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Techno-economic optimisation of the mix of power system flexibility solutions

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THÈSE DE DOCTORAT

DE L'UNIVERSITÉ PSL

Préparée à MINES ParisTech

**Optimisation technico-économique du mix de flexibilité
d'un système électrique**
*Techno-economic optimisation of the mix of power
system flexibility solutions*

Soutenue par

Thomas HEGGARTY

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Acronyms

- CAES** Compressed Air Energy Storage. 6
- CAPEX** Capital Expenditure. 5, 27, 58, 61
- CCGT** Combined Cycle Gas Turbine. xi, 65, 73, 84, 85, 90, 95, 107
- CExM** Capacity Expansion Model. 56, 57, 59–61, 67, 70, 73–76, 78–83, 87, 89, 109, 110, 112–114, 117, 118
- DLR** Dynamic Line Rating. 7
- EnRV** Energie Renouvelable Variable. 11, 53, 75
- ENTSO-E** European Network of Transmission System Operators for Electricity. 3, 8, 10, 63–65, 84
- FACTS** Flexible Alternative Current Transmission System. 7
- FS** Flexibility Solution. 5, 15–26, 28, 52, 99–101, 104, 110, 118
- FSCD** Flexibility Solution Contribution Distribution. ix, xii, xiii, 18–20, 22–30, 99–101, 105–108, 111, 116, 118
- FSMS** Flexibility Solution Modulation Stack. ix, 17–23, 25–30, 116, 118
- GHG** Greenhouse Gas. 1, 2
- GSA** Global Sensitivity Analysis. x, 9, 32, 33, 38, 45, 46, 50
- IEA** International Energy Agency. 3, 57, 88
- IRENA** International Renewable Energy Agency. 57, 79
- LOLE** Loss Of Load Expectation. xii, xiii, 73, 81, 83, 86, 87, 89–95, 97–100, 102–105, 107, 108, 110, 112, 118, 119
- MAF** Mid-term Adequacy Forecast. 64, 65
- NTC** Net Transfer Capacity. 84

- OCGT** Open Cycle Gas Turbine. xi, 65, 73, 84, 90, 95, 107
- OPEX** Operational Expenditure. 5, 27, 58, 61, 119
- OSMOSE** Optimal System Mix Of flexibility Solutions for European electricity. 8, 65, 84, 116, 119
- PCM** Production Cost Model. 57, 60, 78–80, 82, 83, 87, 109, 110, 118
- PHS** Pumped Hydro Storage. 6, 84, 88
- TOTEX** Total Expenditure. xi, 70, 74, 86, 93, 95, 97, 99, 107–110, 112, 118, 119
- TSO** Transmission System Operator. 7, 8, 34, 84
- TUB** Technische Universität Berlin. xvi, 62, 63, 65, 163, 164
- TYNDP** Ten-Year Network Development Plan. 64, 65
- UC-ED** Unit Commitment and Economic Dispatch. 4, 16, 17, 23, 60
- VRE** Variable Renewable Energy. x, 2–8, 14, 15, 20, 32, 33, 36, 38–43, 45–47, 49–51, 56, 58–60, 67, 78–82, 88, 90, 93, 94, 97, 101, 102, 115–117, 120

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Chapter 1

General introduction

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1.1 Context and objectives

Our gradually increasing understanding of the underlying mechanisms and consequences of climate change is revealing just how much of an existential threat it is, if perhaps not for humanity, at the very least for society as we know it [1]. Due to numerous and inter-related feedback loops in the global climate system, avoiding a “hothouse earth” pathway implies drastic and immediate reductions in anthropogenic greenhouse gas (GHG) emissions [2], a majority of which are currently related to our energy consumption. Changes in human behaviour certainly have a role to play, although these are not expected to come quickly enough: convincing people the problem is real and needs to be dealt with is complicated as it is [3], getting convinced people to make effective lifestyle changes is a another issue altogether [4–6].

A more widely accepted way of reducing the GHG emissions resulting from our energy consumption is through technological change, which provides the seductive hope of not having to change our behaviours, moral values and expectations of acceptable levels of physical comfort. Due to the ease of electricity decarbonisation relative to other energy vectors, this is currently expected to take the form of the electrification of heat and transport and replacement of fossil fuel based power generation by low-carbon technologies, with Variable Renewable Energy (VRE), primarily wind and solar, playing a major role [7].

This new role for VRE is leading to increased uncertainty and variability in power systems, driving the need for further flexibility. There are multiple ways of providing flexibility. While many of the solutions used historically are being phased out for the very environmental reasons we just mentioned, other solutions are experiencing falling prices. In such a changing context, a key question that needs to be addressed by power system planners is therefore: what optimal mix of solutions should we use to provide flexibility in a power system with high penetrations of VRE?

Power systems are composed of capital intensive assets with lifetimes in the order of decades. As such, poor planning can lead to costly lock-in effects, not only from an economic point of view, but social and environmental also, as these assets have far-reaching impacts. Ensuring that the future development of the power system meets all three components of the energy trilemma¹ thus requires well-informed policy makers and investors with a clear long-term vision, a well-informed general public given a chance to have a say, and clear policy recommendations grounded in careful modelling, fed with appropriate data and based on study-specific trade-offs between accuracy and robustness. From this context, we define two key objectives for the work presented here:

- **Improve our understanding and ability to communicate on power system flexibility.** As will be made evident throughout this thesis, power system flexibility is a complex, multifaceted concept, which can be used to refer to many different problems depending on what solution one might want to praise or discredit. Providing a clear and instructive framework around flexibility and being able to quantify its different aspects is crucial to rationalising debates, ensuring policy recommendations are understood and making sure the outputs of complex models are appropriately interpreted.
- **Improve the representation of flexibility in capacity expansion planning in order to propose an optimal mix of flexibility solutions.** Considering the multiple ways of providing flexibility, we judge an optimal system to be no different from an optimal flexibility mix, which power system planners have traditionally aimed to obtain using capacity expansion models. For structural reasons, these models struggle to express flexibility, both in terms of its requirement and its provision, with significant implications on model outcomes in high VRE contexts. We propose to address this issue by linking a capacity expansion model with a production cost model.

This introduction chapter contributes to the first of these two objectives, by delving into the definition of power system flexibility and investigating historical

¹Equity, security, environmental sustainability.

evolutions in what has been understood by the term (Section 1.2.1), before proposing our own definition (Section 1.2.2) and discussing the different ways of providing it (Section 1.3). We then discuss the limits to the scope of the presented work (Section 1.4) and describe the structure of this thesis (Section 1.5), providing a broad overview of the work carried out and the links between PhD objectives and thesis chapters.

1.2 Defining power system flexibility

1.2.1 Literature review

“Power system flexibility has become a global priority”, stated the International Energy Agency (IEA) in their 2018 report on the status of power system transformation [8], as the Clean Energy Ministerial launched its “Power system flexibility campaign” [9]. The European Network of Transmission System Operators for Electricity (ENTSO-E) roadmap identified power system flexibility as one of 5 clusters of research and innovation challenges from 2017 to 2026 [10]. Power system flexibility generates ample high-level talk, but remains an elusive, complex idea, prompting institutions and academics to propose a vast number of occasionally conflicting definitions.

Definitions of “power system flexibility” have been proposed for some time; the idea behind the term has evolved with the changing context and perceived challenges². Early mentions of the term can be found in the 1990s, when power system planners were faced with great uncertainty due to deregulation and the introduction of competition. This caused a paradigm change: the system planner would no longer search for the minimal cost solution, but for a flexible one, that could adapt quickly and withstand a great variety of situations with reasonable additional cost [11]. In the early 2000s, in a world where transmission and generation were no longer co-optimised, Bresesti *et al.* discuss the need for flexible transmission planning when the timing, location and size of generation expansion is uncertain [12]. Still, flexibility was understood as a long-term uncertainty issue.

A few years later, when VRE began integrating power systems, the term “flexibility” took on a new meaning and started to thrive. Some definitions even limit its breadth to this sole issue, referring to flexibility as the ability “to balance rapid changes in renewable generation and forecast errors” [13], to “cope with the variability and uncertainty that VRE generation introduces into the system” [14], or a system’s “readiness for high shares of variable renewables” [15].

Different phases of VRE integration have been identified, characterised by different issues [8, 16]. Early integration concerns tend to be short-term focussed: meeting changes in supply-demand balance on timescales of minutes to hours. As VRE penetration increases however, balancing on longer timescales (days, weeks or years) also becomes problematic. This evolution in perceived challenges can again be seen in evolving definitions of flexibility. When VRE penetration in advanced economies was still low, flexibility was often considered to be a short-term concept only [13,

²All definitions referenced in this section are provided in full in Appendix B.

17, 18], while later definitions explicitly state flexibility to be a multi-timescale issue [14, 19–22].

While recent definitions have been gradually converging towards something along the lines of “the ability to cope with variability and uncertainty in generation and demand”, some subtleties can still be found. Some authors adopt the point of view of a flexibility solution provider [18, 23] or that of a power system [8, 22, 24]. Others might refer to flexibility purely for supply-demand matching [19, 22], also mention network congestion management [18] or be much more general and simply define flexibility as the ability to adapt to changing conditions [25].

1.2.2 Definition proposal

Given our analysis of the state of the art, we define flexibility as the power system’s ability to cope with variability and uncertainty. In power systems, these can be found in demand, generation and power flows resulting from their geographical spread. This implies that flexibility is required for both key tasks of a system operator: matching generation with demand and ensuring that power flows do not exceed network thermal and voltage limits, in both N and N-1 conditions. The work presented here, along with the majority of existing literature, focusses on the former.

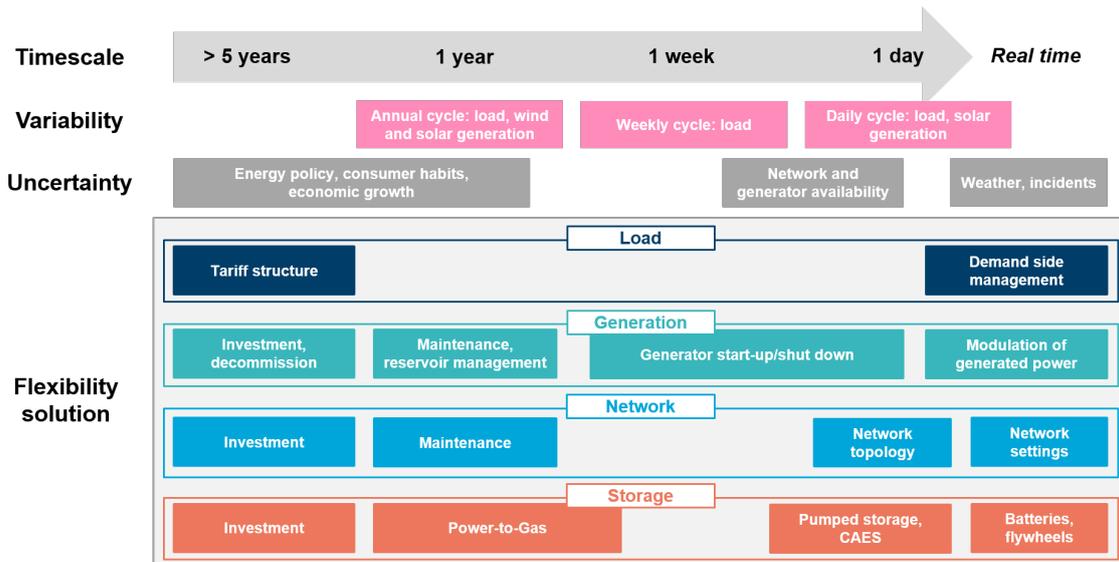


Figure 1.1: Different sources of variability and uncertainty generate a need for flexibility, which can be dealt with by a set of flexibility solutions. These are shown over a range of different timescales.

Variability and uncertainty occur on several timescales, as shown in Figure 1.1. On the long-term (more than a year), matching supply and demand is made uncertain by the difficulty to predict VRE development, the evolution of consumer habits, economic growth etc, with implications on capacity expansion planning. On the medium-term (annual, weekly and daily horizons), power system operators must face cyclical variations in net load (load minus VRE generation), with implications on the Unit Commitment and Economic Dispatch (UC-ED) of dispatchable assets.

On the short-term (intraday), power system operation is constrained by uncertainty through incidents and forecastability of demand and VRE generation, with implications on reserve sizing and activation.

As depicted in Figure 1.1, there are a number of ways one can cope with these sources of variability and uncertainty, *i.e.* provide flexibility. Broadly speaking, one can either (i) modulate generation output (including VRE curtailment), (ii) modulate demand, (iii) store energy in a different form to smooth out variations through time, (iv) interconnect with another system to smooth out variations through space (see Figure 1.1). To cope with long-term uncertainty, one can build, mothball or decommission these flexibility solutions (FS). To cope with medium-term variability and short-term uncertainty, one can activate existing FS.

Note that this discussion has focussed solely on the power system. Sector coupling (strengthening the links between energy vectors) has been shown to be an interesting way of providing flexibility to the power system [26], though it should be kept in mind that it could also increase flexibility requirement if the constraints affecting coupled energy vectors are too similar. Depending on the technology linking energy vectors together, from the power system point of view, this can be considered either as a modulation of generation or demand.

1.3 Different ways of providing flexibility

Historically, uncertainty and variability in supply-demand matching and network congestion management has been dealt with by varying the level of generation and interconnecting systems. Flexible demand and storage currently make a marginal contribution, but decreasing costs combined with partial conventional generation phase-out could change each solution's respective roles. For an extensive review of flexibility solutions, see Lund *et al.* [27].

1.3.1 Flexible generation

Generation can bring flexibility to the power system by modulating its power output over many timescales (from seconds to a year). Its ability to do so is constrained by technical factors: the speed at which it can modulate (ramp rate), the extent to which it can modulate (minimum and maximum power output), minimum and maximum up and down times to name a few. A generating unit's ability to provide flexibility is also constrained by economic considerations. As well as start-up costs and minimum up and down time, the balance between a plant's Capital Expenditure (CAPEX) and Operational Expenditure (OPEX) dictates the number of hours it must run in order to cover its costs. This cost structure dictates whether a plant is to be operated as baseload, mid-merit or peak generation, and therefore the timescales over which it may modulate its power output, bringing flexibility to the power system.

Certain generation technologies may have specific characteristics influencing their ability to provide flexibility. The minimum power output of a nuclear reactor changes over the irradiation cycle, and after modulating power output, it must maintain stable power output for several hours [28]. Hydroelectric dams' maximum power

output depends on head height and therefore on the water level. Dams can only store a certain water volume; making sure it is used at the time where it brings the most value is a challenge. Despite being non-dispatchable by nature, variable renewables can still provide downward flexibility by curtailing power output, and even upward flexibility if operated below maximum power output.

Dispatchable generation is faced with significant challenges. Due to environmental concerns, coal, lignite and nuclear power plants are being phased out in many countries. Remaining baseload generation is being ousted by VRE, as a result of its cost structure [29]. In an attempt to remain competitive in spite of decreasing capacity factors, increasing generation flexibility is seen as a necessity [8, 30, 31].

1.3.2 Flexible demand

By modulating its load curve shape, a consumer may facilitate supply-demand matching and network congestion management, *i.e.* bring flexibility to the power system. This can either be done by changing the point in time when energy is used (e.g. industrial processes, domestic load such as washing-machines or dish-washers) or by decoupling the moment when energy is consumed and when it is drawn from the power system (e.g. water boilers, space heating, electric vehicle batteries).

One can differentiate between explicit (or incentive-based) demand-response, where consumers receive direct payments to change their consumption upon request, and implicit schemes, where consumers choose to be exposed to time-varying electricity prices [32, 33]. These time-varying prices may be static (time-of-use pricing) or dynamic (real-time-pricing), the consumer being exposed to a price schedule or to wholesale market prices respectively.

Flexibility can be provided by demand response on timescales of a few hours, or, in specific cases such as electric vehicles, a few days. Technical constraints include energy capacity, rebound effect and recovery period.

Time-of-use pricing has been in use in certain countries for decades. However, there is a renewed interest for flexible demand due to falling prices of information and communication technologies which have led to the roll-out of smart-meters. Industry stakeholders are calling for the removal of regulatory barriers in order to empower consumers [32].

1.3.3 Energy storage

Another convenient way of providing flexibility to the power system is by storing energy in a different form for future release as electricity, averaging out variations through time. Conditions for storage to make economic sense include a round trip efficiency high enough to make use of a limited spread in electricity prices.

Energy storage has long been present in power systems in the form of Pumped Hydro Storage (PHS), which provides flexibility on daily and weekly timescales. Several other technologies could potentially also play a role: a variety of batteries, flywheels, super capacitors, Compressed Air Energy Storage (CAES), Power-to-Gas-to-Power... [34]. A key question is the relative costs of power and energy, which influences the timescales on which a storage device is likely to provide flexibility [34–

37]. Despite decreasing costs, the economic case for most forms of energy storage is still fragile [21, 38].

1.3.4 System interconnection

From the very first days of electricity use, networks have been used to connect generators and consumers, increase reliability in the face of generator faults and exploit diversity in load profiles [39]. In a power system with significant VRE penetration, interconnection can also exploit diversity in wind and irradiation profiles (the idea that at any time, somewhere, there is likely to be some wind or some sun).

In other words, interconnection can bring flexibility for supply-demand matching by averaging out variations through space³. It may do so on timescales ranging from seconds to a year, depending on considered load profiles and generation mixes. Interconnection can also allow the sharing of other flexibility solutions⁴ (flexible generation, flexible demand and storage).

Interconnection's ability to provide flexibility for supply-demand matching is limited by various operational constraints such as thermal and voltage limits. To avoid power flows exceeding network capacity, one can (i) make the most of the existing network, through topology changes, Dynamic Line Rating (DLR), Flexible Alternative Current Transmission System devices (FACTS) etc. (ii) perform a re-dispatch using previously mentioned flexibility solutions (e.g. reducing generation on the exporting side, while increasing it on the importing side), or (iii) build new network capacity. From a theoretical point of view, new capacity makes sense if investment can be covered by savings in redispatching costs. In practice, network development is severely affected by acceptability issues.

Interconnection is generally understood as creating or enhancing a link between two electricity systems. However, flexibility through interconnection can also be provided by creating a link between energy carriers. This can be particularly interesting in the case of electricity as other energy carriers are easier to store.

1.4 Scope of work

Considering the variety of technologies that can be used to provide flexibility, answering the question of the optimal mix of flexibility solutions cannot reasonably be done without adopting a holistic view. Prior to the unbundling of the European electricity sector, this view could have ably been provided by vertically integrated utilities; today, this responsibility has *de facto* drifted to Transmission System Operators (TSO), which do not necessarily have the means to act on their findings, and must therefore be able to communicate them effectively to policy makers (see PhD objective 1 in Section 1.1).

Many TSOs are required to perform long-term prospective studies, evaluating potential capacity shortfalls that would put the balancing of supply and demand

³This aspect of flexibility provision by interconnection is considered in more detail in Section 3.5.

⁴This aspect of flexibility provision by interconnection is considered in more detail in Section 2.4.4.

at risk (e.g. RTE [40], Elia [41], National Grid [42]). Considering the increasing interconnection capacity in Europe and the anticipated benefits of increasing it further, this task now calls for coordinated action between TSOs, increasing the geographical scope and complexity of the performed studies (see ENTSO-E’s Mid-term Adequacy Forecast [43] and Ten-Year Network Development Plan [44]).

TSO methodologies have traditionally been scenario based, using detailed dispatch simulation of a power system with user-defined capacities to investigate the impact of evolutions in demand and generation portfolio. However, the increasing complexity is generating an interest for capacity expansion optimisation tools, traditionally the focus of the academic world. These tools derive the capacities required to meet a user-defined demand, considering a wider technological scope, and could potentially help TSOs construct relevant scenarios.

The second objective of this PhD (see Section 1.1) provides an opportune platform for the academic world to share their expertise on capacity expansion models, and for TSOs to share theirs on the detailed simulation required to confirm a power system’s ability to meet an acceptable degree of security of supply. This exchange of ideas is made all the easier by the European H2020 Project OSMOSE, for Optimal System-Mix Of flexibility Solutions for European electricity [45], to which this PhD contributes.

In accordance with European TSO requirements, our modelling work covers the European power system, composed of 33 countries aggregated to 17 nodes, and the time period from 2015 to 2050 in 5-year investment steps. The temporal granularity of each investment year depends on the model used and reaches, at best, hourly resolution. We concentrate solely on the power system, the links to the hydrogen and methane systems being studied elsewhere in the OSMOSE project (task 1.3). We adopt a benevolent monopoly approach, maximising social welfare. As such, the methodology aims to achieve an optimal flexibility mix, but does not study the market rules required to obtain it (this is done in OSMOSE work package 2).

