Oversizing and curtailing excess electricity might be more relevant than electricity storage for a low variability.
- The more intermittent the production, the higher the flexibility cost, especially for low two efficiency systems.
- Flexibility cost rises sharply for long time scales.

Beyond electricity: assessing the potential of heat energy vector

This chapter analyzes the potential of thermal storage and heat networks to handle the seasonal variability of electricity demand. Here is a short chapter overview:

- Presentation of a very simplified model of combined heat and power systems for the French territory.
- Highlight of the coupled system's main operating modes through a parametric analysis and calculation trade-offs between each of them.
- Cost analysis determining the contribution of each component of the system to the overall cost.
- Analysis from the economic investment cost standpoint.

Chapter outlook

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I Questions addressed

The previous two chapters examined the electrical system. One of the main conclusions was that the most demanding requirement is to fulfill the seasonal fluctuation of electricity demand. It represents a massive shift in energy to ensure between summer and winter. Today, it is managed by dispatchable power plants. Nevertheless, the development of intermittent energy sources will reduce the share of dispatchable facilities. New flexible means will then have to be installed. We have shown that, both from the standpoint of economic investment and energy return on energy investment, there are no relevant flexibility means using only the electrical system with available technologies.

This chapter now examines the potential of coupling electricity and heat networks to provide the required seasonal flexibility. In particular, we want to assess thermal storage's potential to handle the seasonal variability of energy consumption.

II Method

II.1 Framework & Assumptions

The seasonal variability is modeled using time-series with a single time-scale, similarly to what has been done in the previous chapter 4, section III.

In Chapter 2, we showed that most of the seasonal variability in electricity consumption is related to electricity demand for heating (Figure 2.7). At first order in this study, we consider a constant electricity demand. The seasonal variability is supposed to come entirely from the heat demand.

In this analysis, as well, electricity and heat demand are inputs that must be satisfied.

Energy system presentation

We consider electrical and thermal systems coupled with a heat pump, as described in Figure 5.1. Both systems are national, with the energy flows representing the French energy needs.

The electrical system is modeled in the same way as in the previous chapters. Electricity can be directly consumed, stored, curtailed and now converted to heat using the heat pump. The electricity storage considered is Power-to-Power with hydrogen stored in salt caverns for free. Indeed, our previous analyses have shown that this is the most relevant long-term storage, even if it is not demonstrated at the present time. Electricity production can also be oversized to be greater on average than electricity consumption.

The thermal system is modeled with three production sources: heat pumps, heat boilers using gas or biomass — dispatchable heat sources — and waste heat recovery from waste incineration. We consider that the district heating (DH) networks allow the production of heat to be distributed directly to the consumer or to be stored in a seasonal thermal energy storage.

District heating systems are generally developed at a small scale, usually in a neighborhood or city. Assuming, as we do, that everyone can be connected to DH networks is a strong assumption. It would imply that DHs are developed and located throughout the territory. Most buildings would be connected to it to ensure the link between heat and electricity systems.

Note that all systems reflect the cost and characteristics of large-scale devices. They are not individual technologies.

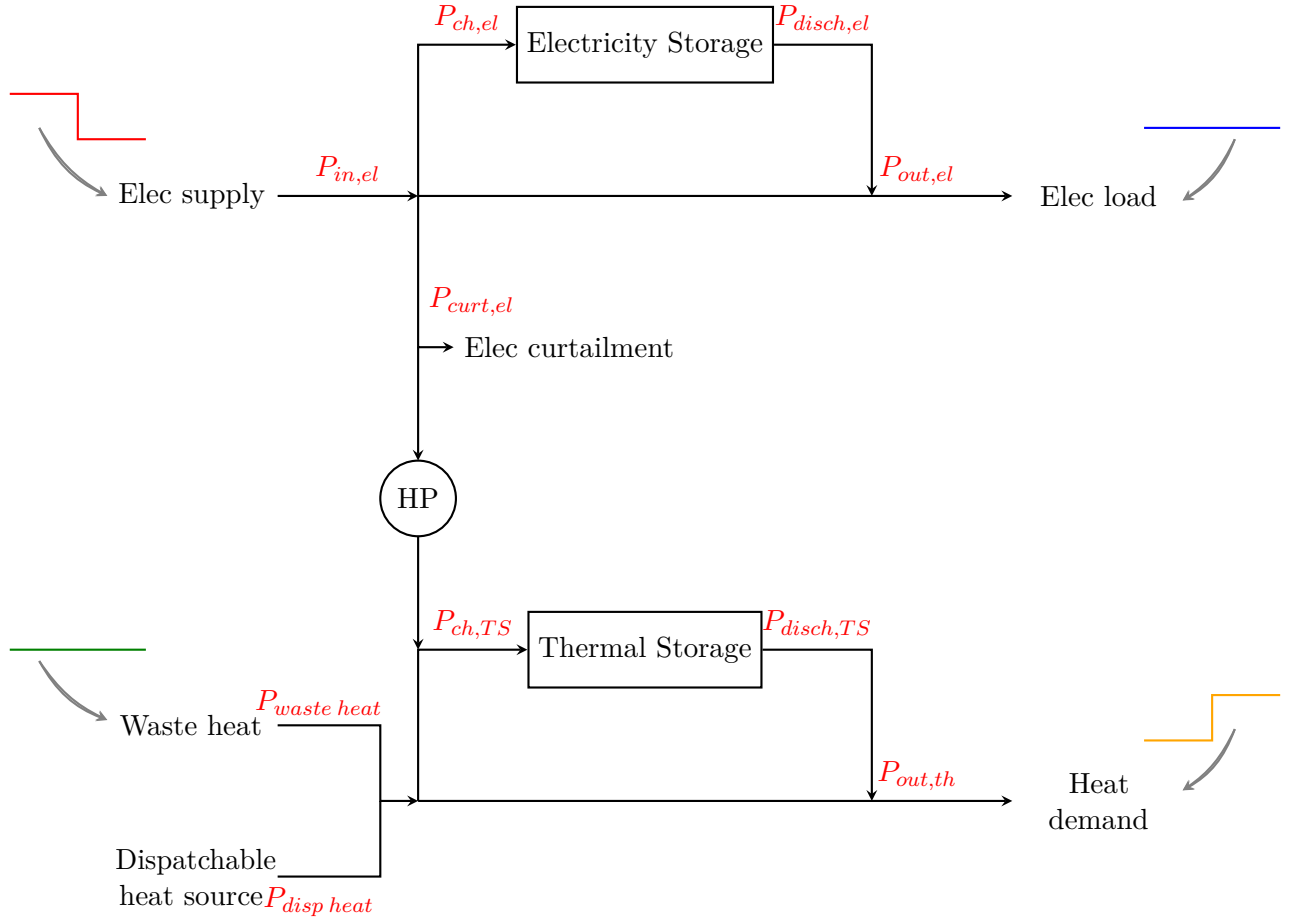


Figure 5.1: Representation of the energy system considered. Electricity and heat systems are coupled through a heat pump (HP).

Time series – Input signals

We consider input signals with a single time-scale, described by its duration, ΔT , equal to one year. The first half of the time-scale represents the summer period, the second half winter, where heat demand is the highest.

Variable signals are symmetrical with an amplitude that varies around its average. We name β the amplitude of the intermittency of electricity power supply, as shown in Figure 5.2a. The average value of electricity production is equal to that of consumption. Following optimization, the solver will return an oversizing factor α per with the production is multiplied.

Electricity demand is constant, as shown in Figure 5.2b. Its average value is a model's input data and equal to 54 GW. It represents the average French electricity consumption.

Waste heat recovery is constant and represented in Figure 5.2c. It corresponds to waste incineration production, with a similar rate than today. As detailed in Chapter 2, section 1.4.2, we use an average yearly heat production of 7 TWh_{th}/yr.

The heating demand in Figure 5.2d corresponds to the French heat demand of residential and tertiary sectors in 2018. This point is detailed in the next paragraph and in Figure 5.3.

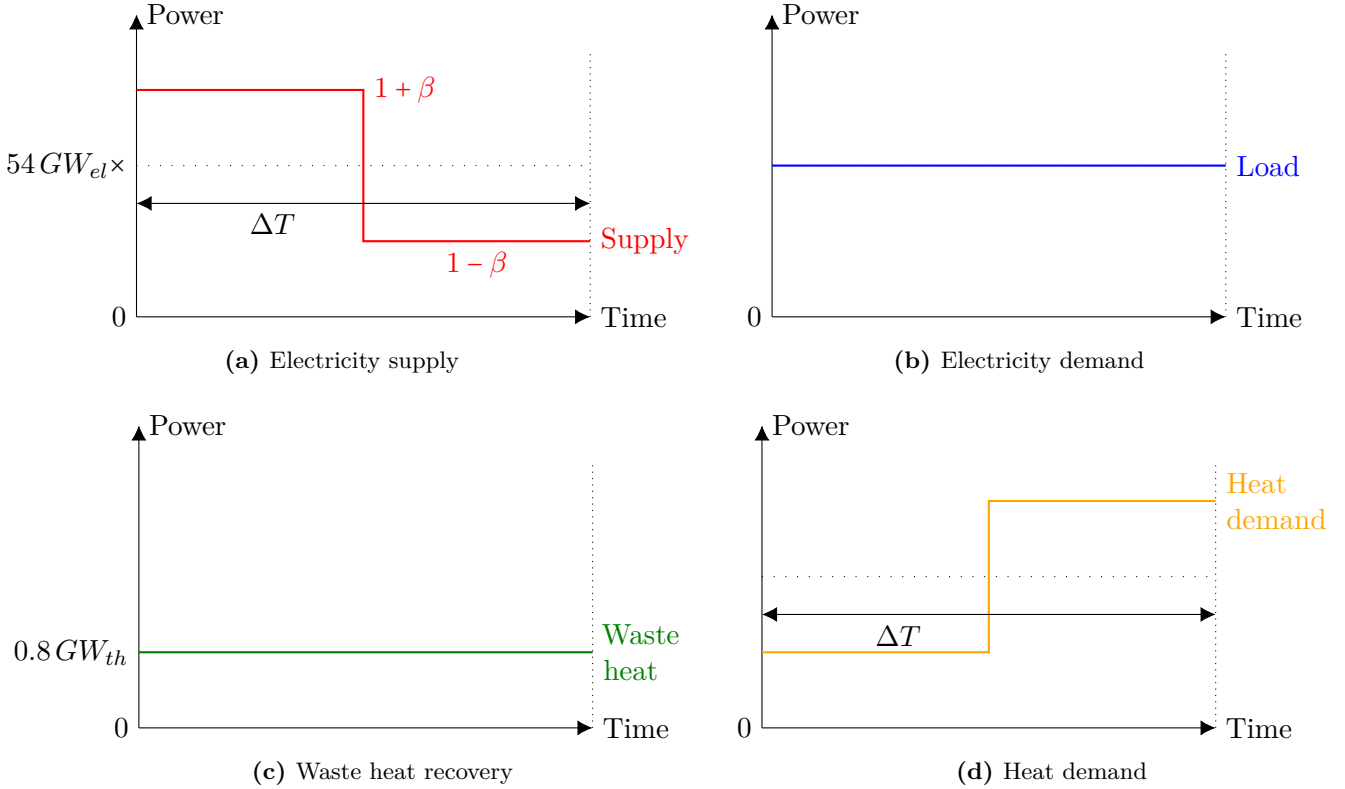


Figure 5.2: Input electricity (top) and heat (bottom) signals of the simulation with a single characteristic time-scale.

Heating demand

French heating demand trends have been described in the Chapter 2, section I.3. We recall them here to explain how heat demand on a single time scale is constructed.

We only consider the heat demand from residential and tertiary sectors. Industrial needs are assumed to be met by other means.

We assume that the demand for domestic hot water, which represents $70.1 TWh/yr$, is constant throughout the year. Conversely, the heating demand of $384.4 TWh/yr$ occurs only in winter, as shown in Figure 5.3 below*.

This seasonal heating demand description is inexact, mainly because heat consumption occurs over 3 to 4 months rather than 6. It is a bias that must be considered.

Amplitude of intermittency β

The variability of electricity generation, at a seasonal scale, depends on the share of solar PV and wind energy sources in the generation mix. Photovoltaic has a higher production in summer than in winter. It is the other way around for wind power. We provide in Appendix D the magnitude of the seasonal fluctuation for electricity consumption, PV and wind power generation. These coefficients have been calculated with a wavelet decomposition. They are given for each year from 2012 to 2018. These values are used to calculate

*It is worth noticing that in 2017, the total heat delivered in France by heating networks was 25 TWh.

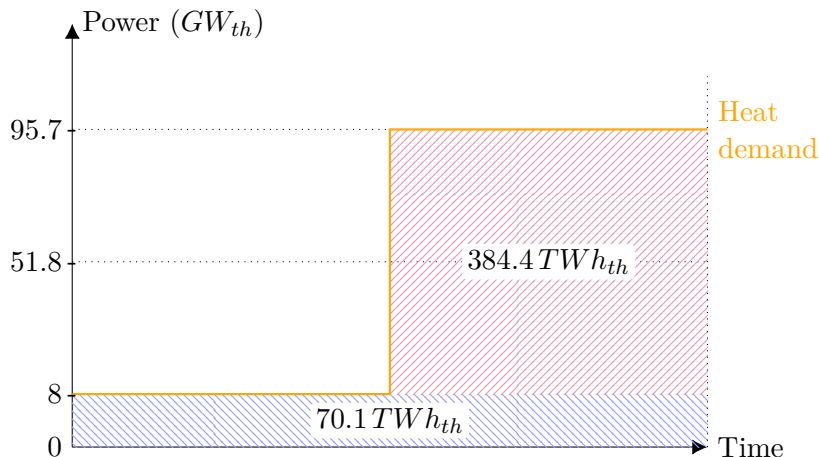


Figure 5.3: Amplitude of the heat demand signal. Values in the power axis are presented as an indication but are not to scale.

the seasonal variability of an electricity generation scenario. We refer to a positive intermittency when production is higher in summer than in winter, negative in the opposite case.

In France, scenarios[†] such as PPE and Ampère are built so that, from our calculation standpoint, production is, for most year, greater in winter than in summer. Depending on the year and on the scenario, we calculate seasonal intermittency range of from -1 to -8 %. We note that 2013 was a year of low wind energy production. As a result, this year the Ampere production mix would have been higher in summer than in winter, with a magnitude of +12 %. However, we decided to analyze a case with higher production in winter than in summer and choose a reference value of -5 %.

$$\beta = -0.05$$

II.2 Methodology

This work is based on a simplified representation of both the intermittency and energy system. This low-detail approach does not allow a perfect representation of the behavior of coupled electricity–heat systems. However, it does enable to grasp its main characteristics and trends.

Thanks to this model, we can perform numerous parametric analyses on costs and performance. This approach highlights the different operating modes — different optimal strategies — to satisfy both electricity and heat consumption. It also allows us to characterize the technological advances that should be implemented in order for a strategy to become relevant.

We start this analysis by defining a reference case, corresponding to the system’s average costs and performance. These values are summarized in Table 5.1. We will refer to it as *reference case*. Then we vary all the parameters listed in the table between a minimum and a maximum value. The ranges are broad and not necessarily realistic. However, they make

[†]Results were also compared with extreme cases: the 100 % RES from ADEME [9]. This scenario considers that 39% of the electricity consumed is provided by wind power, 27.4 % by photovoltaic. From 2012 to 2018, such an electricity generation scenario would have intermittency ranging from -2.5 to 1.6 %.

it possible to grasp the maximum number of operating modes and know if the reference case is far or near a switch to another operation.

Table 5.1: Scope of the parametric analysis: parameters are varying between the minimum and maximum value.

| Facility | Reference value | Unit | Min value | Maximum value |
|---------------------------------|-----------------|-------------------------------|-----------|---------------|
| Electricity cost | 60 | $\text{€}(MWh_{out})^{-1}$ | 0 | 250 |
| Heat cost | 60 | $\text{€}(MWh_{out})^{-1}$ | 0 | 250 |
| Heat Pump | 10^6 | $\text{€}(MWh_{th,out})^{-1}$ | 0 | 10^7 |
| Thermal storage | 1000 | $\text{€}(MWh_{stock})^{-1}$ | 0 | 2000 |
| Power-to- H_2 -to-Power cost | 1 | Actual cost ratio* | 0 | 2 |
| Intermittency amplitude β | -5 | % | -20 | 20 |
| Waste heat recovery | 7 | TWh/yr | 0 | 400 |

Objective Function definition

Similarly to the study presented in Chapter 4, we minimize the energy system's total cost while optimizing its dimensioning. The main costs and relevant parameters of this energy system are reminded in Table 5.2.

Table 5.2: Characteristics of the energy system.

| Component | Symbol | Quantity | Value | Unit |
|-----------------------|----------------------|--|--------|-------------------------------------|
| Heat Pump | COP | Coefficient of performance | 3 | |
| Thermal storage | η_{TS} | Seasonal efficiency | 60 | % |
| Heating network | I_E | Cost of heat delivery | 20 | $\text{€}(MWh_{th,delivered})^{-1}$ |
| | | Losses | 10 | % |
| Alkaline Electrolyzer | $T_{life,use,AEC}$ | Lifetime in continuous use | 10^5 | hours |
| | η_{AEC} | Efficiency ($LHV_{H_2}/Electricity_{in}$) | 65 | % |
| PEM Fuel Cell | $T_{life,use,PEMFC}$ | Lifetime in continuous use | 10^4 | hours |
| | η_{PEMFC} | Efficiency ($Electricity_{out}/LHV_{H_2}$) | 48 | % |
| H_2 storage | I_E | H_2 storage cost storage | 0 | $\text{€}(MJ_{LHV,H_2})^{-1}$ |

The Objective Function we minimize is

$$Cost = Cost_{AEC} + Cost_{PEMFC} + Cost_{TS} + Cost_{prod,el} + Cost_{prod,th} \quad (5.1)$$

Note that the costs of waste heat recovery and heating networks are constant. The optimized variables are those sizing the system: oversizing factor α , dimensioning of heat pump, thermal and electrical storages, use of dispensable heat. All the equations describing the energy system and the cost calculation are detailed in Appendix C.

III Results

III.1 Different strategies to satisfy the energy demand

Different strategies to satisfy both electricity and heat demand are observed in the optimization results. These different *operating modes* are presented in this first part of the

*It is a dimensionless quantity. It is calculated as the ratio of the total cost of the P2P conversion to the reference cost. The cost of hydrogen storage is zero in the conversion chain.

results. Section III.1.1 focuses on the electricity system, section III.1.2 on the heat system's operating modes.

A practical guide for reading Figures 5.4 to 5.11: These figures depict the energy flows of electric (section III.1.1) and heat system (section III.1.2). The thick black lines represent the energy demand (electricity or heat). Input power, such as supply or storage discharge, are positive, whereas output flows — electricity curtailment or storage charge — are represented negatively.

The power is on the ordinate and the time in abscissa. The first half represents the summer period, the second half, winter.

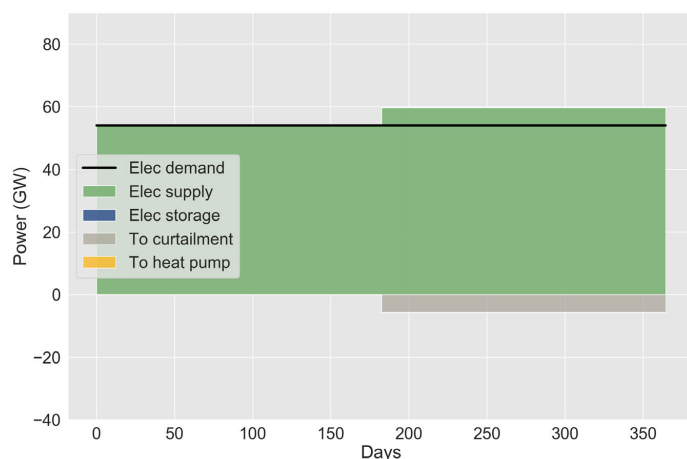
III.1.1 Satisfying electricity demand – Operating Modes

We list and present here the main behaviors that can be observed to fulfill the electricity demand. We start with the simplest operation modes to the more complex ones.

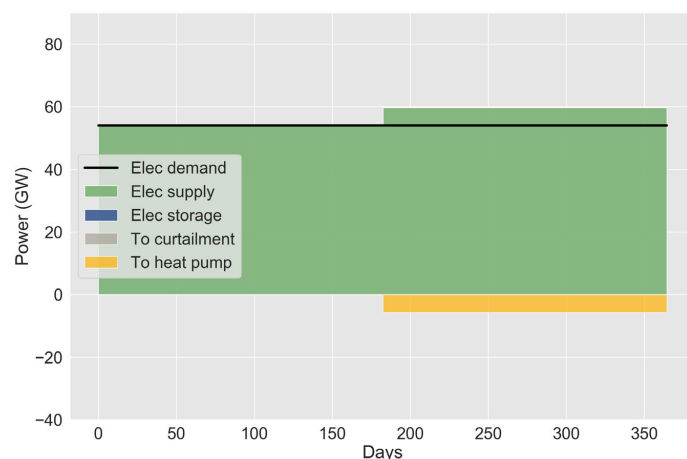
First: Oversizing electricity production *just* to satisfy electricity demand: A first option to satisfy electricity demand is to oversize the production *just* enough such that its minimum value is equal to the consumption. It is shown in Figure 5.4.

There are here two possibilities:

1. Excess electricity produced in winter is curtailed (*gray*), as shown in Figure 5.4a.
2. Excess electricity produced in winter is recovered and converted into heat by the heat pump (*yellow*), as shown in Figure 5.4b.



(a) Excess electricity curtailment



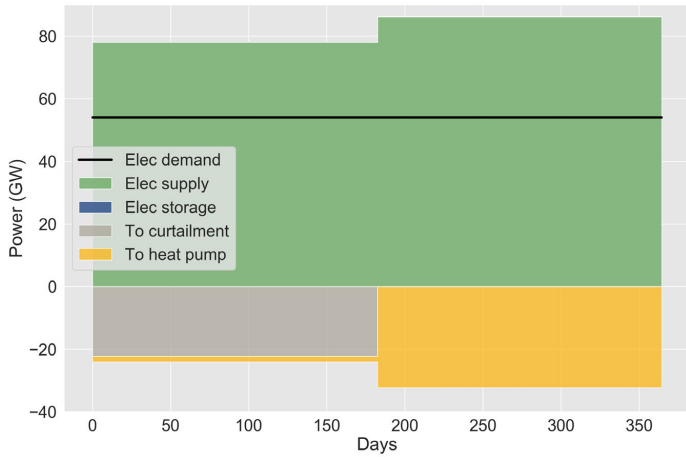
(b) Waste electricity recovery

Figure 5.4: Electricity system operating modes: The production (*green*) is oversized so that its minimum value is equal to the consumption (black line). In (a), excess electricity is curtailed (*gray*), in (b) the excess is converted into heat through the heat pump (*yellow*).

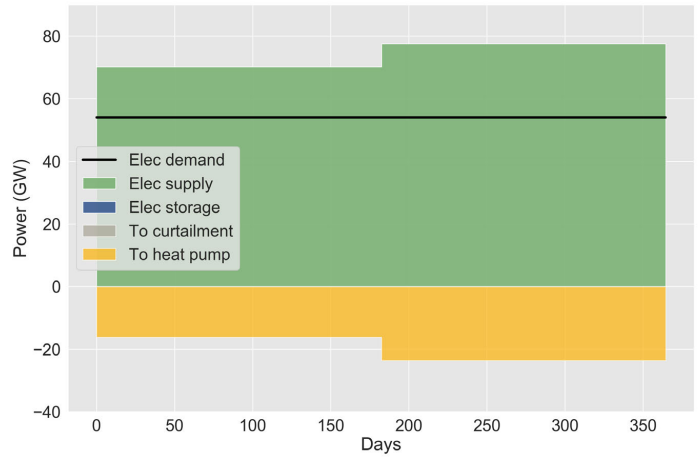
Second: Oversizing electricity production *more than* electricity demand: Alternatively, the production can also be oversized not only to satisfy demand, but also to produce excess electricity on purpose, and convert it into heat. It is the scheme described in Figure 5.5.

This case is also divided into two possibilities:

1. All excess electricity is converted into heat, as shown in Figure 5.5a.
2. Part of excess electricity is curtailed in summer, the rest is converted into heat, as shown in Figure 5.5b.



(a) Production oversizing, excess conversion.



(b) Production oversizing, excess curtailment & conversion.

Figure 5.5: Electricity system operating modes: The production (*green*) is oversized to produce more electricity than what is consumed. In (a), part of excess electricity is curtailed (*gray*) in summer. In (b), all excess is converted into heat through the heat pump (*yellow*).

3. Heat pump can also be operated at a constant power rate in both summer and winter, as shown in Figure 5.6. Excess electricity is then curtailed.

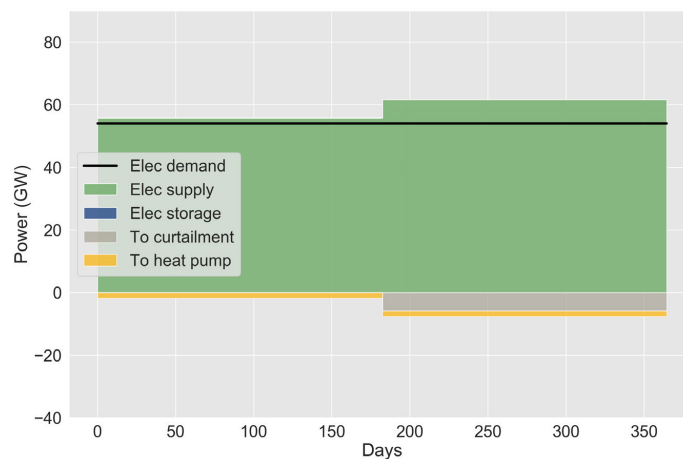


Figure 5.6: Electricity system operating modes: The production (*green*) is oversized. HPs are used with a constant power in both summer and winter to convert electricity into heat. The excess that remains is curtailed.

Third: Involving electricity storage: Eventually, electricity storage can also be charged in summer and discharge in winter, as shown in Figure 5.7. Electricity production is also oversized for heat production.

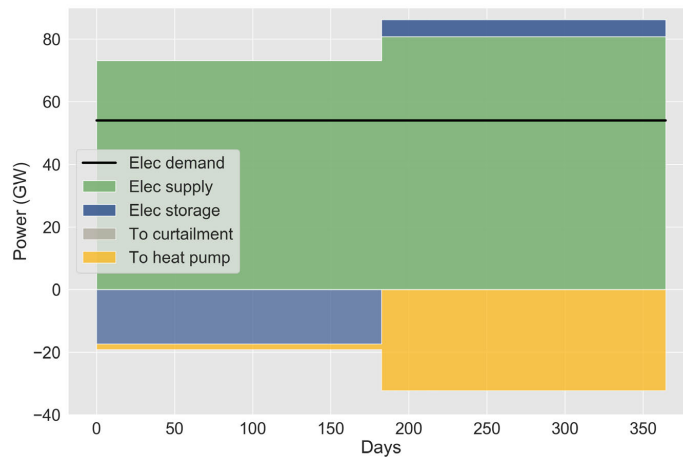


Figure 5.7: Electricity system operating modes: The production (*green*) is oversized. Excess electricity is: 1) charge in summer (*blue*) and discharged in winter, 2) converted into heat.