Uncertainty is a key component of flexibility, which we consider differently in our modelling approach depending on the timescale. When the work presented here requires the consideration of long-term (more than a year) uncertainty related to energy policy, consumer habits, economic growth, technological progress etc, a scenario based approach is used. Medium-term (annual, weekly and daily) uncertainty related to weather patterns is modelled through the use of Monte Carlo weather years. Note that while this ensures that a system is robust to a wide range of possible weather conditions, it does not express lead time related operational challenges, trading off better forecasts with reduced on-hand flexibility. Short-term (intraday) uncertainty related to forecasting errors is modelled in a simplified way using reserves. As for very short-term stability and inertia related issues⁵, in accordance with European H2020 Project MIGRATE [47] and OSMOSE work package 3 which builds on top of it, they are here assumed not to be a blocking issue, but as an additional, unconsidered cost that should not impact the structure of the optimal flexibility mix. This simplification should be kept in mind when the results in this thesis are shown for very high penetrations of VRE.

⁵See [46] for a review discussion on the challenges, technology readiness levels and outstanding questions.

1.5 Thesis structure

This chapter has contributed to the first objective of this PhD: improving our understanding and ability to communicate on power system flexibility. Chapters 2 and 3 complement this qualitative contribution with quantitative analyses. Chapter 2 starts by reviewing existing approaches that have been used to quantify various aspects of flexibility, classifying them depending on the question they attempt to address. This review highlights two gaps in literature, which have led us to propose two new flexibility quantification methods. Like much of existing literature, these quantification methods focus on flexibility for supply-demand matching, *i.e.* not flexibility for congestion management.

Chapter 2 presents a pair of novel tools to quantify a comparatively unexplored aspect of flexibility: who is providing it. These frequency spectrum analysis based tools separately quantify flexibility provision on the annual, weekly and daily timescales. Their effectiveness and versatility is demonstrated through several example applications, analysing both historical and prospective power systems, in several geographical locations with contrasting characteristics.

Chapter 3 focusses on the other gap identified in literature on flexibility quantification methods, that of its requirement on timescales beyond the short-term (intraday). We present a set of metrics quantifying flexibility requirement for a given net load curve, on daily, weekly and annual timescales. These metrics are used to perform a Global Sensitivity Analysis (GSA), inspecting and ranking the effects of the penetrations of wind power, solar power, electric heating, electric cooling and interconnection on the expected evolution of flexibility requirement.

The second objective of this PhD, improving the representation of flexibility in capacity expansion planning, is the focus of Chapters 4 and 5. Chapter 4 reviews existing literature contributing to power system planning, with a specific focus on capacity expansion models and their limited ability to express flexibility. After adding a power transmission module to the OSeMOSYS modelling framework, literature results are confirmed and extended through the study of the impact of timeslice value definition methods on model outcomes.

Chapter 5 then discusses the different strategies that have been proposed to improve the representation of flexibility in capacity expansion planning, reviewing existing work and categorising it from the point of view of the model user. We then investigate one of these strategies, by implementing a bi-directional soft-link between a capacity expansion model (OSeMOSYS) and a production cost model (Antares). The presented work focusses on the crucial element of such a modelling framework: the way information is fed from the production cost model back to the capacity expansion model. An existing feedback technique is compared to two new techniques, one of which is based on the flexibility provision tools presented in Chapter 2.

Chapter 6 provides a summary of each chapter and wraps up this thesis by mentioning a few new research paths this work has opened up.

1.6 Publications resulting from the PhD

Peer-reviewed journal papers:

- Heggarty, T., Game, D., Prévost, T., Bourmaud, J. Y., & Jacquemart, Y. (2018). “Le stockage: un levier de flexibilité parmi d’autres”. *La revue de l’énergie* [48]. <https://www.larevuedelenergie.com/wp-content/uploads/2018/10/Stockage-levier-de-flexibilite.pdf>
- Heggarty, T., Bourmaud, J. Y., Girard, R., & Kariniotakis, G. (2019). “Multi-temporal assessment of power system flexibility requirement”. *Applied Energy*, 238, 1327-1336 [49]. <https://doi.org/10.1016/j.apenergy.2019.01.198> Postprint available at <https://hal.archives-ouvertes.fr/hal-01998837>
- Heggarty, T., Bourmaud, J. Y., Girard, R., & Kariniotakis, G. (2020). “Quantifying power system flexibility provision”. *Applied Energy*, 279, 115852 [50]. <https://doi.org/10.1016/j.apenergy.2020.115852> Postprint available at <https://hal.archives-ouvertes.fr/hal-02939532>
- In preparation: Heggarty, T., Bourmaud, J. Y., Girard, R., & Kariniotakis, G. “Impact of temporal and geographical resolutions on the outputs of a European OSeMOSYS model”.
- In preparation: Heggarty, T., Bourmaud, J. Y., Girard, R., & Kariniotakis, G. “A comparison of bi-directional soft-linking approaches between the capacity expansion model OSeMOSYS and the dispatch model Antares”.

Communications in conferences:

- Heggarty, T. (2019) “Power system flexibility: a case of competing levers over different timescales”. CEEM conference on the market architecture for enhancing flexibility provision in the EU target model [51].
- Heggarty, T. (2019) “Providing tools to grasp power system flexibility”. Poster presentation at the DTU summer school on Data-Driven Analytics and Optimization for Energy Systems [52].
- Heggarty, T. & Bourmaud, J. Y. (2020). “Accounting for uncertainty in power system planning - The OSMOSE approach”. EMP-E conference on modelling climate neutrality for the European green new deal [53].

Communications in expert groups:

- ENTSO-E workshop, IEA task 25 seminar, CIGRE working group, MPDD Chair seminar.

1.7 Résumé en français

L'atténuation du changement climatique implique de réduire les émissions de notre système énergétique de manière substantielle et immédiate. L'électricité étant plus facile à décarboner que les autres vecteurs énergétiques, il est aujourd'hui généralement admis que cette réduction prendra la forme d'une électrification de la chaleur et de la mobilité. Sur le système électrique, les centrales de production à base d'énergies fossiles devront être remplacées par des technologies bas-carbone, les énergies renouvelables variables (EnRV), principalement éoliennes et solaires, jouant un rôle de plus en plus important.

Ce rôle croissant des EnRV augmente la variabilité et l'incertitude auxquelles le système électrique doit faire face, nécessitant davantage de flexibilité. Parmi les technologies capables de fournir cette flexibilité, que nous appellerons leviers, nombres de celles jouant historiquement le plus grand rôle doivent disparaître du fait des considérations environnementales susmentionnées, tandis que de nouveaux leviers voient leurs coûts baisser. Une question clé pour la planification du système électrique est donc celle de la combinaison optimale de leviers de flexibilité permettant de faire fonctionner un système à forte pénétration d'EnRV.

De cette question, nous tirons deux objectifs pour les travaux de thèse : (i) améliorer notre compréhension et notre capacité à communiquer sur la flexibilité du système électrique, et (ii) améliorer la représentation de la flexibilité dans les outils d'expansion de capacité, de manière à proposer des mix optimaux de leviers de flexibilité.

Ce chapitre contribue de manière qualitative au premier de ces deux objectifs, en commençant par une analyse des différentes définitions de la flexibilité du système électrique, proposées par le monde académique, institutionnel et industriel. Nous identifions des évolutions dans le sens donné à ce terme, à mesure que le contexte historique a changé, et proposons notre propre définition, en accord avec les contributions les plus récentes. Nous comprenons la flexibilité comme la capacité d'un système à s'adapter à des variations et des incertitudes. Celles-ci peuvent survenir sur de nombreux horizons temporels, et impacter les deux rôles du gestionnaire du système : l'équilibre offre-demande et le respect des contraintes réseaux. Les travaux présentés dans cette thèse se focalisent sur le premier de ces deux rôles.

Nous présentons ensuite les différentes manières de fournir de la flexibilité au système électrique : la production flexible, la consommation flexible, le stockage et l'interconnexion. Pour chaque famille de levier, nous mentionnons les contraintes spécifiques qui peuvent s'appliquer, et les éventuelles évolutions en cours qui pourraient jouer sur leur compétitivité dans les années à venir.

Nous décrivons ensuite brièvement le cadre des travaux de thèse, délimitant leurs contours et la façon dont ils s'inscrivent dans le contexte industriel de RTE, qui finance cette thèse CIFRE, et dans le projet européen H2020 OSMOSE. La structure du manuscrit et la liste de publications associées aux travaux sont ensuite détaillées. Chaque chapitre de ce manuscrit fait l'objet d'un résumé en français.

Chapter 2

Quantifying flexibility provision

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2.1 Introduction

As can be seen from the sheer number of proposed definitions (see Section 1.2), power system flexibility is an elusive, complex idea. Even with literature converging to a common understanding along the lines of “the ability to cope with variability and uncertainty in generation and demand”, grasping its physical meaning is not that straightforward. We need tools that can delve into flexibility, quantifying related notions.

There are two main motivations for such quantification tools:

- Condensing information: whether it be historical data or outputs of a model, understanding power system behaviour implies considering large amounts of data. There is significant value in synthesising this information and extracting that which relates to flexibility: it helps build a quick understanding of a complex situation, making such tools powerful both for analysis and teaching purposes.
- Rationalising debates: there is a profusion of claims closely linked to power system flexibility, praising or discrediting specific technologies (the miracle solution of batteries, Demand Response or Power-to-Gas, the flexible/inflexible nature of nuclear power, the “myth” of diversity of wind profiles...). The accuracy of such claims is beside the point, they often lack credible evidence to back them up. Quantification provides a neutral basis on which discussions can be held, leading to social welfare maximisation decision making [54]. This is a key issue considering the magnitude of the investments at stake to ensure adequate provision of power system flexibility in the future.

This chapter starts with a review of existing flexibility quantification methods, classifying them depending on the question they attempt to address (Section 2.2). We propose a pair of novel tools to quantify a comparatively unexplored aspect of flexibility: who is providing it. These frequency spectrum analysis based tools separately quantify flexibility provision on the annual, weekly and daily timescales (Section 2.3). The tools’ effectiveness and versatility is demonstrated through several example applications, analysing both historical and prospective power systems, in several geographical locations with contrasting characteristics (Section 2.4). The proposed tools are of particular value to the capacity expansion planner, allowing them to quantify changes in flexibility provision as new solutions are introduced, or as carbon taxes, generation and interconnector capacities evolve.

2.2 Review of flexibility quantification methods

A significant number of metrics have been proposed, exploring different facets of flexibility¹. It is worth noting that the vast majority of approaches focus on flexibility for supply-demand matching, *i.e.* not congestion management. As shown in Figure 2.1 and loosely based on the categorisation proposed by Tuohy *et al.* [25], we classify quantification methods depending on the question they address: *how much flexibility does my system need?* (Section 2.2.1), *how flexible is my flexibility solution?* (Section 2.2.2), *how flexible is my power system?* (Section 2.2.3), and *who is providing flexibility in my power system?* (Section 2.2.4).

2.2.1 How much flexibility does my system need?

As a general rule, a power system’s flexibility requirement is dictated by the amount of variability and uncertainty in net load (load minus VRE generation). Kondziella

¹All papers cited in this review of flexibility quantification methods are further described in the tables of Appendix C



Figure 2.1: Structure of the review of flexibility quantification methods.

and Bruckner [55] classified methods quantifying short-term FS potential as defined by the Intergovernmental Panel for Climate Change [56]: theoretical, technical, economic and market potentials. What they define as FS theoretical potential can be equated to flexibility requirement. Various metrics have been proposed, generally focussing on the short-term (intraday): one or multiple hour ramps, expressed in MW or as a percentage of maximum power output [24, 57, 58], ramp acceleration and volatility [58], standard deviation of VRE output and net load, forecast error statistics [59]... Tracking intra-hour deviations between scheduled and actual net load has also been proposed, describing these deviations in terms of their magnitude, ramp rate and ramp duration [60]. In their “flexibility envelope” framework, Nosair *et al.* [61] identify flexibility requirement as 95% of the probability distribution function of VRE intra-hourly deviation from forecast.

As discussed in Section 1.2, flexibility is a multi-timescale issue. With that in mind, we proposed a method going beyond short-term aspects, using a frequency spectrum analysis based method to quantify flexibility requirement on annual, weekly and daily timescales [49]. This method and its application to a case study is the object of Chapter 3. Olsen *et al.* [62] extended this idea to also include shorter timescales, while making their source code available online [63].

Other studies have also tried to quantify storage required to cope with a subset of flexibility [35, 64–69] (see Appendix C for further details, or Zerrahn and Schill [70] for a review of such work). Curtailment and mismatch between hour ahead forecast and reality are examples of flexibility requirement subsets. Note that storage is one of several means to a common end: coping with variability and uncertainty in generation and demand (*i.e.* provide flexibility). Hence “storage requirement” could be argued to be a flawed approach, or at least a poor choice of words.

Energy resource complementarity is a field of study closely related to the concept of flexibility requirement. Metrics have been proposed to quantify the degree of complementarity between energy resources, essentially providing an indication of how flexibility requirement can be reduced by carefully choosing the size and location of renewable generation (see Jurasz *et al.* [71] for a review of such metrics).

2.2.2 How flexible is my flexibility solution?

In their simplest form, metrics quantifying a solution’s ability to provide flexibility are input parameters of UC-ED models. Typical examples include minimum power output, operational range (the difference between maximum and minimum power output), up/down ramping capability, start-up and shut-down times, response time, and minimum up and down times [72]. Some FSs may require additional metrics to express distinctive constraints, e.g. energy capacity, rebound effect and recovery period for storage or flexible load [70]. The ability to provide reserve has also been mentioned [59].

Composite metrics have been proposed to condense this information. Ma *et al.* [20] proposed a flexibility index composed of a weighted sum of operational range and ramping ability, normalised by maximum power output. Oree and Hassen [72] extended this idea, with an index combining 8 metrics mentioned in the previous paragraph, weighted using an analytic hierarchy process. This approach was also employed by Wu *et al.* [73]. A different way of condensing this information was suggested by Nosair and Bouffard [61]: for individual time steps, they maximised a FS’s upward and downward deviation from a scheduled output, subject to maximum and minimum power output, ramping and energy constraints.

Another approach consists in simulating power system behaviour and analysing outputs. Ulbig and Andersson [74], for example, evaluated, for a given point in time, the ability to provide up/down regulation, energy storage and ramping.

2.2.3 How flexible is my power system?

This category of metrics is the most varied in terms of approaches. One option is simply to aggregate flexibility indices of individual FSs. This has been performed in various ways by several aforementioned studies [20, 61, 72–74].

Another intuitive approach involves analysing historical or UC-ED simulation data to identify times when flexibility is lacking. Traditional adequacy metrics already provide some information: expected unserved energy, loss of load probability and duration [61, 75]. Curtailment and use of interruptible load, common last resort FSs in power system models (slacks), are other regularly used indicators of a flexibility deficit [59, 61, 76]. Lannoye and Tuohy [25, 77] proposed a set of metrics identifying flexibility deficiency: Periods of Flexibility Deficits, Insufficient Ramping Resource Expectation, and Expected Unserved Ramping. These can be used to identify particularly challenging lead times for power system operation. With a similar goal in mind, Zhao *et al.* [78] track the evolution over time of upper and lower boundaries of net load uncertainty that can be accommodated for a given cost.

Instead of identifying flexibility deficits, another possibility is to simply check, typically for a single point in time, whether FSs can cover flexibility requirement. Ulbig and Andersson [74] represent this graphically, in terms of up/down regulation, energy storage and ramping. Zhao *et al.* [78] propose a Boolean metric indicating whether or not a system’s largest variation range is within a target range. Menemenlis *et al.* [79] develop an index measuring the probability that a balancing reserve strategy might satisfy various scenarios.

Identifying limits to flexibility is another way of measuring a power system’s

degree of flexibility. For example, Deane *et al.* [80] extract a ramping shadow price, in their study of the impact of sub-hourly modelling of a power system. This is also carried out by Vithayasrichareon *et al.* [81] when they quantify the cost implications of various flexibility constraints: ramping, minimum power output, start-up costs and minimum synchronous generation. In broader terms, Morales *et al.* [82] recommend, as a measure of the value of flexibility, analysing the sensitivity of a UC-ED problem’s optimal value, primal and dual variables to input parameter values.

Two indices stand out by their consideration of flexibility for network congestion rather than for supply-demand matching. Bresesti *et al.* [12] compare the flexibility of different network configurations, which can be used both in expansion and operational contexts. With a similar understanding of flexibility, Cappaso *et al.* [83] quantify the additional generation a transmission system can accommodate, based on an Optimal Power Flow algorithm.

Lastly, Papaefthymiou *et al.* [15] take the stance that assessing the degree of flexibility of a power system requires both technical and non-technical metrics. They therefore provide a list of 80 key performance indicators scanning a broad range of flexibility issues, from assets to market design.

2.2.4 Who is providing flexibility in my power system?

A comparatively unexplored question one might ask when quantifying flexibility is who is providing it. Yasuda *et al.* [84] propose a “flexibility chart” (also see [16] for an example application), which gives a quick overview of the installed capacities of a few assets that could provide flexibility in a given power system. The number of start-ups of various generating units has also been used for flexibility provision quantification [80, 81], along with ramping up/down intensity (sum of ramping up/down throughout the year divided by ramping time) and available thermal flexibility (amount of additional generation that could be provided given the current commitment state of a unit) [85].

However, as pointed out by Cochran *et al.* [86], capacity is not a proxy for flexibility. Start-up and ramping limitations are only one of many ways FS behaviour is constrained, as expressed by metrics covered in Section 2.2.2. We need a way of quantifying flexibility provision while simultaneously accounting for all technical and economic constraints facing FSs, that can equally treat all four FS categories (flexible generation, flexible load, storage and interconnection), that is able to express how the role of a FS varies with the considered timescale, and that can be applied to both real and simulated power systems. The method presented in Section 2.3 fulfils each of these objectives.

2.3 Methodology

The review of existing flexibility quantification methods in Section 2.2 has shown a lack of appropriate methods addressing the question “who is providing flexibility in my power system”. Based on frequency spectrum analysis, we introduce two graphical tools, (i) the Flexibility Solution Modulation Stack (FSMS), which shows how

FSs provide flexibility on annual, weekly and daily timescales, (ii) and the Flexibility Solution Contribution Distribution (FSCD), which quantifies contributions to flexibility on the same three timescales. These tools simultaneously consider flexibility provided by all solutions: flexible generation, flexible load, storage and interconnection. FSMS and FSCD can be derived both from historical data and power system simulation data.

Condensing significant amounts of information, FSMS's and FSCD's ability to describe the relative roles of flexibility on different timescales is of significant value to highlight differences between countries or illustrate the impact of evolving conditions on power system operation (changes in carbon tax, increase in generation or interconnector capacity, introduction of new FSs such as Power-To-Gas, or even temporary conditions such as low nuclear availability due to planned outages).

As described in Figure 2.2, after discussing input data (both its nature and its preprocessing by feeding it through frequency filters), the methodology used to build the Flexibility Solution Modulation Stacks (FSMS) will be covered, detailing the stacking rules specific to flexible generation, storage, interconnection and flexible load. Lastly, we will discuss how this graphical information can be further condensed to more of a metric, using the Flexibility Solution Contribution Distribution (FSCD).

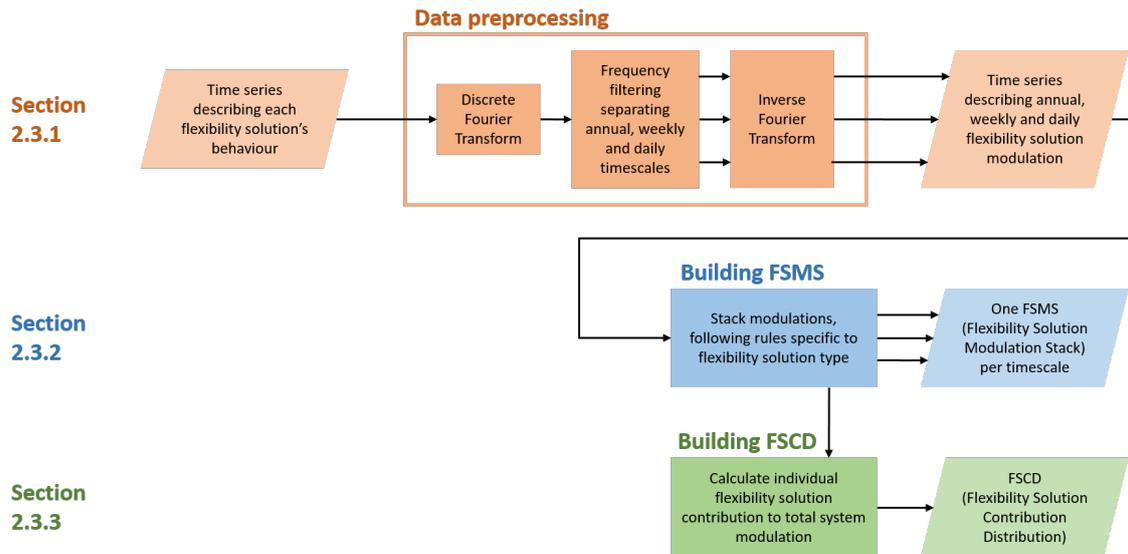


Figure 2.2: Overview of the methodology used to build FSMS and FSCD.