III.1.2 Satisfying heat demand – Operating Modes

Figures 5.8 to 5.10 depict the main behaviors of the thermal system observed. There is always a constant supply from waste heat recovery (*light green*). In the reference case, it is only a small share of the production. The thermal demand is then supplied either with heat produced by dispatchable plants (*dark green*), heat pumps (*yellow*), or thermal storage (*purple*). The following cases are distinguished:

First: Dispatchable heat supply provides heat in summer & winter: Figure 5.8a shows that dispatchable heat can be operated both in summer and winter and supply the entire heat demand. There is just a trade-off with the heat supplied by the heat pump. Figure 5.8b shows that there is a competition to use boilers or HP in winter.

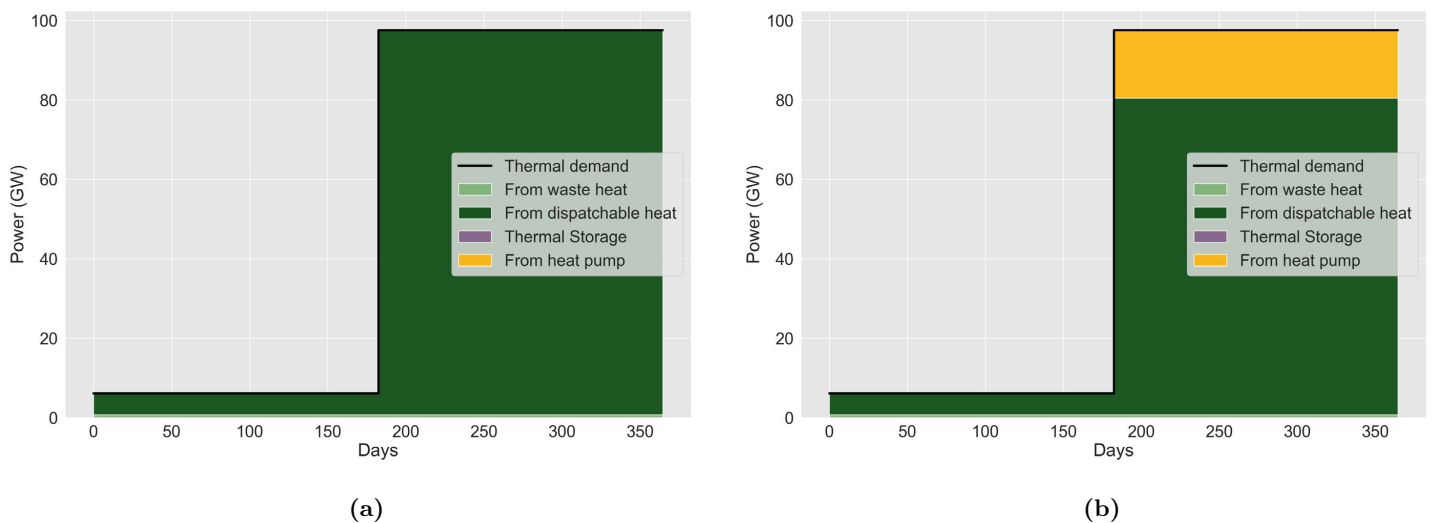


Figure 5.8: Thermal system operating modes: Heat boilers are both used in summer and winter. In (a), it is the unique heat source. In (b), heat is also provided by heat pumps in winter.

Second: Dispatchable heat supply is not operated in summer: Conversely, we saw in Figure 5.9 that the system is operated differently. Dispatchable heat is only supplied in summer, whereas HP is working in winter.

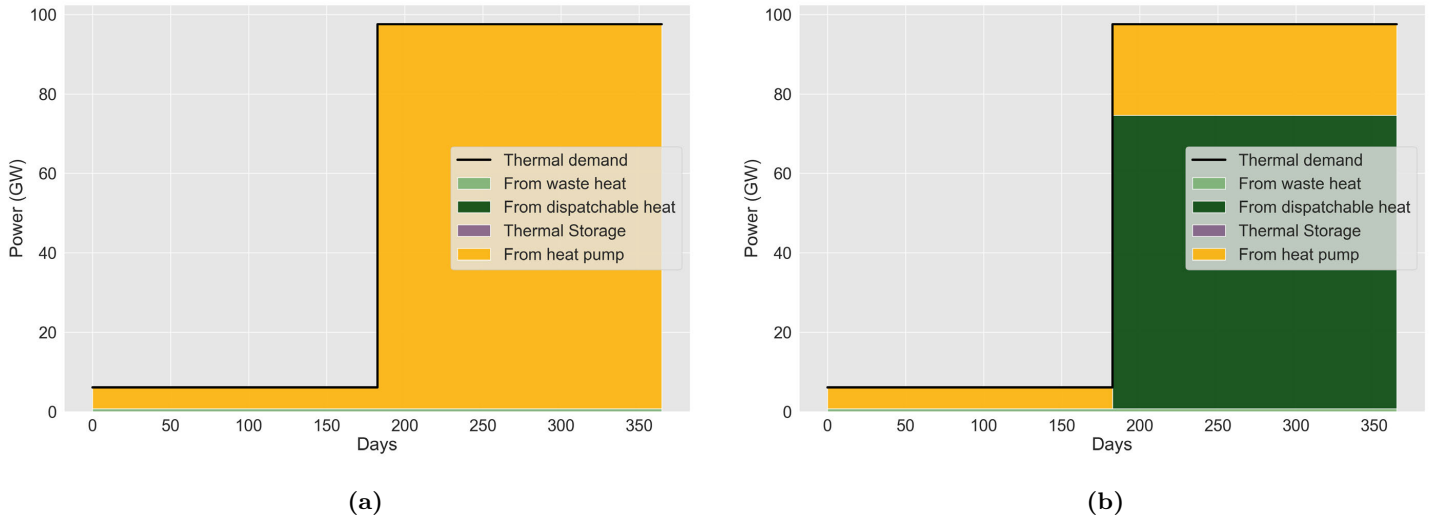


Figure 5.9: Thermal system operating modes: Heat pumps are used both in summer and winter. (a) shows a case where HPs entirely provide the required heat. In (b), the demand is also supplied with dispatchable heat in winter.

Third: Use of thermal storage: Eventually, there are also cases where thermal storage is used, as shown in Figure 5.10. Excess electricity provided by the HP is stored in summer and used in winter.

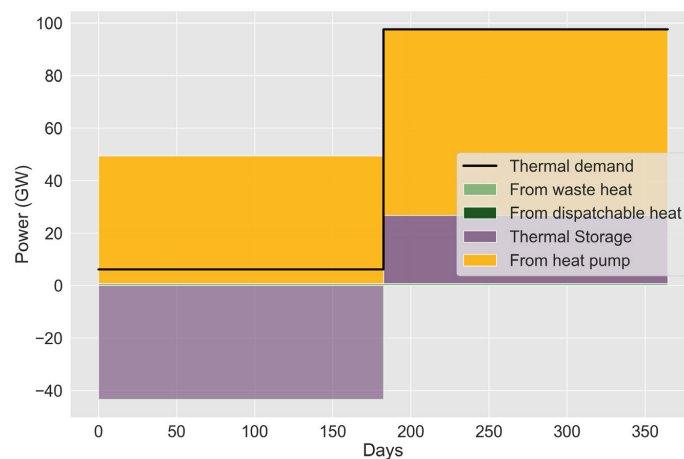


Figure 5.10: Thermal system operating modes: Heat is entirely provided by heat pumps. The summer excess production is stored to be used in winter.

III.1.3 Vocabulary: Describing all operating modes

The parametric analysis revealed the different operating modes listed above for the combined heat and power system. We describe each of these modes (electricity & heat) by how

thermal energy is produced. A simulation result can use one or several of the following strategies to provide thermal energy:

1. When the electricity system is deliberately oversized to produce heat, we refer to this strategy as **Oversizing**. It is what we observe in Figures 5.5, 5.6 & 5.7.
2. When heat is produced from waste electricity (not oversized on purpose for heat production), as shown in Figure 5.4b. We refer to it as **Electricity recovery**.
3. When heat is produced with dispatchable power plants, as shown in Figures 5.8 & 5.9b, we refer to this strategy as **Gas**.
4. When thermal storage is involved to store excess heat, as in Figure 5.10, we refer to this strategy as **Thermal storage**.
5. When electricity storage is involved, as in Figure 5.7, we refer to this strategy as **Hydrogen**.
6. The heat pump can be used in two different ways. It could be operated with a constant power both in summer and winter, as shown in Figure 5.6. It could also have different powers in each time step. When both summer and winter input power are equal, we will refer to this case as **Constant HP**.

III.1.4 Reference case

With the reference case’s costs and characteristics — see Table 5.1 and 5.2 — we observe the behavior presented in Figure 5.11. Figure 5.11a corresponds to the electricity system and Figure 5.11b to the thermal system.

The system is operated as follows. Electricity production is *oversized* to produce more electricity than consumed. All excess is converted, there is no curtailment. The heat pump does not have the same output power in summer and winter. Electricity storage is not used and the *thermal storage* is charged in summer. Based on the vocabulary presented above, this reference case is characterized as “*Oversizing & Thermal Storage*”.

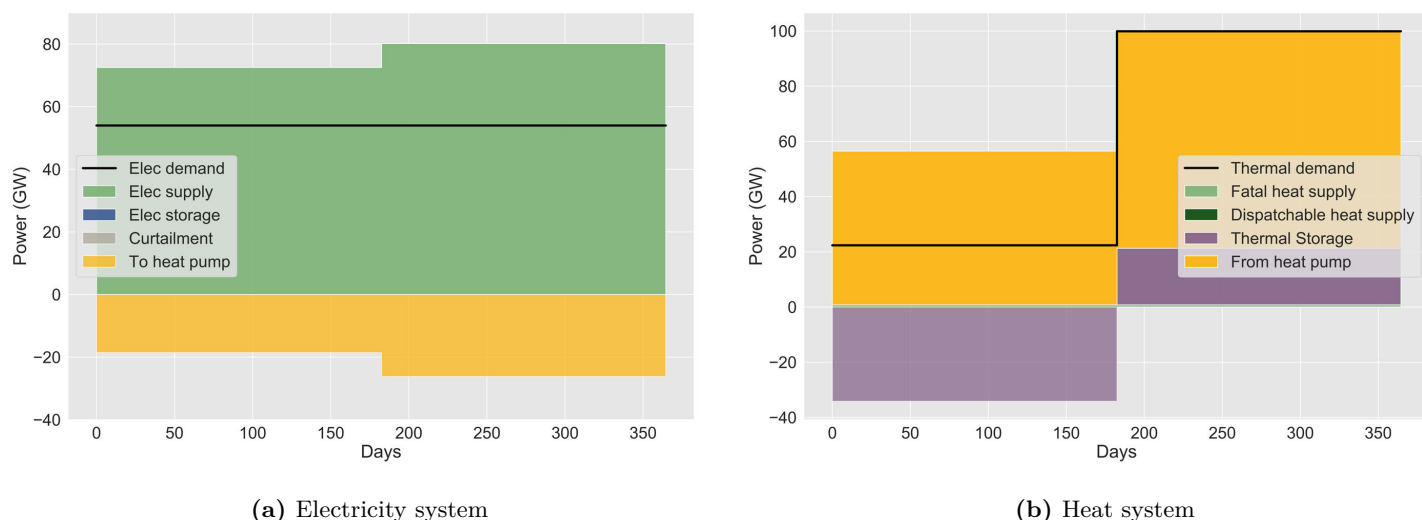


Figure 5.11: Behavior of electricity (a) and thermal (b) systems in the *reference case*.

This description will be used to qualify all operating modes observed in the following parametric analysis.

III.2 Results of the parametric analysis

This analysis is performed varying parameters listed in Table 5.1 one at a time between the minimum and maximum values.

A practical guide for reading results: Results are all built in the same manner and constituted of three parts. Figures 5.12, can be used as an example.

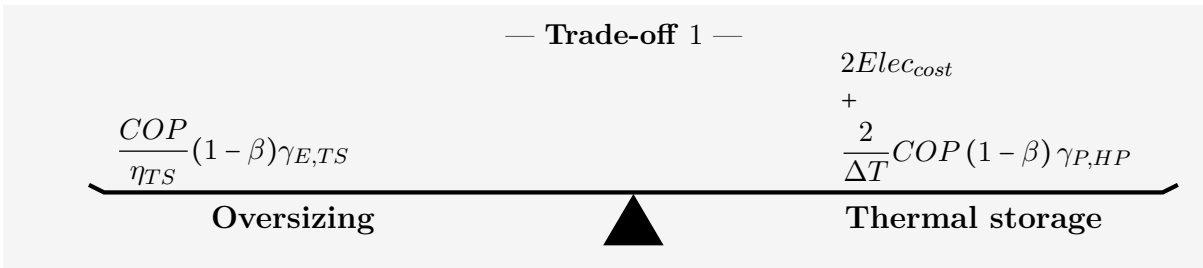
- Each point (i.e., each vertical line) corresponds to a simulation using a new parameter value. We calculate for each of them the distribution of electricity production over the year. One part, invariably the same, satisfy the electricity demand (*turquoise*); another part can go to the heat pump (*yellow*), is curtailed (*gray*) or stored (*blue*). Similarly, for the heating system (b), we represent the different contributions that satisfied the heat demand: waste heat recovery (*light green*), heat pump (*yellow*), gas (*dark green*), heat discharged by the thermal storage (*purple*). A *red* vertical line indicates the reference parameter value.
- The bottom figure (c) summarizes the different operation modes observed. Numerical values of boundaries between each case are given. These values are calculated from a trade-off calculation detailed in Appendix C and summarized in the gray box that follows, entitled *Trade-off*. The red point in figures (c) is the value of the reference case.
- Those gray boxes sketch the trade-off between two strategies, for example oversizing electricity production or using thermal storage. This balance is depicted with the shape of a weighing scale. The boundary between two cases is reached when members on each side of the scale are equal.

III.2.1 Thermal storage cost analysis

We present in Figure 5.12 the sensitivity analysis on the thermal storage cost.

Analysis We remark that there is a competition between two modes: storing excess heat in summer (*left, for low TS cost*) or oversizing electricity production to generate enough heat (*right, for high TS cost*). Switching from one to the other depends on the trade-off between system parameters. It is shown in the box below (**Trade-off 1**). The calculation leading to this is detailed in Appendix C, section II.1.

The left side represents the weight of the *oversizing strategy*, the right side the *thermal storage strategy*. The chosen solution is the one with the higher weight.



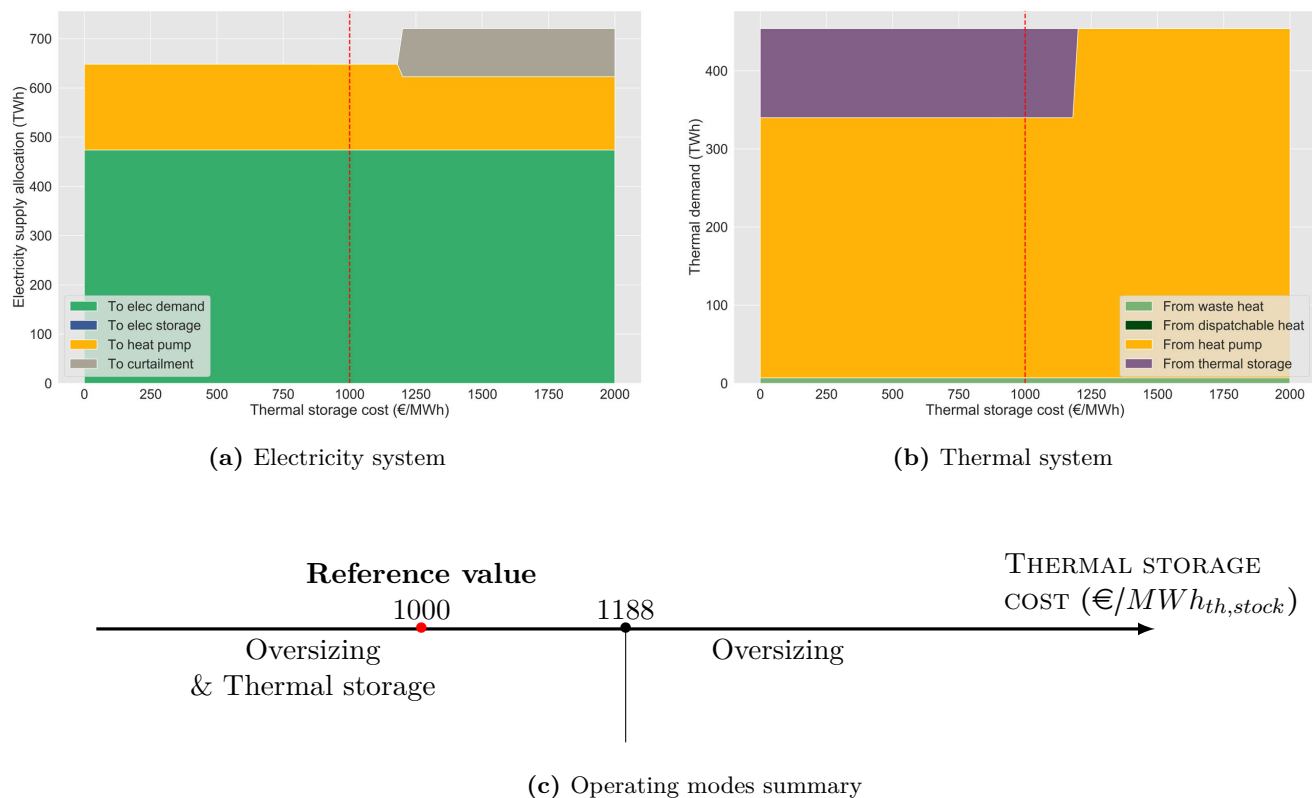


Figure 5.12: *Thermal Storage cost* sensitivity analysis.

Calculation The boundary between the two cases is reached when both sides are equal. Using values from the reference case, we calculate the following limit cost.

$$Cost_{TS}^{lim} = 1188 \text{ €/MWh}_{th,stock} \quad (5.2)$$

Results summary Current costs and parameters make the system behave by providing all heat requirements using electricity and heat pumps. Excess electricity is not curtailed but stored as heat in long-term thermal storage. It is what we call the *reference case*.

Sensitivity analysis of the *thermal storage cost* shows that this strategy is very close, in terms of cost, to an operating mode in which excess electricity production is not stored but curtailed. It emphasizes that thermal storage must have low costs to compete with electricity generation.

III.2.2 Heat pump cost

We present in Figure 5.13 the sensitivity analysis of the HP cost.

Analysis Figure 5.13 shows that there are four different boundaries. From left to right, while the cost of heat pump increases, we see that

1. It first becomes relevant to store excess heat provided by the HP.
2. Then heating with gas becomes competitive and cheaper than storing excess heat.
3. Eventually, only part of the waste electricity is converted into heat. The heat pump is operated at a constant rate and not oversized to convert all excess electricity, as shown in Figure 5.6.

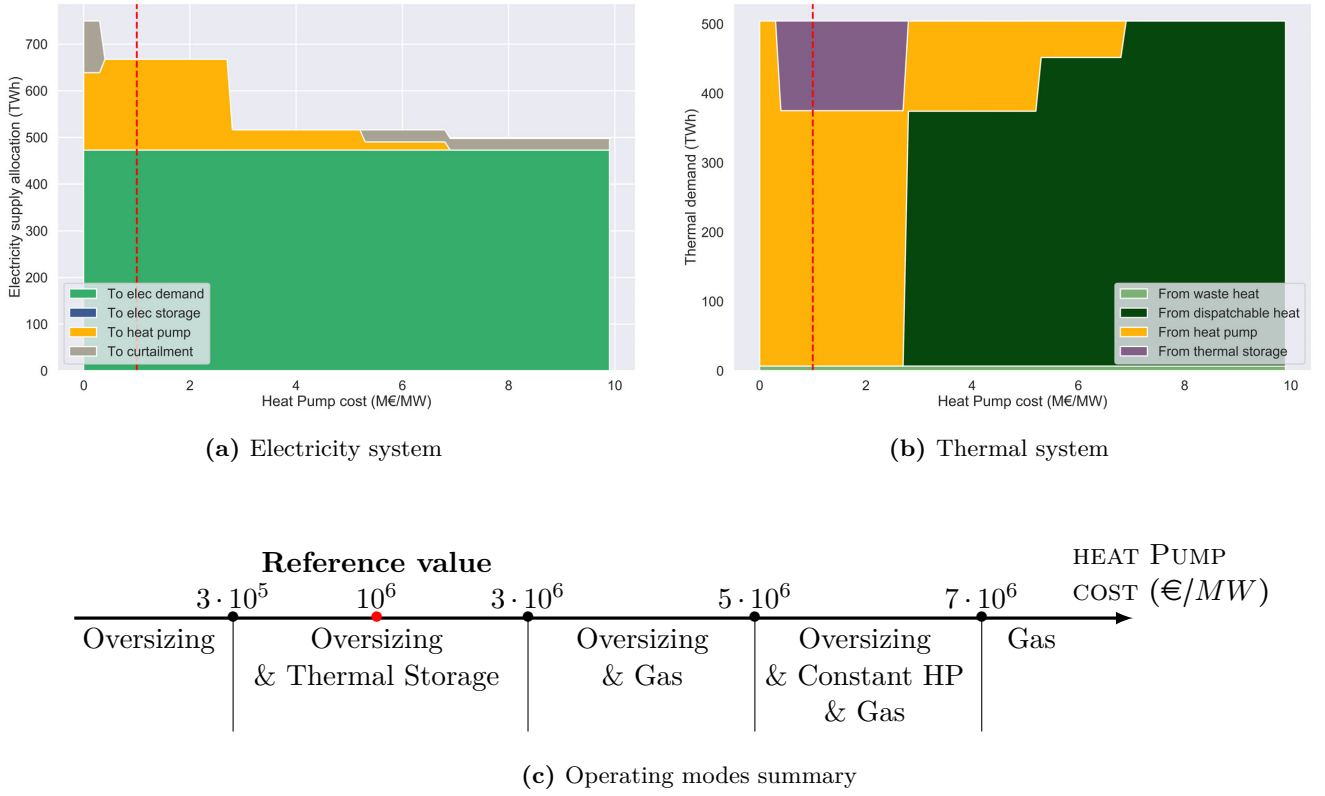


Figure 5.13: Heat pump cost sensitivity analysis.

- Heat pump becomes too expensive, electricity recovering stops. Heat demand is entirely satisfied with dispatchable means.

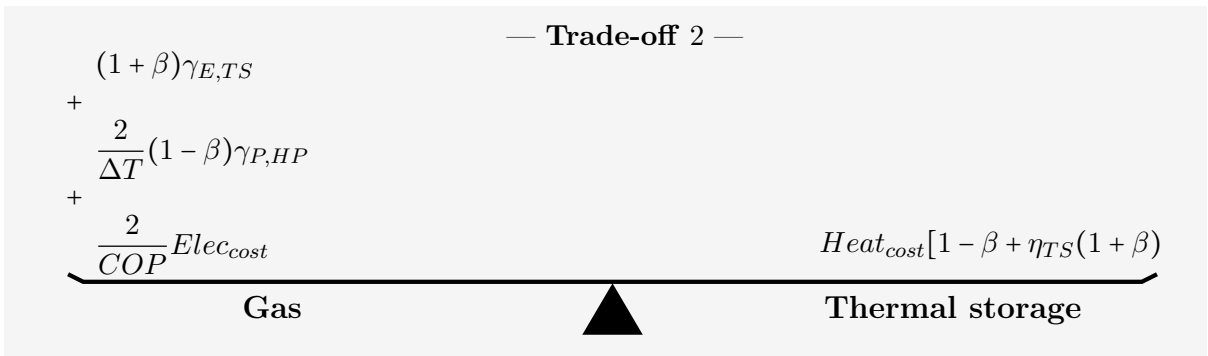
In the following paragraphs, we present the calculation of those four boundaries.

Boundary 1 – Oversizing vs. Thermal Storage This is the Trade-off 1 already computed in the previous section III.2.1.

We calculate

$$Cost_{HP}^{lim} = 3.1 \times 10^5 \text{€}/MW_{out,th} \quad (5.3)$$

Boundary 2 – Thermal storage vs. Dispatchable heat supply We proceed here to a new calculation, detailed in Appendix C, section II.2. Results are summarized in the box below.

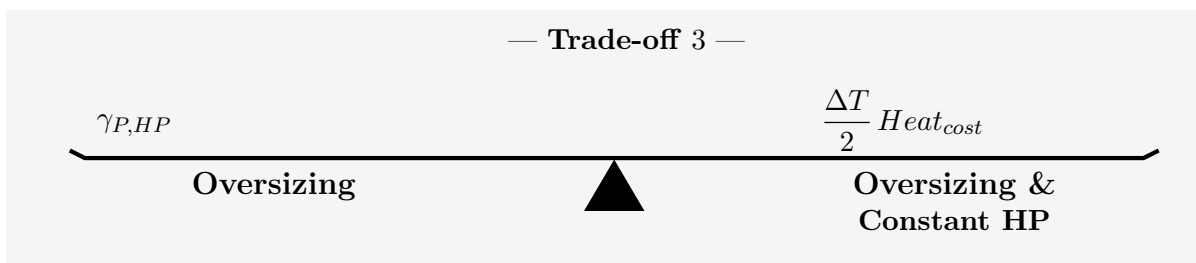


The limit cost of this boundary is

$$Cost_{HP}^{lim} = 2.8 \times 10^6 \text{ €/}MW_{out,th} \quad (5.4)$$

Boundary 3 – Operating heat pump at constant rate or Recovering all excess electricity In the fourth mode, named *Oversizing & Constant HP & Gas* in Figure 5.13c, the heat pump is operated at a constant rate in summer and winter, all excess electricity is not recovered. This third boundary is the switch from one mode where all excess electricity is converted — i.e., HP is oversized and does not operate at full load all the year — to a case where HP becomes too expensive to be operated only half of the year, in comparison with dispatchable heat supply.

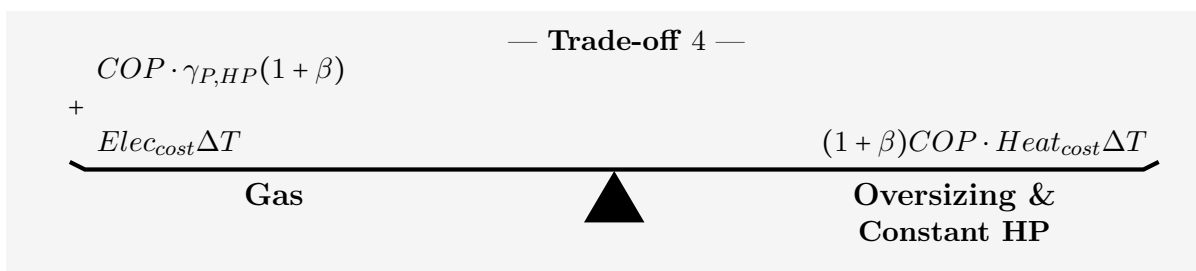
The boundary between those two schemes is driven by the balance between the costs presented in the following Trade-off box. Calculations are detailed in Appendix C, section II.3.



We calculate the following limit

$$Cost_{HP}^{lim} = 5.3 \times 10^6 \text{ €/}MW_{out,th} \quad (5.5)$$

Boundary 4 – Oversizing vs. Gas cost This last boundary represents the trade-off between the cost of electricity production — i.e., oversizing — and the cost of heat generation. Results are presented below. Calculations are detailed in Appendix C, section II.5.



We calculate the following limit

$$Cost_{HP}^{lim} = 6.8 \times 10^6 \text{ €/}MW_{out,th} \quad (5.6)$$

Results summary This analysis on *heat pump cost* shows that coupled with cheap electricity ($60 \text{ €/}MWh_{el,out}$), producing heat from electricity is economically more profitable

than gas. This conclusion is robust — in our very simplified framework — as it remains valid for a cost of up to $3 \cdot 10^6 \text{ €/MWh}_{th,out}$. It is three times more than today’s average.

III.2.3 Electricity cost

The sensitivity analysis of the electricity cost shows that it is the parameter that influences the most the total cost of the energy system. This point will be detailed in the next section III.3.

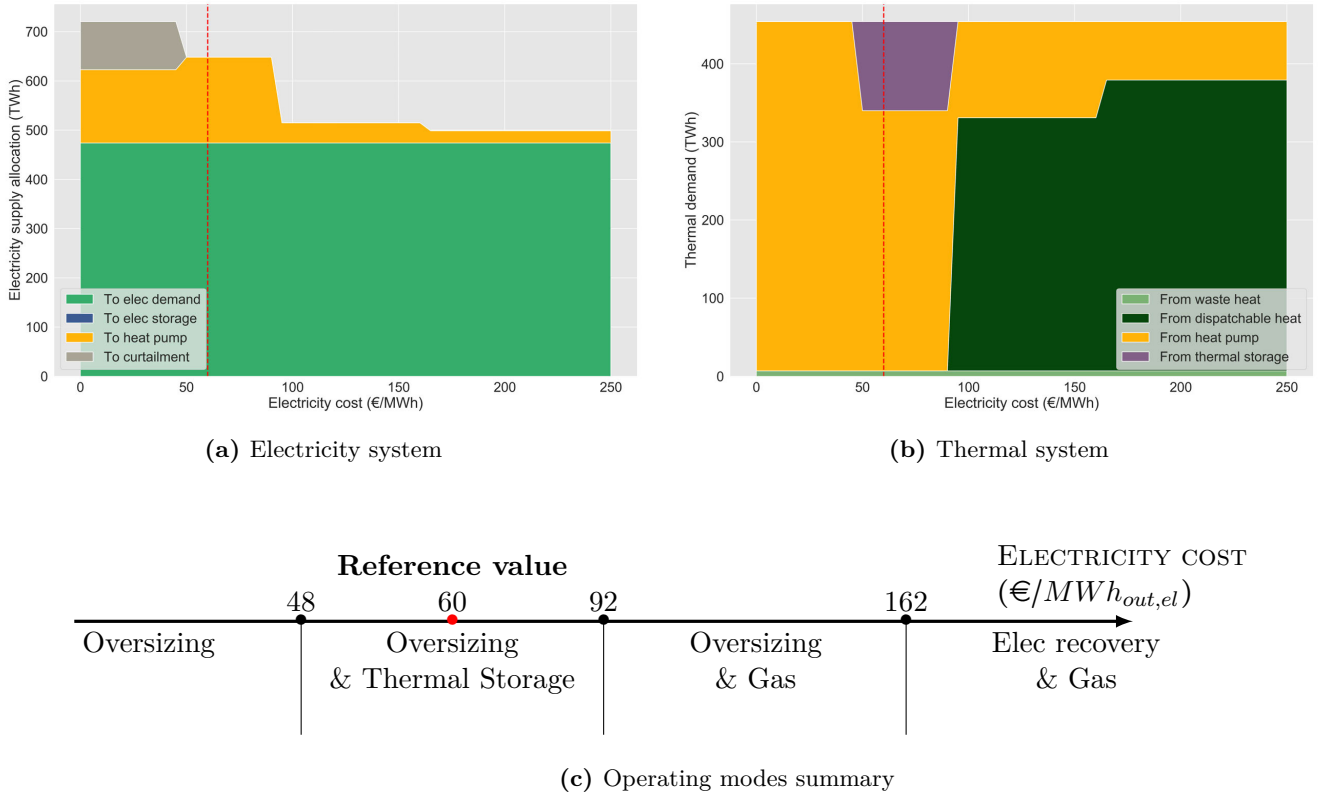


Figure 5.14: Electricity cost sensitivity analysis.

Analysis Figure 5.14 shows that there are three different boundaries. From the lower (left) to the higher (right) cost we see that:

1. There is a first competition between the cost of electricity and thermal storage. Similarly to HP’s sensitivity analysis, it is no longer relevant to waste electricity. All excess electricity is converted to heat, even if it implies using thermal storage and its associated losses.
2. Then, instead of producing excess electricity for heat and using thermal storage, the production is less oversized. Electricity is only used to produce heat when it can be directly consumed. Otherwise, heat is produced with dispatchable plants.
3. Eventually, electricity production is no longer oversized for heat generation purposes, but free excess electricity is recovered.

The sensitivity analysis of the electricity cost shows that it is the parameter that influences the most the total cost of the energy system. This point will be detailed in the next section III.3.

Boundary 1 – Oversizing vs. Thermal Storage This is the Trade-off 1 already computed above.

It shows that

$$Elec_{cost}^{lim} = 47.6 \text{ €/}MWh_{out,el} \quad (5.7)$$

Boundary 2 – Thermal storage vs. Dispatchable heat supply This case was also already addressed in Trade-off 2 box and detailed in Appendix C II.2.

It shows that

$$Elec_{cost}^{lim} = 92.2 \text{ €/}MWh_{out,el} \quad (5.8)$$

Boundary 3 – Heat vs. Electricity production The calculation of this trade-off is detailed in Appendix C II.6. It leads to the following costs budget.



The calculation shows that

$$Elec_{cost}^{lim} = 162 \text{ €/}MWh_{out,el} \quad (5.9)$$

Results summary In the same track as previous conclusions, this analysis shows that as long as electricity cost remains below $90 \text{ €/}MWh_{el,out}$, it is economically more relevant to produce heat with electricity and heat pumps than gas. However, the first three cases correspond to plausible values of the electricity cost. The economic interest of thermal storage and heat pumps is highly sensitive to electricity cost, compared to the cost of gas. As these prices fluctuate and are difficult to predict in the long term, this does not favor investments.

III.2.4 Heat cost

The sensitivity analysis of the heat cost is presented in Figures 5.15. We observe three boundaries, already computed previously.

Analysis From the lowest cost (left), to the highest (right), we observe that:

1. When cost of heat generation increases, it becomes more profitable to recover waste electricity.
2. Then, producing excess on purpose and converting it into heat becomes competitive with dispatchable heat.
3. Eventually, all heat is produced from excess electricity. The thermal storage is charged in summer and discharged in winter.

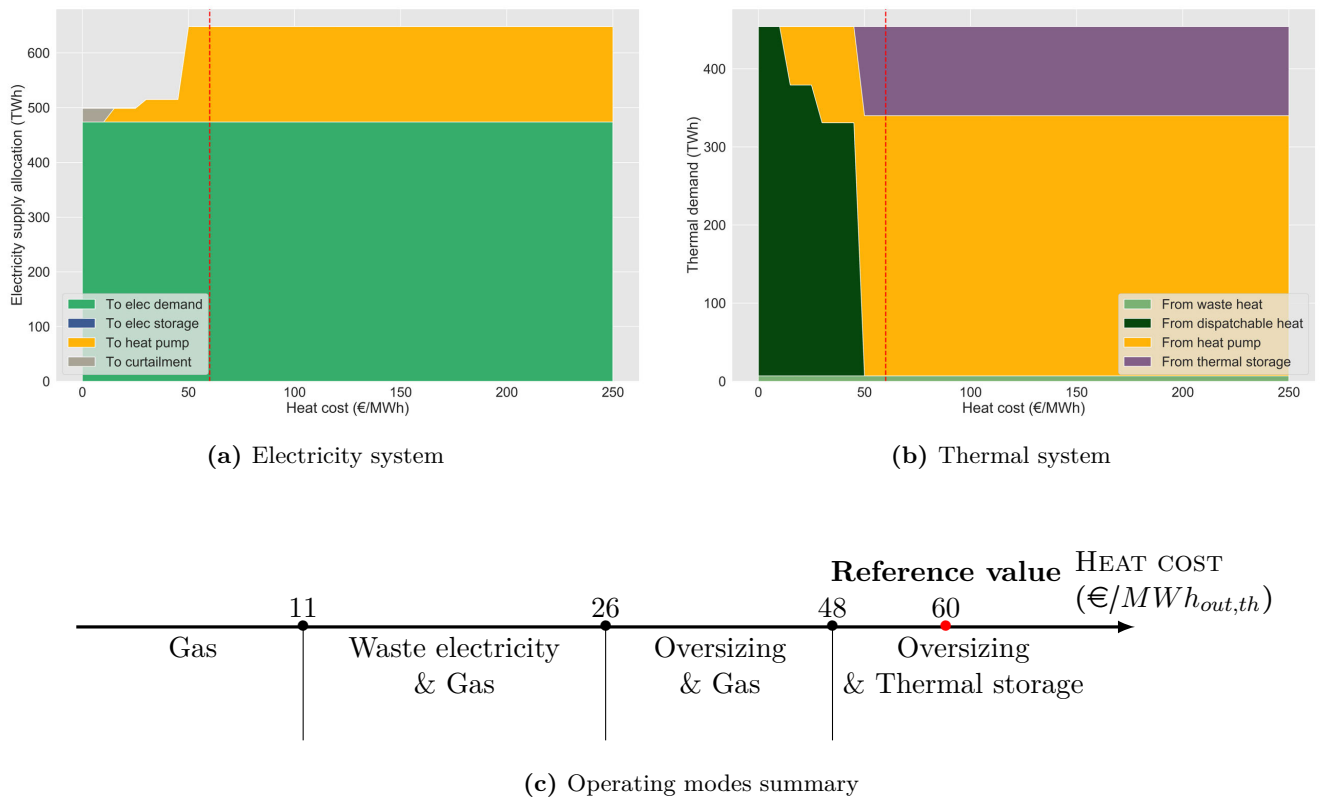
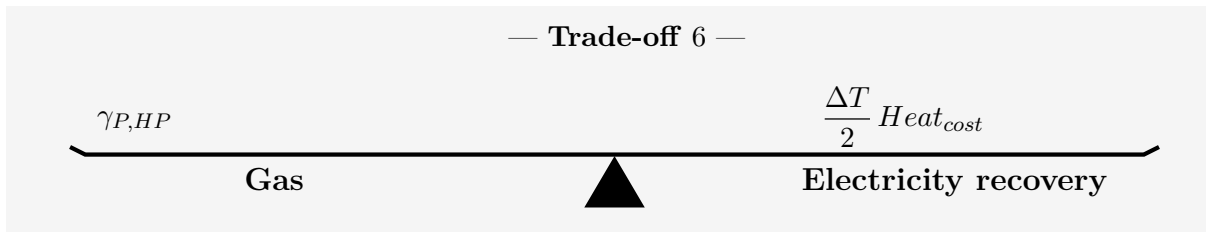


Figure 5.15: Heat cost sensitivity analysis.

Boundary 1 – Waste electricity recovery vs. Gas Calculations are presented below and detailed in Appendix C, section II.4.



The calculation shows

$$Heat_{cost}^{lim} = 11.4 \text{ €/}MW h_{out,th} \quad (5.10)$$

Boundary 2 – Oversizing vs. Gas It corresponds to the Trade-off 5 presented above and detailed in Appendix C, section II.5.

Thus, we calculate

$$Heat_{cost}^{lim} = 25.9 \text{ €/}MW h_{out,th} \quad (5.11)$$

Boundary 3 – Thermal storage vs. Dispatchable heat supply It corresponds to the Trade-off 2 presented above and detailed in Appendix C, section II.2.

It lead to the following boundary calculation

$$Heat_{cost}^{lim} = 47.6 \text{ €/}MWh_{out,th} \quad (5.12)$$

Results summary Sensitivity analysis of thermal power plants cost shows that their use is relevant below $50 \text{ €/}MWh_{th,out}$. Today, these costs can be accessible to gas. However, CO_2 taxes could easily prevent their use. This cost limit has not yet been reached for biofuels.

III.2.5 Electricity storage

We present here the sensitivity analysis of power-to- H_2 -to-power storage. We vary both costs of electrolyzer and fuel cell at the same time, introducing the factor X . It represents the ratio of both electrolyze and fuel cell costs in relation to their reference costs.

i.e.,

$$\begin{cases} \gamma_{P,AEC} & = X \times \gamma_{P,AEC}^{ref} \\ \gamma_{P,PEMFC} & = X \times \gamma_{P,PEMFC}^{ref} \end{cases} \quad (5.13)$$

where superscript ref referring to the *reference value*.

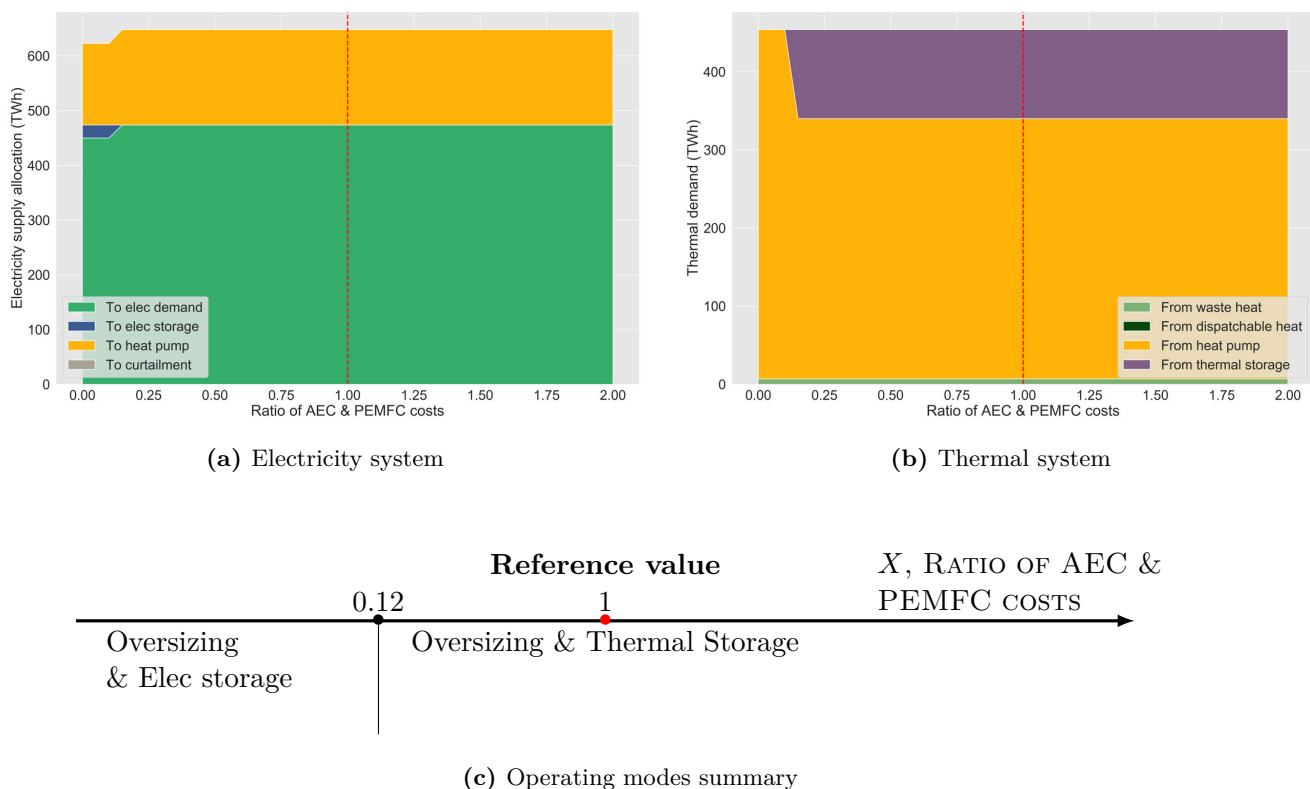


Figure 5.16: Hydrogen cost sensitivity analysis.

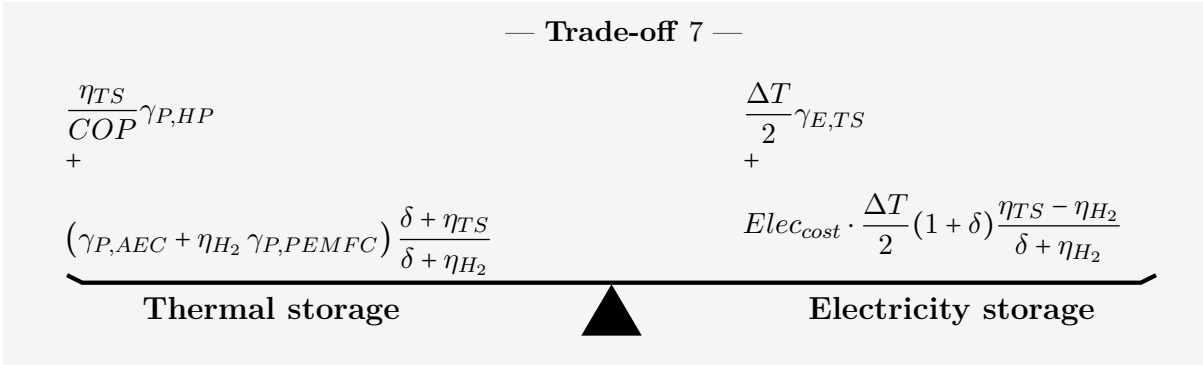
Analysis The results are presented in Figure 5.16. It shows only two operating modes. When the electricity storage cost is small, hydrogen is used to manage the electricity supply's seasonal variability, excess production is converted to heat. This scheme is depicted

in Figure 5.6.

To determine the boundary between both cases, we introduce the parameter δ , such that

$$\delta = \frac{P_{in}^2}{P_{in}^1} = \frac{1 + \beta}{1 - \beta} \quad (5.14)$$

The trade-off between hydrogen and thermal storage is synthesized in the following Trade-off.



Results summary This analysis shows that power-to-power costs would have to be reduced by a factor of 8 for the system to be competitive, despite the fact that hydrogen is already stored for free. It shows that TS is a more suitable solution to handle the seasonal heating demand because of its low cost and good efficiency.

Storage efficiency analysis Additionally, our analysis shows that no matter the Power-to-Power efficiency, even at 100 %, Hydrogen storage is never used with the reference case values. Varying the efficiency from 0 to 100 % does not change the operating mode.

III.2.6 Sensitivity to the amplitude of the intermittency β

Results of this analysis are presented in Figure 5.17a. It shows that the system is not very sensitive to the amplitude of the production variability, even though this analysis is carried out over a wide range of parameter values. When electricity generation increases in winter (i.e., β gets smaller), the operating mode remains. Production oversizing eventually decreases. Indeed there is more and more energy produced when needed.

Conversely, if the production increases in summer, the oversizing α also increases to ensure that enough energy is produced in winter. However, the operating mode also remains and heating demand is satisfied using heat pump and thermal storage.

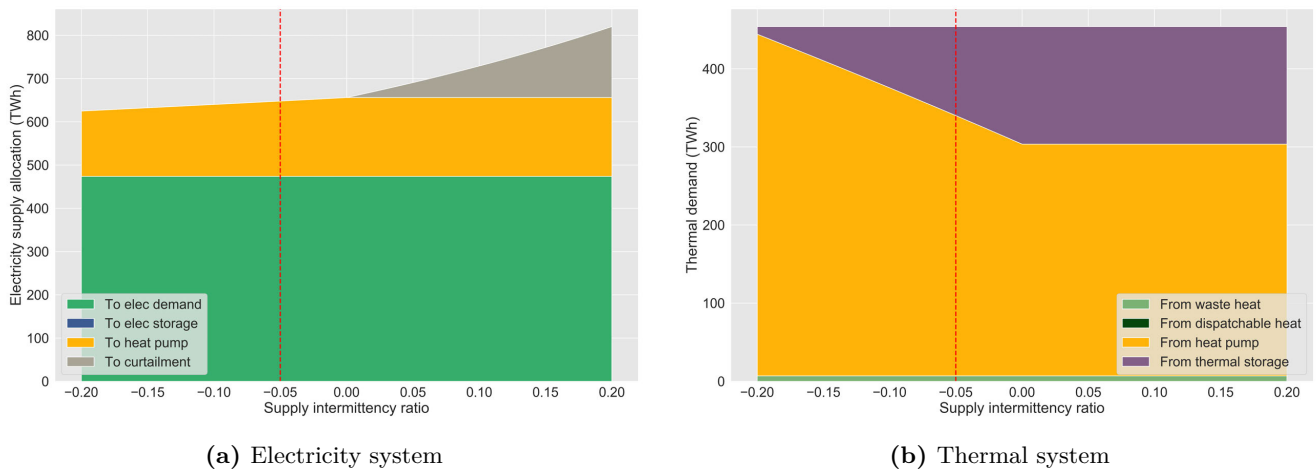


Figure 5.17: Hydrogen cost sensitivity analysis

III.2.7 Waste heat recovery

Sensitivity analysis of the amount of waste heat recovery is presented in Figure 5.18. This shows that the system is not sensitive to this parameter magnitude. Regardless of its value, the operating mode remains unchanged. The waste heat only progressively replaces the heat from the oversizing of the power generation.

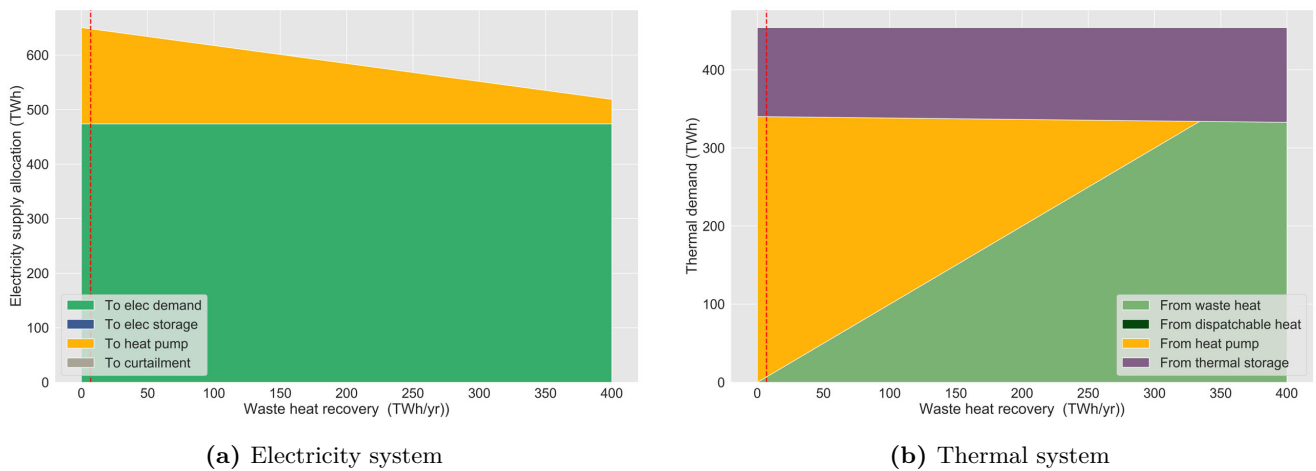


Figure 5.18: Waste heat recovery sensitivity analysis.

III.3 Cost analysis

Results of the cost analysis are presented in Figure 5.19. For each of the sensitivity analyses performed in the previous section, we calculate the cost of every component of the energy system. We distinguish the heating network, heat pump, electricity and thermal production (waste or dispatchable), as well as thermal and electrical storage. Each of these contributions added together are equal to the total cost, presented in sub-figures (b) to (g).

The comparison of each of the results with each other enables us to draw several conclusions regarding the system's overall functioning.

First of all, we note that the cost of electricity (b) is the parameter with the most significant impact on the total cost, ranging from 10 to 160 G€. On the contrary, for the other sensitivity analyses — Figures (c) to (g) — the overall cost varies between 40 and 70 G€*. This shows that most of the operating modes are equivalent in terms of cost. It shows that it is possible to consider other aspects, such as environmental impact, without having a significant impact on the total cost. As future work, it shows the interest of replicating the present analysis from the global warming potential standpoint.

Second, it shows that the cost of energy production, electricity and thermal, represents most of the total cost. It means that, when it comes to handling the seasonal variability, the cost of storage devices has such a substantial impact that it is only used a little. It is the energy production that needs to remain low.

It emphasizes that it is of prime importance to maintain abundant and low cost electricity production.

Second, it shows that the cost of energy production, electricity and thermal, represents most of the total cost. It means that, when it comes to handling the seasonal variability, the cost of storage devices has such a substantial impact that it is only used a little. It is the energy production that needs to remain low.

It emphasizes that it is of prime importance to maintain abundant and low cost electricity production.

*It is worth noticing that this value range is consistent with the cost of energy delivered by district heating in France. The 2019ADEME report [90] assess the average cost of production and distribution in the country is $76 \text{ €/MWh}_{th,delivered}$. In the reference case, there is $60 \text{ €/MWh}_{el} \times 473 \text{ TWh} = 28 \text{ G€}$ invested in the electricity system. The remaining $58 - 28 = 30 \text{ G€}$ are dedicated to the thermal system, which implies a cost of energy delivered of $\frac{30 \text{ G€}}{450 \text{ TWh}_{th}} = 66 \text{ €(MWh}_{th,delivered})^{-1}$.