2.3.1 Input data description and preprocessing

The only inputs required for both FSMS and FSCD are time series of system load, generation per source, storage in/out flows, and interconnector flows (historical or simulated data). Installed capacities are not required, nor are FS technical and economic parameters. To consider a flexible load, the user must provide two time series, expressing the way a flexible load has behaved and the way it would have behaved had it not been flexible. Ideally, these curves should be based on mea-

sured data, but they can also be the result of a modelling process. Time series should be one year long and typically have hourly resolution. Any system size will do, however, note that FSMS and FSCD will only consider flexibility provision for supply-demand matching, *i.e.* they will ignore flexibility provision for congestion management purposes.

Load curves show clear cyclical patterns of various time periods: demand is higher during the day than during the night, higher during weekdays than the weekend, and either higher in summer or winter depending on geographical location. These patterns are sufficiently deterministic that, using a Fourier series based model, Yukseltan *et al.* [87] were able to predict Turkish national load within 3% Mean Absolute Percentage Error. The behaviour of a FS mix is dictated by cycles in net load, it hence shows the same annual, weekly and daily patterns. As can be seen in Figure 2.3, solutions play different roles on each timescale. Baseload generation such as nuclear modulates mostly on the annual timescale (1 cycle per year), while pumped hydro storage modulates mostly on the daily and half-daily timescale (365 and 730 cycles per year). Mid-merit generation such as coal and gas shows an intermediate behaviour.

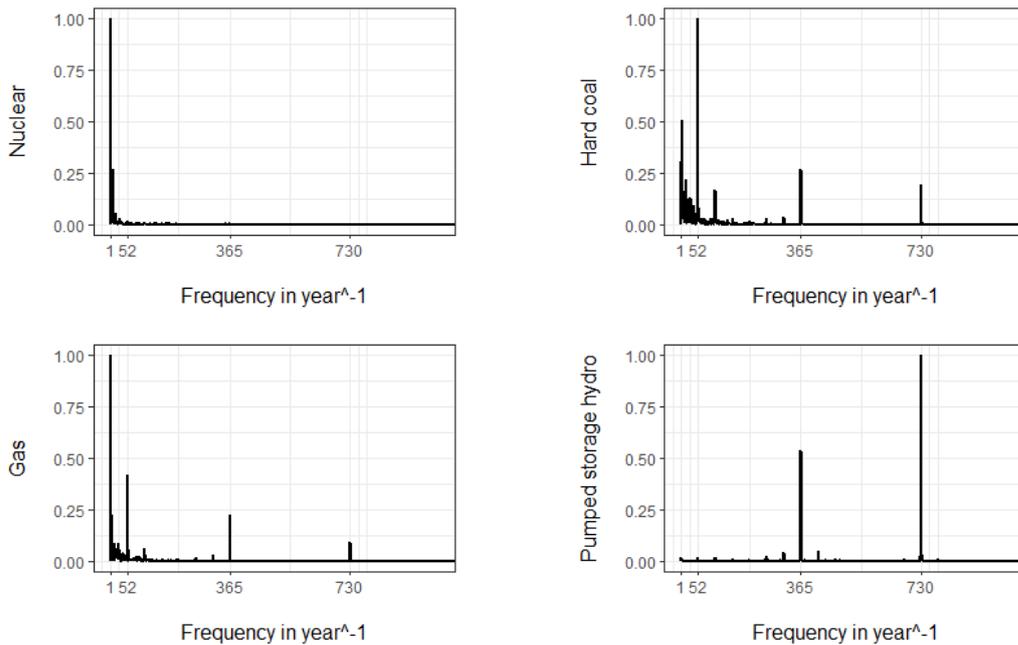


Figure 2.3: How different are the roles of flexibility solutions over different timescales? Normalised power spectral densities show the timescales over which behaviour is modulated, for nuclear, coal, gas and pumped hydro storage time series, on the German power system in 2018 (data from [88]). Marked out frequencies correspond to periods of a year, a week, a day and half a day.

To analyse these timescale specific behaviours separately, frequency filtering is applied to FS time series. Cut off frequencies are set at 20 and 180 year^{-1} *i.e.* periods of about 18 and 2 days. Note that different or even additional cut off frequencies may be used. Following extensive testing, these were judged to be the most appropriate

to investigate flexibility, notably to make the weekday vs weekend load cycle appear clearly on the weekly timescale.

The filtering process consists of three steps. First, each time series is fed through a Discrete Fourier Transform (see Equation 2.1), the DC offset (annual mean) having been removed. Then, as was done in previous work [49], band pass filters with unit magnitude within the band and zero magnitude outside the band are applied. Finally, the three resulting signals are passed back into time domain using the inverse Fourier Transform, thus obtaining three time series each containing a fragment of the initial signal’s information, respectively annual, weekly and daily modulations.

$$X_f = \sum_{t=0}^{N-1} x_t e^{-i2\pi ft/N} \quad f = 0, \dots, N - 1 \quad (2.1)$$

As expressed in Figure 2.2, this filtered data constitutes the input to FSMS. This process is very straightforward for observable historical data. For distributed solutions such as flexible domestic load or rooftop solar curtailment, some modelling assumptions on “would-be” behaviour will be required (see Section 2.3.2). For simulated data, FSMS and FSCD will only be as good as the power system model: the poor representation of technical constraints or lead times might lead to unrealistic behaviour of flexibility solutions, which FSMS and FSCD will reflect. This issue may appear in an inflexible power system, most likely on the daily timescale.

Note that frequency based approaches have been used for a variety of other reasons in power system planning, e.g. to integrate a flexibility constraint in a unit commitment problem [89], for storage sizing [34, 35, 37, 64, 65], for short-term VRE forecasting [90–92] or simply as a visualisation tool to complement the time domain vision [93, 94].

2.3.2 Stacking flexibility contributions: FSMS

As discussed in Section 1.2.2, a power system copes with variability and uncertainty (*i.e.* provides flexibility) by adjusting the behaviour of its FSs. The aim of FSMS is to help its user understand how individual FSs modulate over time to provide flexibility in order to match generation with demand, on the annual, weekly and daily timescales.

By tracking how each FS modulates around its mean value (each signal’s integral is equal to zero), this is exactly what is expressed by the signals resulting from the preprocessing. To show FSs’ relative roles, these modulations can then be stacked in a plot (FSMS), as one would stack generation time series to see how electricity demand is covered. By construction, at any point in time, the sum of FS modulations is equal to the variations of net load (here, load minus wind, solar and run-of-river hydro). The following paragraphs describe the rules to follow when stacking each FS’s signal, depending on the FS type.

Flexible generation modulations simply express the extent to which a technology generates more or less than on average. In Figure 2.4, this translates to the following: if a generator’s ribbon is above that of the previous FS ribbon, this generator’s output is above its average value for either the annual, weekly or daily part of the frequency spectrum. Conversely, if under, its output is below its average value. The

majority of the time, flexible generator modulations neatly add up *i.e.* all generators contribute towards coping with net load variation. However, in some cases, flexible generators may be forced by technical or economic factors to contribute negatively to flexibility, modulating “with” net load rather than “against” it. An example of such a case on the French power system is that of hydro in the month of June, snow melts causing abundant water supply. FSMS expresses this by overlapping the hydro and gas ribbons (see Figure 2.4).

For *storage modulations*, the input time series corresponds to the hourly sum of inflows and outflows. Due to round trip efficiencies, inflows are greater than outflows, therefore a storage modulation above the previous FS ribbon does not necessarily mean that this storage technology is supplying power to the grid.

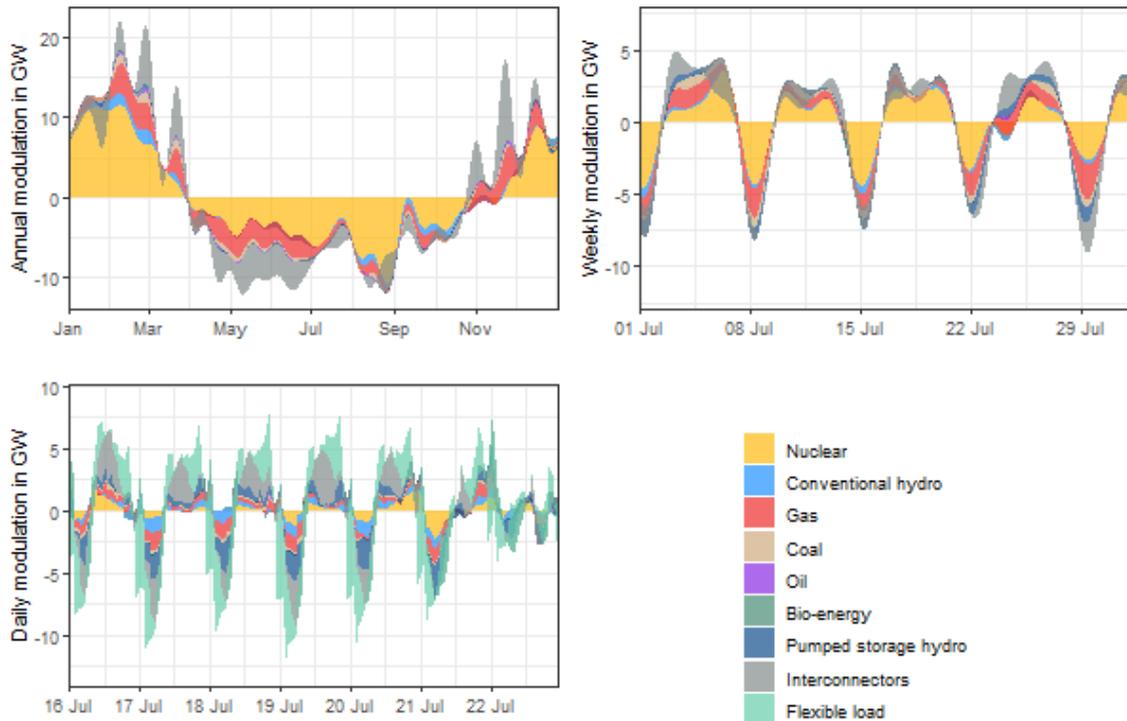


Figure 2.4: Who currently provides flexibility? Annual (top left), weekly (top right) and daily (bottom left) flexibility solution modulation stacks, on the French power system in 2018. Generation and interconnector flow data comes from [95], flexible load data was generated by an unpublished RTE model based on consumer panels.

For *interconnector flow modulations*, the input time series corresponds to the hourly sum of exports and imports to and from neighbouring systems. In most results shown in this section, all borders are considered simultaneously; treating each border independently is also possible but may hinder readability and give a biased representation of Kirchhoff’s laws. Depending on a system’s annual exporting or importing status, an interconnector flow modulation above the previous FS ribbon may reflect a higher import or a lower export than on average. One should keep in mind that the best way of providing flexibility is determined by an optimal dispatch performed at the European level. As such, when the interconnector ribbon is neatly

stacked in the same direction as the others, the considered system is effectively benefiting from the modulation of another FS (generation, demand or storage) in a neighbouring system. Conversely, when the interconnector ribbon overlaps other ribbons, the considered system's own FS are modulating for the benefit of its neighbours. As can be seen from Figure 2.4, most of the time, France benefits from the modulations of FS in neighbouring countries, due to its significant base load capacity. In countries with FS's that are cheaper to modulate, the interconnector ribbon overlaps other ribbons more often.

For *flexible load modulations*, the input time series corresponds to the difference between flexible and inflexible load curves. As a result, the ribbon expresses the additional variability the power system would have to cope with, were load not flexible. Depending on data availability, flexible load can be aggregated to a single ribbon, or split by use. In France, flexible load consists mostly of residential and commercial hot water boilers, which only provide flexibility on the daily timescale.

Note that all these modulations do not express a flexibility solution's deliberate intent to provide flexibility, nor its ability to provide flexibility (for this purpose, see metrics in Section 2.2.2), but rather the flexible aspect of its behaviour, defined while considering the entire power system's capacities, technical and economic constraints.

2.3.3 Summarising this information further: FSCD

While FSMS provides a graphical representation of what is going on in a power system regarding flexibility, it is not a quantified metric. Such a metric could be argued as artificial, as a flexibility solution's contribution cannot be boiled down to a single figure: it may vary considerably over the course of a year (this is particularly true on the daily and weekly timescales), it might occasionally contribute negatively, or modulate beyond variations in net load. Expressing the distribution of modulations, FSCD is more of a metric, condensing the information held in FSMS further but without distorting or losing too much of it.

As detailed in Equation 2.2, for each time step, a FS's contribution to total modulation of a power system's FS set is recorded, as a percentage. Time steps where the absolute value of this total system modulation is smaller than 20% of its maximum are removed, to avoid spuriously giving credit to a FS because of asymptotic behaviour when net load modulation is close to zero. The primary interest being FS contributions when flexibility is a constraint for power system operation, this has a limited impact on results, as confirmed by extensive tests with different thresholds.

$$\forall t = [1, 8760] : \left| \sum_{FS} M_{FS}(t) \right| \geq 0.2 * \max\left(\left| \sum_{FS} M_{FS}(t) \right|\right)$$

$$C_{FS}(t) = \frac{M_{FS}(t)}{\sum_{FS} M_{FS}(t)} * 100\% \quad (2.2)$$

where: C_{FS} Contribution time series (%)
 M_{FS} Modulation time series (MW)

This whole process is performed separately for the annual, weekly and daily timescales. FSCD is defined as the set of three distributions of $C_{FS}(t)$ (one per timescale), and can be represented as a box plot, as shown in Figure 2.5.

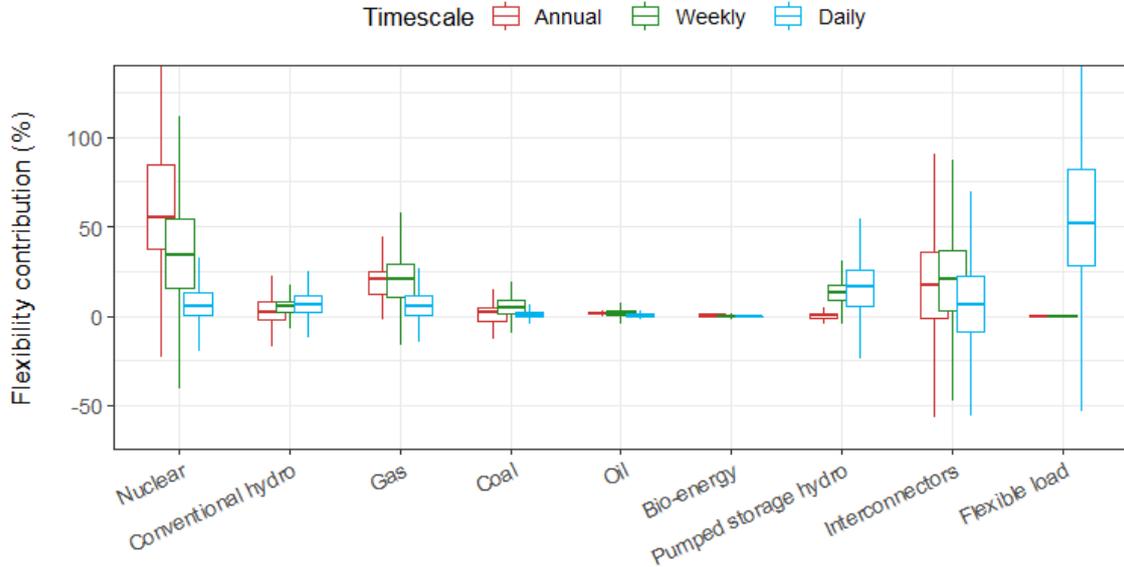


Figure 2.5: How do solutions currently contribute to flexibility? Flexibility solution contribution distributions on annual, weekly and daily timescales, on the French power system in 2018. Generation and interconnector flow data from [95], flexible load data was generated by an unpublished RTE model based on consumer panels.

Situations where contributions are beyond 100% or negative correspond to time steps where ribbons overlapped in the FSMS. The former situation occurs when a FS modulates “against” net load as required, but so much so that other FS end up compensating to balance supply with demand. The latter situation occurs when a FS modulates “with” net load rather than “against” it, due to technical and economic constraints or, in the case of interconnectors, because other FS are modulating for the benefit of neighbouring countries.

2.4 Example applications

2.4.1 Potential future role of flexibility solutions

By applying the FSMS methodology to the outputs of a UC-ED model, one can quickly get an idea of how a fictional system is expected to cover its flexibility requirements. This is of particular value when performing long-term adequacy or capacity expansion studies. Figure 2.6 shows an example application of FSMS for a prospective 2035 French power system. Results are from a study analysing the future role of electric vehicles in the power system, based on the French government’s latest multi-annual energy plan [96]. The results shown are for a scenario considering 11,7

million electric vehicles, 60% of which are smartly charged (see [97] for full study details). For clarity, electric vehicle smart charging is the only form of demand side management which is represented.

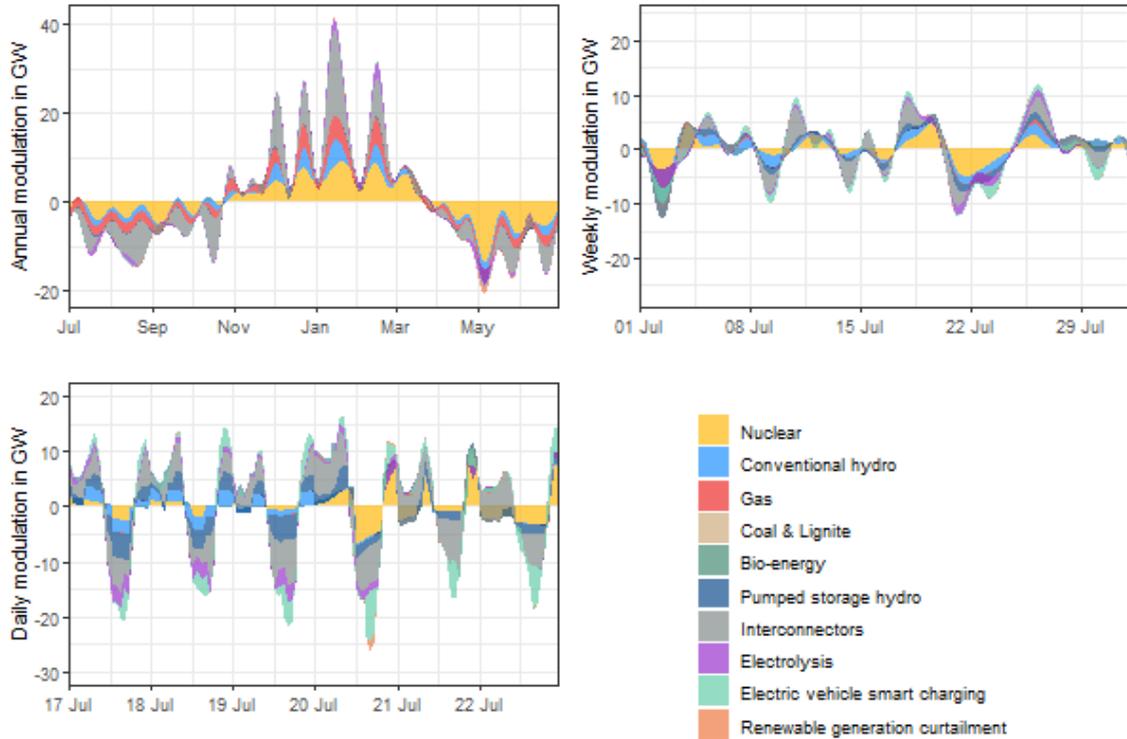


Figure 2.6: Who could be providing flexibility in the future? Annual (top left), weekly (top right) and daily (bottom left) flexibility solution modulation stacks, for a prospective 2035 French power system (study described in [97]).

Note that in 2035, particularly in the summer, troughs in net load no longer correspond to nighttime but to midday hours. By comparing Figure 2.4 to Figure 2.6, one may note that net load variability greatly increases between 2018 and 2035. In Chapter 3, we quantify this increase, and perform a sensitivity analysis to identify the long-term variables at play.

2.4.2 Potential evolution of the role of flexibility solutions

By applying the FSCD methodology, one can also quantify and visualise the evolution of the respective roles of flexibility solutions. Example results of such an analysis are shown in Figure 2.7, for the period running from 2021 to 2036 on the French power system. Results are from a study based on the French government’s latest multi-annual energy plan [96], that has been used as a reference scenario in several recent RTE (French Transmission System Operator) reports [97, 98]. Note that for clarity, only a few FSs have been represented, and electrolysis is the only type of flexible load that has been considered.