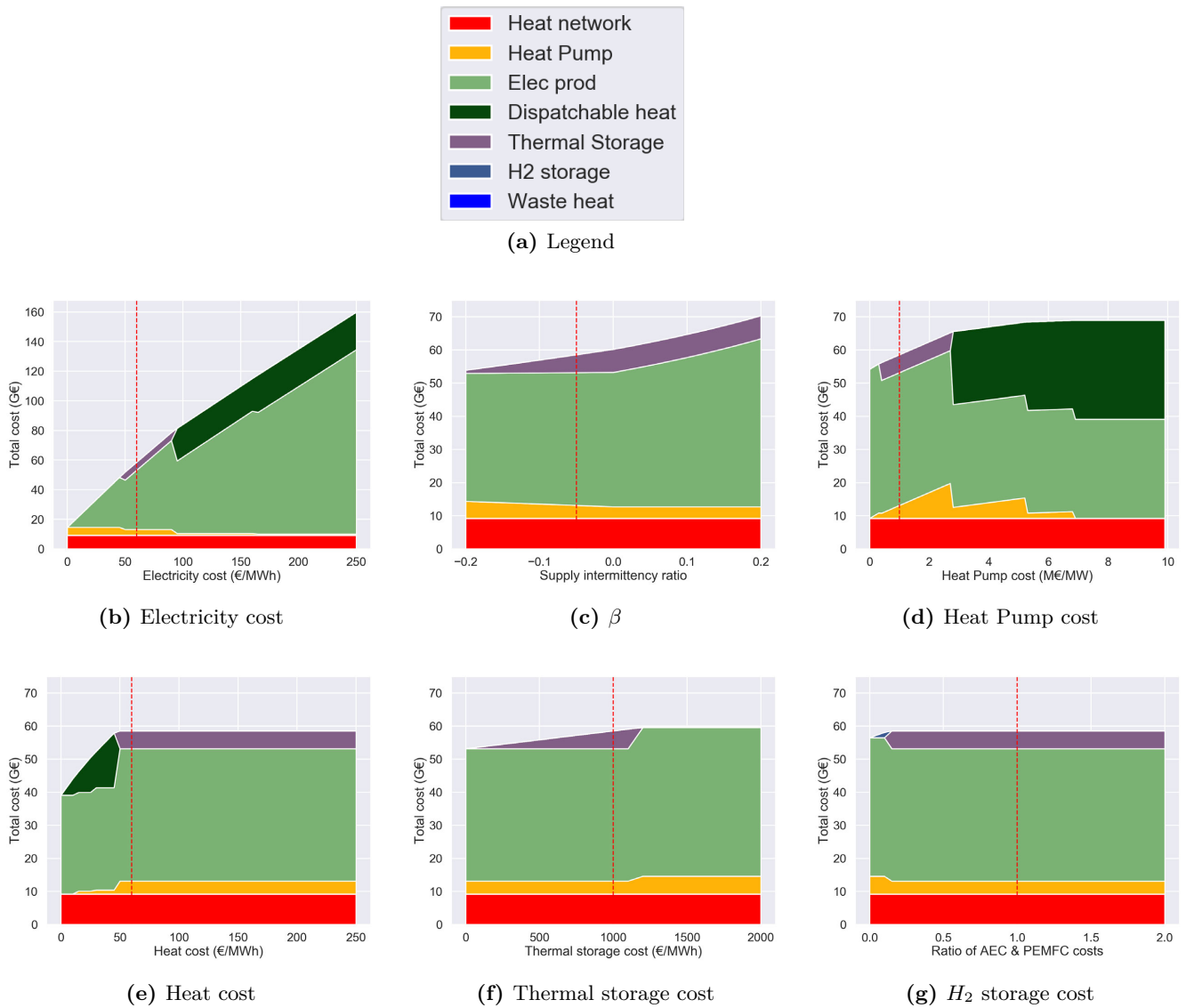


Figure 5.19: Cost allocation between the different components of the energy system. This distribution is for six sensitivity analysis. (a) shows the common legend to all figures. On each one, the red vertical line indicates the reference value. (b) represents the electricity cost analysis, (c) corresponds to electricity production intermittency amplitude β , (d) the HP cost, (e) the heat cost, (f) the TS cost and (g) the ratio of H_2 electricity storage cost.

IV Discussion and Conclusion

The analysis of the results presented above emphasizes two main conclusions. First of all, it shows that most operation modes can be in a very close range of costs. Starting from the reference case — where the entire heat production comes from electric power plants — a small change of costs would completely modify the way heating demand is satisfied. For example, in the reference case, the electricity cost is $60 \text{ €/MWh}_{el,out}$. If it increases in accessible ranges, it would be more cost-effective to produce most heat using gas boilers rather than heat pumps.

Most modes of operating are potentially accessible with the current costs and characteristics of energy systems. This is the case for heat production with gas, heat pumps, or from each, seasonality management with thermal storage, or oversizing of electricity production. However, some operating modes, such as hydrogen storage to manage seasonality, are not achievable.

This analysis highlights the technological improvements that would be the most efficient to realize. For example, to be competitive with electricity production, thermal storage needs to remain at a low investment cost.

It additionally shows the action levers to support a technical solution. For example, in the spirit of sustainable development, we see that a sufficient gas cost can provide an incentive to produce heat from electricity. This value should be compared to the CO_2 footprint of carbon taxes. A methane tax of $100 \text{ €/MWh}_{th,product}$ is equivalent to a CO_2 tax of 500 €/ton_{CO_2} .

Second, we saw that thermal storage is much more competitive than hydrogen for seasonal storage. Indeed, it is a cheaper system with higher efficiency. This work shows that hydrogen electricity storage would need to be almost 8 times cheaper to be made competitive with thermal storage.

V Limits and Further research

This work is based on simple models of intermittence and energy systems. The conclusions drawn must therefore be considered as such. There are mainly three sources of bias.

First, only the seasonal variability of time-series is modeled. This analysis cannot account for potential complementarities between seasonal and shorter time scales. Additionally, the symmetric shape in summer and winter of heating demand does not reflect real behaviors.

Second, heating networks are omnipresent, energy components have high power. For example, individual heat boilers are not considered and could have been an alternative solution to district heating.

Thirdly, in cases where the entire heating demand is supplied by electrical means — via heat pump and district heating — a reinforcement of the electricity network would be expected. It represents additional costs that are not considered here. Additionally, each existing electric heating system would also have to be replaced by hot water radiators.

The very construction of this study implies that the calculated costs must be considered in a relative and not an absolute way. Above all, this work describes different operating modes and highlights the system's sensitivity to various parameters.

Due to lack of time, this analysis could not be sufficiently thorough. Therefore, there are still many avenues of research to be explored. First of all, still based on this single time-scale model, the following points could be explored.

- Until now, heating systems have been modeled as large scale devices connected to heat networks. However, district heating is not widespread worldwide, and many buildings are equipped with small individual boilers or heat pumps. A balance between DH connection and individual heating systems might exist.

Integrating large and small-scale heating technologies in our model would reveal the competition mechanisms between collective and individual heating.

- This analysis could be carried with other indicators. In particular, using the Global Warming Potential would provide meaningful comparisons to get an intuition of the stakes to decarbonize heating systems.

This analysis could then be extended to models using real time-series.

VI Chapter's highlights

We developed in this chapter a simplified approach of seasonal intermittency, using time series with a single time-scale. Based on those signals, we model the complementarity of heat and electricity systems to understand District Heating potential to satisfy the seasonal heat demand. The major conclusions of this study are listed below.

Take home message

- Power-to-heat and thermal storage can be cost-competitive with gas.
- We have highlighted different operation modes to satisfy heat demand, using electricity production and heat pumps, gas boilers or storage. Each of these cases depends on the system parameters: cost efficiency, etc . Many operating modes are in close cost ranges. This means that technological improvements or financial constraints such as taxes could easily promote a technical solution.
- Thermal storage is preferred to hydrogen storage for seasonal duration.
- The availability of cheap, abundant, low-carbon electricity is necessary to decarbonize our heating system.

CONCLUSION

Chapter outlook

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This thesis work developed a methodology applied to the French specificities. The research questions motivating this study have two aspects.

First, we sought to understand the implications of the development of intermittent renewable energy sources, particularly photovoltaic and wind power. Precisely, we answer the question: “*What constraints does the variability of electricity production and consumption create for supply to meet demand at all times?*”

After understanding and quantifying the variability impact, we addressed the question of the technical solutions: “*What is the potential of electricity storage and its complementarity with heating networks to match supply and demand at all times?*”

Overall, this thesis presents a methodology to assess the two questions raised above. The conclusions drawn in this manuscript are, as a reminder, only valid in the French context. With a temperate climate, this country has its own energy consumption patterns, sunshine and wind regimes. However, the method we provide can be generalized, as long as the required data are available as inputs of the reasoning.

I Synthesis – Answers to the questions addressed in this Ph.D.

The guiding theme of this study is the time-scales analysis of the intermittency. Daily, weekly or seasonal fluctuations in electricity production and consumption must be distinguished. These are sources of very different so-called *flexible needs* to ensure the balance between supply and demand. We synthesize in the following paragraphs the main results of this work. Every conclusion drawn depends on the time-scale considered, from 45 minutes to seasonal fluctuation.

In particular, we have shown that the need for electricity storage dramatically increases with the duration considered. Matching electricity supply with demand at the seasonal scale requires an energy capacity — e.g., storage size — which is 3 to 4 orders of magnitude bigger than at the hour scale.

Today, this enormous amount of seasonal flexible energy can only be provided by dispatchable power plants, here nuclear shutdowns for maintenance. We have shown that this seasonal need is caused by the summer and winter differences in electricity consumption. Since wind energy produces more in winter than in summer, a power generation mix with a higher share of wind energy than photovoltaics can even slightly reduce the seasonal bump.

After seeing that without the use of dispatchable power plants, the seasonal variability of electricity consumption could not be met, we evaluated the potential of electricity storage to provide the necessary flexibility. One of our main findings is that various technologies are relevant to handle variability for up to a month, especially hydroelectricity storages (PHS) and Li-ion batteries (week). However, it must be highlighted that there are today no relevant solutions for longer-term storage. Power-to-gas-to-power would be the most suitable option for the seasonal duration, if storing large volumes of hydrogen in underground caverns were a mature technical solution.

Note that in this conclusion, we will refer by *short-term* to time-scales shorter than a month, whereas *long-term* will range from monthly to seasonal fluctuations.

Our optimizations have shown that oversizing the production and curtailing excess electricity can be a more relevant strategy than long-term storage. It is especially true when electricity generation is slightly variable: the less intermittent the production, the more the power generation plant will be oversized. On the contrary, the more intermittent the production, the more storage is needed. It can be understood using an extreme example, the case where production is 100 % solar PV. Since the production is null every night, electricity demand cannot be satisfied by oversizing the generation sources, but only thanks to storage.

The analysis of the complementarity between the different time-scales has shown that several storage solutions can work in conjunction. Comparing signals with a single time-scale or several shows that the more the signal integrates time scales, the more the production oversizing is preferred. It is worth remembering that a complete analysis of the signal favors oversizing when compared to the analysis of a single time scale independently of the others.

Additionally, the comparison of different flexible strategies has shown that the selection of electricity storage is based on a trade-off between cost and efficiency. A system dedicated to short-term storage will go through many cycles (charge–discharge). It is then its efficiency rather than its investment cost that will be the decisive factor. On the contrary, for long-term storage, the investment cost prevails over efficiency.

It is one of the reasons why thermal storage makes sense for the long-term. Its seasonal efficiency is greater than hydrogen — the best candidate for long-term electricity storage, based on our cost/efficiency trade-off — and its investment cost is also lower. We have shown that coupling electricity and heating networks has excellent potential for handling the seasonal variability. It should also be noted that in France, most of the seasonal difference in electricity consumption is due to the demand for heating. It is a use that could be shifted to the thermal rather than the electrical system.

As a final note, we remind that optimizations have been carried from different standpoints. Whether it is from the economic investments or the environmental footprint (*embodied energy* and *equivalent CO₂*), the main trends described above remain valid.

II Contribution to the *state of the art*

The main contributions of this thesis are summarized in the following points:

- **Enhance the importance of time-scale analysis for energy system modeling.** Overall, through different models, this work has shown that the different time-scales of the intermittency must be distinguished. They represent different needs that require different technical solutions.
- **Quantify the flexibility needs.** To our knowledge, the need for flexibility in the electrical system is rarely quantified for different time-scales. It has also been done in France in the work of T. Heggarty [128]. We propose here new indicators to quantify this need for flexibility.
- **Enhancing the interest of parametric analysis.** Based on minimally detailed energy models, this work shows the interest of carrying parametric analysis. It enables to determine trade-offs between storages' cost and efficiency. These calculations are easier to perform using a parametric analysis than a more conventional energy scenario analysis.

Those trade-offs underline the leverage to promote or prohibit the development of a given technology. For example, we can calculate a CO_2 tax threshold at which one technological solution has become more relevant than another. It highlights potential levers for action to decarbonize a sector of the energy system.

Additionally, the analysis shows each system's weak points and the technical improvements that would make it relevant and competitive for a given use. For example, this method can tell the expected efficiency or cost improvement that would be necessary to make hydrogen usage relevant for short and long time-scale.

In general, the flexibility quantification methodology and associated results could be used by system operators to identify and understand future challenges.

III Critical thinking about the limitations of this work

In this section, we present and discuss the different limitations of this work. It will eventually lead to detailing future research perspectives.

To begin with, this work has inherent limitations. Based on models with a low level of detail, we seek to highlight the energy system's main trends. This energy modeling approach allows comparative but not absolute analysis between different flexibility strategies. Since we do not model the entire energy system, several sources can lead to over or

underestimating cost and impact calculations. The following points detail the potential overestimation bias.

Overestimate bias of costs and impacts:

- *Electrical dispatchable power plants are operated at a constant load:* This is one of the basic assumptions of this work. We do not take into account the flexibility that nuclear or hydroelectric power plants allow.
- *No import-export:* Interconnections with neighboring countries can be a source of flexibility which is not considered here.
- *No demand-side management:* Electricity demand cannot be adapted to the production. However, it is a potential source of flexibility, especially for short time-scales. It has been shown by *Heggarty et al, 2018 [128]* that price signals on domestic hot water amounts for half of the daily flexibility requirements.
- *No Power-to-X:* In Chapter 5, the potential of Power-to-Heat was briefly studied. However, the electrical system could be coupled to other sectors and uses. For example, electric mobility or using hydrogen for methanation, fertilizers or biomass.
- *Technology performances:* Technologies considered here are the existing ones. We do not consider any potential improvements in cost or efficiency.

Similarly, sources of cost under-estimate are listed below.

Under-estimate bias of costs and impacts:

- *Electricity demand and production is perfectly known in advance:* We are working with electricity production and consumption time series. It means that both demand and production are known in advance when optimizing the system size and operation.
- *No electricity grid:* Neither the investments for the power grid nor the associated losses during electricity transmission are considered.
- *No boundaries to technology development:* Our models do not account for any kind of limitations such as resource depletion, land availability, social acceptance.

IV Directions for future research

Future improvements to this work could be pursued in the following directions.

First, this work has highlighted the potential of coupled electricity and heat systems. There is an interest in carrying a complete analysis, following two distinct tracks. The first one would be to model individual and collective heat productions. On the one hand, personal equipment — such as heat boiler and heat pump — are not connected with the heating network. This solution is competitive because it is free of the heating network, which represents a significant investment and involves associated costs and energy losses. On the other hand, collective heat production is cheaper thanks to the scaling effects. Besides, it can benefit from large scale thermal storage and waste heat recovery. There must be a balance of costs between individual and collective equipment use.

Then, the modeling of the heating system could be more detailed. Including Combined Heat and Power generation sources would especially account for additional complementarities between both vectors.

Second, in this study, the flexibility provided by dispatchable power plants is not modeled. Indeed, in Europe, dispatchable power plants are under pressure and are shutting down in favor of renewable sources. We wanted to study the consequences of these closures. It would now be relevant to analyze its complementarity with storage, answering questions like “*with how many units of intermittent sources and storage can a dispatchable power unit be replaced with?*”. This investigation would lead to *Pareto fronts* between electricity storage and dispatchable power plants. It would highlight compromises to be made to replace it with other flexible means.

Third, the analysis could be extended to other sectors, including electric mobility and gas usages. In particular, a parametric analysis could highlight fields of the relevance of other hydrogen usages and its variety of applications for chemistry (fertilizer, reduction of iron oxides, biofuels) or methanation.

Fourth, considering power grids and energy networks, along with their investment costs, would be an improvement of interest. This analysis could be coupled with Geographic Information System models to introduce spatial limits to the deployment of production sources and networks.

Eventually, one could apply this existing model to other case studies. For example, applying the methodology to another territory, with different climate and habits. What would be California’s conclusions, which has a much greater solar irradiance, larger consumption for air conditioning, and lower heating need? And what about an equatorial country that does not undergo the same seasonal variability?

Similarly, the methodology could be applied to assess and compare existing energy transition scenarios with common foundations. It would allow understanding the very different and incompatible results that come out of various studies. For example, how and why 100 % RES scenarios come with very different costs.

To conclude on further research, this work has highlighted the interest of carrying out parametric analysis. It allows to determine the relevant fields of use for different technologies. In the future, the energy modeling community could adopt good practices and save time by first mapping these different areas of relevance before engaging in more detailed modeling. This applies not only to the scientific community, but also to the development of industrial projects.

V Mistakes to avoid

Throughout this research, we noticed several pitfalls that must be avoided when dealing with energy systems and energy modeling. Those recommendations are listed below for future energy modelers and even scientists who aim to tackle this issue.

- *Do not confuse MWh produced and MWh delivered.* The cost of flexibility, storage, for example, is a non-negligible part that must be added to the cost of electricity production. It is especially true for intermittent energy sources like photovoltaic and wind power. Energy is not necessarily produced when needed.

Thus, comparing energy sources based on their Levelized Cost Of Energy (LCOE) is not representative of the system’s total cost.

- *Photovoltaic and wind power.* Energy modeling must be based on the analysis of several years of energy production, and not only one. Indeed, photovoltaic and wind

power production can change from one year to another. In other words, the optimal energy system of one year will not be optimal in other meteorological configurations.

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APPENDICES

Additional investigation: Square *versus* sine shape wavelets

This appendix provides additional details to chapter 3 on wavelet decomposition. We compare decomposition using sets of square and sine wavelets.

At first, we chose to use square wavelets^a because they relates to charge-discharge power patterns of electrical storage.

^aAlso known as *Haar* wavelets.

Sine and square wavelets used are drawn in Figure A.1.

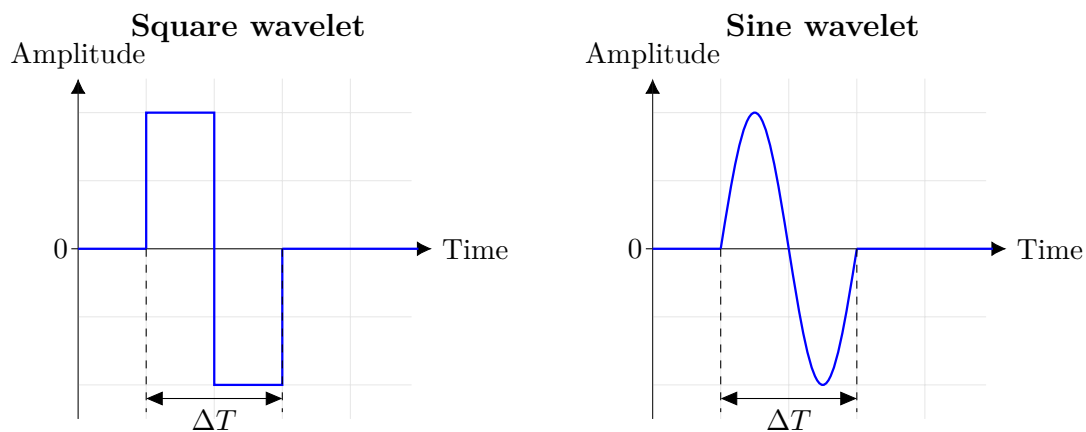


Figure A.1: A square and sine wavelets with time scale ΔT

An example of a signal filtered with 24 hours square and sine wavelets is presented on Figure A.2.

The Figure A.3 compares a square and sine wavelet decomposition in the case of a 100 % PV residual demand. This specific case is very interesting because of its strong features at the day and the seasonal scale. We notice on Figure A.3a a hump at day/4 and year/4 scale which does not appear for the sinusoidal decomposition on Figure A.3b.

This hump is an artifact highlighted by the high daily and seasonal variability in the residual demand of photovoltaic energy. Indeed, as shown in Figure A.4, to represent a gentle slope of an oscillation of duration ΔT , one needs both square wavelets of ΔT and $\Delta T/4$ length.

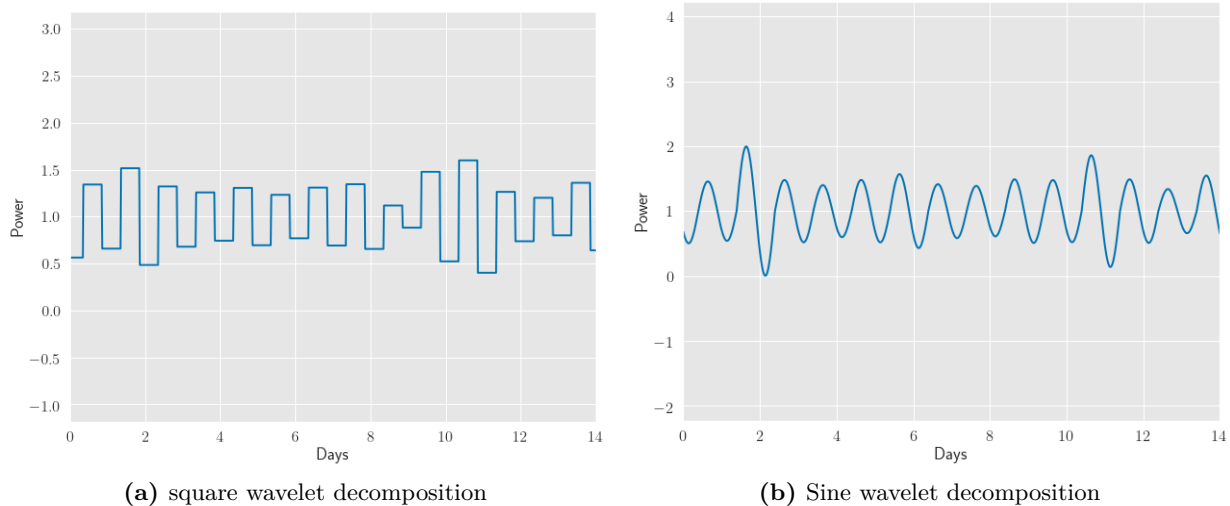


Figure A.2: 2013 PV power supply filtered with $\Delta T = 24h$ square and sine wavelets.

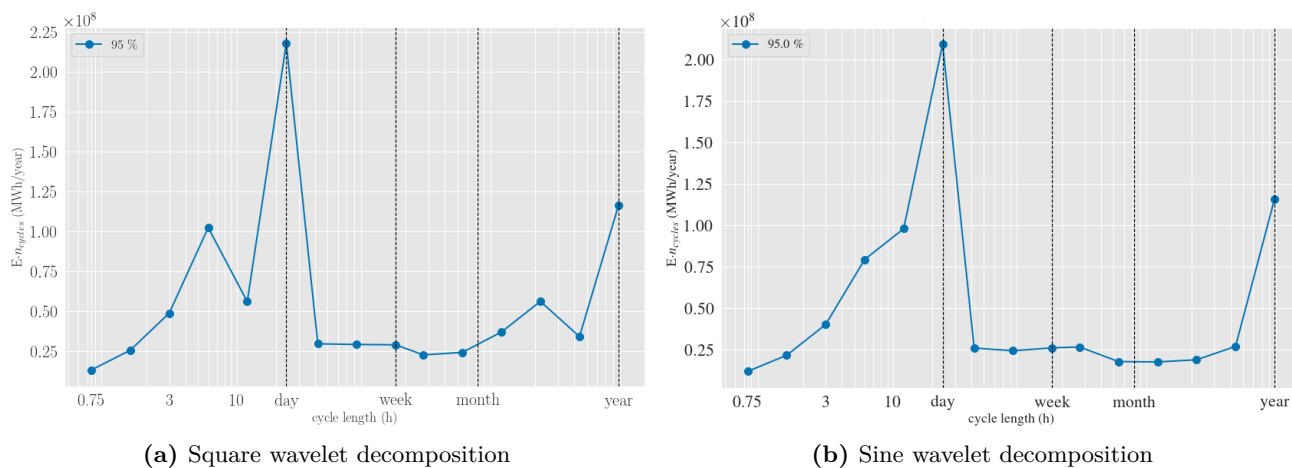


Figure A.3: Calculation of the service as defined by Equation 3.5. The calculation is performed for a residual demand of 100 % PV, as described in IV.2. The decomposition is carried out with a square wavelet set (left) and a sinusoidal set (right).

Despite this artifact, square wavelets will be used for the rest of the study. Indeed, their simple form of charge/discharge makes them more relevant to our further research.

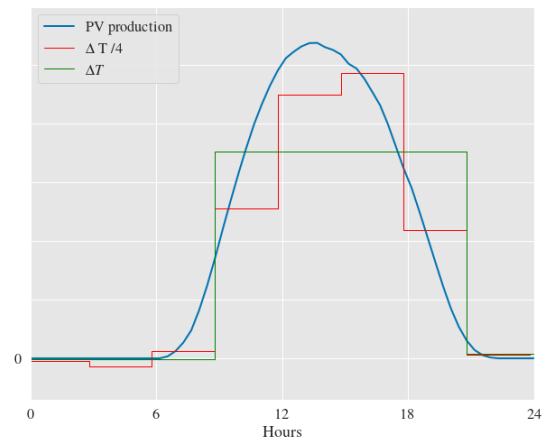


Figure A.4: Illustration of how the square wavelets are arranged to fit a bell curve (e.g. daily solar PV output).

Calculation details of Chapter 4

This appendix is a complement to Chapter 4 where we investigate the inter-dependencies between time scales. We provide here mathematical details of the first section “*Single time-scale*” and develop the resolution of the optimization problem.