In this prospective study where installed capacities are an input data assump-

tion², on the annual timescale, one can note the decreasing role of nuclear as it is partly replaced by interconnection and, at the end of the period, by electrolysis. On the weekly and daily timescales, the role of conventional hydro is significantly reduced, with interconnection becoming the most important FS and electrolysis also appearing at the end of the period. Note that contributions are expressed in percentage of total system modulation, not in GW. This reduced role for hydro may therefore only be true in relative terms as on these timescales, flexibility requirement significantly increases over the period (see Chapter 3 for more on this).

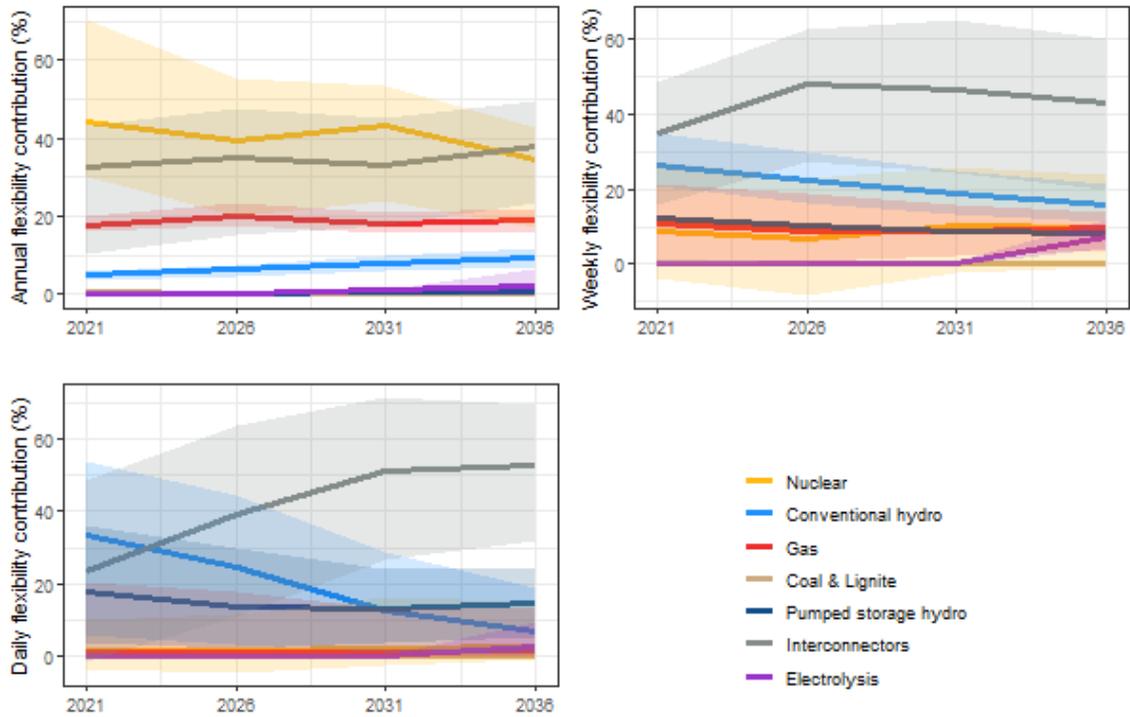


Figure 2.7: How could the roles of flexibility solutions evolve in the coming years? Evolution of flexibility solution contribution distribution between 2021 and 2036, on the French power system (data from the reference scenario used in [97, 98]). Uncertainty bounds correspond to the 25th and 75th percentiles of FSCDs, full lines correspond to the median.

2.4.3 The case of highly interconnected systems

Applying FSMS and FSCD to power systems with high interconnection relative to peak load can give very different and interesting results, in which case considering borders separately rather than simultaneously can add significant value to the analysis. Figure 2.8 illustrates such a situation through box plots of FSCDs for the Western Denmark power system in 2018. All interconnectors but that with Germany being Direct-Current, the representation does not violate Kirchhoff's laws.

²Not our own set of assumptions, see [98] for their justification.

For clarity, not all FS contributions are represented, but coal and gas are still included to provide context. The limited contribution of generation highlights the role of Western Denmark interconnection in European electricity balancing.

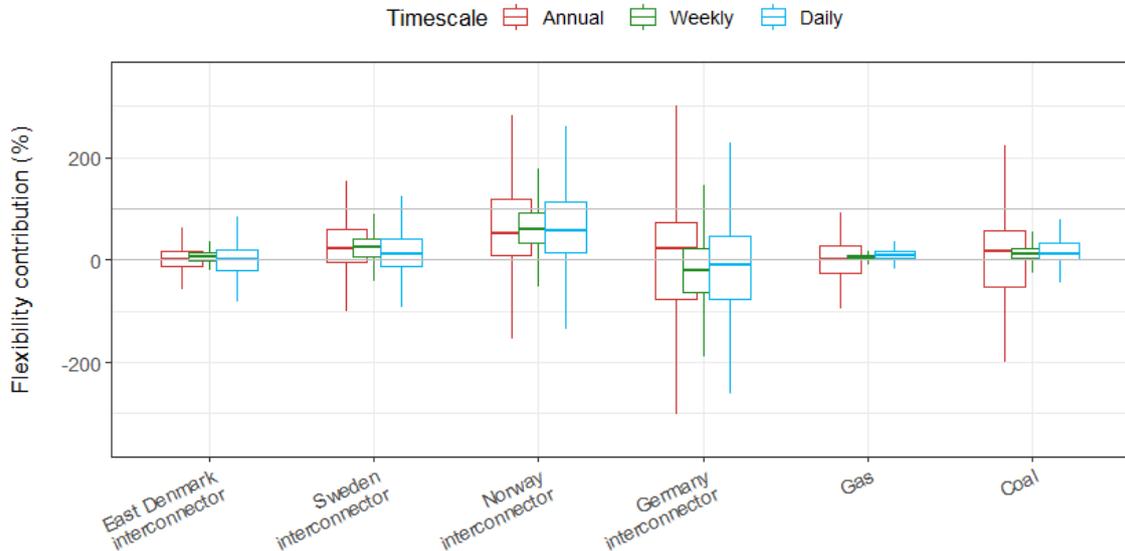


Figure 2.8: How do interconnectors contribute to flexibility in highly interconnected systems? Flexibility solution contribution distribution on annual, weekly and daily timescales, for the western Denmark power system in 2018 (data from [88]).

One may note the significant width of FS contribution distributions, single FSs often contributing far beyond modulations in Western Danish net load (represented by the 100% line). Of particular interest is the German interconnector, which very frequently contributes negatively to local flexibility requirement, particularly on the weekly and daily timescales where this occurs more than 50% of the time. This is to be expected as, on these timescales, German net load is highly correlated to that of Western Denmark. Closer inspection using FSMS (see Figure A.1 in the Appendix) shows that this is compensated by modulations in interconnector flows to Norway and Sweden (*i.e.* modulations in their hydro generation), as suggested in Figure 2.8.

2.4.4 Varying the size of the considered system

As previously mentioned, modulation in interconnector flows may imply modulation of another FS (generation, demand or storage) in a neighbouring system. To understand the cost, environmental and social implications of a flexibility mix, it would be helpful to know what hides behind these interconnector flow modulations. To this end, we can change the size of the considered system, and apply FSMS and FSCD to geographical aggregations of FS time series. One should keep in mind that these methods ignore any modulation for internal congestion management purposes, which may become more significant as the size of the considered system grows.

Figure 2.9 shows annual, weekly and daily FSMS for a prospective 2021 European power system³. Results are from the aforementioned study based on the French government’s latest multi-annual energy plan [96], used as a reference scenario in several recent RTE reports [97, 98]. Note that in this figure, interconnectors refer to links to countries beyond the considered system, which are negligible in this case.

This figure highlights the predominant role of fossil fuels in flexibility provision on the European system to date, on all three of the considered timescales. On the annual timescale, it is worth differentiating the roles of nuclear generation and fossil fuels. The former primarily has very low frequency components, *i.e.* it is mostly used to deal with the mismatch between summer and winter load. The latter also contribute to this task, but additionally modulate on periods of around one to two months, particularly in winter, *i.e.* they are used as “back-up” in periods of low wind. These differences in behaviours are intrinsically linked to differences in the balance between these plants’ CAPEX and OPEX, which dictates the number of hours they must run in order to cover their costs.

Keeping these observations in mind, it is interesting to look back at Figure 2.6, which shows the situation for France in 2035. On these same periods of around one to two months, nuclear generation modulates a lot more. This suggests that there is no technical barrier preventing nuclear from providing flexibility on these timescales, but if other flexibility solutions are available, an optimal dispatch implies modulating these other solutions.

2.5 Conclusion

This chapter presented an extensive review of flexibility quantification methods, classifying approaches depending on the question they attempt to address: *how much flexibility does my system need?* (Section 2.2.1), *how flexible is my flexibility solution?* (Section 2.2.2), *how flexible is my power system?* (Section 2.2.3), and *who is providing flexibility in my power system?* (Section 2.2.4).

Existing methods addressing this last question were shown to be limited in terms of their number, scope and relevance. A pair of novel tools were therefore presented to close this gap in literature: the Flexibility Solution Modulation Stack (FSMS) and the Flexibility Solution Contribution Distribution (FSCD). These frequency spectrum analysis based tools quantify flexibility provided by all four categories of flexibility solutions, separately considering their roles on the annual, weekly and daily timescales. Note that the proposed tools do not express a flexibility solution’s deliberate intent to provide flexibility, nor its ability to provide flexibility, but rather the flexible aspect of its behaviour, defined while considering the entire power system’s capacities, technical and economic constraints.

Several example applications were provided, for both historical and prospective power systems, in several geographical locations with contrasting characteristics. Condensing significant amounts of information, FSMS and FSCD were shown to

³Modelled countries, each as a single node unless specified otherwise: Austria, Belgium, Czechia, Denmark (4 nodes), France, Germany, Great-Britain, Ireland, Italy (6 nodes), Luxembourg, Northern-Ireland, Netherlands, Norway (3 nodes), Poland, Portugal, Spain, Sweden (4 nodes), Switzerland.

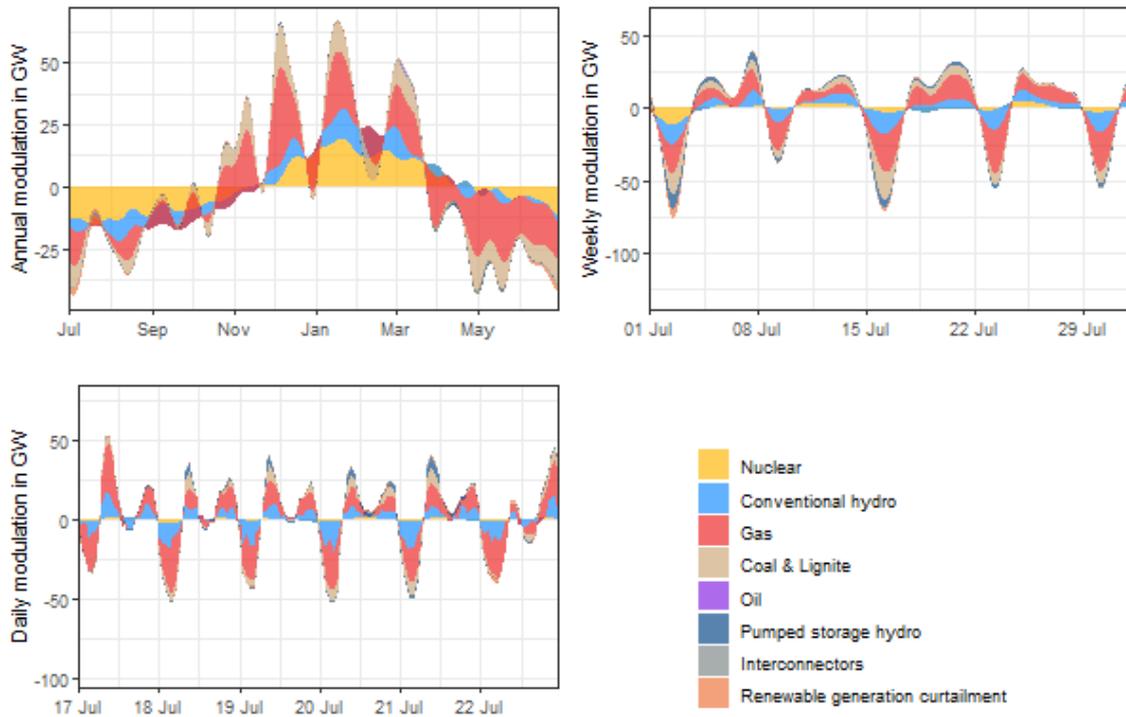


Figure 2.9: Ignoring congestion management, what are the technologies providing flexibility at the European level? Annual (top left), weekly (top right) and daily (bottom left) flexibility solution modulation stacks, for a prospective 2021 European power system.

be able to support a wide range of narratives, from shedding light on interactions between FSs, ranking their contributions and analysing the roles of future solutions, to tracking the evolution of a FS's importance. An extension of this work could involve broadening the analysis beyond the power system to include other energy vectors, such as gas or hydrogen.

These tools are very effective in describing the impact of the structure of a flexibility mix on the way flexibility is provided. However, they are rather blind where the structure of net load is concerned: FS modulations sum up to net load modulation, but FSMS and FSCD do not know why net load has such a shape, nor why this shape could be expected to change. This is the focus of the following chapter, where the impact of structural changes in net load on flexibility requirement is studied in extensive detail.

2.6 Résumé en français

Le nombre et la diversité des définitions existantes de la flexibilité du système électrique soulignent la complexité et l'aspect multi-facette de cet objet. Pour mieux le saisir, de nombreux chercheurs ont proposé de compléter l'analyse qualitative décrite dans le Chapitre 1 par une analyse quantitative de la flexibilité. Ces méthodes de quantification visent à fournir une base neutre sur laquelle une discus-

sion rationnelle peut avoir lieu, et à condenser de vastes quantités d'information, facilitant l'analyse d'une situation complexe.

Ce chapitre commence par une revue de littérature approfondie des méthodes de quantification de la flexibilité, se concentrant de facto sur la flexibilité pour l'équilibre offre-demande, puisque la flexibilité pour la gestion des contraintes réseau est un sujet nettement moins exploré sous l'angle de la quantification. Les différentes méthodes sont classées selon la question abordée : quel est le besoin de flexibilité de mon système ? (Section 2.2.1), quel est le degré de flexibilité de mon levier ? (Section 2.2.2), quel est le degré de flexibilité de mon système ? (Section 2.2.3) et qui fournit la flexibilité dans mon système ? (Section 2.2.4).

Les méthodes se focalisant sur la dernière question sont limitées tant en nombre qu'en pertinence, c'est pourquoi nous présentons deux nouveaux outils d'analyse : l'empilement de modulation des leviers de flexibilité (FSMS), et la distribution des contributions des leviers à la flexibilité (FSCD). En appliquant des méthodes d'analyse fréquentielle à des chroniques décrivant le comportement horaire des leviers de flexibilité, ces outils quantifient la fourniture de flexibilité de différents leviers sur les horizons annuels, hebdomadaires et journaliers. Ces outils sont capables de considérer chacune des 4 familles de leviers : production flexible, consommation flexible, stockage et interconnexion. Il est important de garder en tête que les résultats n'expriment pas la volonté d'un levier de fournir de la flexibilité, ni même sa capacité à le faire, mais simplement le caractère modulable de son comportement, défini en considérant l'ensemble du système (capacités, contraintes techniques et économiques).

Nous appliquons ces outils à de nombreux cas d'étude, décrivant des systèmes électriques aux caractéristiques techniques contrastées, et en se basant non seulement sur des données historiques mais aussi sur des données issues de simulations du fonctionnement de systèmes électriques prospectifs. Dans ce dernier cas de figure, il faut noter que si l'outil de simulation fait des approximations inappropriées, celles-ci se retrouveront dans les FSMS et FSCD générés, sans que l'utilisateur n'en soit nécessairement conscient. Au travers de ces cas d'études, nous démontrons la versatilité des FSMS et FSCD, qui permettent de mettre en lumière les interactions entre leviers de flexibilité, de hiérarchiser leurs contributions, ou d'évaluer l'évolution de l'importance de leur rôle dans les années à venir. Ces travaux pourraient être poursuivis en adaptant nos outils à une utilisation en multi-énergie.

À la question de qui fournit la flexibilité, les résultats des cas d'études soulignent la grande variété de situations, selon l'horizon de temps ou la structure du système considéré. En France, sur l'horizon annuel, le nucléaire est le contributeur majoritaire. Sur l'horizon hebdomadaire, le nucléaire, le gaz et les interconnexions jouent un rôle à peu près équivalents ; quant à l'horizon journalier, les stations de transfert d'énergie par pompage et les interconnexions ont un rôle significatif, mais nettement inférieur à celui de la consommation de l'eau chaude sanitaire asservie au signal heures-creuses/heures-pleines (voir Figure 2.5). Dans un système différent, du fait d'un mix énergétique différent, d'une capacité d'interconnexion plus importante, de la recharge intelligente d'un grand parc de véhicules électriques ou d'une capacité importante d'électrolyseur, la contribution des différents leviers de flexibilité peut varier grandement.

Ces outils se sont avérés très efficaces pour décrire l'impact de la structure d'un mix de flexibilité sur la manière dont celle-ci est fournie. Cependant, comme les modulations des leviers s'additionnent pour reproduire la modulation de la consommation résiduelle, les FSMS et FSCD sont incapables de comprendre la forme de la consommation résiduelle, ni les raisons de ses éventuelles évolutions. Ce sera le sujet du chapitre suivant, où nous évalueront en détail l'impact de changements structurels de la consommation résiduelle sur le besoin de flexibilité du système électrique.

Chapter 3

Quantifying flexibility requirement

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3.1 Introduction

In Chapter 1, we established that flexibility reflects the power system's ability to adapt to variability and uncertainty in demand and generation, which occur on different timescales. Through structural changes in both demand and the generation mix, the ongoing energy transition is expected to significantly increase variability and uncertainty in the power system, hence increasing the need for flexibility. The

research presented in this chapter aims to quantify both how and why medium-term¹ flexibility requirement will evolve under the influence of long-term variables. As shown in Chapter 2, the power system assets used to provide flexibility on the annual, weekly and daily timescales are very different, hence being able to describe how the situation will evolve on each timescale is fundamental to understanding and explaining how the system is to adapt to its changing environment.

As highlighted in our review of flexibility quantification methods (see Section 2.2.1), studies evaluating flexibility requirement have so far been short-term (intra-day) focussed. To the best of our knowledge, prior to this work, there had been very little work on quantifying flexibility requirement on the medium-term. The work presented in this chapter bridges this gap by proposing a set of frequency spectrum analysis based indicators that allow the separation of annual, weekly and daily flexibility requirements, the three relevant timescales when considering load and net load (load minus VRE generation) variability. Note that the proposed quantification methodology focusses on the flexibility required for supply-demand matching, not for congestion management.

Flexibility requirement is affected by several uncertain long-term variables, which have up to now been investigated separately. This chapter simultaneously examines flexibility requirement sensitivity to the penetration of wind power, solar power, electric heating and cooling, as well as to the degree of network interconnection between countries. The impact of these variables on each timescale is examined, along with the interactions between variables. An estimation of how flexibility requirements are expected to evolve is provided; the use of Global Sensitivity Analysis (GSA) enables the identification of the variables responsible for the expected evolutions.

This chapter starts with a review of existing work studying the impact of uncertain long-term variables on flexibility requirement. We then present our methodology used to quantify flexibility requirement and analyse its sensitivity to the five previously mentioned variables (Section 3.3), before applying it to a case study (Section 3.4) focussing on the French power system, while accounting for its electrically connected neighbours. Chosen for data availability reasons and authors' personal interests, it is an interesting system to examine as all five of the considered long-term variables are expected to evolve significantly in years to come, as France undergoes its energy transition. Results for other European countries are occasionally shown or mentioned to provide a reference and discuss limitations in results. The proposed metrics and analysis framework are then used to evaluate the potential for network interconnection to reduce flexibility requirement by exploiting diversity in load and VRE generation profiles (Section 3.5). A conclusion (Section 3.6) summarises key findings and discusses differences in results had the case study been performed on another country.

¹In this thesis, short-term refers to intraday, medium-term to daily, weekly and annual horizons, long-term refers to more than a year.