Chapter outlook

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I Energy system description

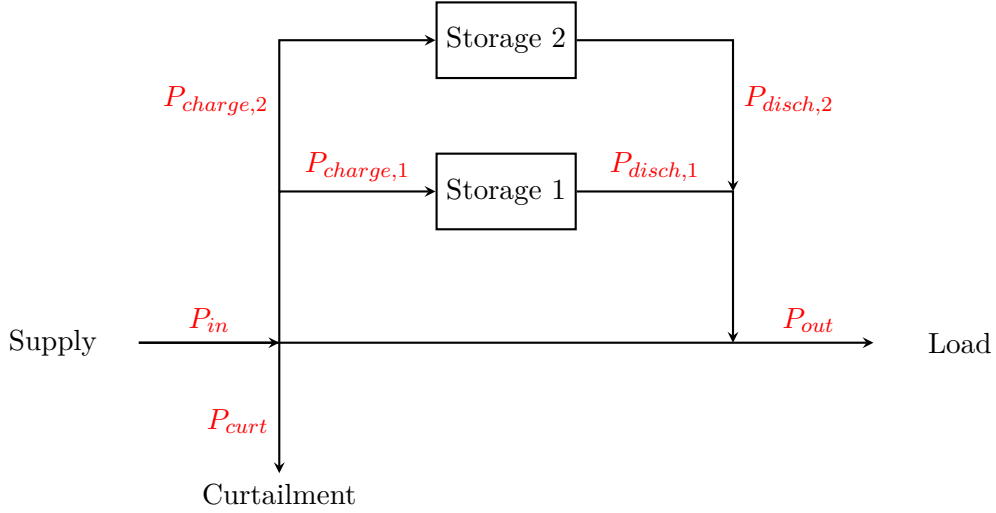


Figure B.1: Representation of the energy system. Electricity supply can either be directly consumed, stored or curtailed.

Electricity storage is characterized by its size E , η_c its charge efficiency, with a discharge efficiency $\eta_d = 1$. To make it easier to read we refer to the efficiency in charge by η .

Therefore the equation driving the states of charges E_1 and E_2 are

$$\begin{cases} \frac{dE_1(t)}{dt} = P_{charge,1}(t) \cdot \eta_1 - P_{disch,1}(t) \\ \frac{dE_2(t)}{dt} = P_{charge,2}(t) \cdot \eta_2 - P_{disch,2}(t) \end{cases} \quad (\text{B.1})$$

The nodal rule written is written such that

$$P_{in} - P_{out} = P_{charge,1} + P_{charge,2} - P_{disch,1} - P_{disch,2} + P_{curt} \quad (\text{B.2})$$

To simplify the understanding, we refer to storage 1 or 2 with the index i .

The storage system is sized in energy and power by respectively $E_{max,i}$ and $P_{max,i}$.

$$E_i(t) \leq E_{max,i} \quad (\text{B.3})$$

$$P_{i,discharge}(t) \leq P_{max,i} \quad (\text{B.4})$$

Load and *Supply* are input signals of the model that last 1 year. We define a periodic condition for the storage state of charge:

$$E_i(t_0) = E_i(t_{end}) \quad (\text{B.5})$$

The objective function *Cost* of this model is

$$Cost = Production\ cost + Storage\ cost\ 1 + Storage\ cost\ 2 \quad (\text{B.6})$$

where

$$\text{Production cost} = \alpha \cdot \langle P \rangle \cdot \gamma_3$$

and

$$\text{Storage cost } i = E_{max,i} \cdot \gamma_i$$

I.1 Additional constraints

We have reduced the number of degrees of freedom of this linear problem to ensure that its behavior matches the appropriate patterns of energy systems. More specifically:

- A storage cannot be charged and discharged at the same time.
- An infinitely low cost is added to the operation of a storage to ensure that it operates in the most stable way possible and not on a very short on/off sequence.
- A storage can be sized by the maximum power it can provide or receive. In this case, its energy size varies for the same cost between a minimum and a maximum equal to the maximum power times the duration of use. In this case, we constrain the size in energy so that it remains at the minimum.

In the same way, if it is the energy size that determines the cost, the power will take the minimum possible value.

These three constraints have been implemented by adding infinitesimal costs, which ensures that the problem remains linear.

II Shape of Power Time Series

We demonstrate here that *Power* variables of the optimal solution have a shape similar to the supply.

Demonstration

Let $\overline{\mathbf{X}(t)}_{t \in [0, T]}$ be the mean value of a function X over the duration T .

Let $P_{charge,i}(t)$, $P_{disch,i}(t)$, $P_{curt,i}(t)$, $E(t)$ and α be the optimal solution optimal solution of the problem described on Figure B.1.

Let $P'_{charge,i}(t)$, $P'_{disch,i}(t)$, $P'_{curt,i}(t)$, $E'(t)$ and α' any solution of the problem such that

$$\begin{aligned} \alpha' &= \alpha \\ E'_{max,i} &= E_{max,i} \\ P'_{max,i} &= P_{max,i} \end{aligned}$$

Charge and discharge power signals P' are built as follow:

$$\begin{aligned}
 P'(t) &= \overline{\mathbf{P}(\mathbf{t})}_{t \in [0, T/2]} & t \in [0, T] \\
 P'(t) &= \overline{\mathbf{P}(\mathbf{t})}_{t \in [T/2, T]} & \text{for } t \in [0, T/2] \\
 P'(t) &= \overline{\mathbf{P}(\mathbf{t})}_{t \in [T/2, T]} & \text{for } t \in [T/2, T]
 \end{aligned}$$

As a consequence, P' are rectangular type signals of half-period $T/2$.

P'_{curt} is shaped to fulfil the nodal law of Equation 4.2. Since all signals are rectangular type, P'_{curt} is also rectangular.

E'_i are built in order to fulfil the state of charge Equation 4.1.

Let's now show that this solution do fulfill every equation:

1. **Nodal Law:** This equation is checked because of the linearity of the average
2. $P' \leq P_{max}$?

Proof.

$$P(t) \leq P_{max} = P'_{max}$$

but

$$\max\left(\overline{\mathbf{P}(\mathbf{t})}_{t \in [0, T/2]}, \overline{\mathbf{P}(\mathbf{t})}_{t \in [T/2, T]}\right) \leq \overline{\mathbf{P}(\mathbf{t})}_{t \in [0, T]} \leq P_{max}$$

Hence

$$\forall t \in [0, T] \quad P'_i(t) \leq P'_{max}$$

□

3. $E' \leq E_{max}$?

Proof.

$$E'(t) = \int_0^t (\eta P'_{charge} - P'_{disch}) dt \leq \int_0^{T/2} (\eta P'_{charge} - P'_{disch}) dt$$

with

$$\int_0^{T/2} (\eta P'_{charge} - P'_{disch}) dt = \int_0^{T/2} (\eta P_{charge} - P_{disch}) dt \leq E_{max}$$

Therefore,

$$\forall t, E'(t) \leq E_{max}$$

□

Temporary conclusion: α', P', E' satisfy equations of this section. as a consequence it is a solution. Let's now calculate it's cost.

$$\text{cost}(X') = E'_{max,1}\gamma_1 + E'_{max,2}\gamma_2 + \alpha' \overline{\mathbf{P}_{\text{Supply}}}\gamma_3$$

With

$$\begin{cases} \alpha' & = \alpha \\ E'_{max} & = E_{max} \\ P'_{max} & = P_{max} \end{cases}$$

$$\text{cost}(X') = \text{cost}(X)$$

Since X denotes the optimal solution, the previous equality implies that X' is the optimal solution.

We have demonstrated that optimal signals of this problem are rectangular.

■

III Step 1: Writing the optimization problem

We assume that storages are charged over the first half of the time-scale and discharged during the second half. This statement can be assessed using a proof by contradiction (not carried here).

$$\begin{cases} P_{disch,1}^1 = 0 & \cdot & P_{ch,1}^2 = 0 \\ P_{disch,2}^1 = 0 & \cdot & P_{ch,2}^2 = 0 \end{cases} \quad (\text{B.7})$$

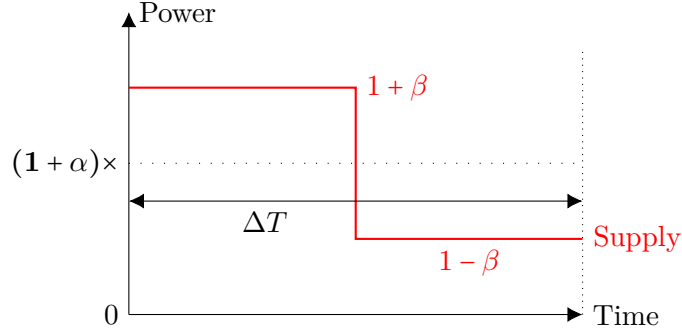
where i refers to the first or second time step. To simplify the writing of the equations we introduce P_1 and P_2 the discharge power.

$$\begin{cases} P_{disch,1}^2 = P_1 \\ P_{disch,2}^2 = P_2 \end{cases} \quad (\text{B.8})$$

Since there is here only two time steps we have:

$$\begin{cases} \eta_1 \cdot P_{ch,1} = P_{disch,1} \\ \eta_2 \cdot P_{ch,2} = P_{disch,2} \end{cases}$$

α is the supply over-sizing factor so that



For this specific example, the Nodal Law can be written as

$$\begin{cases} (1 + \beta) \cdot (1 + \alpha) - 1 \geq P_1/\eta_1 + P_2/\eta_2 & \text{on the first half of the wavelet} \\ (1 - \beta) \cdot (1 + \alpha) - 1 \leq P_1 + P_2 & \text{on the second half of the wavelet} \end{cases}$$

i.e., by rewriting the L.H.S. as

$$\begin{cases} \beta + \alpha(1 + \beta) \geq P_1/\eta_1 + P_2/\eta_2 \\ \beta - \alpha(1 - \beta) \leq P_1 + P_2 \end{cases} \quad (\text{B.9})$$

Additional, discharged power and over-sizing are positive:

$$\alpha \geq 0 \quad P_1 \geq 0 \quad P_2 \geq 0 \quad (\text{B.10})$$

Let Σ be the total cost we want to minimize:

$$\Sigma = \gamma_1 \frac{\Delta T}{2} P_1 + \gamma_2 \frac{\Delta T}{2} P_2 + \alpha \gamma_3 \bar{P} \quad (\text{B.11})$$

The optimisation problem is as follow:

$$\begin{array}{lll} \min & \Sigma & = \gamma_1 \frac{\Delta T}{2} P_1 + \gamma_2 \frac{\Delta T}{2} P_2 + \alpha \gamma_3 \bar{P} \\ \text{Subject to} & \beta + \alpha(1 + \beta) \geq & P_1/\eta_1 + P_2/\eta_2 \\ & \beta - \alpha(1 - \beta) \leq & P_1 + P_2 \\ & \alpha, P_1, P_2 \geq & 0 \end{array} \quad (\text{B.12})$$

where α, P_1, P_2 are the variables and $\beta, \gamma_1, \gamma_2, \gamma_3, \Delta T$ parameters of the problem.

IV Step 2: Solving the Linear Problem using the Simplex algorithm

We are going to solve the above linear program using the Simplex algorithm:

Let us denote the variables with the letter x_i .

$$\begin{cases} x_1 = P_1 \\ x_2 = P_2 \\ x_3 = \alpha \end{cases}$$

We introduce x_4 and x_5 two positive variables:

$$\begin{cases} x_4 = \beta + x_3(1 + \beta) - x_1/\eta_1 - x_2/\eta_2 \\ x_5 = x_1 + x_2 - \beta + x_3(1 - \beta) \end{cases}$$

Thus, the linear problem is equivalent to

$$\begin{array}{lll} \min & \Sigma & = \gamma_1 \frac{\Delta T}{2} x_1 + \gamma_2 \frac{\Delta T}{2} x_2 + \gamma_3 x_3 \\ \text{Subject to} & x_4 & = -x_1/\eta_1 - x_2/\eta_2 + \beta + x_3(1 + \beta) \\ & x_5 & = x_1 + x_2 - \beta + x_3(1 - \beta) \\ & x_i \geq 0 & \forall i \in \llbracket 1 ; 5 \rrbracket \end{array} \quad (\text{B.13})$$

An optimal solution is achieved when 3 out of the 5 variables x_i are equal to 0. In fact, this problem has 3 independent variables and is defined by 5 linear inequalities that define a 3-D polytope as a feasible region. The optimal solution is reached at one of a vertex (corner) of the volume, i.e., at the intersection of 3 planes, when 3 out of the 5 variables are equal to 0. Therefore, there is potentially $\binom{5}{3} = 10$ cases, depending on values of $\beta, \gamma_1, \gamma_2, \gamma_3, \Delta T$, to this problem.

However $x_3 = 0$ (no oversizing) is not an accessible solution since we consider storages with an efficiency lower than 100% and an intermittency $\beta \neq 0$. Thus, there is $\binom{4}{3} = 4$ solutions, reduced to 3 since storages 1 and 2 have a symmetric.

Thus, we analyze here the three following cases:

1. $x_1 = x_4 = x_5 = 0$
2. $x_1 = x_2 = x_4 = 0$
3. $x_1 = x_2 = x_5 = 0$

We will refer to them as *assumptions*.

IV.1 First assumptions

Assumption 1-A. *An optimal solution is achieved when $x_1 = x_4 = x_5 = 0$.*

Let $\mathcal{B} = \{2, 3\}$ and $\mathcal{N} = \{1, 4, 5\}$. We now want to write the Linear Problem (LP) B.13 as a function of the basis \mathcal{B}

$$\begin{cases} \frac{x_4}{1+\beta} - \frac{x_5}{1-\beta} = -x_1 \cdot \left(\frac{1}{\eta_1(1+\beta)} + \frac{1}{1-\beta} \right) - x_2 \cdot \left(\frac{1}{\eta_2(1+\beta)} + \frac{1}{1-\beta} \right) + \frac{2\beta}{1-\beta^2} \\ \eta_2 \cdot x_4 + x_5 = x_1 \cdot \left(1 - \frac{\eta_2}{\eta_1} \right) + x_3 \cdot [\eta_2(1+\beta) + (1-\beta)] + \beta(\eta_2 - 1) \end{cases}$$

i.e.,

$$\begin{cases} x_4(1-\beta) - x_5(1+\beta) = -x_1 \cdot \left(\frac{1-\beta}{\eta_1} + 1 + \beta \right) - x_2 \cdot \left(\frac{1-\beta}{\eta_2} + 1 + \beta \right) + 2\beta \\ x_3 = \frac{1}{\eta_2(1+\beta) + (1-\beta)} \left[x_5 + \eta_2 \cdot x_4 - x_1 \left(1 - \frac{\eta_2}{\eta_1} \right) - \beta(\eta_2 - 1) \right] \end{cases}$$

i.e.,

$$\begin{cases} x_2 = \frac{1}{\frac{1-\beta}{\eta_2} + 1 + \beta} \left[-x_4(1-\beta) + x_5(1+\beta) - x_1 \cdot \left(\frac{1-\beta}{\eta_1} + 1 + \beta \right) + 2\beta \right] \\ x_3 = \frac{1}{\eta_2(1+\beta) + (1-\beta)} \left[x_5 + \eta_2 \cdot x_4 - x_1 \left(1 - \frac{\eta_2}{\eta_1} \right) - \beta(\eta_2 - 1) \right] \end{cases}$$

Thus the LP can be rewritten as follows:

$$\begin{array}{ll} \min & \Sigma = \gamma_1 \frac{\Delta T}{2} x_1 + \gamma_2 \frac{\Delta T}{2} x_2 + \gamma_3 x_3 \\ \text{Subject to} & x_2 = \frac{1}{\frac{1-\beta}{\eta_2} + 1 + \beta} \left[-x_4(1-\beta) + x_5(1+\beta) - x_1 \cdot \left(\frac{1-\beta}{\eta_1} + 1 + \beta \right) + 2\beta \right] \\ & x_3 = \frac{1}{\eta_2(1+\beta) + (1-\beta)} \left[x_5 + \eta_2 \cdot x_4 - x_1 \left(1 - \frac{\eta_2}{\eta_1} \right) - \beta(\eta_2 - 1) \right] \\ & x_i \geq 0 \quad \forall i \in [1 ; 5] \end{array} \tag{B.14}$$

We write Σ as a function of x_1, x_4, x_5 .

$$\begin{aligned}
 \Sigma &= \gamma_1 \frac{\Delta T}{2} x_1 + \gamma_2 \frac{\Delta T}{2} x_2 + \gamma_3 x_3 \\
 &= x_1 \cdot \left[\gamma_1 \frac{\Delta T}{2} - \gamma_2 \frac{\Delta T}{2} \left(\frac{\frac{1-\beta}{\eta_1} + 1 + \beta}{\frac{1-\beta}{\eta_2} + 1 + \beta} \right) - \gamma_3 \left(\frac{1 - \frac{\eta_2}{\eta_1}}{\eta_2(1+\beta) + (1-\beta)} \right) \right] \\
 &\quad + x_4 \cdot \left[-\gamma_2 \frac{\Delta T}{2} \left(\frac{1-\beta}{\frac{1-\beta}{\eta_2} + 1 + \beta} \right) + \gamma_3 \left(\frac{\eta_2}{\eta_2(1+\beta) + (1-\beta)} \right) \right] \\
 &\quad + x_5 \cdot \left[\gamma_2 \frac{\Delta T}{2} \left(\frac{1+\beta}{\frac{1-\beta}{\eta_2} + 1 + \beta} \right) + \gamma_3 \left(\frac{1}{\eta_2(1+\beta) + (1-\beta)} \right) \right] \\
 &\quad + 2\beta \cdot \gamma_2 \frac{\Delta T}{2} + \gamma_3 \left[\frac{\beta(1-\eta_2)}{\eta_2(1+\beta) + (1-\beta)} \right]
 \end{aligned} \tag{B.15}$$

We do not obtain a simple expression of Σ because it is a function of $\beta \in [0 ; 1]$. Let's look at the extrema to give a physical meaning to this equation:

Case 1: $\beta \rightarrow 1$:

$$\begin{aligned}
 \Sigma_{\beta \rightarrow 1} &= x_1 \cdot \left[\gamma_1 \frac{\Delta T}{2} - \gamma_2 \frac{\Delta T}{2} - \frac{\gamma_3}{2} \left(\frac{1}{\eta_2} - \frac{1}{\eta_1} \right) \right] \\
 &\quad + x_4 \cdot \left[\frac{\gamma_3}{2} \right] \\
 &\quad + x_5 \cdot \left[\gamma_2 \frac{\Delta T}{2} + \frac{\gamma_3}{2} \frac{1}{\eta_2} \right] \\
 &\quad + \frac{\gamma_3}{2} \left(\frac{1-\eta_2}{\eta_2} \right) + \gamma_2 \Delta T
 \end{aligned}$$

Analysis: The solution is optimal only and only if coefficients of x_1, x_4, x_5 are ≥ 0

$$\iff \gamma_1 \frac{\Delta T}{2} - \gamma_2 \frac{\Delta T}{2} - \frac{\gamma_3}{2} \left(\frac{1}{\eta_2} - \frac{1}{\eta_1} \right) \geq 0$$

$$\boxed{\iff \gamma_1 \frac{\Delta T}{2} + \frac{\gamma_3}{2\eta_1} \geq \gamma_2 \frac{\Delta T}{2} + \frac{\gamma_3}{2\eta_2}} \tag{B.16}$$

Result: If this inequality B.16 is verified, the *Storage 2* will be used instead of *Storage*

1. Symmetrically if B.16 is not satisfied, *Storage 1* will be used instead of *Storage 2*. In this specific case when $\beta \rightarrow 1$ curtailment is not an optimal solution.

Case 2: $\beta \rightarrow 0$:

$$\begin{aligned} \Sigma_{\beta \rightarrow 0} = & x_1 \cdot \left[\gamma_1 \frac{\Delta T}{2} - \gamma_2 \frac{\Delta T}{2} \left(\frac{1}{\eta_2} + 1 \right) - \gamma_3 \left(\frac{1 - \frac{\eta_2}{\eta_1}}{\eta_2 + 1} \right) \right] \\ & + x_4 \cdot \left[-\gamma_2 \frac{\Delta T}{2} \left(\frac{\eta_2}{1 + \eta_2} \right) + \gamma_3 \left(\frac{\eta_2}{1 + \eta_2} \right) \right] \\ & + x_5 \cdot \left[\gamma_2 \frac{\Delta T}{2} \left(\frac{\eta_2}{1 + \eta_2} \right) + \gamma_3 \left(\frac{1}{1 + \eta_2} \right) \right] \end{aligned}$$

Analysis: The solution is optimal only and only if coefficients of x_1, x_4, x_5 are ≥ 0

$$\Leftrightarrow \begin{cases} \left(\frac{\gamma_1 \frac{\Delta T}{2} \cdot \eta_1}{\eta_1 + 1} \right) - \left(\frac{\gamma_2 \frac{\Delta T}{2} \cdot \eta_2}{\eta_2 + 1} \right) - \left(\frac{1 - \frac{\eta_2}{\eta_1}}{\eta_2 + 1} \right) \cdot \frac{1}{\frac{1}{\eta_1} + 1} \geq 0 \\ \gamma_3 \geq \gamma_2 \frac{\Delta T}{2} \end{cases} \quad (\text{B.17})$$

Besides,

$$\left(\frac{1 - \frac{\eta_2}{\eta_1}}{\eta_2 + 1} \right) \cdot \frac{1}{\frac{1}{\eta_1} + 1} = \frac{\eta_1 - \eta_2}{(\eta_1 + 1) \cdot (\eta_2 + 1)} = \frac{1}{\eta_2 + 1} - \frac{1}{\eta_1 + 1}$$

Therefore,

$$\boxed{(\text{B.17}) \Leftrightarrow \begin{cases} \frac{1}{\eta_1 + 1} \left(\eta_1 \gamma_1 \frac{\Delta T}{2} + \gamma_3 \right) \geq \frac{1}{\eta_2 + 1} \left(\eta_2 \gamma_2 \frac{\Delta T}{2} + \gamma_3 \right) \\ \gamma_3 \geq \gamma_2 \frac{\Delta T}{2} \end{cases}} \quad (\text{B.18})$$

Result: The first inequality is driving the storage usage. If it is satisfied, storage 2 will be used. In contrast to (B.16) there is here an additional inequality ($\gamma_3 \geq \gamma_2 \Delta T$) that has to be satisfied in order to use storage instead of curtailing excess electricity. If this condition is not satisfied, the assumption 1-A turns out to be wrong.

Hence, we have to make the following new new assumption:

IV.2 Second assumptions

Assumption 2-A. An optimal solution is achieved when $x_1 = x_2 = x_4 = 0$.

Let $\mathcal{B} = \{3, 5\}$ and $\mathcal{N} = \{1, 2, 4\}$. We now want to write the Linear Problem (LP) B.13 as a function of the basis \mathcal{B}

$$(B.13) \Rightarrow \begin{cases} \frac{x_4}{1+\beta} - \frac{x_5}{1-\beta} = -x_1 \cdot \left(\frac{1}{\eta_1(1+\beta)} + \frac{1}{1-\beta} \right) - x_2 \cdot \left(\frac{1}{\eta_2(1+\beta)} + \frac{1}{1-\beta} \right) + \frac{2\beta}{1-\beta^2} \\ \eta_2 \cdot x_4 + x_5 = x_1 \cdot \left(1 - \frac{\eta_2}{\eta_1} \right) + x_3 \cdot [\eta_2(1+\beta) + (1-\beta)] + \beta(\eta_2 - 1) \end{cases}$$

i.e.,

$$\begin{cases} x_4(1-\beta) - x_5(1+\beta) = -x_1 \cdot \left(\frac{1-\beta}{\eta_1} + 1 + \beta \right) - x_2 \cdot \left(\frac{1-\beta}{\eta_2} + 1 + \beta \right) + 2\beta \\ x_4 = -x_1/\eta_1 - x_2/\eta_2 + \beta + x_3(1+\beta) \end{cases}$$

i.e.,

$$\begin{cases} x_5 = x_1 \cdot \left[\frac{1}{\eta_1} \cdot \frac{1-\beta}{1+\beta} + 1 \right] + x_2 \cdot \left[\frac{1}{\eta_2} \cdot \frac{1-\beta}{1+\beta} + 1 \right] + x_4 \cdot \left[\frac{1-\beta}{1+\beta} \right] - \frac{2\beta}{1+\beta} \\ x_3 = x_1 \cdot \left[\frac{1}{\eta_1} \cdot \frac{1}{1+\beta} \right] + x_2 \cdot \left[\frac{1}{\eta_2} \cdot \frac{1}{1+\beta} \right] - x_4 \cdot \left[\frac{1}{1+\beta} \right] + \frac{\beta}{1+\beta} \end{cases}$$

The first equation shows that x_5 is negative if $\beta > 0$, whereas it is a positive variable. Hence, this assumption 2-A is not valid.

We now assume that $x_5 = 0$:

IV.3 Third assumption

Assumption 3-A. *An optimal solution is achieved when $x_1 = x_2 = x_5 = 0$*

Let $\mathcal{B} = \{3, 4\}$ and $\mathcal{N} = \{1, 2, 5\}$. We now want to write the Linear Problem (LP) B.13 as a function of the basis \mathcal{B}

$$(B.13) \Rightarrow \begin{cases} \frac{x_4}{1+\beta} - \frac{x_5}{1-\beta} = -x_1 \cdot \left(\frac{1}{\eta_1(1+\beta)} + \frac{1}{1-\beta} \right) - x_2 \cdot \left(\frac{1}{\eta_2(1+\beta)} + \frac{1}{1-\beta} \right) + \frac{2\beta}{1-\beta^2} \\ x_5 = x_1 + x_2 + x_3(1+\beta) - \beta \end{cases}$$

i.e.,

$$\begin{cases} x_4(1-\beta) - x_5(1+\beta) = -x_1 \cdot \left(\frac{1-\beta}{\eta_1} + 1 + \beta \right) - x_2 \cdot \left(\frac{1-\beta}{\eta_2} + 1 + \beta \right) + 2\beta \\ x_3 = -x_1 \left(\frac{1}{1-\beta} \right) - x_2 \left(\frac{1}{1-\beta} \right) + x_5 \left(\frac{1}{1-\beta} \right) + \frac{\beta}{1-\beta} \end{cases}$$

i.e.,

$$\begin{cases} x_4 = -x_1 \cdot \left[\frac{1}{\eta_1} + \frac{1+\beta}{1-\beta} \right] - x_2 \cdot \left[\frac{1}{\eta_2} + \frac{1+\beta}{1-\beta} \right] + x_5 \cdot \left[\frac{1+\beta}{1-\beta} \right] + \frac{2\beta}{1-\beta} \\ x_3 = -x_1 \left(\frac{1}{1-\beta} \right) - x_2 \left(\frac{1}{1-\beta} \right) + x_5 \left(\frac{1}{1-\beta} \right) + \frac{\beta}{1-\beta} \end{cases}$$

The problem can be rewritten such that:

$$\begin{array}{lll} \min & \Sigma & = \gamma_1 \frac{\Delta T}{2} x_1 + \gamma_2 \frac{\Delta T}{2} x_2 + \gamma_3 x_3 \\ \text{Subject to} & x_3 & = -x_1 \cdot \left[\frac{1}{1-\beta} \right] - x_2 \cdot \left[\frac{1}{1-\beta} \right] + x_5 \cdot \left[\frac{1}{1-\beta} \right] + \frac{\beta}{1+\beta} \\ & x_4 & = -x_1 \cdot \left[\frac{1}{\eta_1} + \frac{1+\beta}{1-\beta} \right] - x_2 \cdot \left[\frac{1}{\eta_2} + \frac{1+\beta}{1-\beta} \right] + x_5 \cdot \left[\frac{1+\beta}{1-\beta} \right] + \frac{2\beta}{1-\beta} \\ & x_i \geq 0 & \forall i \in \llbracket 1 ; 5 \rrbracket \end{array}$$

(B.19)

Let's write the Σ as a function of x_1, x_2, x_4 .

$$\begin{aligned}
 \Sigma &= \gamma_1 \frac{\Delta T}{2} \cdot x_1 + \gamma_2 \frac{\Delta T}{2} \cdot x_2 + \gamma_3 x_3 \\
 &= x_1 \cdot \left[\gamma_1 \frac{\Delta T}{2} - \gamma_3 \left(\frac{1}{1-\beta} \right) \right] \\
 &\quad + x_2 \cdot \left[\gamma_2 \frac{\Delta T}{2} - \gamma_3 \left(\frac{1}{1-\beta} \right) \right] \\
 &\quad + x_5 \cdot \left(\gamma_3 \frac{1}{1-\beta} \right) \\
 &\quad + \gamma_3 \frac{\beta}{1+\beta}
 \end{aligned} \tag{B.20}$$

Analysis: The solution is optimal only and only if coefficients of x_1, x_2, x_5 are ≥ 0

$$\Leftrightarrow \begin{cases} \gamma_1 \frac{\Delta T}{2} \geq \frac{\gamma_3}{1-\beta} \\ \gamma_2 \frac{\Delta T}{2} \geq \frac{\gamma_3}{1-\beta} \end{cases}$$

Thus, optimal solution of equation B.19 is achieved

$$\Leftrightarrow \begin{cases} \gamma_1 \frac{\Delta T}{2} \geq \frac{\gamma_3}{1-\beta} \\ \gamma_2 \frac{\Delta T}{2} \geq \frac{\gamma_3}{1-\beta} \end{cases} \tag{B.21}$$

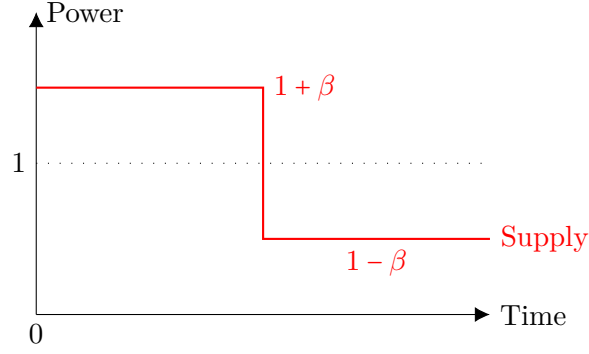
Additionally, when $\beta \rightarrow 0$, Equation, B.21 match with Equation B.18.

V Results summary and physical interpretation

We tried to solve in the previous sections the following Linear Program:

$$\begin{array}{lll}
 \min & \Sigma & = \gamma_1 \frac{\Delta T}{2} P_1 + \gamma_2 \frac{\Delta T}{2} P_2 + \alpha \gamma_3 \bar{P} \\
 \text{Subject to} & \beta + \alpha(1 + \beta) & \geq P_1/\eta_1 + P_2/\eta_2 \\
 & \beta - \alpha(1 - \beta) & \leq P_1 + P_2 \\
 & \alpha, P_1, P_2 & \geq 0
 \end{array}$$

An analytical solution is found (Equation B.14 and B.19) using the Simplex Algorithm. However, the solution depends on β . As a result, it is hard to give a physical meaning to the solution of the problem (see Equations B.15 and B.20).



$\beta \in [0, 1]$ We tested β boundaries:

1. $\beta \rightarrow 1$: Strong variability case
Equation B.16 is reminded:

$$\boxed{\text{Storage 2 is used instead of Storage 1} \iff \gamma_1 \frac{\Delta T}{2} + \frac{\gamma_3}{2\eta_1} \geq \gamma_2 \frac{\Delta T}{2} + \frac{\gamma_3}{2\eta_2}} \quad (\text{B.22})$$

This is the figure of merit of a storage. Additionally, it shows that in this scenario there is no optimal solution that will go through electricity curtailment: excess electricity has to be stored. Indeed, when $\beta = 0$ electricity production is 0 half of the time, a storage is needed.

2. $\beta \rightarrow 0$: low variability case

If, on the contrary, $\beta \rightarrow 0$, over-sizing the production by a factor α the excess electricity can be relevant. Equations B.18 and B.21 show that

$$\boxed{\text{Electricity is stored} \iff \begin{cases} \gamma_1 \frac{\Delta T}{2} \leq \gamma_3 \\ \gamma_2 \frac{\Delta T}{2} \leq \gamma_3 \end{cases}} \quad (\text{B.23})$$

The figure of merit of a storage usage:

$$\boxed{\text{Storage 2 is used instead of Storage 1 is used} \iff \frac{1}{\eta_1 + 1} \left(\eta_1 \gamma_1 \frac{\Delta T}{2} + \gamma_3 \right) \geq \frac{1}{\eta_2 + 1} \left(\eta_2 \gamma_2 \frac{\Delta T}{2} + \gamma_3 \right)} \quad (\text{B.24})$$

VI Service allocation calculation

Equation 4.16 and reminded just below shows that the service calculation.

$$\begin{aligned}
 \text{Service} &= \int_{P_{\text{Load}} > \dot{P}_{\text{Supply}}} (P_{\text{load}}(t) - P_{\text{supply}}(t)) \cdot dt \\
 &= \sum_i \int_{\text{Load} > \text{Supply}} (P_{\text{discharge},i}(t) - P_{\text{charge},i}(t)) (dt) + \int_{P_{\text{Load}} > \dot{P}_{\text{Supply}}} (\alpha P_{\text{supply}}(t) - P_{\text{curt}}(t)) dt
 \end{aligned}$$

However, after the wavelet decomposition, one of the three terms — *useful oversizing*, *useful storage* 1 & 2 — can be negative. It can occur, for example, when electricity production is very much oversized. Even if consumption was greater than consumption (e.g., $\text{Service} > 0$), the system is so much oversized than a storage is charged.

Thus we need to bring small corrections, presented below, to calculate useful oversizing and useful discharge. Note that we ensure that those corrections are not changing much the results.

$$\text{Storage contribution} = \int_{\text{Load} > \text{Supply}} (P_{\text{load}}(t) - P_{\text{supply}}(t))^+ \cdot dt \quad (\text{B.25})$$

$$\text{Oversizing contribution} = \int_{\text{Load} > \text{Supply}} (\alpha P_{\text{supply}}(t) - P_{\text{curt}}(t))^+ dt \quad (\text{B.26})$$

where $^+$ is the positive part of a function.

We define two quantities, *Useful oversizing* and *Useful discharge* such that

$$\text{Service} = \text{Useful oversizing} + \text{Useful discharge}$$

Therefore

$$\text{Useful discharge} = \text{Service} \times \frac{\text{Storage contribution}}{\text{Oversizing contribution} + \text{Storage contribution}} \quad (\text{B.27})$$

and

$$\text{Useful oversizing} = \text{Service} \times \frac{\text{Oversizing contribution}}{\text{Oversizing contribution} + \text{Storage contribution}} \quad (\text{B.28})$$

Calculation details of Chapter 5

We present in this appendix all the calculations conducted in Chapter 5 to obtain the Trade-off expressions.

I Problem presentation

I.1 Energy system

We remind here in Figure C.1 the different variables and notations used of the energy system. Note that time-series have a single time-scale of duration ΔT .

The optimization variables are the following:

- α , the oversizing factor of the electricity production.
- $E_{max H_2}$, the energy capacity of the electricity storage, i.e., P2P through the hydrogen vector.
- $E_{max TS}$, the energy capacity of the thermal storage.
- $P_{max,HP,out}$, the maximum thermal energy output from the heat pump.
- $P_{waste\ heat}(t)$, the thermal power supplied by the heat boiler.

An of course every other power and energy variables depending on these variables.

I.2 Equations

We present here the general equations of the energy system. Superscripts ¹ and ² on variables refers to the first or second half of the time series. Indexes _{el} and _{th} respectively refers to electricity or heat energy vector. *in* and *out* states whether it is the input or output power from an element of the energy system.

Electrical system equations: The derivative of nodal law for the electricity system is written on both time-scales such that:

$$\begin{cases} dP_{in,el}^1 = dP_{out,el} + dP_{curt,el}^1 + dP_{in,HP}^1 + dP_{disch,el}^1 - dP_{ch,el}^1 \\ dP_{in,el}^2 = dP_{out,el} + dP_{curt,el}^2 + dP_{in,HP}^2 + dP_{disch,el}^2 - dP_{ch,el}^2 \end{cases} \quad (C.1)$$

With $P_{in,el}$ defined such that

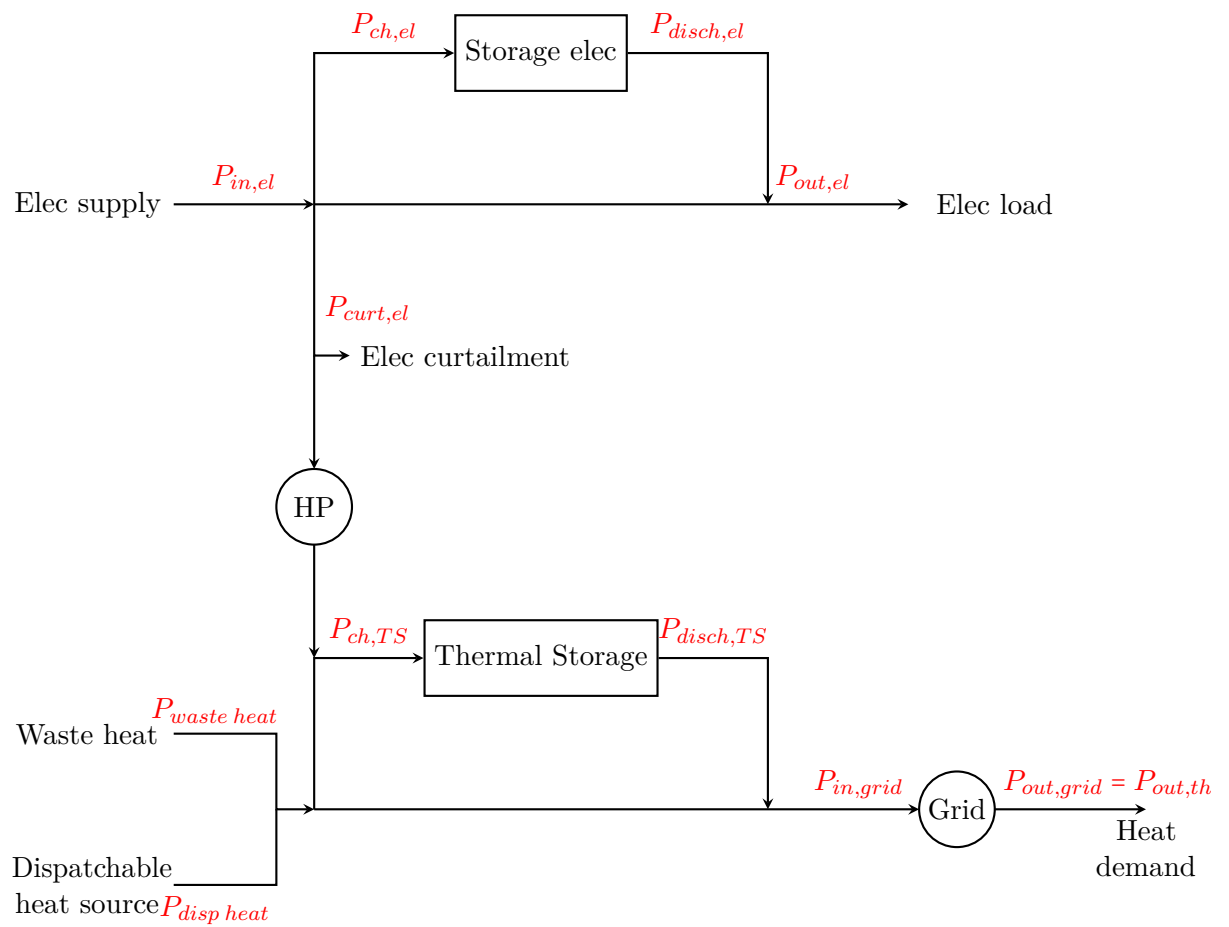


Figure C.1: Energy system definition.

$$\begin{cases} P_{in,elec}^1 = (1 + \alpha)(1 + \beta) \\ P_{in,elec}^2 = (1 + \alpha)(1 - \beta) \end{cases} \quad (C.2)$$

Thus

$$dP_{in,elec}^i = d\alpha \times \frac{P_{in,elec}^i}{1 + \alpha} \quad (C.3)$$

Efficiency η_{el} of the storage is defined such that

$$\eta_{el} \times dP_{ch,el}^i = dP_{disch,el}^j \quad (C.4)$$

Where $i, j \in \{1, 2\}_{i \neq j}$

Thermal system equations: The conversion through the heat put is

$$COP \cdot dP_{in,HP} = dP_{out,HP} \quad (C.5)$$

The nodal law of the thermal system provides

$$\begin{cases} dP_{disp\ heat}^1 + dP_{out,HP}^1 = dP_{disch,TS}^1 - dP_{ch,TS}^1 \\ dP_{disp\ heat}^2 + dP_{out,HP}^2 = dP_{disch,TS}^2 - dP_{ch,TS}^2 \end{cases} \quad (C.6)$$

To simplify the calculation we assumed that the thermal storage has no self discharge but a seasonal efficiency η_{TS} , such that

$$\eta_{TS} \times dP_{ch,TS}^i = dP_{disch,TS}^j \quad (C.7)$$

Where $i, j \in \{1, 2\}_{i \neq j}$

We present in the next section all the *trade-off calculations* whose results were presented in Chapter 5.

We model the grid losses η_{grid} in the heating grid as the ratio between the input and output power, such that

$$P_{out,grid} = \eta_{grid} P_{in,grid} \quad (C.8)$$

Optimization variables: The optimization variables are the following:

- α , the oversizing factor of the electricity production.
- E_{max,H_2} , the energy capacity of the electricity storage, i.e., P2P through the hydrogen vector.
- $E_{max,TS}$, the energy capacity of the thermal storage.
- $P_{max,HP,out}$, the maximum thermal energy output from the heat pump.
- $P_{waste\ heat}(t)$, the thermal power supplied by the heat boiler.

Moreover, all the other dependent power and energy variables presented above.

Cost calculation: We reused the notation γ defined in Chapter 4 to express the costs of the different components.

$$\left\{ \begin{array}{l}
 Cost_{prod,elec} = \int_t P_{el,out}(t)dt Elec_{cost}/N_{years} \\
 Cost_{HP} = P_{max,HP,out} \cdot \gamma_{P,HP} \\
 Cost_{TS} = E_{max,TS} \cdot \gamma_{E,TS} \\
 Cost_{heat\ network} = \int_t P_{out,HP}(t)dt \cdot \gamma_{E,grid}/N_{years} \\
 Cost_{disp\ heat} = \int_t P_{disp\ heat}(t)dt \cdot Waste\ Heat_{cost}/N_{years} \\
 Cost_{waste\ heat} = \int_t P_{waste\ heat}(t)dt \cdot Heat_{cost}/N_{years} \\
 Cost_{AEC} = P_{max,AEC,in} \cdot \gamma_{P,AEC} \\
 Cost_{PEMFC} = P_{max,PEMFC,out} \cdot \gamma_{P,PEMFC}
 \end{array} \right. \quad (C.9)$$

where N_{years} is the number of years of the signal last. In this simulation case, $N_{years} = 1$.

$$\left\{ \begin{array}{l}
 \gamma_{P,HP} = \frac{I_{P,HP}}{T_{cal,HP}} \\
 \gamma_{P,TS} = \frac{I_{E,TS}}{T_{cal,TS}} \\
 \gamma_{E,grid} = I_{E,grid} \\
 \gamma_{P,AEC} = \frac{I_{P,AEC}}{T_{use,AEC}} \times \frac{\int_t P_{max,in,AEC}dt}{\int_t P_{in,AEC}(t)dt} \\
 \gamma_{P,PEMFC} = \frac{I_{P,PEMFC}}{T_{use,PEMFC}} \times \underbrace{\frac{\int_t P_{max,out,PEMFC}dt}{\int_t P_{in,PEMFC}(t)dt}}_{=2\ here}
 \end{array} \right. \quad (C.10)$$

II Calculation

II.1 Thermal storage vs. Electricity production oversizing

We present the calculation of the boundary between the two schemes shown in Figure C.2.

In both cases, electricity production is oversized to produced electricity for heat generation. Figures (a) and (b) represent the reference case. All excess electricity is converted into heat. The heating demand is only satisfied using HP and thermal storage.

In Figures (c) and (d), the energy system is even more oversized, so that it satisfies the entire heating demand, without storage or dispatchable power plant. As a consequence, there is excess electricity curtailed in summer.

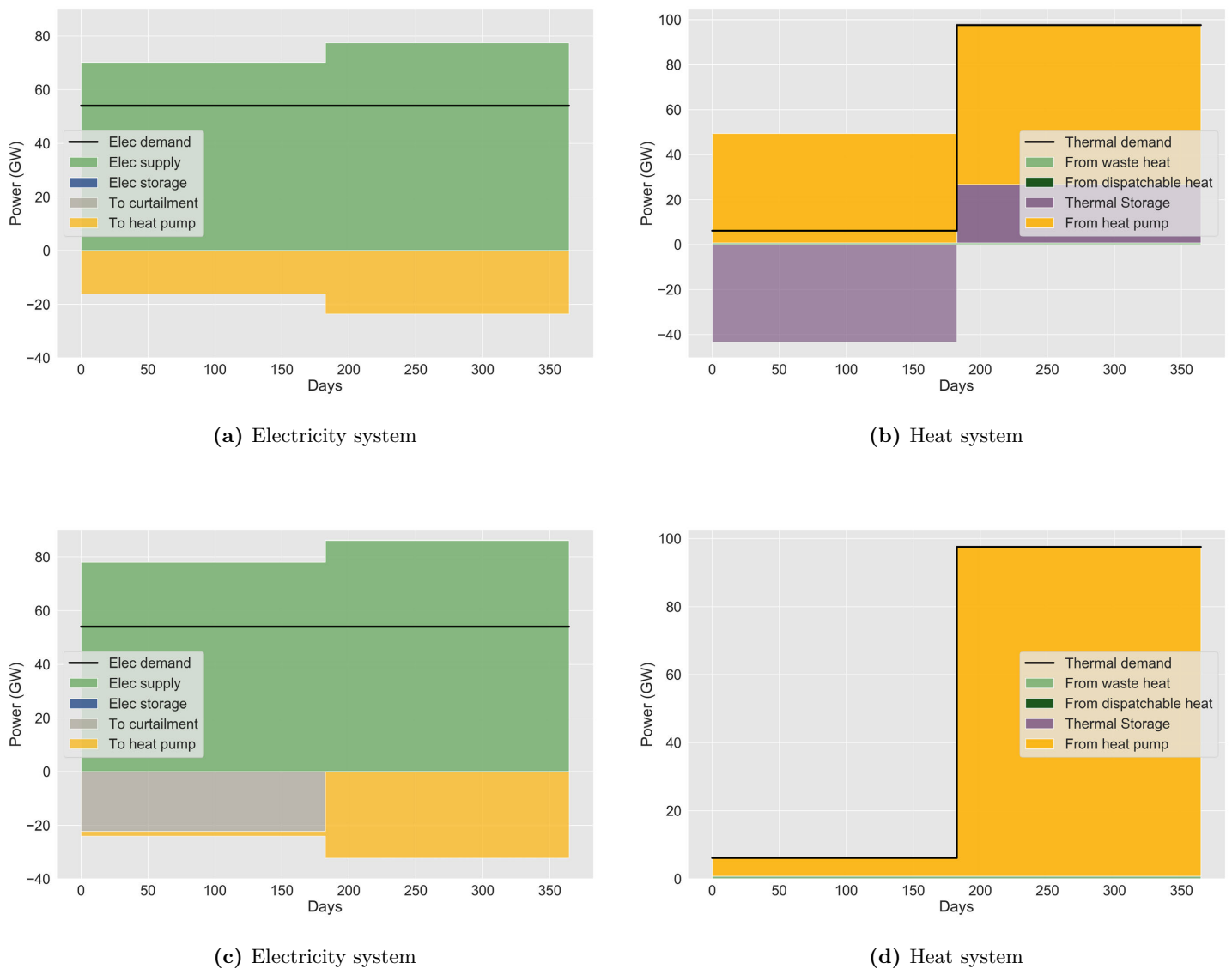


Figure C.2

The equations presented in previous section 1.2 are adapted here to this specific problem

Electrical system equations:

$$\begin{cases} P_{in,elec}^1 = P_{out,elec} + P_{curt,elec}^1 + P_{in,PAC}^1 \\ P_{in,elec}^2 = P_{out,elec} + P_{in,PAC}^2 \end{cases} \quad (C.11)$$

Thermal system equations: The derivative of the nodal law on the second half of the time scale is now equal to:

$$COP \cdot dP_{in,HP}^2 + dP_{disch,TS}^2 = 0 \quad (C.12)$$

which can be simplified such that

$$dP_{disch,TS}^2 = -COP \cdot dP_{in,el}^2 \quad (C.13)$$

We now calculate the cost variations

$$\begin{cases} dCost_{prod,elec} &= Elec_{price} \cdot \frac{\Delta T}{2} [dP_{in,el}^1 + dP_{in,el}^2] \\ dCost_{HP} &= dP_{out,HP}^2 \cdot \gamma_{P,HP} \\ dCost_{TS} &= \gamma_{E,TS} \cdot \frac{1}{\eta_{TS}} \cdot dP_{dech,TS}^2 \times \frac{\Delta T}{2} \\ dCost_{heat\ network} &= dP_{out,HP}^2 \cdot \gamma_{P,heat\ network} \end{cases} \quad (C.14)$$

Once simplified we get

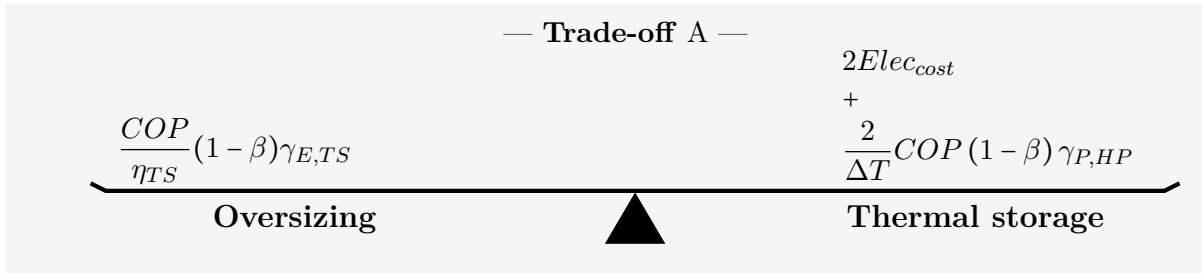
$$\begin{cases} dCost_{prod,elec} &= Elec_{price} \cdot \frac{\Delta T}{2} [dP_{in,el}^1 + dP_{in,el}^2] \\ dCost_{HP} &= dP_{in,el}^2 \cdot COP \cdot \gamma_{P,HP} \\ dCost_{TS} &= -\gamma_{E,TS} \cdot \frac{1}{\eta_{TS}} \cdot dP_{in,el}^2 \times \frac{\Delta T}{2} \\ dCost_{heat\ network} &= COP \cdot dP_{in,el}^2 \cdot \gamma_{P,heat\ network} \end{cases} \quad (C.15)$$

Wrap-up: We now compute the total cost:

$$\boxed{\frac{1}{1+\alpha} \cdot \frac{dTotal\ cost}{d\alpha} = \frac{\Delta T}{2} \cdot \left[2 Elec_{cost} - \frac{COP}{\eta_{TS}} (1-\beta) \gamma_{E,TS} + \frac{2}{\Delta T} COP (1-\beta) \gamma_{P,HP} \right]} \quad (C.16)$$

$\frac{dTotal\ cost}{d\alpha} < 0$, implies that optimal solution need to be oversized, we move from the reference case and start satisfying heat demand only thanks to electricity generation and conversion.

We represent the trade-off of costs between those two cases, *oversizing electricity production* or using the *thermal storage* in the following weighing scale. The side with the highest value determines the operating mode.



II.2 Thermal storage vs. Dispatchable heat supply

We present the calculation of the boundary between the two schemes shown in Figure C.3.

In both cases, electricity production is oversized for heating generation. Figures (a) and (b) represent the reference case. All excess electricity is converted into heat. The heating demand is only satisfied using HP and thermal storage.

In Figures (c) and (d), the energy system is oversized so that the conversion of excess electricity to heat in summer is equal to the heating need. Overall, all excess electricity is converted. In winter heat boiler compensate the lack of energy.