3.2 Review of long term variables impacting flexibility requirement

Power system flexibility requirement is affected by several uncertain long-term variables; VRE penetration has been the most investigated. An early study by Holttinen *et al.* [57] analysed the effect of large wind penetrations on ramps, showing an increase in their magnitude and change in their occurrence patterns, both diurnal and monthly. Using one and multiple hour ramps, Huber *et al.* [24] have extended the analysis to both onshore wind and solar photovoltaics impacts on European net load curves. Deetjen *et al.* [58] have performed a similar study on the ERCOT system, with a wide variety of ramp derived indicators. Both of these studies highlight the fact that increased solar photovoltaics penetration generates a significant additional ramping requirement, the effect of wind is much more limited. In another study, Belderbos *et al.* [35] optimise a storage portfolio for different so-called remaining load profiles, where both VRE and conventional generation are subtracted from load. Steinke *et al.* [66] aim to determine the backup generation required in a high VRE share system, examining the potential role of storage and interconnection. In both these last two studies, it can be seen that for increased VRE shares, the storage energy capacity requirement is much more affected than the power capacity requirement.

The specificity of network interconnection when compared to other flexibility solutions makes it quite complicated to characterise it in the same way. As such, the degree of interconnection can be an interesting parameter to vary when evaluating flexibility requirement. Expressing the ability of grid interconnection to average net load over space has been a focus point of several aforementioned studies [24, 66]. The European project e-Highway 2050 [99] developed a scenario based methodology to determine least regret options for European grid expansion. In two other studies, Fursch *et al.* [100] and Kristiansen *et al.* [101] highlight the grid's role in capacity expansion modelling.

Another key variable affecting flexibility requirement is load temperature sensitivity, which so far has not been treated as such in literature. Papers on the subject adopt a policy approach, examples of which are analyses of long-term climate change impacts on European load curves [102, 103], or the implications of an ongoing increase of temperature sensitivity of summer electricity demand on asset maintenance scheduling [104]. Several papers issue a warning to countries considering heat electrification, in a move towards heat decarbonisation [105–107]. The security of supply risk and the approximate associated cost resulting from this added load variability is quantified.

Flexibility requirement is affected by several uncertain long-term variables, which have up to now been investigated separately. The work presented in this chapter provides novel insights by simultaneously examining flexibility requirement sensitivity to the penetration of wind power, solar power, electric heating and cooling, as well as to the degree of interconnection. The impact of these variables on each timescale is examined, along with the interactions between variables. An estimation of how flexibility requirements are expected to evolve is provided; the use of Global Sensitivity Analysis (GSA) enables the identification of the variables responsible for

the expected evolutions.

3.3 Methodology

A general overview of the proposed methodology is shown in Figure 3.1, it also states in which subsection each step is detailed.

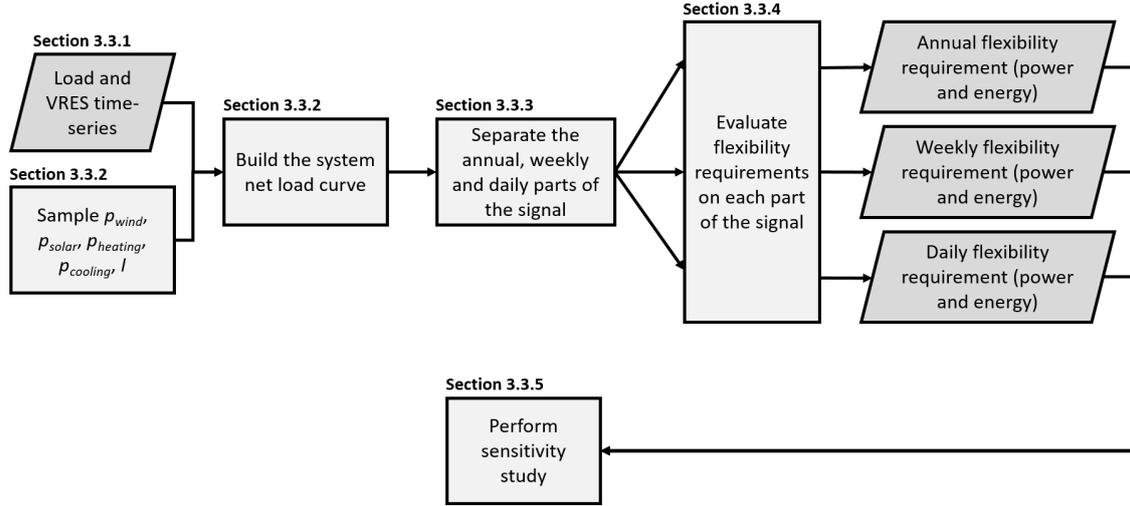


Figure 3.1: General overview of the proposed methodology. The process described in the top line is performed several tens of thousands of times, the resulting flexibility requirements are then fed the sensitivity study at the end of the chain.

3.3.1 Data used

Météo-France, the French national meteorological service, has developed the ARPEGE-Climat model which, coupled with ocean, sea ice and surface models, simulates long-term climate evolution [108]. With energy related applications in mind, Météo-France has used this model to produce 200 years of synthetic weather time series, representative of our current climate [109]. Covering the whole globe, outputs such as temperature, solar radiation, atmospheric pressure and wind speed and direction at different altitudes are expressed at hourly and, for Europe, 0.5° latitude and longitude resolutions.

RTE, the French Transmission System Operator (TSO), has applied a transfer function based process to these weather time series to derive load and wind and solar generation data, allowing temporal, spatial and inter-variable correlations to be kept [110]. The resulting data is expressed at hourly and country level resolution. This spatial aggregation implies that, when scaling up capacity, its geographical spread is kept constant, and internal network congestions are ignored. Load is modelled using a bottom-up approach [40]; electric heating and cooling load can therefore be varied independently from temperature insensitive load. Used in numerous RTE studies including the French adequacy report, legal obligation of RTE [40], these time series

are the basis of the analysis presented in this section on flexibility requirement quantification.

3.3.2 Building the system net load curve

The data just described was used to build our own set of net load curves, by applying the following process. First, as our load data was generated using a bottom-up approach, we can specify the extent of electric heating and cooling demand in a country's load curve, as shown in Equation 3.1.

$$L^c(t) = L_{ti}^c(t) + p_{heat}^c L_{heat}^c(t) + p_{cool}^c L_{cool}^c(t) \quad (3.1)$$

where:	t	time, from hour 1 to hour 8760 * 200
	c	country
	p_{heat}	electric heating penetration (unitless)
	p_{cool}	electric cooling penetration (unitless)
	$L_{ti}(t)$	temperature insensitive load time series (MW)
	$L_{heat}(t)$	electric heating load time series (MW)
	$L_{cool}(t)$	electric cooling load time series (MW)

Each country's net load is then defined as follows:

$$L_{net}^c(t) = L^c(t) - p_{wind}^c \frac{\overline{L}^c}{\overline{W}^c} W^c(t) - p_{solar}^c \frac{\overline{L}^c}{\overline{S}^c} S^c(t) \quad (3.2)$$

where:	p_{wind}	wind penetration (unitless)
	p_{solar}	solar penetration (unitless)
	$W(t)$	wind generation time series (MW)
	$S(t)$	solar generation time series (MW)
	$\overline{L}^c, \overline{W}^c, \overline{S}^c$	200 year mean load, wind and solar generation

The final step of the process, expressed in Equation 3.3, consists in taking the central country's net load and adding parts of its neighbours' net loads. The resulting system net load curve is the object on which flexibility requirements can then be evaluated.

$$L_{net}^{system}(t) = L_{net}^{cc}(t) + \sum_c \frac{I^c}{\overline{L}^c} L_{net}^c(t) \quad (3.3)$$

where:	cc	central country
	I^c	interconnection capacity with country c (MW)

For the purpose of Global Sensitivity Analysis, several tens of thousands of combinations of I , p_{wind} , p_{solar} , p_{heat} and p_{cool} are sampled from uniform distributions within specific intervals.

I^c represents the capacity of country c's link with the central country. Divided by c's mean load, it indicates the proportion of c's net load that is included in the system net load. For each neighbouring country, a specific interval is defined based on current and prospective interconnection capacities. A single relative position

inside those intervals is sampled. For example, if countries A and B have intervals of $[2000,4000]$ and $[0,1000]$, a result of the sampling could be $I^A = 2800$ MW and $I^B = 400$ MW.

p_{wind} represents the share of annual load covered by annual wind generation, averaged over the 200 years of synthetic data. Multiplied by the 200 year mean load over the 200 year mean wind generation, it acts as a scaling factor of a homothetic transformation, ensuring that the wind generation time series covers the required load share. p_{solar} works in a similar way. The sampling of p_{wind} and p_{solar} is done in the same way as I : each country is given an interval reflecting local potential and objectives and a single relative position in those intervals is sampled. In other words, VRE deployment is assumed to be synchronous across countries, but each at its own pace.

p_{heat} and p_{cool} are factors that reflect the volume of electric heating and cooling load respective to an initial situation. Individual country policy regarding heating cannot be assumed to be synchronous (e.g. France is trying to reduce its electric heating demand while the UK and Germany are considering heat electrification). Therefore, only the central country's p_{heat} and p_{cool} were varied. A country's flexibility requirement sensitivity to its neighbours' load temperature sensitivity could also be evaluated, but this would require adding variables to be sampled, severely affecting computation time.

3.3.3 Separating the signal components

As discussed in Section 2.3.1, load curves show clear cyclical patterns of various time periods: demand is higher during the day than during the night, higher during weekdays than the weekend, and either higher in summer or winter depending on geographical location.

Figure 3.2 offers a view of national load curves in the frequency domain, expressed as a cumulative share of power spectral density. The load data used is the one described in Section 3.3.1, with 2017 electric heating and cooling penetrations. It can be seen that a selected few frequency components (annual, weekly and its harmonics, daily and semi-daily) contain most of the information carried in the signal. It can also be seen that the balance between these frequency components varies from one country to another, the most obvious example being the very significant annual component in the French load curve due to the high penetration of electric heating.

Flexibility requirements are quantified for three timescales: annual, weekly and daily. Hence, following a similar procedure to the one applied in our flexibility provision quantification method (see Section 2.3.1), net load curve data was first fed through a Discrete Fourier Transform (see Equation 2.1). The band pass filters described in Section 2.3.1 were then applied, with unit magnitude within the band and zero magnitude outside the band, and cut off frequencies at 20 and 180 year⁻¹ *i.e.* periods of about 18 and 2 days. The DC offset (multi-annual mean) is removed prior to the filtering process. Note that different or even additional cut off frequencies may be used. However, following extensive testing, these were judged to be the most appropriate to investigate flexibility, notably to make the weekday vs weekend load cycle appear clearly on the weekly timescale.

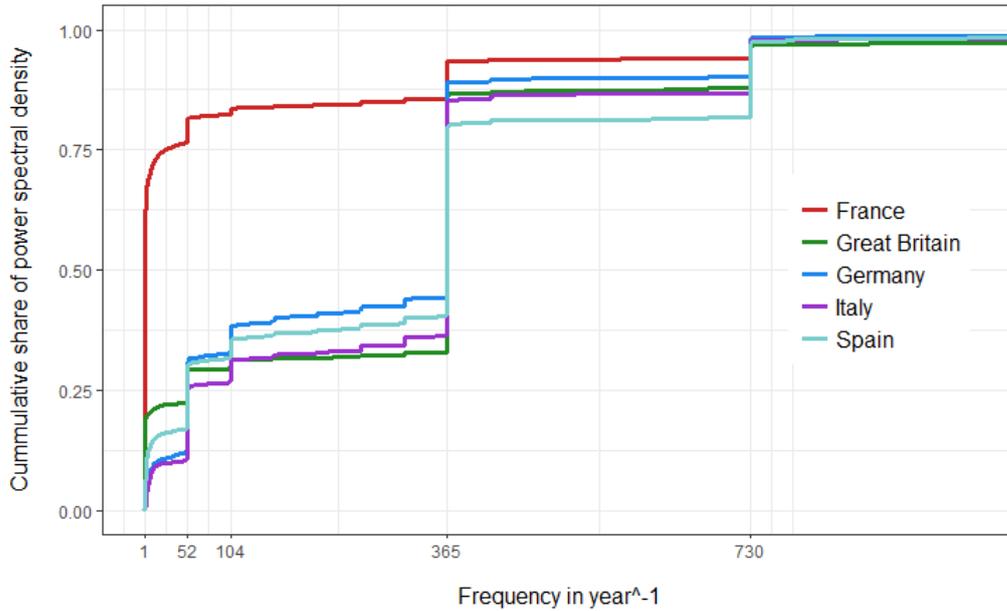


Figure 3.2: Cumulative frequency spectrum share of national load curves.

The three resulting signals were then passed back into time domain using the inverse Fourier Transform.

3.3.4 Evaluating flexibility requirement

For each year of the low-frequency time series, the difference between its minimum and maximum levels was recorded; the resulting vector of 200 values was defined as the annual flexible power requirement (FPR_a). Similarly, the integral of the low frequency time series was computed, obtaining what could be equated as a “storage level”. The difference between the minimum and maximum of this “storage level” was recorded; the resulting vector of 200 values was defined as the annual flexible energy requirement (FER_a).

The process was repeated for each week of the mid-frequency and each day of the high-frequency parts of the load curve signal, obtaining 200×52 and 200×365 values for weekly and daily requirements respectively, both in terms of power and energy ($FPR_w, FER_w, FPR_d, FER_d$).

In order to reflect the benefit brought by interconnection, the resulting flexibility requirements were then normalised by the system’s maximum load for the flexible power requirement and by the system’s mean annual demand for the flexible energy requirement (n.b. not net load).

3.3.5 Global sensitivity analysis

Flexibility requirement sensitivity to $X = [I, p_{wind}, p_{solar}, p_{heat}, p_{solar}]$ was evaluated using the GSA Sobol method [111]. This variance-based method quantifies the contribution of each input variable to the output’s variance. It has been used regularly

on energy related matters [112–116] and shows significant advantages over other sensitivity analysis methods: it makes no assumption on the model’s behaviour (e.g. linearity), provides straightforward interpretation through quantitative ranking of variable importance and is capable of evaluating interactions between variables [117]. However, the method assumes variable independence and can be computationally expensive, all the more so as the number of considered variables increases [117, 118].

Based on Monte Carlo runs of the flexibility requirement module previously described, the method calculates first order (see Equation 3.4) and total (see Equation 3.5) Sobol indices.

$$S_i = \frac{V_{X_i}(E_{\mathbf{X}_{\sim i}}(Y | X_i))}{V(Y)} \quad (3.4)$$

$$S_{T_i} = \frac{E_{\mathbf{X}_{\sim i}}(V_{X_i}(Y | \mathbf{X}_{\sim i}))}{V(Y)} \quad (3.5)$$

The numerators in equations 3.4 and 3.5 respectively represent “the expected reduction in variance that would be obtained if X_i could be fixed” and “the expected variance that would be left if all factors but X_i could be fixed” [118]. S_i therefore gives the effect of a factor by itself, while S_{T_i} gives the total effect of a factor, including its interactions with other factors.

The Sobol method needs a single output value to work with, not a vector. As a result, the sensitivity analysis was performed on the 95th percentile of flexibility requirement distributions. This is a fairly arbitrary choice, however, varying the chosen percentile between 90 and 100 was shown to have negligible impact on results.

3.4 Case study

GSA has certain limits which prevent it from providing a full picture of the flexibility problem. If it expresses flexibility requirement’s sensitivity to input variables, it does not give the flexibility requirement itself nor its balance between different timescales, it does not convey the sign of the output’s sensitivity to an input variable (positive or negative contribution to flexibility) and it ignores effects outside of the chosen intervals.

For these reasons, the case study starts by setting the context by applying the flexibility requirement sizing method to current load curves. The impact of the input variables on flexibility requirement is then illustrated by a few 2 dimensional cuts of the 5 dimensional problem, for a wide range of values. Finally, we present a prospective power system’s flexibility requirements, GSA is used to express each input variable’s contribution to flexibility requirement evolution.

3.4.1 Base case

The method described in Section 3.3.4 was applied to the data described in Section 3.3.1. Load curves were constructed using 2017 electric heating and cooling levels, each country was treated by itself *i.e.* no interconnections were taken into account, VRE generation curves were not deducted from the load.

The results of the flexibility requirement evaluation are shown using two violin plots in Figure 3.3. This graphical representation shows the full distribution of flexibility requirements (200 , $200 \cdot 52$ and $200 \cdot 365$ values for annual, weekly and daily requirements respectively²). The width of each distribution has been normalised so that the area of each violin in a plot is equal. A summary of the considered power systems' modelled demands is shown in Table 3.1.

Table 3.1: Summary of considered power systems' demand

	France	Germany	Great Britain	Italy
Mean annual load (TWh)	480	553	329	309
Peak load (GW)	112.2	86.9	63.7	54.4

The flexible power requirement is of the same order of magnitude for the three considered time horizons. Conversely, the flexible energy requirement is much higher for longer timescales: the annual requirement is 100 to 1000 times more important than the daily requirement. This general observation was also made in previous papers [35, 64, 65].

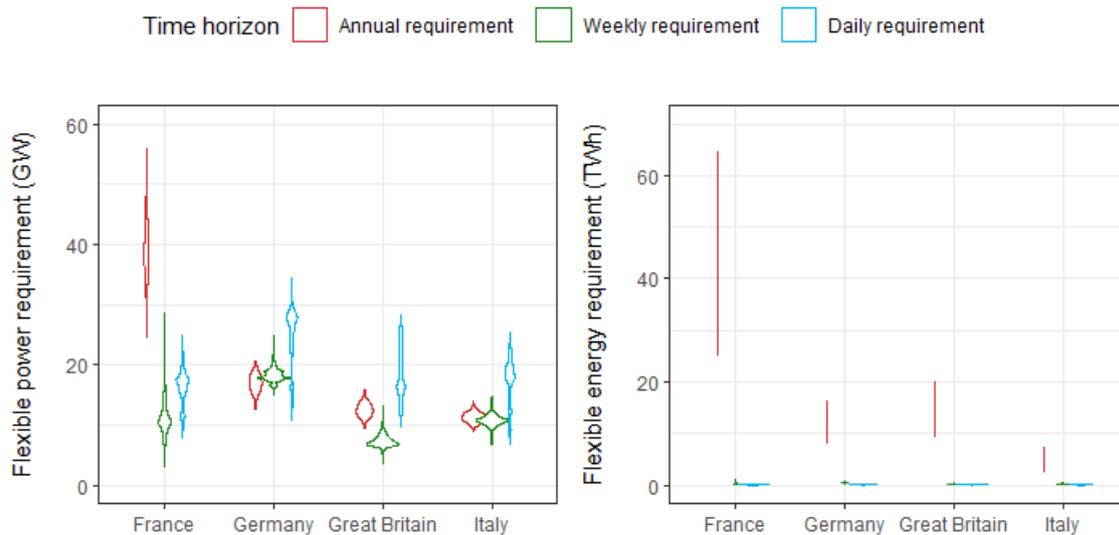


Figure 3.3: Flexibility requirements for different timescales and different countries. Electric heating and cooling levels are at 2017 levels, VRE generation has not been deducted from the load, interconnection has not been taken into account.

It can also be noted that for the flexible power requirement, the balance between the three time horizons is not the same in each country. In France, the electric heating penetration induces a very high annual flexibility requirement, relative to the country's annual and peak load. This sensitivity to temperature also generates

²Note that this approach considers all days and weeks in the same way. An extension to this work could use wavelet analysis to differentiate between summer and winter weekly and daily requirements.

particularly wide distributions of annual and weekly requirements, both in terms of power and energy.

3.4.2 Input variable impact on flexibility requirement

Network interconnection, wind, solar, electric heating and cooling penetrations all affect flexibility requirement in different ways, on different timescales and to various degrees. Bearing succinctness and clarity in mind, a select number of level-plots of flexibility requirement with respect to pairs of input variables are presented. The effect of varying other variables is discussed when relevant.

Note that in all of the proposed graphs, little credit should be given to flexibility requirement values when total VRE penetration reaches 70% or beyond: the net load curves our descriptive statistics approach generate would be very unlikely to occur in practice, due to significant curtailment for stability concerns, but also for both supply-demand balancing and congestion management.

Annual flexibility requirement

Figure 3.4 shows the 95th percentile of the need for annual flexible power and energy observed in the French net load curve (FPR_a and FER_a). Again, the choice of the 95th percentile is fairly arbitrary, but varying the percentile between 90 and 100 had negligible impact on the general shape of results. The requirements are expressed in terms of solar and wind penetrations (0.3 wind indicates that on average, 30% of annual energy demand is covered by wind generation). Electric heating and cooling were set to their 2017 value, interconnection was set to zero. As mentioned in Section 3.3.4, the power requirement was normalised by the system's maximum load (n.b. not net load). Similarly, the energy requirement was normalised by the system's mean annual demand. For reference, in 2017, France had solar and wind penetrations of about 2% and 5% respectively.

From a yearly perspective, solar generation and French electricity demand are out of phase, hence solar penetration increases the annual flexibility requirement. For wind generation, the situation is more complex: it is in phase with net demand up to a certain threshold under which wind penetration reduces the flexibility requirement. This threshold is high for the flexible energy requirement, however, due to its volatility, wind power quickly becomes detrimental where flexible power requirement is concerned.

From the direction of isolines, it can be seen that when a VRE type dominates, the flexible power requirement is determined solely by that type's penetration. This is not the case for the flexible energy requirement which mostly depends on solar penetration.

Minimising flexibility requirement for a given VRE penetration will give a wind dominated electricity mix (more so for energy than power). This conclusion is affected if electric heating penetration is reduced: this causes a reduction in flexibility requirement, particularly in solar dominated mixes. For the energy requirement, it also unfortunately reduces the threshold beyond which wind becomes detrimental (this threshold is beyond 50% wind penetration for the 2017 French situation). Another illustration of this can be seen by analysing the situation of different countries:

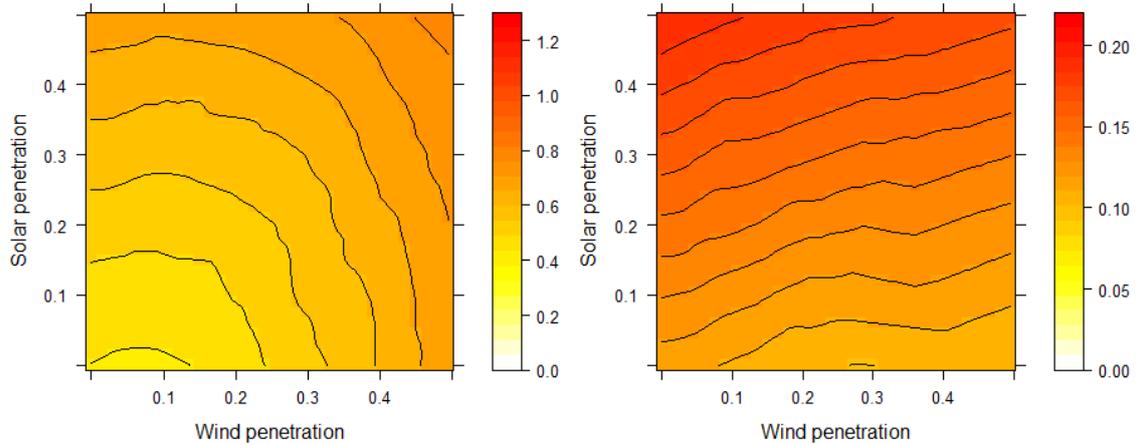


Figure 3.4: 95th percentile of annual flexible power requirement FPR_a in MW/MW (normalised by system maximum load, left) and energy requirement FER_a in TWh/TWh (normalised by system mean annual demand, right) in terms of wind and solar penetrations.

where there is summer peak load or less electric heating, high VRE mixes less in favour of wind generate lesser annual flexibility requirements.

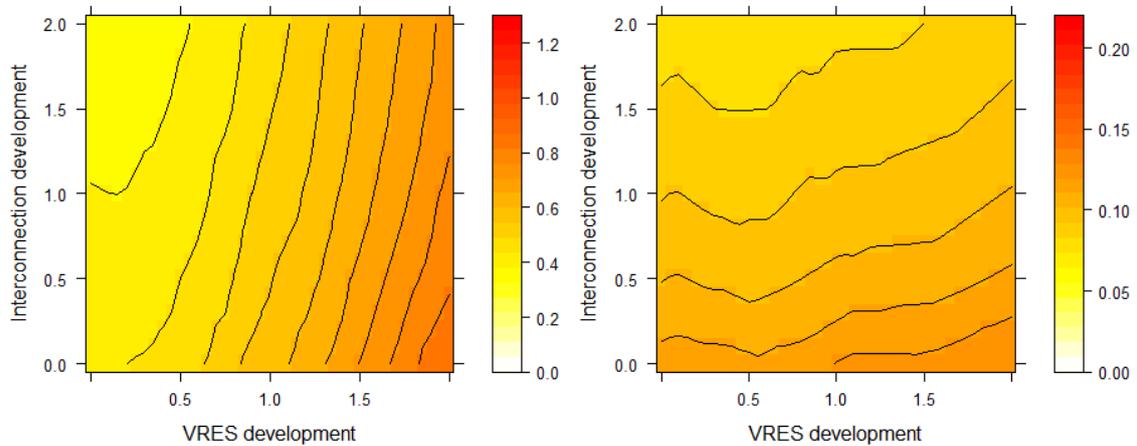


Figure 3.5: 95th percentile of normalised annual flexible power (left) and energy (right) requirement in terms of VRE and network developments.

Figure 3.5 shows the annual flexibility requirements in terms of VRE and network interconnection development. A development of 1 corresponds to that of the Ampere Scenario in 2036, as described in RTE's 2017 adequacy report [40]. This scenario corresponds to ambitious VRE development in western Europe and slightly conservative network interconnection development; a brief description is provided in Table 3.2. The balance between wind and solar and between border capacities is kept constant throughout the plots, meaning that the 2017 situation is not represented.

However, it would roughly be placed at 0.1 VRE and 0.7 interconnection.

Table 3.2: Ampere scenario 2036 description

Country	p_{wind}	p_{solar}	I/\bar{L}
France	0.34	0.12	NA
Great Britain	0.42	0.09	0.17
Belgium	0.26	0.08	0.48
Germany	0.40	0.13	0.07
Switzerland	0.02	0.09	0.50
Italy	0.12	0.14	0.09
Spain	0.32	0.25	0.15

The main conclusion to draw from these graphs is that the expected network development will compensate most of the increase in annual flexible energy requirement caused by VRE development, but only a small fraction of the increase in annual flexible power requirement. One can also note that, both for power and energy, network interconnection provides more value as VRE penetration increases (reduced vertical gap between isolines as VRE development increases) and that the value brought by interconnection decreases as new interconnection is added (increased vertical gap between isolines as interconnection development increases). These notions are investigated further in Section 3.5.

Varying the balance between solar and wind slightly changes these conclusions. From a yearly perspective, network interconnection provides value no matter the electricity mix, but more so in wind dominated ones. As can be understood by bearing Figure 3.4 in mind, when solar plays a more prominent role, network development is unable to compensate the dramatic increase in flexible energy requirement.

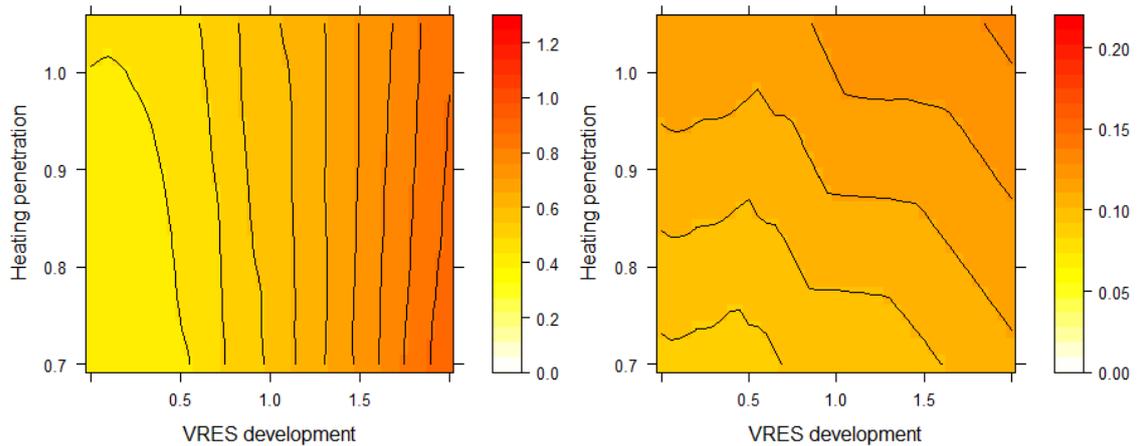


Figure 3.6: 95th percentile of normalised annual flexible power (left) and energy (right) requirement in terms of VRE and electric heating penetrations.

Figure 3.6 shows the annual flexibility requirements in terms of VRE and electric heating penetrations. VRE development is expressed in the same manner as for Figure 3.5; an electric heating penetration of 1 corresponds to 2017 levels.

Save for low VRE penetration cases, reducing the penetration of electric heating barely has any impact on the annual flexible power requirement, the intermittent nature of wind being too much of a constraint. For high VRE cases, it even slightly increases the requirement. However, reducing electric heating penetration is beneficial where annual flexible energy is concerned and can compensate to some degree the increasing requirement caused by increased VRE penetrations.

As for electric cooling, it causes an insignificant decrease in annual flexibility requirement for very low VRE penetrations. There is too little electric cooling load in France for its penetration to have much of an impact in the foreseeable future.

Weekly flexibility requirement

Figure 3.7 shows the 95th percentile of the need for weekly flexible power and energy observed in the French net load curve (FPR_w and FER_w), expressed in terms of solar and wind penetrations. Electric heating and cooling were set to their 2017 value, interconnection was set to zero. As seen previously, the power requirement was normalised by the system's maximum load (n.b. not net load), the energy requirement by the system's average annual demand. Note that the scale for the flexible energy requirement is different from the one used in Section 3.4.2.

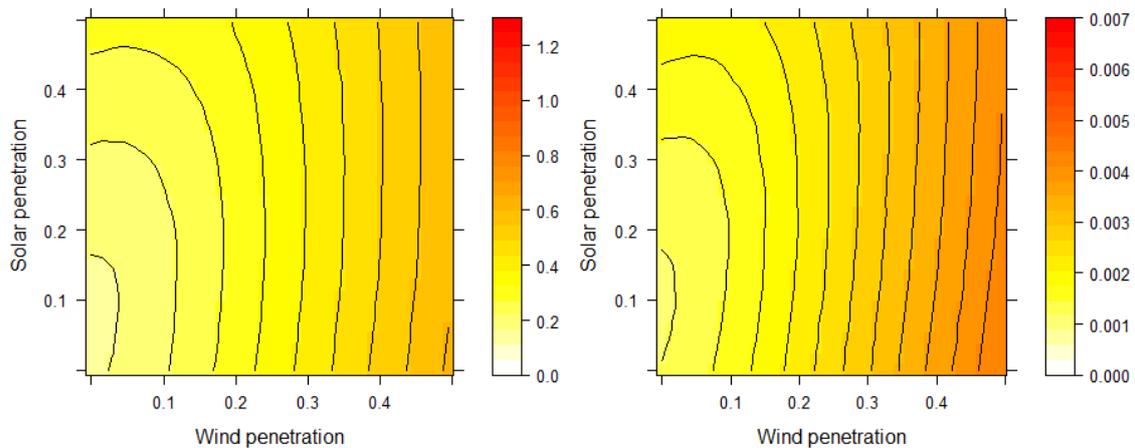


Figure 3.7: 95th percentile of normalised weekly flexible power (left) and energy (right) requirement in terms of wind and solar penetrations.

From a weekly perspective, if solar penetration has a slight impact for low wind penetrations, flexibility requirement is primarily a function of the share of wind in the electricity mix. It is interesting to note that the interactions between wind and solar are of the same nature for both flexible energy and flexible power requirements, contrary to the annual timescale. Interconnection development has a very limited impact for low VRE penetrations, but induces a notable requirement reduction in high VRE mixes. Reducing electric heating or increasing electric cooling penetrations has next to no impact.

The observations made in Section 3.4.1 concerning the balance of requirements between different timescales partially hold. The flexible energy requirement remains

2 to 3 orders of magnitude smaller on the weekly timescale than the annual one. However, the dominating flexible power requirement can vary: network interconnection and electric heating penetration reduction having more impact on the annual requirement than the weekly one, even in France, when wind penetration is high, weekly flexible power requirement can be the most important.

Daily flexibility requirement

Figure 3.8 shows the 95th percentile of the need for daily flexible power and energy observed in the French net load curve (FPR_d and FER_d), expressed in terms of solar and wind penetrations. Electric heating and cooling were set to their 2017 value, interconnection was set to zero. Note that the scale for the flexible energy requirement is different from the one used in Sections 3.4.2 and 3.4.2.

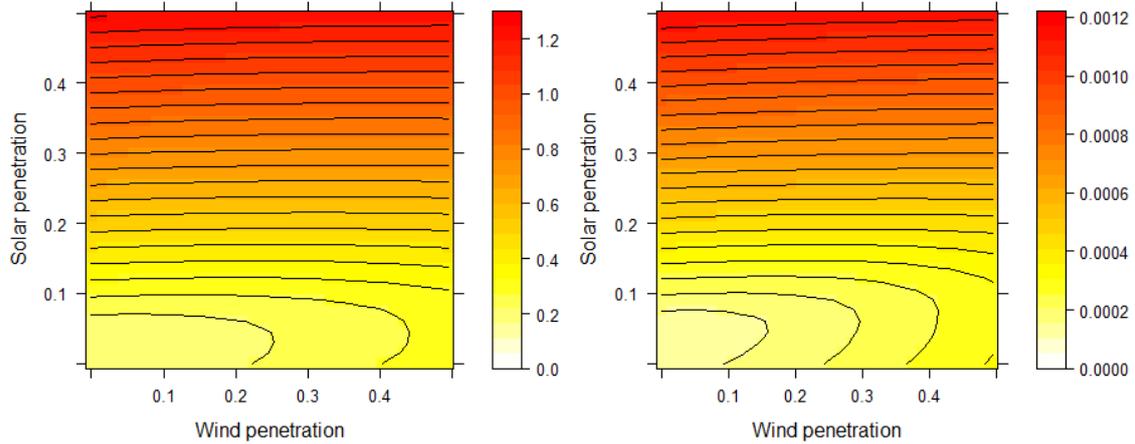


Figure 3.8: 95th percentile of normalised daily flexible power (left) and energy (right) requirement in terms of wind and solar penetrations.

From a daily perspective, solar generation and electricity demand are in phase, thus slightly reducing the flexibility requirements (both power and energy), up to a certain threshold. Beyond that threshold, however, flexibility requirements are drastically increased (this phenomenon is well illustrated by the famous “duck curve”). For high solar penetrations, the flexible power requirement is higher than what was observed for annual and weekly requirements, and higher even than P_{\max} (*i.e.* curtailment is required if load is not adapted). Wind penetration has somewhat of an effect for low solar penetrations, slightly increasing the daily flexibility requirements (more so for energy than power). Varying network interconnection, electric heating or cooling penetrations has next to no impact.

The threshold beyond which solar starts causing an increase in daily flexibility requirement varies with the considered country, it tends to occur at higher penetrations in southern European countries compared to northern European ones.

3.4.3 Prospective power system flexibility requirements

Figure 3.9 shows the distributions of normalised flexibility requirements in 2017 and in the Ampere Scenario in 2036 (see Table 3.2). Results are evaluated on net load curves, network interconnections have been considered, electric heating and cooling penetrations in 2036 are set at 0.89 and 2.5 respectively (relative to values of 1 for 2017).

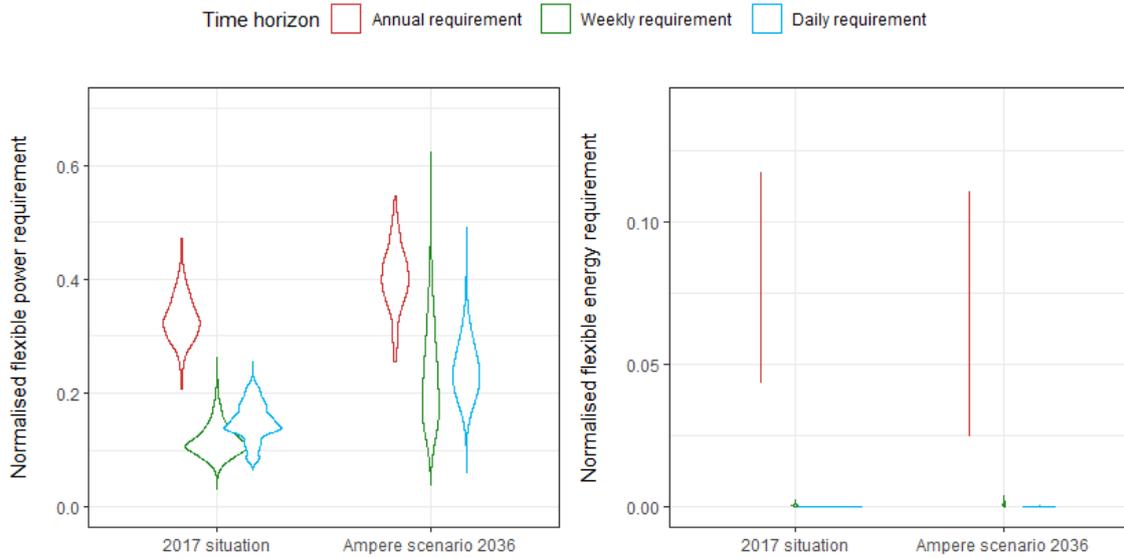


Figure 3.9: Flexibility requirements evaluated with I , p_{wind} , p_{solar} , p_{heat} and p_{cool} set at 2017 and Ampere scenario 2036 levels.

Figure 3.10 shows the first order Sobol indices of I , p_{wind} , p_{solar} , p_{heat} and p_{cool} , for flexible power and energy requirements. The input variable values were sampled in the interval [2017, Ampere 2036] using a uniform distribution. The sum of first order indices being very close to one, total Sobol indices have not been shown.

Combining results from figures 3.9 and 3.10 with observations made in Section 3.4.2, the following conclusions may be drawn regarding flexible power: (i) the annual flexible power requirement will slightly increase, the expected network interconnection development and heating penetration reduction being insufficient to match the increase in requirement caused by wind (and to a much smaller degree, solar) power development, (ii) the weekly flexible power requirement will become very variable, its maximum will double under the sole influence of wind power development, exceeding the maximum annual requirement, (iii) the daily flexible power requirement will become very variable, its maximum will double almost entirely due to solar power development, reaching the current level of annual requirement.

If input variable values are sampled in the interval [Ampere 2036, 1.5 x Ampere 2036], GSA results are not particularly affected; if anything, the dependency of French flexible power requirements on VRE levels is further enhanced.

Similarly, the following conclusions may be drawn regarding flexible energy: (i) the annual flexible energy requirement will slightly decrease, expected wind and network interconnection development and electric heating penetration reduction com-

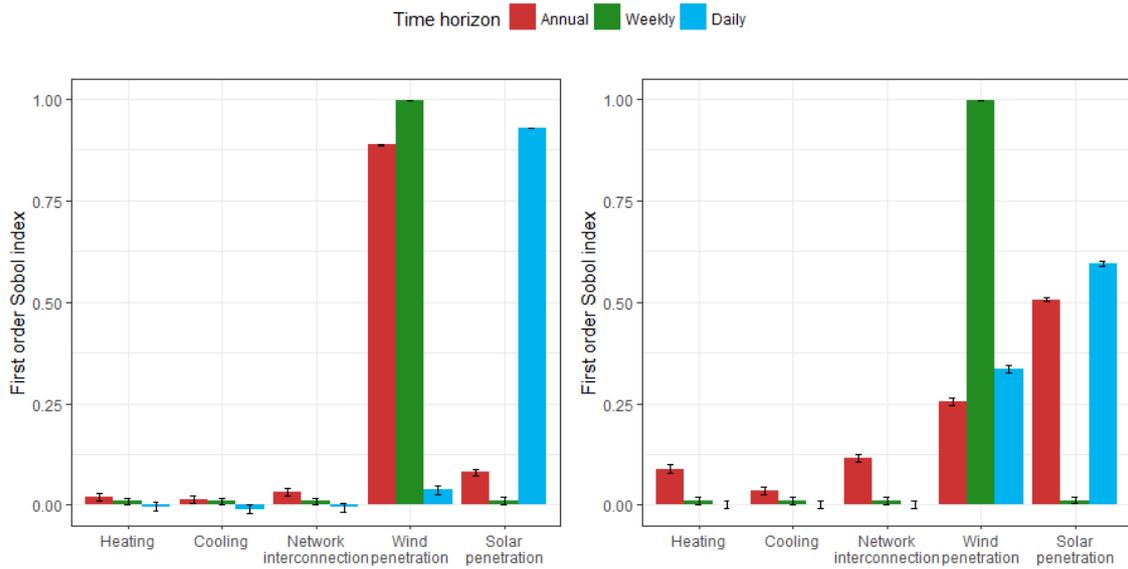


Figure 3.10: GSA results for flexible power (left) and flexible energy (right) requirements.

compensating the upward effect of solar power development, (ii) the weekly flexible energy requirement will become more variable, its maximum will double solely due to wind power development, but will remain about 25 times smaller than the annual requirement, (iii) the daily flexible power requirement will become more variable, its maximum will double due to VRE development, but will remain about 250 times smaller than the annual requirement.