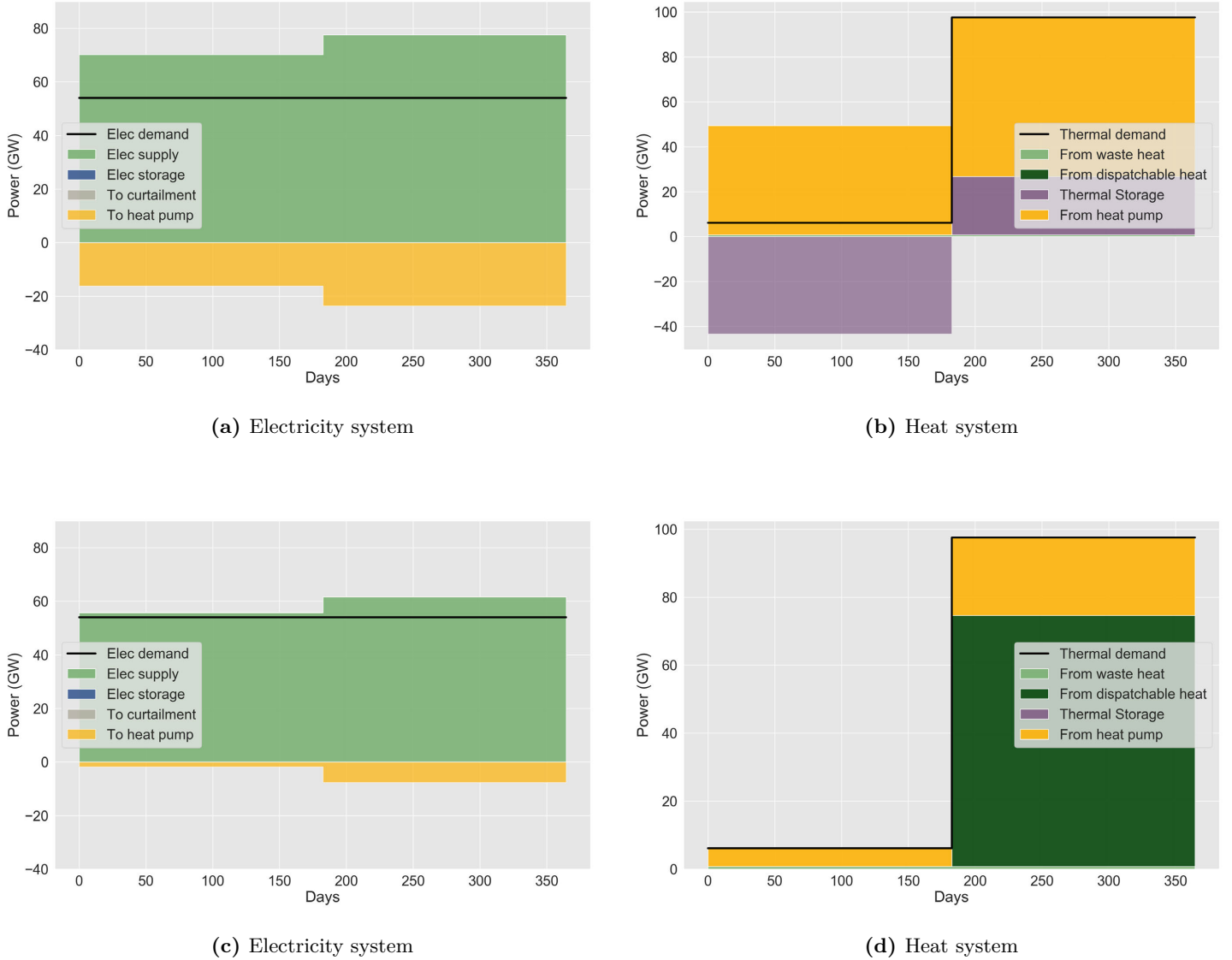


Figure C.3

Equations of the system are now:

$$\begin{cases} dP_{out,HP}^2 & = dP_{ch,TS}^1 \\ COP \cdot dP_{in,HP}^2 + dP_{in,disp\ heat}^2 + dP_{disch,TS}^2 & = 0 \end{cases} \quad (C.17)$$

With the same nodal low for the electricity system

$$\begin{cases} dP_{in,el}^1 &= dP_{in,HP}^1 \\ dP_{in,el}^2 &= dP_{in,HP}^2 \end{cases} \quad (C.18)$$

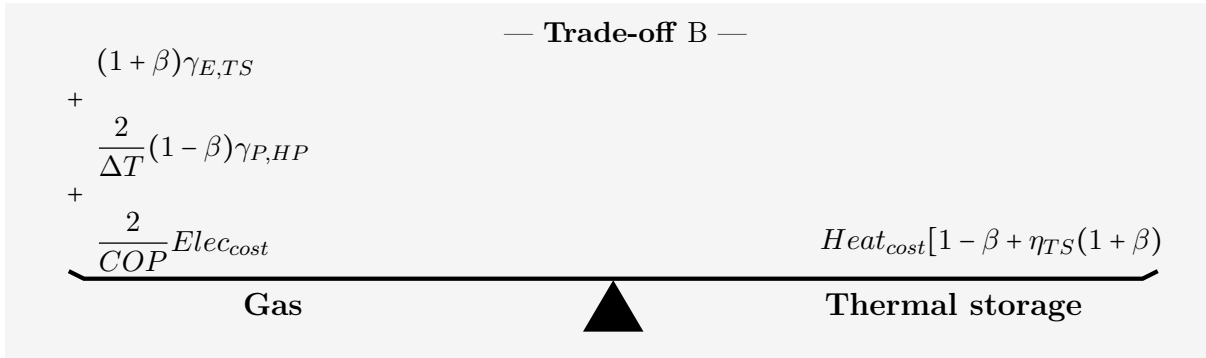
With the costs derivative equal to

$$\begin{cases} dCost_{prod,elec} &= Elec_{price} \cdot \frac{\Delta T}{2} [dP_{in,el}^1 + dP_{in,el}^2] \\ dCost_{HP} &= dP_{out,HP}^2 \cdot \gamma_{P,HP} \\ dCost_{TS} &= dP_{ch}^1 \frac{\Delta T}{2} \gamma_{E,TS} &= COP \frac{\Delta T}{2} \gamma_{E,TS} dP_{in,el}^1 \\ dCost_{disp\ heat} &= \frac{\Delta T}{2} dP_{disp\ heat}^2 Heat_{cost} &= -\frac{\Delta T}{2} (dP_{in,el}^2 + \eta_{TS} dP_{in,el}^1) Heat_{cost} \end{cases} \quad (C.19)$$

$$dT_{total\ cost} = 0 \iff$$

$$\frac{2}{\Delta T} (1 - \beta) \gamma_{P,HP} + \frac{2}{COP} Elec_{cost} + (1 + \beta) \gamma_{E,TS} = Heat_{cost} [1 - \beta + \eta_{TS} (1 + \beta)] \quad (C.20)$$

To synthesize:



II.3 Oversizing vs. Oversizing with constant HP

We present the calculation of the boundary between the two schemes shown in Figure C.4.

In both cases, electricity production is oversized with the same factor. The remaining heating need is provided by heat boilers. Figures (a) and (b) depict a system where all waste electricity is recovered and transformed into heat.

In Figures (c) and (d), on the contrary, the heat pump is operated with a constant rate over the year, excess electricity is curtailed in winter.

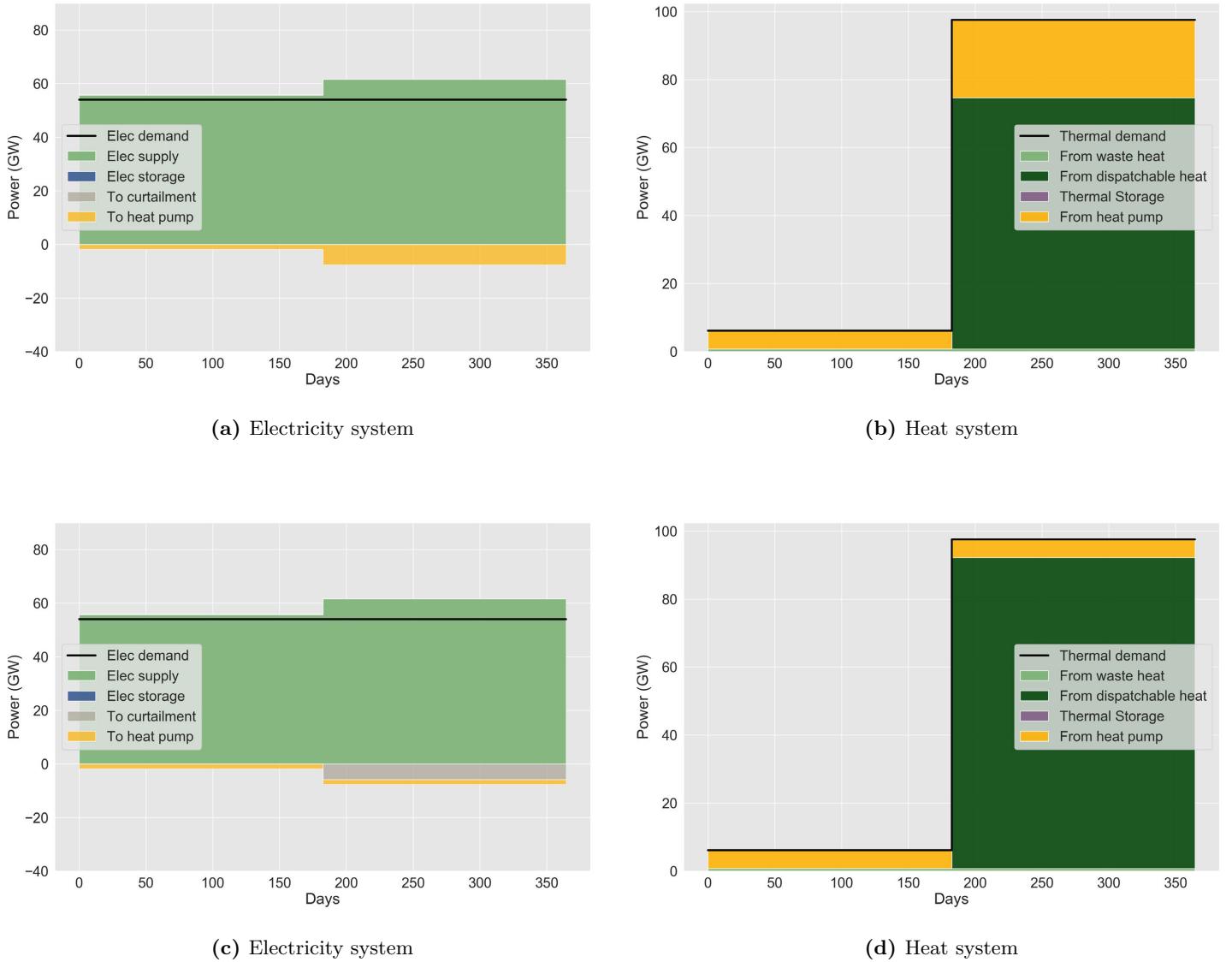


Figure C.4

From one case to the other, the production oversizing does not change:

$$dP_{in,el} = 0 \quad (C.21)$$

The nodal law on the electricity system show that:

$$dP_{in,HP}^2 + dP_{curt}^2 = 0 \quad (C.22)$$

Similarly for the thermal system:

$$dP_{out,HP}^2 + dP_{disp\ heat}^2 = 0 \quad (C.23)$$

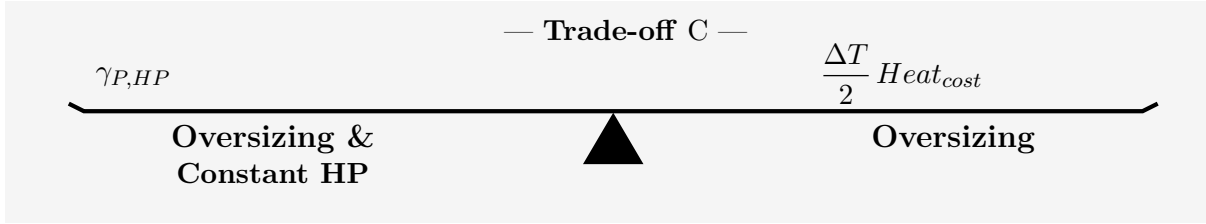
Cost variations of the energy systems are the following:

$$\begin{cases} dCost_{HP} & = dP_{out,HP}^2 \gamma_{P,HP} \\ dCost_{disp\ heat} & = \frac{\Delta T}{2} dP_{disp\ heat}^2 Heat_{cost} \end{cases} \quad (C.24)$$

Thus

$$dTotal\ cost = dP_{disp\ heat}^2 \left[\gamma_{P,HP} - \frac{\Delta T}{2} Heat_{cost} \right] \quad (C.25)$$

We deduct that the boundary between those two scheme is driven by the balance between the following cost.



II.4 Electricity recovery vs. Gas

We present the calculation of the boundary between the two schemes shown in Figure C.5.

Here, electricity production is only oversized to satisfy the electricity demand. In Figures (a) and (b), waste electricity is recovered and transformed into heat.

In Figures (c) and (d), on the contrary, excess electricity is not recovered and replaced with gas.

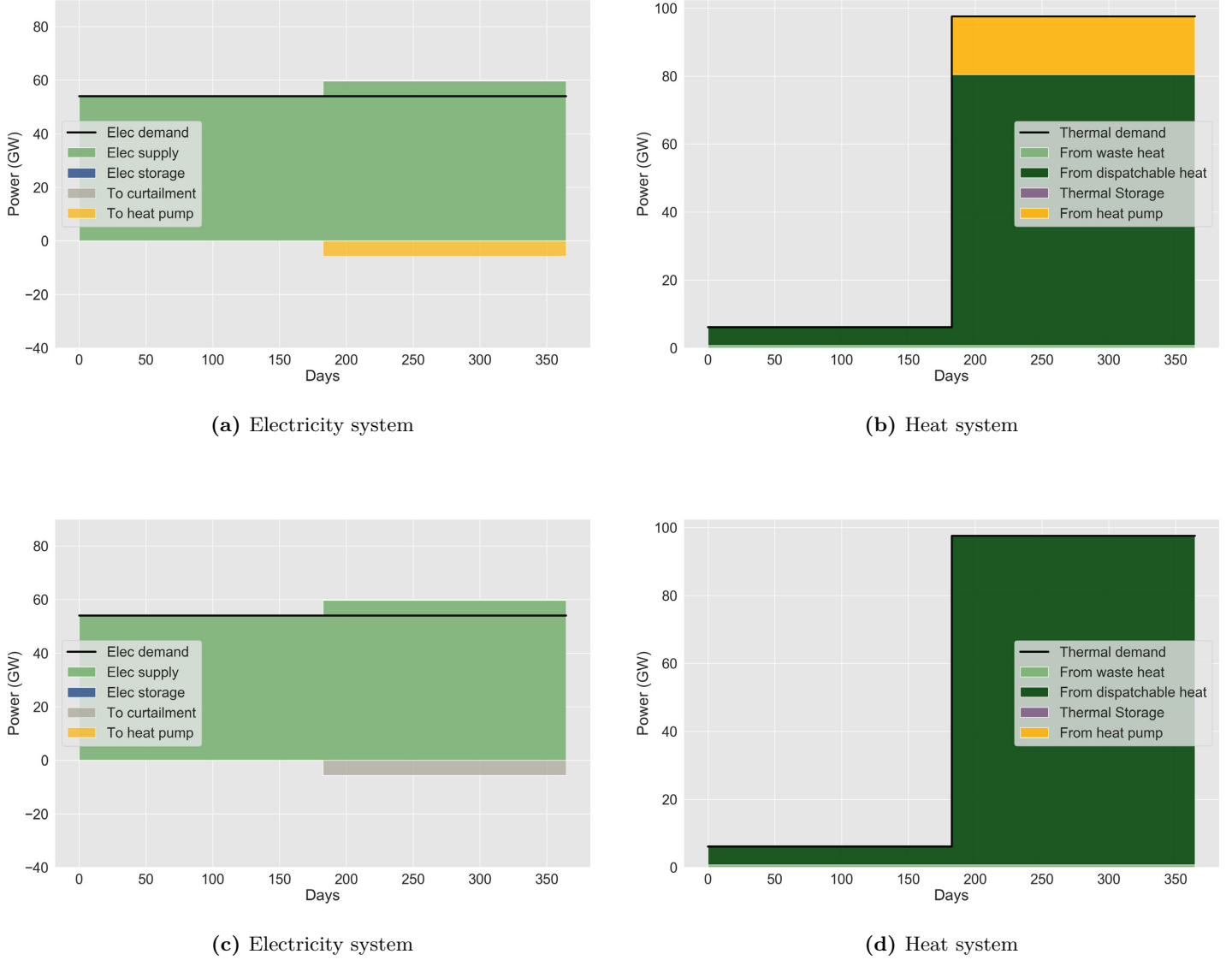


Figure C.5

It must be noted that the equations depicting this boundary are the exact same ones than in the previous case.

$$dP_{in,HP}^2 + dP_{curt}^2 = 0 \quad (C.26)$$

For the thermal system:

$$dP_{out,HP}^2 + dP_{disp\ heat}^2 = 0 \quad (C.27)$$

Cost variations of the energy systems are the following:

$$\begin{cases} dCost_{HP} & = dP_{out,HP}^2 \gamma_{P,HP} \\ dCost_{disp\ heat} & = \frac{\Delta T}{2} dP_{disp\ heat}^2 Heat_{cost} \end{cases} \quad (C.28)$$

Thus

$$dTotal\ cost = dP_{disp\ heat}^2 \left[\gamma_{P,HP} - \frac{\Delta T}{2} Heat_{cost} \right] \quad (C.29)$$

We deduct that the boundary between those two scheme is driven by the balance between the following cost.



II.5 Waste electricity recovery with constant HP vs. Gas

We present the calculation of the boundary between the two schemes shown in Figure C.6.

In Figures (a) and (b) is only oversized to satisfy the electricity demand. Waste electricity is not recovered and heating need is provided by heat boilers.

In figures (c) and (d), the electricity production is oversized just enough to be able, thanks to the heat pump, to meet the thermal demand in summer. The HP is used with a constant power in summer and winter. In the second time step, the excess electricity is curtailed. The remaining thermal energy need in winter is supplied by dispatchable heat plant.

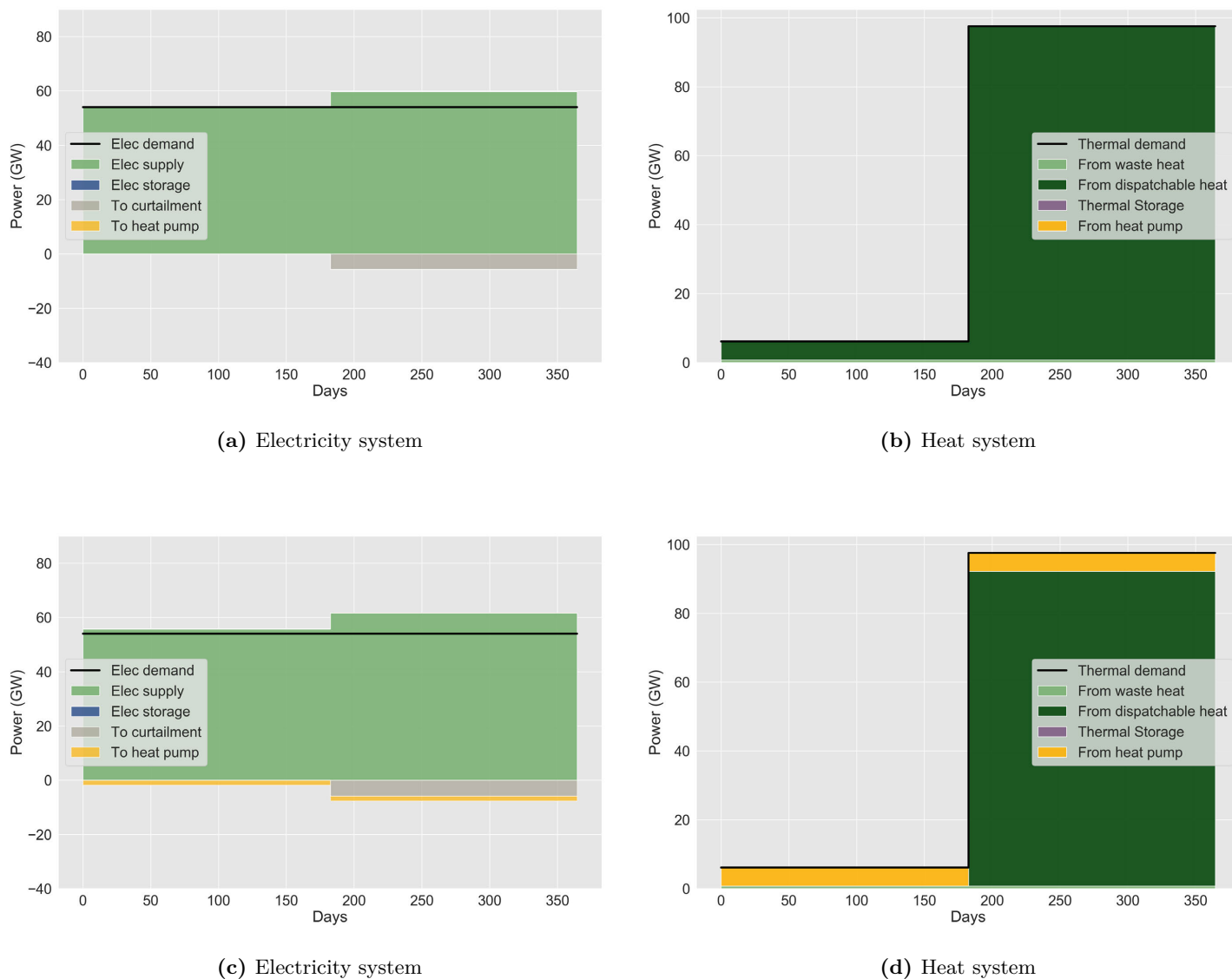


Figure C.6

The variations of nodal law of the electricity system shows that

$$\begin{cases} dP_{in,el}^1 = dP_{in,HP}^1 \\ dP_{in,el}^2 = dP_{in,HP}^2 + dP_{curt}^2 \end{cases} \quad (C.30)$$

For the thermal system:

$$\begin{cases} dP_{out,HP}^1 + dP_{disp\ heat}^1 = 0 \\ dP_{out,HP}^2 + dP_{disp\ heat}^2 = 0 \end{cases} \quad (C.31)$$

In this case, the heat pump is operated at a constant power:

$$dP_{out,HP}^1 = dP_{out,HP}^2 \quad (C.32)$$

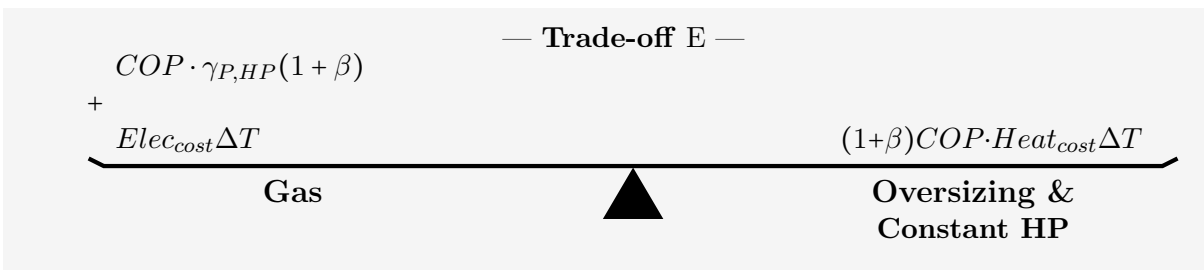
Cost variations of the energy systems are the following:

$$\begin{cases} dCost_{prod,elec} = Elec_{cost} \cdot \frac{\Delta T}{2} [dP_{in,el}^1 + dP_{in,el}^2] \\ dCost_{HP} = dP_{out,HP}^1 \gamma_{P,HP} \\ dCost_{disp\ heat} = \Delta T Heat_{cost} dP_{disp\ heat}^1 \end{cases} \quad (C.33)$$

Thus

$$dT_{total\ cost} = [dP_{in,el}^1 + dP_{in,el}^2] \times \frac{\Delta T}{2} Elec_{cost} - \Delta T Heat_{cost} dP_{in,el}^1 + \gamma_{P,HP} COP dP_{in,el}^1 \quad (C.34)$$

We deduct that the boundary between those two schemes is driven by the balance between the following cost.



II.6 Oversizing vs. Gas

We present the calculation of the boundary between the two schemes shown in in Figure C.7.

In Figures (a) and (b), electricity production is oversized and all excess are converted into heat. Dispatchable gas plants are operated in winter to satisfy the remaining heating demand.

In Figures (c) and (d), electricity production is only oversized to satisfy the electricity demand and waste energy is recovered.

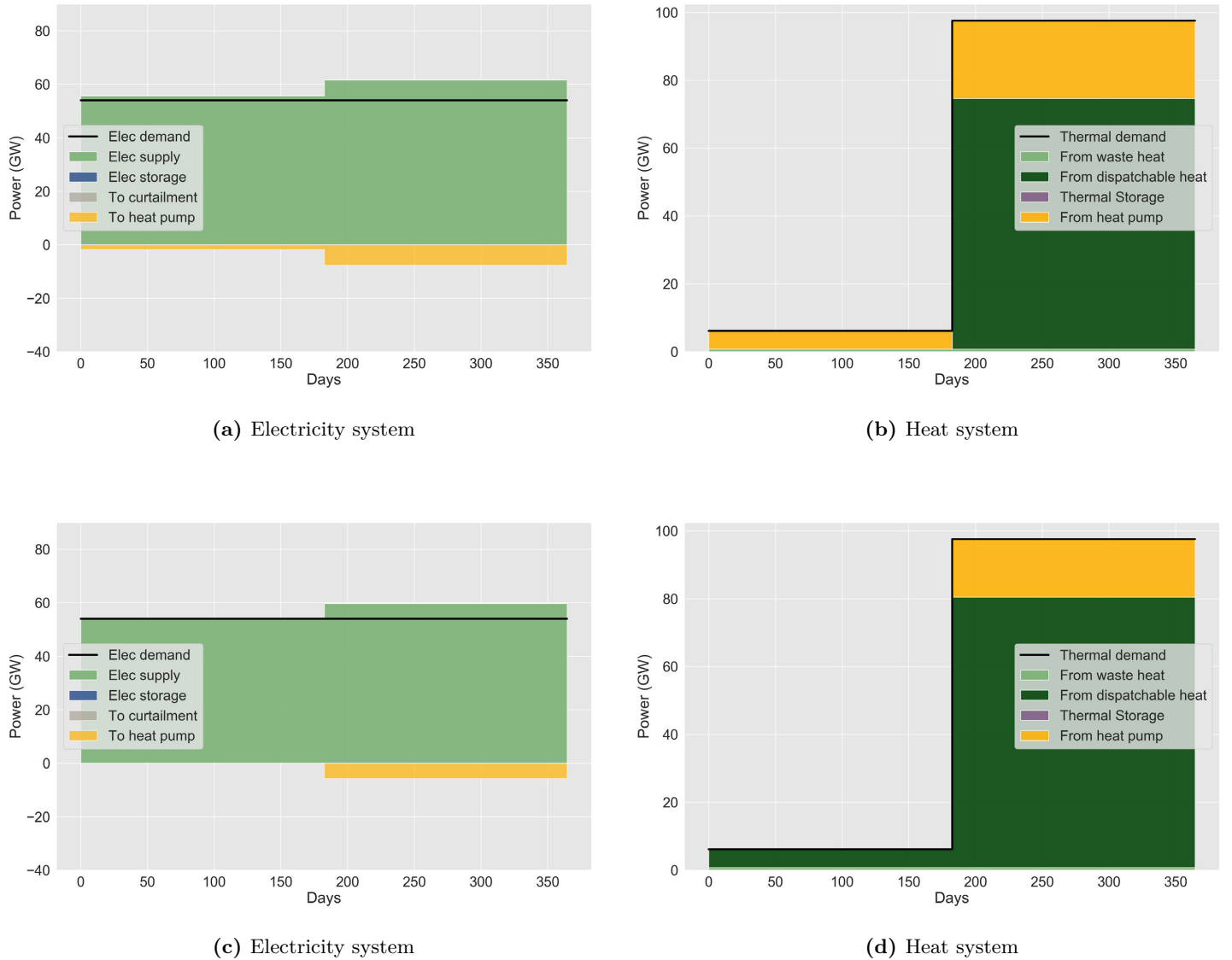


Figure C.7

The variations of nodal law of the electricity system shows that

$$\begin{cases} dP_{in,el}^1 = dP_{in,HP}^1 \\ dP_{in,el}^2 = dP_{in,HP}^2 \end{cases} \quad (C.35)$$

For the thermal system:

$$\begin{cases} dP_{out,HP}^1 + dP_{disp\ heat}^1 = 0 \\ dP_{out,HP}^2 + dP_{disp\ heat}^2 = 0 \end{cases} \quad (C.36)$$

Cost variations of the energy systems are the following:

$$\begin{cases} dCost_{prod,elec} = Elec_{cost} \cdot \frac{\Delta T}{2} [dP_{in,el}^1 + dP_{in,el}^2] \\ dCost_{HP} = dP_{out,HP}^2 \gamma_{P,HP} \\ dCost_{disp\ heat} = \frac{\Delta T}{2} Heat_{cost} [dP_{disp\ heat}^1 + dP_{disp\ heat}^2] \end{cases} \quad (C.37)$$

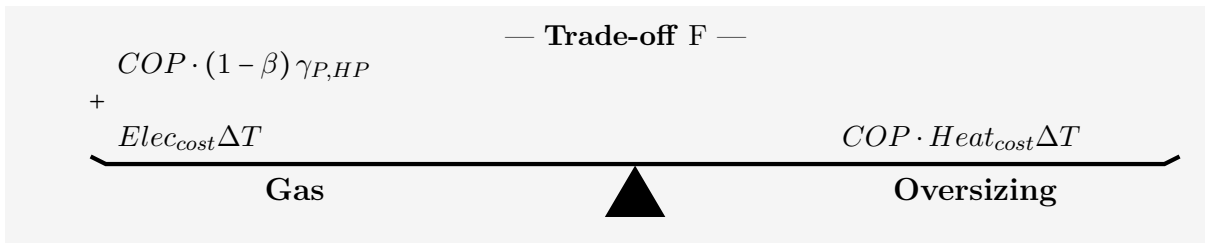
i.e.,

$$\begin{cases} dCost_{prod,elec} = Elec_{cost} \cdot \frac{\Delta T}{2} [dP_{in,el}^1 + dP_{in,el}^2] \\ dCost_{HP} = dP_{in,el}^2 COP \cdot \gamma_{P,HP} \\ dCost_{disp\ heat} = -\frac{\Delta T}{2} \cdot COP Heat_{cost} [dP_{in,el}^1 + dP_{in,el}^2] \end{cases} \quad (C.38)$$

Thus

$$\begin{aligned} dTotal\ cost &= [dP_{in,el}^1 + dP_{in,el}^2] \times \frac{\Delta T}{2} \times [Elec_{cost} - COP \cdot Heat_{cost}] \\ &\quad + dP_{in,el}^2 \times \gamma_{P,HP} COP dP_{in,el}^1 \end{aligned} \quad (C.39)$$

We deduct that the boundary between those two schemes is driven by the balance between the following cost.