GSA results for flexible energy requirement are slightly sensitive to the chosen boundaries. If input variable values are sampled between 1 and 1.5 times Ampere Scenario development in 2036, (i) network interconnection has an increased impact on the annual timescale, the impact of electric heating and wind power is reduced, (ii) network interconnection starts having a slight impact on the weekly timescale, (iii) solar power becomes the sole determinant on the daily timescale.

It is important to note that, as this quantification of the flexibility required to match supply with demand is based on net-load variations, it assumes that all VRE generation has been absorbed by the system, which is implicitly considered as a “copper-plate”. In practice, some of this generation may have to be curtailed to respect internal network constraints. This will likely reduce net load variations, the estimated flexibility requirement should hence be considered as an upper bound.

3.5 Interconnection’s role in reducing flexibility requirement

As discussed in Chapter 1, interconnection can provide flexibility both by sharing other flexibility solutions between neighbouring systems, and by exploiting diversity in their load and VRE generation profiles. The former is considered in Chapter 2,

we will now adapt the metrics and analysis framework presented above to explore the latter.

3.5.1 Methodology

The question addressed in the previous section is that of the relative roles of five ongoing structural changes in the power system on flexibility requirement, network interconnection development being one of them. Another question worth investigating is that of the potential for network interconnection to reduce flexibility requirement, and the impact of the four other structural changes we studied on this potential. In simpler terms: for what combinations of VRE development does network interconnection bring the most value? Note that these ideas are not too distant from the concept of energy resource complementarity, covered in detail by Jurasz *et al.* [71].

As expressed in equations 3.6 and 3.7, a theoretical value for this potential can be evaluated by comparing the sum of flexibility requirements evaluated on individual countries to the flexibility requirement evaluated on a “copper-plate” system. The result effectively gives the reduction in flexibility requirement that the move from a system with no interconnection to one with infinite interconnection capacity would allow.

$$IFPP_h = \sum_c FPR_h(L_{net}^c(t)) - FPR_h(\sum_c L_{net}^c(t)) \quad (3.6)$$

$$IFEP_h = \sum_c FER_h(L_{net}^c(t)) - FER_h(\sum_c L_{net}^c(t)) \quad (3.7)$$

where:	h	horizon, <i>i.e.</i> annual, weekly or daily
	$IFPP$	Interconnection flexible power potential (GW)
	$IFEP$	Interconnection flexible energy potential (TWh)
	FPR	Flexible power requirement function, see Section 3.3.4
	FER	Flexible energy requirement function, see Section 3.3.4
	$L_{net}^c(t)$	Net load of country c , see Equation 3.2

The analysis framework described in Figure 3.1 can then be applied in the same way as previously: values of p_{wind} , p_{solar} , p_{heat} and p_{cool} are sampled to build net load curves, on which $IFPP$ and $IFEP$ can then be evaluated.

3.5.2 Results

Due to the limitations mentioned previously, it is preferable to study the qualitative impact of input variables on $IFPP_h$ and $IFEP_h$ before interpreting the results of the Global Sensitivity Analysis. A few 2 dimensional cuts of the 4 dimensional problem are hence shown in Figure 3.11 for the most impacting variables, which, unsurprisingly, are p_{wind} and p_{solar} . Interconnection flexibility potentials are evaluated on the same geographical scale as in the previous section (France, Great-Britain, Belgium, Germany, Switzerland, Italy and Spain), using the same load and VRE generation data from RTE's 2017 adequacy report [40].

Based on the 95th percentiles of FPR and FER , Figure 3.11 shows the inter-connection flexibility potentials on the annual, weekly and daily timescales. As was done in the previous section, these potentials are expressed in terms of wind and solar penetrations, with electric heating and cooling set to their 2017 values. For example, 0.3 wind indicates that on average, in France, annual wind generation amounts to 30% of annual energy demand, with p_{wind} in other countries taking a value reflecting a similar development relative to their 2036 penetration expressed in Table 3.2.

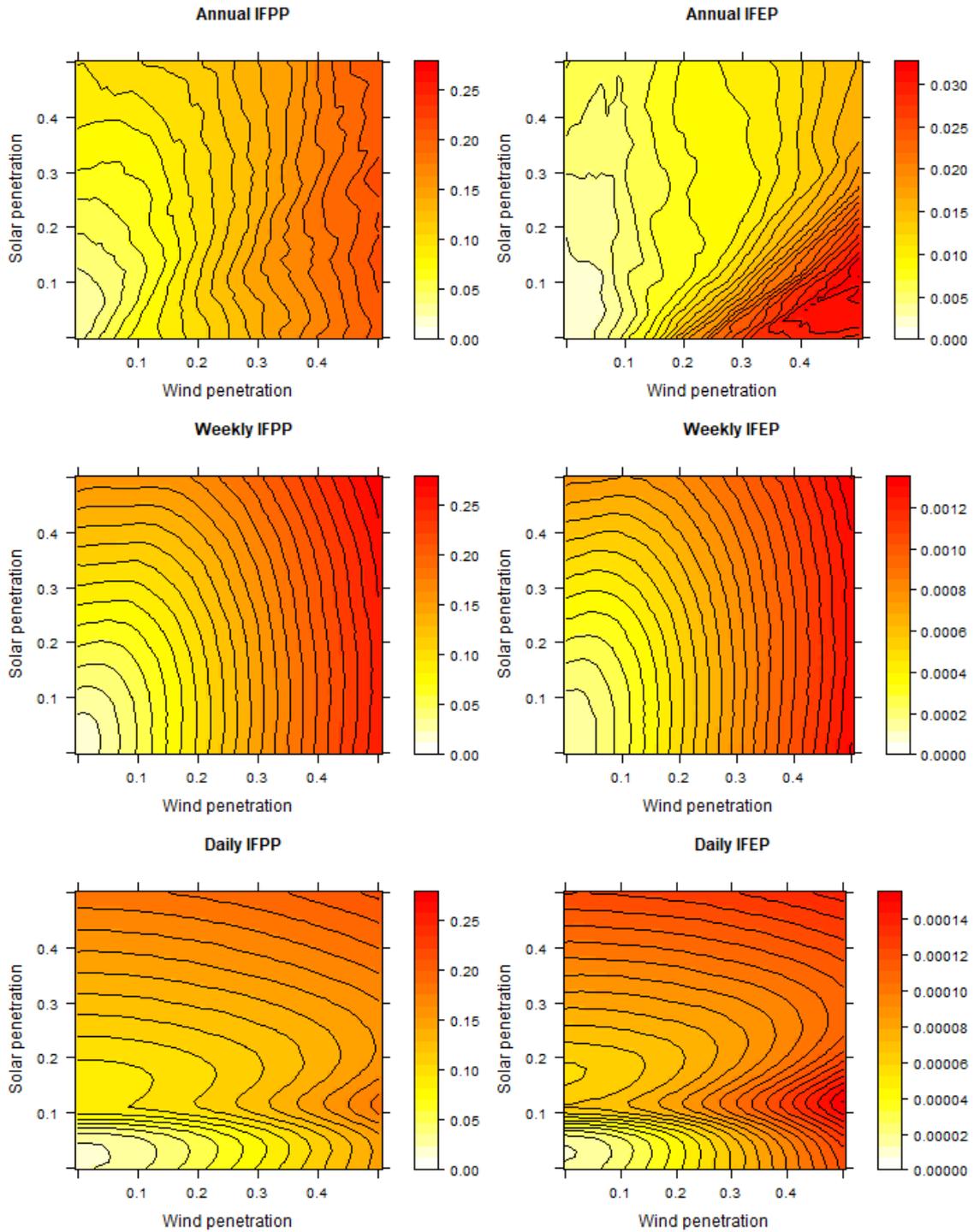


Figure 3.11: Based on the 95th percentiles of FPR and FER , interconnection flexible power potential ($IFPP$) in GW (left) and energy potential ($IFEP$) in TWh (right) in terms of wind and solar penetrations. Top, middle and bottom rows show results for the annual, weekly and daily timescales respectively.

These results clearly confirm what was more difficult to interpret in Figure 3.5: network interconnection provides more value as VRE penetration increases. On the daily timescale, this is true regardless of the wind/solar balance, while on the

annual and weekly timescales, this effect is more significant in wind dominated systems. One should however keep in mind that, as seen in Section 3.4.2, this increase in interconnection flexibility potential is accompanied by an increase in flexibility requirement. If $IFPP$ and $IFEP$ are expressed as a percentage of $\sum_c FPR$ and $\sum_c FER$ respectively, for the annual and weekly timescales, the general observation holds: higher VRE penetration means higher $IFPP$ and $IFEP$ (see Figure A.2 in the appendix). For the daily timescale however, there is a solar penetration level for which perfect interconnection meets the highest proportion of flexibility requirement, around 10%.

Considering the difference between the 2017 situation ($p_{wind} \approx 0.02$ and $p_{solar} \approx 0.05$) and the 2036 Ampere scenario situation ($p_{wind} = 0.34$ and $p_{solar} = 0.12$), we can expect network interconnection to become an increasingly important flexibility solution over all three considered timescales. This result corroborates observations made on the potential evolution of the role of flexibility solutions made in section 2.4.2. From Figure A.2 in the appendix, we can read that in the 2036 Ampere scenario situation, perfect interconnection reduces flexibility requirements from 5 to 30% depending on the requirement type.

These results are of course very dependent on the size of the interconnect and on the diversity and complementarity between its climate conditions. Considering a larger zone will further increase $IFPP$ and $IFEP$, all the more so as VRE penetrations increase. Different regional characteristics will have different impacts: interconnecting regions with greater longitude differences will increase interconnection flexibility potential on the daily timescale, while interconnecting regions with greater latitude differences may increase interconnection flexibility potential on the annual timescale (peak summer vs peak winter load).

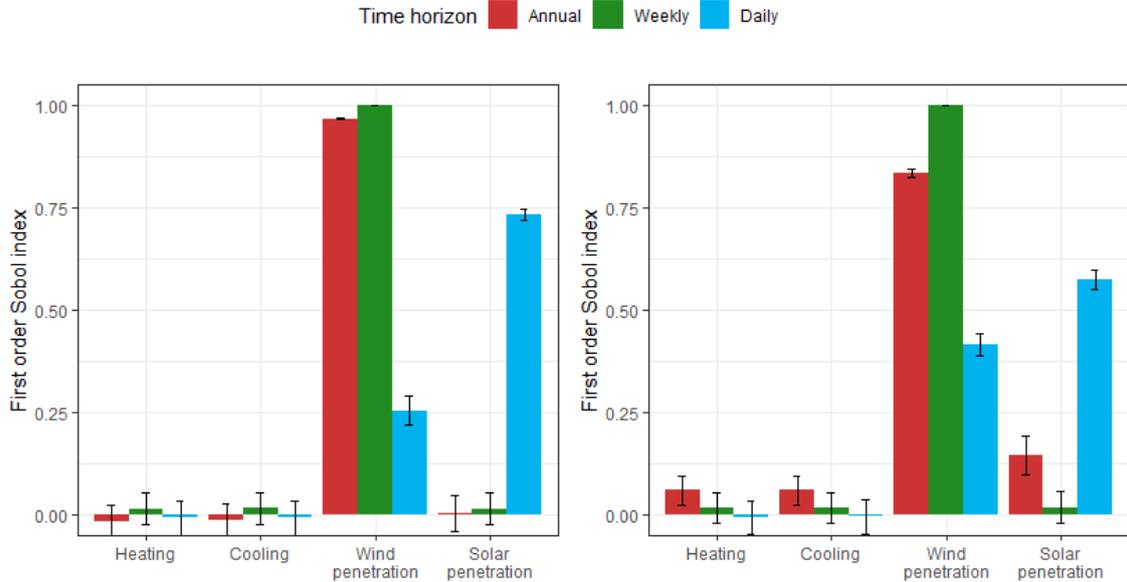


Figure 3.12: GSA results for interconnection flexible power (left) and flexible energy (right) potentials.

Figure 3.12 shows the results of the GSA with p_{wind} , p_{solar} , p_{heat} and p_{cool} sampled

in the interval [2017, Ampere 2036] using a uniform distribution. Considering the expected changes on the Western-Europe power system in the years to come, the change in the potential for network interconnection to provide flexibility is almost exclusively due to increases in VRE penetrations. Combining this information with Figure 3.11, we can confirm this change will be in the form of an increase, due to wind on the annual and weekly timescales, and both due to wind and solar on the daily timescale.

3.6 Conclusion

This chapter presented a set of frequency spectrum analysis based metrics to quantify annual, weekly and daily flexibility requirements, expanding the current metric paradigm which has concentrated on shorter timescales. The proposed methodology also allows the examination of these requirements' sensitivity to five variables: the degree of network interconnection and the penetration of wind power, solar power, electric heating and cooling. The metrics have been applied to a case study, evaluating flexibility requirements for potential evolutions of the French power system, accounting for interconnection with electrically connected countries. A particular focus was given to the 2017 situation and to a 2036 scenario with an ambitious VRE deployment.

The Global Sensitivity Analysis has shown that the most impacting variables differ with the considered aspect of the flexibility problem. Both daily and weekly requirements are set to increase, the prior primarily due to solar power development, the latter almost exclusively due to wind power development. On the annual timescale, electric heating penetration reduction, wind power development and network interconnection should overcome the increasing effect of solar power where flexible energy is concerned. In terms of flexible power, wind power should drive the requirement up.

These conclusions are valid for France, they may change with location, depending on VRE penetrations, on the balance between wind and solar power and on the amount of electric heating. Several general conclusions can however be drawn: (i) flexible power requirements are of the same order of magnitude for annual, weekly and daily timescales, (ii) annual flexible energy requirements are greater than weekly and daily ones by one or two orders of magnitude, (iii) daily flexibility requirements are highly dependent on solar penetration, (iv) weekly flexibility requirements are highly dependent on wind penetration, and (v) annual flexibility requirements are a function of several factors.

The proposed metrics and analysis framework were also used to evaluate the potential for network interconnection to reduce flexibility requirement by exploiting diversity in load and VRE generation profiles. This potential was shown to increase with VRE penetration. For the annual and weekly timescales, this is particularly true in wind dominated systems, while on the daily timescale, increases in both solar and wind penetrations lead to increases in interconnection flexibility potential.

Most of the work presented in this Chapter was published in article format in 2018 [49]. Note that the proposed flexibility requirement metrics have since then been extended by Olsen *et al.* [62] to look at additional, smaller timescales.

Saarinen *et al.* [119] also made an interesting extension to these metrics, splitting the flexibility power requirement into upwards and downwards regulation, easing their comparison with FS operational constraints. They can be used to build a better intuition of technologies and capacities that could be used to balance supply and demand, without having to use complex dispatch or investment models.

Flexibility metrics are very valuable to build these intuitions, condensing vast amounts of system data into a limited number of key characteristics. Their descriptive nature make them an effective teaching tool, explaining optimisation model outputs or policy recommendations. However, descriptive statistics are of little use when searching for robust and effective ways of dealing with the identified evolutions in power system flexibility requirement. Such a question, that of the optimal combination of flexibility solutions, calls for optimisation techniques, and is covered in the following two chapters.

3.7 Résumé en français

Comme introduit dans le Chapitre 1, la transition énergétique en cours augmente la variabilité et l'incertitude auxquels le système électrique doit faire face, conduisant à une augmentation du besoin de flexibilité. Dans le Chapitre 2, la revue de littérature des méthodes de quantification de la flexibilité a mis en valeur le fait que les indicateurs de besoin de flexibilité existants se concentrent sur la mise en lumière de phénomènes de court-terme³. Le travail présenté dans ce chapitre vise à compléter et étendre la compréhension actuelle en quantifiant comment et pourquoi le besoin de flexibilité moyen-terme va évoluer du fait de changements long-terme dans la structure de la consommation résiduelle.

Les résultats du Chapitre 2 ont montré à quel point les leviers fournissant la flexibilité sont très différents selon que l'on considère l'horizon annuel, hebdomadaire ou journalier. Considérer ces horizons séparément dans notre analyse du besoin de flexibilité est donc primordial pour pouvoir comprendre et expliquer comment le système électrique doit s'adapter à son environnement en mutation.

Notre méthode d'analyse est construite sur la base de deux indicateurs exprimant deux besoins de flexibilité, l'un en puissance, l'autre en énergie. Ces indicateurs sont appliqués séparément sur les composantes annuelles, hebdomadaires et journalières de la consommation résiduelle, obtenues grâce aux filtres fréquentiels également utilisés dans le Chapitre 2. Ce processus de quantification est appliqué à des dizaines de milliers de consommations résiduelles différentes, construites en faisant varier la pénétration de l'éolien, du solaire, la consommation de chauffage, de la climatisation, et le degré d'interconnexion entre pays (voir Figure 3.1). Sur la base des données de sortie, nous pouvons effectuer une analyse de sensibilité du besoin de flexibilité à ces 5 variables long-terme.

Cette méthode d'analyse de sensibilité est appliquée au système électrique français en considérant ses voisins électriques, avec un focus particulier sur la situation 2017 et sur un scénario prospectif à horizon 2036, présentant un développement des EnRV

³Dans ce manuscrit, le court-terme fait référence à l'infra-journalier ; le moyen-terme au journalier, hebdomadaire et annuel ; le long-terme au pluriannuel.

ambitieux. L'analyse de sensibilité montre que les variables qui impactent le plus le besoin de flexibilité dépendent du type de besoin considéré. Les besoins sur les horizons journaliers et hebdomadaires seront amenés à augmenter, le premier principalement dû à l'augmentation de la pénétration de solaire, le second quasi exclusivement du fait de l'augmentation de la pénétration de l'éolien. Sur l'horizon annuel, pour le besoin de flexibilité en énergie, le développement des interconnexions, de l'éolien, et la baisse de la consommation du chauffage électrique devraient compenser l'effet haussier du solaire. Le besoin de flexibilité en puissance, lui, devrait augmenter du fait du développement de l'éolien.

Ces conclusions, valides pour le cas français, pourraient être différentes sur un autre système, selon la pénétration des EnRV, l'équilibre entre éolien et solaire, et le niveau de consommation de chauffage électrique. Nous pouvons néanmoins tirer quelques enseignements généraux :

- Les besoins de puissances flexibles sont du même ordre de grandeur pour les horizons annuels, hebdomadaires et journaliers.
- Pour les besoins d'énergie flexible, les besoins annuels sont supérieurs aux besoins hebdomadaires et journaliers d'un ou deux ordres de grandeur.
- Les besoins de flexibilité journaliers sont très dépendants de la pénétration du solaire.
- Les besoins hebdomadaires sont très dépendants de la pénétration de l'éolien.
- Les besoins annuels sont fonction de nombreux facteurs.

Les indicateurs et le cadre d'analyse présentés ont également servi à évaluer le gisement de flexibilité que peut apporter l'interconnexion de systèmes voisins, grâce au foisonnement des consommations et des productions EnRV. Nous montrons que ce gisement augmente avec la hausse de la pénétration des EnRV. Sur les horizons annuels et hebdomadaires, cette conclusion est particulièrement vraie dans des systèmes à dominante éolienne, tandis que sur l'horizon journalier, des augmentations des pénétrations de l'éolien et du solaire mènent toutes deux à une augmentation du gisement de flexibilité.

Suite à la publication des travaux présentés dans ce chapitre, nos métriques de besoin de flexibilité ont été utilisées par Olsen *et al.* [62] pour analyser des horizons de temps supplémentaires, plus courts. Saarinen *et al.* [119] ont également repris ces indicateurs en séparant le besoin de puissance flexible en deux parties, à la hausse et à la baisse, de manière à faciliter la comparaison avec les contraintes techniques de différents leviers de flexibilité. Ceux-ci permettent de construire une première intuition des technologies et des capacités susceptibles de pouvoir maintenir l'équilibre offre-demande, sans recourir à des modèles de dispatch ou d'expansion de capacité, plus lourds en termes de développement et d'utilisation, et aux sorties plus complexes à analyser.

Les méthodes de quantification de la flexibilité sont très utiles pour construire ces intuitions, condensant de gros volumes d'information en un nombre limité de caractéristiques clés. Leur nature descriptive en font un excellent outil pédagogique, facilitant l'explication des sorties d'outils d'optimisation ou des recommandations de politique énergétique. Néanmoins, les statistiques descriptives atteignent leurs

limites quand il s'agit de proposer des stratégies d'investissement efficaces et robustes pour affronter les défis identifiés. La question du mix optimal de leviers de flexibilité nécessite l'usage de techniques d'optimisation, qui font l'objet des deux prochains chapitres.

Chapter 4

Representing flexibility in capacity expansion planning

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4.1 Introduction

Flexibility is the ability to cope with variability and uncertainty in generation and demand (see Section 1.2.2). It can be provided by flexible generation, flexible demand, energy storage or system interconnection (see Section 1.3). As all power system assets can effectively be considered to be flexibility solutions, we do not consider an optimal mix of flexibility solutions to be different from an optimal system. The optimisation problem we propose to solve is a cost-minimisation of a power system's capital and operational expenditure, under investment and operational constraints.