II.7 Electricity storage vs. Thermal storage

We present the calculation of the boundary between the two schemes shown in Figure C.8. Figures (a) and (b) represent the reference case. In Figures(c) and (d), the system is slightly less oversized and electricity storage is charged in summer.

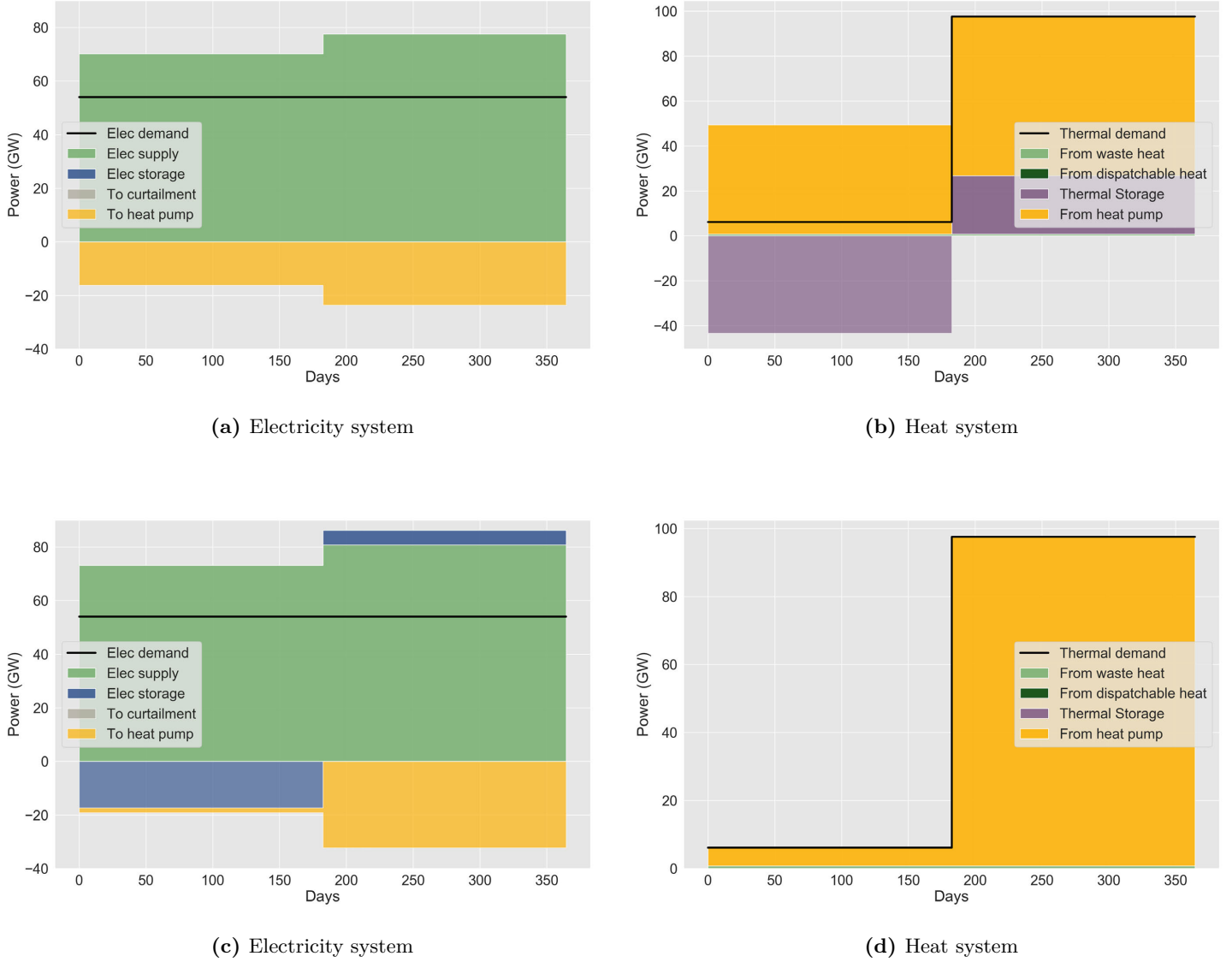


Figure C.8

The derivative of the nodal law of the electricity system is

$$dP_{in,el} + dP_{disch,el} = dP_{ch,el} + dP_{dP_{in,HP}} \quad (C.40)$$

Rewritten on the two time steps it implies

$$\begin{cases} dP_{in,el}^1 & = dP_{ch,el}^1 + dP_{in,HP}^1 \\ dP_{in,el}^2 + dP_{disch,el}^2 & = dP_{in,HP}^2 \end{cases} \quad (C.41)$$

knowing that

$$\eta_{H_2} dP_{ch,el}^1 = dP_{disch,el}^2 \quad (C.42)$$

The nodal law for the thermal system gives

$$dP_{out,HP} + dP_{dichch,th} = dP_{ch,th} \quad (C.43)$$

Rewritten on the two time steps it implies

$$\begin{cases} dP_{out,HP}^1 = dP_{ch,th}^1 \\ dP_{out,HP}^2 + dP_{dich,th}^2 = 0 \end{cases} \quad (C.44)$$

And

$$\eta_{TS} dP_{ch,th}^1 = dP_{disch,th}^2 \quad (C.45)$$

Costs variations are

$$\begin{cases} dCost_{prod,elec} = Elec_{cost} \cdot \frac{\Delta T}{2} [dP_{in,el}^1 + dP_{in,el}^2] \\ dCost_{HP} = dP_{out,HP}^2 \cdot \gamma_{P,HP} \\ dCost_{TS} = dP_{ch,th}^1 \frac{\Delta T}{2} \gamma_{E,TS} \\ dCost_{AEC} = dP_{ch,el}^1 \gamma_{P,AEC} \\ dCost_{PEMFC} = dP_{dech,el}^2 \gamma_{P,PEMFC} \end{cases} \quad (C.46)$$

From the nodal laws we deduct that

$$\begin{cases} dP_{in,HP}^2 = -\frac{\eta_{TS}}{COP} dP_{ch,TS}^1 \\ dP_{in,HP}^1 = \frac{1}{COP} dP_{ch,TS}^1 \end{cases} \quad (C.47)$$

We now introduce the parameter δ such that

$$\delta = \frac{P_{in}^2}{P_{in}^1} = \frac{1 + \beta}{1 - \beta} \quad (C.48)$$

Thus we found

$$\begin{cases} dP_{ch,el}^1 = -\frac{\delta + \eta_{TS}}{\delta + \eta_{H_2}} \frac{dP_{ch,TS}^1}{COP} \\ dP_{in,el}^1 = \frac{\eta_{H_2} - \eta_{TS}}{\delta + \eta_{H_2}} \frac{dP_{ch,TS}^1}{COP} \\ dP_{in,el}^2 = \delta dP_{in,el}^1 \end{cases} \quad (C.49)$$

Thus

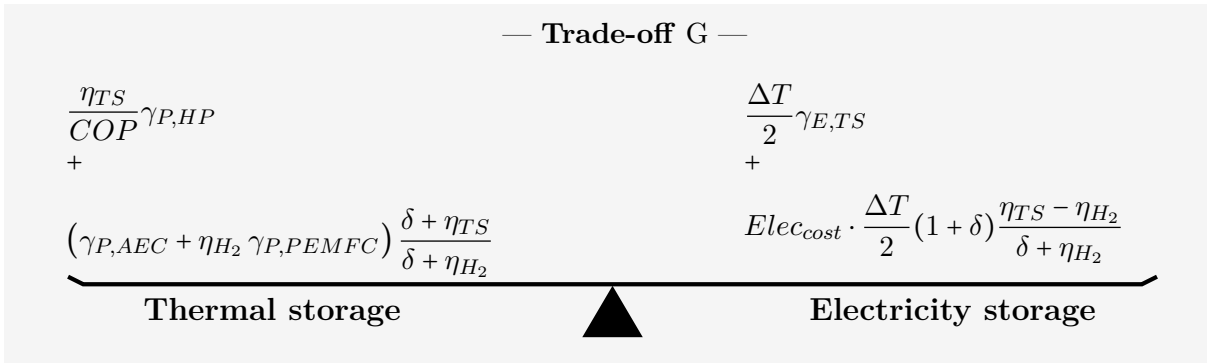
$$\left\{ \begin{array}{l} \frac{dTotal\ cost}{dP_{ch,TS}^1} \times \frac{COP}{COP} = Elec_{cost} \cdot \frac{\Delta T}{2} (1 + \delta) \frac{\eta_{H_2} - \eta_{TS}}{\delta + \eta_{H_2}} \\ - \frac{\eta_{TS}}{COP} \gamma_{P,HP} \\ + \frac{\Delta T}{2} \gamma_{E,TS} \\ - (\gamma_{P,AEC} + \eta_{H_2} \gamma_{P,PEMFC}) \frac{\delta + \eta_{TS}}{\delta + \eta_{H_2}} \end{array} \right. \quad (C.50)$$

If $\frac{dTotal\ cost}{dP_{ch,TS}^1} < 0$, the optimal solution is that electricity storage must be used. On the contrary, if $\frac{dTotal\ cost}{dP_{ch,TS}^1} > 0$, Thermal storage must be used.

$$dTotal\ cost = 0 \iff$$

$$\left\{ \begin{array}{l} 0 = Elec_{cost} \cdot \frac{\Delta T}{2} (1 + \delta) \frac{\eta_{H_2} - \eta_{TS}}{\delta + \eta_{H_2}} \\ - \frac{\eta_{TS}}{COP} \gamma_{P,HP} \\ + \frac{\Delta T}{2} \gamma_{E,TS} \\ - (\gamma_{P,AEC} + \eta_{H_2} \gamma_{P,PEMFC}) \frac{\delta + \eta_{TS}}{\delta + \eta_{H_2}} \end{array} \right. \quad (C.51)$$

To synthesize we display the positive and negative elements in the following table.



Wavelet decomposition results — Annual coefficients

We present in Table D.1 the wavelet decomposition’s annual coefficient of three different time series: electricity consumption, solar PV and wind power production. This decomposition was performed for 7 years, from 2012 to 2018. RTE, the French TSO provided signals. They represent the French electricity production and consumption.

This mathematical decomposition was performed with signals all normalized so that their average power is equal to 1:

$$\langle Consumption \rangle = \langle Production \rangle = 1$$

Table D.1: Year coefficient β of the wavelet decomposition applied to electricity consumption, wind power and solar PV electricity generation. 7 years are presented, from 2012 to 2018. Coefficients β are homogeneous to a power.

| Year | Consumption | Wind | PV |
|------|-------------|-------------|------------|
| 2012 | -0.16523455 | -0.19720483 | 0.33182331 |
| 2013 | -0.17265803 | -0.1851417 | 0.32649377 |
| 2014 | -0.14118912 | -0.23367684 | 0.3261212 |
| 2015 | -0.15341743 | -0.20785706 | 0.34021658 |
| 2016 | -0.15502052 | -0.28905911 | 0.32847584 |
| 2017 | -0.15913309 | -0.21398865 | 0.27145239 |
| 2018 | -0.16752552 | -0.32904521 | 0.39920688 |

Coefficients are homogeneous to a power. For example, multiplying the electricity demand coefficient by the annual French power consumption will return the power difference between summer and winter. When the coefficients are positive, the signal is higher in winter than in summer, and vice versa when it is negative.

Note that wind coefficients vary between -0.18 and -0.32. It is a more dispersed range around its average than that of photovoltaics. This year-to-year variability implies that intermittent energy mixes, especially if they include a significant wind energy amount, will have very different production from year to year. An energy system configuration that would be optimal for one year to manage seasonal variability in residual demand may not

GAMS optimization source code

We provide in this appendix the source code used to minimize the cost of an electricity system that includes two electricity storages. This is a simplified example of codes used in chapters 3 and 4.

I Energy model description

The energy system modeled is described in Figure E.1. Electricity production can be directly consumed, stored or curtailed. The system includes two electricity storages.

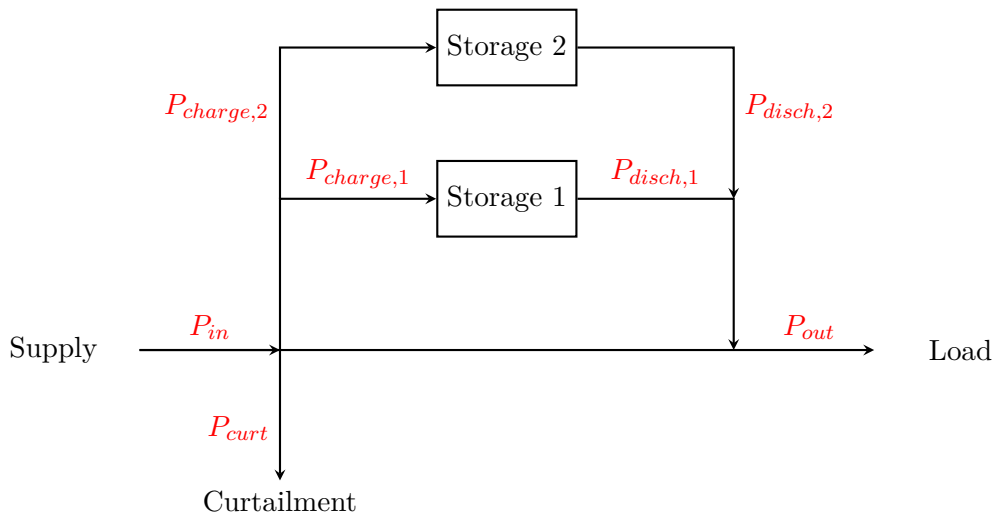


Figure E.1: Representation of the energy system. Electricity supply can either be directly consumed, stored or curtailed.

Input time series

Electricity production (*Supply*) and consumption (*Load*) are imported using the *Table data* presented in Listing E.1. Both time series are normalized so that their mean value are equal to 1. However, the electricity production can be oversized by the factor *Supply factor*, which is a positive variable.

Nodal law and charge–discharge equations

Equations driving this energy system are described in appendix B and reminded here.

Electricity storage is characterized by its size E , η_c its charge efficiency, with a discharge efficiency $\eta_d = 1$. To make it easier to read we refer to the efficiency in charge by η .

Therefore the equation driving the states of charges E_1 and E_2 are

$$\begin{cases} \frac{dE_1(t)}{dt} = P_{charge,1}(t) \cdot \eta_1 - P_{disch,1}(t) \\ \frac{dE_2(t)}{dt} = P_{charge,2}(t) \cdot \eta_2 - P_{disch,2}(t) \end{cases} \quad (\text{E.1})$$

The nodal rule written is written such that

$$P_{in} - P_{out} = P_{charge,1} + P_{charge,2} - P_{disch,1} - P_{disch,2} + P_{curt} \quad (\text{E.2})$$

To simplify the understanding, we refer to storage 1 or 2 with the index i .

The storage system is sized in energy and power by respectively $E_{max,i}$ and $P_{max,i}$.

$$E_i(t) \leq E_{max,i} \quad (\text{E.3})$$

$$P_{i,discharge}(t) \leq P_{max,i} \quad (\text{E.4})$$

$$E_i(t_0) = E_i(t_{end}) \quad (\text{E.5})$$

The objective function *Cost* of this model is

$$Cost = Production\ cost + Storage\ cost\ 1 + Storage\ cost\ 2 \quad (\text{E.6})$$

Costs

The production cost represents the cost of oversizing the power generation system. It is calculated so that

$$Production\ cost = \frac{\alpha \times \zeta_P}{T_{life,cal} \times CF} \quad (\text{E.7})$$

where α is the oversizing factor (= *supply factor* – 1), ζ_P the investment cost in power and CF the capacity factor.

Using nations from chapter 3, cost of electricity storage devices is calculated such that

$$Storage\ cost_i = \frac{max(E_{max,i} \times \zeta_E; P_{max,i} \times \zeta_P)}{T_{life,cal}} \quad (\text{E.8})$$

where $E_{max,i}$ and $P_{max,i}$ are the size in respectively energy and power of storage i .

Artifacts to avoid using integer variables

To avoid computational burden and the use of integer variables, we introduce two artifacts in the code. It enables to proceed to a Linear Programming (LP) resolution instead of a Multi Integer Linear programming (MILP) one.

1. Preventing charge–discharge to occur at the same time

Without any constraints, a storage can charge and discharge energy at the same time to mimic a curtailment behavior. To prevent this, we introduce an infinitesimally small cost (`transit_cost_Storage`) in comparison to the other quantities which is added to the cost of storage. It is calculated such that

$$\text{transit_cost_Storage}_i = \int_t P_{\text{charge},i}(t) dt \times \underbrace{\text{storage_transit_cost}}_{\ll 1} \quad (\text{E.9})$$

2. Minimize the size in energy and power

The cost of a storage can be determined either by its size in *energy* or *power*, as shown by equation E.8. As a result, for example, if $E_{\text{max}_i} \cdot \zeta_E > P_{\text{max}_i} \cdot \zeta_P$, P_{max_i} is not set and can fluctuate.

To set its value to a minimum, we introduce an additional infinitesimally small cost `lower_bound_energy_storage_cost`.

II Optimization code

The following code is automatically generated using the Python API for GAMS 25.1.1.

```

1 Set
2   t 'half days'          / t000001*t000730 / ;
3
4   Table data(t,*) Power signals normalized to 1MW elec
5       load          supply
6   t000001    1.00000    1.20000
7   t000002    1.00000    1.00000
8   t000003    1.00000    1.20000
9   .
10  .
11  t000730    1.00000    0.80000;
12 Scalar
13
14  eta_c_Storage1  "Charge efficiency"      / 1.0 /
15  eta_d_Storage1  "Discharge efficiency"   / 1.0 /
16  Storage1_cost_power  "(MJ)prim/(MW)elec" / 0.1 /
17  Storage1_cost_energy "(MJ)prim/(MWh)elec" / 731.764430395 /
18  Tlife_Storage1  "Calendar life time (years)" / 60.0 /
19
20  eta_c_Storage2  "Charge efficiency"      / 0.7 /
21  eta_d_Storage2  "Discharge efficiency"   / 1.0 /
22  Storage2_cost_power  "(MJ)prim/(MW)elec" / 0.1 /
23  Storage2_cost_energy "(MJ)prim/(MWh)elec" / 29.2705772158 /
24  Tlife_Storage2  "Calendar life time (years)" / 60.0 /
25
26  Tprod          "years"          / 30.0 /
27  Prod_cost      "MJ/(MW)elec"    / 250000.0 /
28  CF_Prod        "Capacity Factor (%)" / 0.13 /
29
    
```

```

30 lower_bound_energy_storage_cost      "(MJ)prim/(MWh)elec"
   /0.0001/
31 storage_transit_cost      " avoid charge-discharge at the same time -
   MJprim/MWhelec"      /0.0001/
32 dt "Time step of the simulation = time scale/2"      /12.0/
33
34
35 Variables
36
37 Pin(t)      Input electricity power (Supply)
38 Pout(t)     output electricity power (Load)
39 cost       Cost in (MJ) prim of storage + production oversizing;
40
41
42 Positive variables
43
44 E_Storage1(t)
45 Pch_Storage1(t)
46 Pdech_Storage1(t)
47 Emax_Storage1
48 Pmax_Storage1
49 Pmax_dech_Storage1
50 SOC0_Storage1
51 cost_Storage1
52 transit_cost_Storage1      An artificial cost to make sure the
   optimisation will curtail and not charge discharge the storage at the
   same time
53
54 E_Storage2(t)
55 Pch_Storage2(t)
56 Pdech_Storage2(t)
57 Emax_Storage2
58 Pmax_Storage2
59 Pmax_dech_Storage2
60 SOC0_Storage2
61 cost_Storage2
62 transit_cost_Storage2      An artificial cost to make sure the
   optimisation will curtail and not charge discharge the storage at the
   same time
63
64 Pcurt(t)     electricity curtailed
65 Cost_Prod
66 supply_factor      The over-sizing factor of the power generation mix ;
67
68 Equations Load(t), Supply(t), eq1_Storage1(t), eq2_Storage1(t),
   eq3_Storage1(t), eq4_Storage1(t), eq5_Storage1,
   NoChargeDischarge_Storage1, cost1_Storage1, cost2_Storage1, eq1_Storage2(t)
   ), eq2_Storage2(t), eq3_Storage2(t), eq4_Storage2(t), eq5_Storage2,
   NoChargeDischarge_Storage2, cost1_Storage2, cost2_Storage2,
   Nodal_law_node1(t), Eq_cost_Prod, ObjectiveFunction ;
69
70 Load(t).. Pout(t) =e= data(t,'load');
71 Supply(t).. Pin(t) =e= data(t,'supply')*supply_factor ;
72
73 eq1_Storage1(t).. E_Storage1(t) =e= E_Storage1('t000730')$(ord(t)=
   000001) + E_Storage1(t-1)$(ord(t)>1) + Pch_Storage1(t)*eta_c_Storage1*
   dt - Pdech_Storage1(t)/eta_d_Storage1*dt ;
74 eq2_Storage1(t).. E_Storage1(t) =l= Emax_Storage1 ;
75 eq3_Storage1(t).. Pch_Storage1(t) =l= Pmax_Storage1/eta_c_Storage1 ;
76 eq4_Storage1(t).. Pdech_Storage1(t) =l= Pmax_Storage1 ;
77 eq5_Storage1.. E_Storage1('t000001') =e= SOC0_Storage1 ;
78 NoChargeDischarge_Storage1.. transit_cost_Storage1 =e= sum(t,
   Pch_Storage1(t)) * dt * storageS_transit_cost ;

```

```

79
80 cost1_Storage1..      cost_Storage1 =g= Emax_Storage1 * Storage1_cost_energy
      / Tlife_Storage1 + transit_cost_Storage1 +
      lower_bound_energy_storage_cost *Pmax_Storage1 ;
81 cost2_Storage1..      cost_Storage1 =g= Pmax_Storage1 * Storage1_cost_power
      / Tlife_Storage1 + transit_cost_Storage1 +
      lower_bound_energy_storage_cost * Emax_Storage1 ;
82
83 eq1_Storage2(t)..      E_Storage2(t) =e= E_Storage2('t000730')$(ord(t)=
      000001 ) + E_Storage2(t-1)$(ord(t)>1) + Pch_Storage2(t)*eta_c_Storage2*
      dt - Pdech_Storage2(t)/eta_d_Storage2*dt ;
84 eq2_Storage2(t)..      E_Storage2(t) =l= Emax_Storage2 ;
85 eq3_Storage2(t)..      Pch_Storage2(t) =l= Pmax_Storage2/eta_c_Storage2 ;
86 eq4_Storage2(t)..      Pdech_Storage2(t) =l= Pmax_Storage2 ;
87 eq5_Storage2..      E_Storage2('t000001') =e= SOCO_Storage2 ;
88 NoChargeDischarge_Storage2..      transit_cost_Storage2 =e= sum(t,
      Pch_Storage2(t)) * dt * storageS_transit_cost ;
89
90 cost1_Storage2..      cost_Storage2 =g= Emax_Storage2 * Storage2_cost_energy
      / Tlife_Storage2 + transit_cost_Storage2 +
      lower_bound_energy_storage_cost *Pmax_Storage2 ;
91 cost2_Storage2..      cost_Storage2 =g= Pmax_Storage2 * Storage2_cost_power
      / Tlife_Storage2 + transit_cost_Storage2 +
      lower_bound_energy_storage_cost * Emax_Storage2 ;
92 Eq_cost_Prod..      Cost_Prod =e= Prod_cost / Tprod / CF_Prod * (
      supply_factor - 1);
93
94 Nodal_law_node1(t)..      Pin(t) + Pdech_Storage1(t) + Pdech_Storage2(t) =
      e= Pcurt(t) + Pout(t) + Pch_Storage1(t) + Pch_Storage2(t);
95
96 ObjectiveFunction..      cost =e= cost_Storage1+ cost_Storage2+ Cost_Prod;
97
98 Model 2Storage_elec/ all /;
99 Option LP = OSICplex;
100 solve 2Storage_elec using mip minimize cost;

```

Listing E.1: GAMS code for an electricity system with two storages.