This Chapter starts with a review of existing literature covering this well-known power system planning problem (Section 4.2). A particular focus is made on the limited ability of Capacity Expansion Models (CExM) to express flexibility, both in terms of its requirement and its provision, and on the impact this might have on model outcomes.

A well-identified factor limiting the ability of CExMs to express flexibility is timeslices, the condensed model time steps designed to capture variations in load and VRE generation. This Chapter proposes an analysis of the impact of timeslice definition methods on capacity expansion model outcomes, varying both timeslice number and structure (Section 4.3). After having briefly described the open-source capacity expansion model OSeMOSYS, a new power transmission module is added to the framework, improving on existing work. Different timeslice definition methods are then presented and applied to a European case study consisting of 17 nodes, simultaneously considering investment in generation, storage and interconnection, on an investment period ranging from 2015 to 2050 in 5-year investment steps (Section 4.4).

4.2 Review of flexibility modelling in power system planning

4.2.1 Categories of power system planning models

As well as being an essential part of our modern way of life, power systems are technically and organisationally complex, are composed of capital intensive assets with lifetimes in the order of decades, and have far-reaching impacts on society. To avoid costly lock-in effects, not only in economic terms but in social and environmental terms also, careful modelling is required to accurately depict a power system's behaviour and to ensure that its future development meets all three components of the energy trilemma (equity, security, environmental sustainability).

Dozens of models¹ have been proposed by companies, institutions and academics alike to assist policy makers in power system planning. These model types fulfil a wide variety of goals:

- Stability studies and production cost models validate the technical feasibility of a given power system.
- Capacity expansion models optimise investment in new generation and transmission.
- Integrated assessment models evaluate the interactions between the power system and the rest of the energy system, macro-economic conditions or even global climate.

¹The terms “tool”, “model”, or “framework” can have different meanings depending on the speaker. Here, we use the term “model” to refer to a set of rules defining the relations between a problem's parameters and variables.

The sheer number of models has led to the publication of many review studies [70, 120–131]². These typically target the model user, helping him to choose from existing models. This can entail drawing up simple lists [122], proposing a framework to classify models [124, 125, 130, 131], or extracting key model features and comparing them in table form (typical features include model purpose, geographical coverage, temporal resolution, modelling horizon, mathematical approach) [70, 120, 126, 129, 130]. Connolly *et al.* gives an estimate of the training time required for a typical application, another useful criterion when selecting a model [120].

More recently, reviews have also provided useful information for model developers. Several papers have adopted a historical approach, identifying trends in modelling methodologies, particularly how these are being adapted to improve the representation of current changes to the power system (most notably increased uncertainty and variability) [124, 127, 128]. Discussing future challenges to be met by model developers is another common feature, improving the treatment of variability and uncertainty being the most recurrent issue [70, 130, 131].

Despite efforts made in reviewing and classifying existing models, choosing one for a particular task still is a complicated matter. A review necessarily considers a subset of literature, be it models solving a particular problem [123], applied to a specific country [126], developed after a certain date [126, 130] or some unspecified selection. Ideally, reviewing requires hands-on experience with increasingly complex models, which are often opaque and inaccessible [126]. As well as being time-consuming, it can also be expensive, when considering proprietary models. To bypass this issue, Ringkjøb *et al.* asked developers to validate and update the information provided in their paper [130]. Similarly, Connolly *et al.* based their review on the results of a survey sent to model developers [120]. Yet when the International Renewable Energy Agency (IRENA) re-used Connolly’s results in one of their reports, they still felt the need to modify some evaluations based on their own experience [129]. Misinterpretations are made all the easier by the number of existing terminologies, which may draw different limits between model types, e.g. power system models vs long-term energy system models [125, 132], techno-economic vs macroeconomic models [133], operational power system models vs energy system optimisation models [128], operation decision support vs investment decision support [130]. Furthermore, as stated by Ringkjøb *et al.* models undergo continuous development, meaning the reviewer is effectively “shooting at a moving target” [130].

In this thesis, we will adopt the terminology used by the IEA and the IRENA and focus on two model types: Capacity Expansion Models (CExM) and Production Cost Models (PCM) [8, 129]. We differentiate them according to the considered problem: the former solves an investment problem, the latter a dispatch problem. Both model types are briefly described in Table 4.1, focussing on what they can and cannot do. The following section further investigates how the representation of flexibility can be improved in power system planning.

²Faced with a choice, one would pick [130] for its clarity and the fact that its contents were validated by model developers.

Table 4.1: Brief overview of the key differences between Capacity Expansion Models and Production Cost Models

	Capacity Expansion Models	Production Cost Models
Objective	Minimise CAPEX and a rough approximation of OPEX. Salvage value may also be included in the minimisation.	Minimise the OPEX of a system with fixed capacities. Unsupplied energy and curtailments costs may also be included in the minimisation.
Scope	Timeframe of several decades. Short- and medium-term variability represented through the use of timeslices. Usually considers the full energy system.	Focuses on a single year, of which there may be several instances in case of stochastic studies. Full year represented, usually with hourly resolution. Usually considers only the power system.
Inputs	Timeslice values for load and VRE. Limited technical and economic parameters of power system components (generators, storage and transmission network).	Load and VRE hourly time series. Detailed technical and economic parameters of power system components.
Outputs	Installed capacities of power system components, costs, emissions...	Hourly behaviour of power system components.
Limitations	Poor representation of short and medium-term flexibility due to low temporal resolution, lack of chronology and the limited account of technical constraints.	Considers static installed capacities.
Example studies	Define investment pathways, analyse the total system cost implications of policy decisions such as electrification, emission tax, VRE subsidies, nuclear phase-out...	Validate a prospective system's feasibility in terms of adequacy and flexibility, compare system development scenarios in terms of OPEX, energy mix, emissions, curtailment...
Example models	TIMES [134], MESSAGE [135], PRIMES [136], OSeMOSYS [137].	PLEXOS [138], Continental [139], Crystal Energy Planner [140], Antares [141].

4.2.2 Accuracy issues in Capacity Expansion Models due to simplified consideration of flexibility

Capacity Expansion Models (CExMs) play a crucial role in power system planning and energy policy: they provide the basis on which stakeholders decide when, where, how much and what technology type to build or retire. To keep the problem tractable, their representation of flexibility is simplified. While this was historically acceptable, in the face of growing variability and uncertainty on the short (see Section 2.2) and medium-term³ (see Chapter 3), it can strongly affect the validity of results, as we will see shortly. In mankind’s struggle to reduce its carbon emissions, this is proving problematic as non power system experts (climate scientists, environmental engineers or NGOs) use these models to build 100% renewable energy plans (see Heard *et al.* [142] for a review of such studies, and Brown *et al.* [143] for a rebuttal of their analysis).

Due to the reasons exposed in Figure 4.1, the poor representation of flexibility in CExMs has repeatedly been shown to cause an underestimation of total system cost and system-specific errors in the evaluation of emissions, two crucial parameters in system planning [132, 144–152]. In studies that evaluated loss-of-load, it has been shown to reach unacceptably high levels, making the proposed power systems arguably irrelevant for planning purposes [149, 153]. Errors relating to capacity and energy mix tend to be more significant still. Studies consistently show the following model behaviour: the underestimation of the value of flexibility leads to an overestimation of baseload generation and VRE capacity, and an underestimation in flexibility solution capacity, be it mid-merit generation, storage, interconnection or flexible demand [132, 144–150, 154–157]. The extent of these effects has been shown to depend on system characteristics [149, 151, 157–160] (if there is ample flexibility in a system, poor flexibility representation is less of an issue), but it becomes consistently more significant as VRE penetration increases [144, 151, 154].

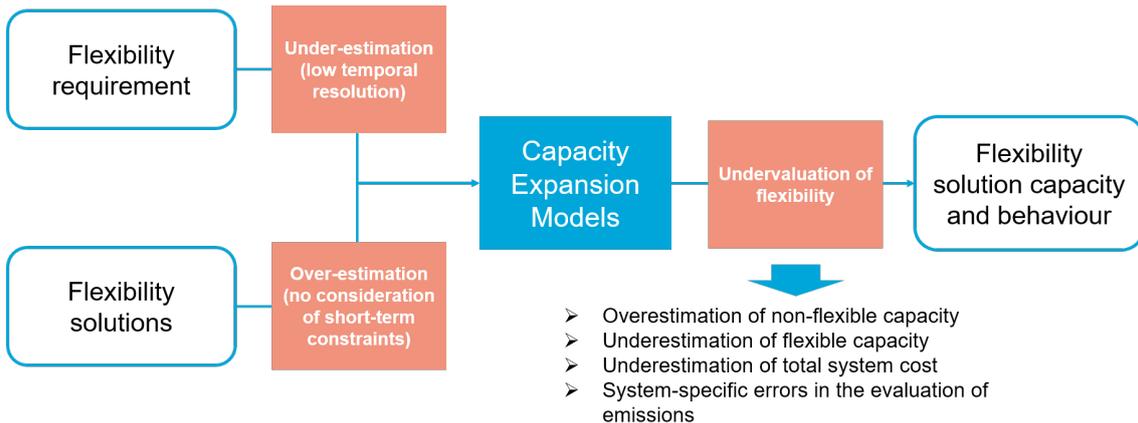


Figure 4.1: Simplifications made in Capacity Expansion Models cause flexibility to be undervalued. This leads to errors in optimal installed capacities, total system cost and emissions.

³In this thesis, short-term refers to intraday, medium-term to daily, weekly and annual horizons, long-term refers to more than a year.

CExMs underestimate flexibility requirement

The first reason behind described model accuracy issues is the under-estimation of flexibility requirement. In most CExMs, variability has traditionally been expressed using timeslices, the condensed model time steps designed to capture variations in load and VRE generation. A typical setup might express seasonal variations, weekday vs weekend and night-time vs day-time vs peak load, totalling $4 \times 2 \times 3 = 24$ timeslices. The load and VRE generation timeslice values are typically built by averaging hourly time series values on respective sections of an hourly time series, hence underestimating variability and preventing adequate expression of chronology between time steps. Several studies have evaluated the impact of this simplified approach by running CExM simulations with different numbers of timeslices, with the aforementioned observations [144, 146, 154, 161].

Other work has tried to determine how many timeslices should be used to capture sufficient variability. After having optimised the choice of timeslices using a hierarchical clustering technique on hourly time series to group similar simulations, Merrick *et al.* [162] compared CExM outputs while varying the number of timeslices. They found that without VRE, around 10 timeslices were sufficient to capture variability. Once VRE is added to the system however, this number increased to the order of 1000. The fact that VRE capacities are endogenous in CExMs makes the task of selecting the appropriate timeslices and an adequate number of them challenging.

Another timeslice limitation is the inability to accurately reflect geographical aspects of variability in multi-region studies: relevant timeslice choice in a region with high wind resource will be very different to that of a region with high solar resource. Besides, expressing geographical correlations in VRE profiles is potentially feasible, but may require such a high number of timeslices that one might as well use time series data.

CExMs overestimate flexibility provision

The second reason behind described model accuracy issues is the over-estimation of flexibility provision. Power system operators must manage many technical and economic parameters affecting flexibility solution behaviour (see Section 2.2.2 for more details). Due to the absence of chronology between timeslices and low model temporal resolution, such constraints can be difficult to implement in CExMs [163].

Several studies have attempted to quantify the impact of not including these constraints, comparing results with that of a Unit Commitment and Economic Dispatch model (UC-ED)⁴. Noteworthy studies include:

- Poncelet *et al.* [144], where the poor representation of flexibility requirement (temporal resolution) is shown to have greater impact on model outputs than the poor representation of flexibility provision (operational constraints).

⁴The Unit Commitment problem determines which units are switched on and off. The Economic Dispatch problem determines how much power each unit generates. Both are integral parts of PCMs.

- Palmintier [164], who studies the impact of constraints individually rather than collectively, showing that operating reserves and maintenance are the most important and hour-to-hour ramping the least, though it must be pointed out that generation was the sole flexibility source considered in the study.
- Shortt *et al.* [151], where sensitivity analyses show that the impact of ignoring chronology and operational constraints is highly system specific, and increases with growing wind capacity, though again, generation was the only flexibility source
- Poncelet *et al.* [158], where adding storage as a flexibility solution was shown to limit the impact of ignoring UC constraints, suggesting that they could potentially be neglected if sufficient flexibility is provided by non-generator based solutions.

Note that model outputs should ideally be validated against real world data, and that this is very rarely performed in literature based on CExMs (Pina *et al.* [161] is a notable exception). The computation time implications of methods proposed in papers is another crucial element which is often lacking (Palmintier [164] is a notable exception).

4.3 Modelling framework setup

4.3.1 Description of OSeMOSYS

OSeMOSYS is a capacity expansion model first presented and made publicly available in 2008, and first described in a peer-reviewed paper in 2011, with multiple levels of abstraction (plain English, algebraic formulation, and GNUMathprog code) [165]. Since then, it has undergone continued development, has been translated into other programming languages (Pyomo [166], which is the version used in this work, and GAMS), and has been used for many peer-reviewed case studies⁵.

OSeMOSYS was designed to be open-source, to have a less significant learning curve than other long-established energy system models (MARKAL/TIMES, MESSAGE, PRIMES, EFOM, POLES...), and to have a modular structure easing its integration with other tools. OSeMOSYS can be used to build both linear and mixed-integer linear problems depending on whether the user wants to define the capacity of a technology unit, and can work with many solvers. In the work presented here, only linear problems were formulated, and they were solved using the XPRESS solver [167].

Its objective is to minimise the net present cost of an energy system while meeting demand for energy carriers, energy services or their proxies. A system is modelled by a succession of *technologies* and *fuels*, the former able to both use and produce the latter. Total cost, assigned to each *technology*, *year* and *region*, consists of CAPEX, OPEX and emission penalties, minus salvage value. The full description of the up-to-date OSeMOSYS problem (sets, parameters, variables, objective function and constraints) is available online in the OSeMOSYS manual [168].

⁵See OSeMOSYS website for a list [137].

Appendix D provides the full description of the problem we solved, which includes additions and modifications made to the “official” OSeMOSYS problem. The most significant change concerns the power transmission module, described in the following Section 4.3.2. Another noteworthy change is the addition of two constraints imposing an annual cycle in storage level. In case studies with a significantly decreasing CO₂ allowance, or significantly increasing CO₂ cost, the absence of these constraints can lead to storage assets being charged up at the start of the investment period for energy release at the end of the period. Note that the problem formulation in Appendix D also includes additional functionality presented in Chapter 5, which is not used in this Chapter.

To ease the understanding of the equations presented in this Chapter, the different sets used in OSeMOSYS are presented in Table 4.2, along with their symbols.

Name	Symbol	Description
REGION	r	Defines the regions to be modelled, e.g. different countries.
TECHNOLOGY	t	Defines the elements of the energy system that change a fuel from one form to another, use it or supply it.
FUEL	f	Defines the energy vectors, energy services or proxies entering or exiting technologies.
STORAGE	s	Defines the storage facilities in the model.
EMISSION	e	Defines the emission types that can potentially result from the operation of the defined technologies.
MODE_OF_OPERATION	m	Number of modes of operation that the technologies can have.
YEAR	y	Investment time frame of the model, it contains all the years to be considered in the study.
TIMESLICE	l	List of model time-steps within an investment year.
SEASON	ls	Defines the seasons that are accounted for and their order.
DAYTYPE	ld	Defines the day types that are accounted for and their order.
DAILYTIMEBRACKET	lh	Defines how many parts a day is split into and their order.

4.3.2 Power transmission module

Existing OSeMOSYS and GENeSYS-MOD trade modules

The standard version of OSeMOSYS allows the trading of *fuels* between *regions*, though the adopted modelling is very rough. It consists of (i) a single parameter, TradeRoute, defining the possible links between regions r and rr, and (ii) two variables, Trade and TradeAnnual, which respectively define the quantity of fuel traded between regions r and rr in a given timeslice and aggregated over a year. The concept of capacity, fundamental for the modelling of electric power transmission, is absent. The concept of cost is also absent, which makes the modelling of the exchange of other *fuels* fairly precarious also.

In GENeSYS-MOD, Technische Universität Berlin’s (TUB) own model largely based on OSeMOSYS, a transport module has been added to improve the represen-

tation of electricity interconnectors [133]. Modifications include the introduction of a trade loss between regions, an interconnection capacity limiting power exchanges, which the solver can build more of, and an investment cap to transmission capacity with a maximum growth rate.

There are several problems with the transport module proposed by TUB. (i) An interconnector has neither operational life nor salvage value. This distorts the competition between flexibility solutions by discouraging investment in transmission capacity when compared to generation or storage. (ii) The use of a maximum growth rate for interconnector capacity means it is not possible to build new capacity on a border that doesn't already have some (as well as requiring the addition of specific equations to deal with the limits of the investment period). (iii) The modelling doesn't allow asymmetric interconnector capacity, a common feature on the European Power System we are to model, as shown in ENTSO-E's datasets [44]. Besides these functional issues, there are also a few problems with style. The nomenclature of parameters and variables doesn't match that of the other OSeMOSYS modules, nor do several structural organisations, most notably the way residual trade capacity⁶ is dealt with. These differences make the use of the transport module very prone to error.

New power transmission formulation

The transport module was therefore re-written to solve these issues, and integrated to the original OSeMOSYS problem. The resulting model will hereafter be referred to as OSeMOSYS for simplicity. Its sets, parameters, variables, objective function and constraints are fully described in Appendix D. A few of its main differentiating features will now be discussed.

The key balancing equation (EBa11) is similar in nature to that of OSeMOSYS: for all time steps (both investment *years* and *timeslices*), a *region's fuel* production must be able to cover local demand, local *fuel* use by *technologies* and net trade with interconnected regions. Net trade is defined as the sum over interconnected regions of imports and trade loss corrected exports (EBa12).

$$\forall_{r,f,y,l} \quad \text{Production}_{r,f,y,l} \geq \text{Demand}_{r,f,y,l} + \text{Use}_{r,f,y,l} + \text{NetTrade}_{r,f,y,l} \quad (\text{EBa11})$$

In equations TRC1a and TRC1b, the modified formulation imposing a capacity limit to imports and exports means that, unlike in GENeSYS-MOD, interconnector capacity can be asymmetrical. This occurs when the trade capacity between two regions is limited by congestion on the internal network rather than on the actual interconnector. Besides, the power flow levels at which these congestions occur vary with weather conditions, load and generation patterns. As such, except in simple cases, reducing an interconnector's capacity to a single number is but a necessary approximation. When investing in new interconnection capacity, equation TRC5 ensures that the solver cannot invest only in one direction. This is, of course,

⁶Remaining available trade capacity from before the modelling period, see Appendix D.13.

another approximation, which also happens to be the one ENTSO-E takes in the Ten Year Network Development Plan (TYNDP) and Mid-term Adequacy Forecast (MAF) exercises.

$$\forall_{r,rr,f=Power,y,l} \quad \frac{\text{TotalTradeCapacityAnnual}_{r,rr,f,y} * (1 + \text{TradeLossBetweenRegions}_{r,rr,f,y})}{\text{CapacityToActivityUnit}_{r,t} * \text{YearSplit}_{y,l}} \geq \text{Export}_{r,rr,f,y,l} \quad (\text{TRC1a})$$

$$\forall_{r,rr,f=Power,y,l} \quad \frac{\text{TotalTradeCapacityAnnual}_{r,rr,f,y} * (1 + \text{TradeLossBetweenRegions}_{r,rr,f,y})}{\text{CapacityToActivityUnit}_{r,t} * \text{YearSplit}_{y,l}} \geq \text{Import}_{r,rr,f,y,l} \quad (\text{TRC1b})$$

The key functional difference between the transport modules of OSeMOSYS and GENeSYS-MOD lies in the consideration of the salvage value of interconnector capacity, which levels the playing field for the different flexibility solution types. This is done with the exact same structure (parameters, variables and constraints) that OSeMOSYS uses to evaluate the salvage value of generation and storage assets, as is shown in equations TRC8, TRC9 and TRC10.

$$\forall_{r,rr,f,y} \quad \text{if } (y + \text{OperationalLifeTrade}_{r,rr,f} - 1) > \text{EndYear} : \\ \text{SalvageValueTrade}_{r,rr,f,y} = \text{CapitalInvestmentTrade}_{r,rr,f,y} * \left(1 - \frac{\text{EndYear} - y + 1}{\text{OperationalLifeTrade}_{r,rr,f}}\right) \quad (\text{TRC8})$$

else :

$$\text{SalvageValueTrade}_{r,rr,f,y} = 0$$

$$\forall_{r,rr,f,y} \quad \text{DiscountedSalvageValueTrade}_{r,rr,f,y} = \frac{\text{SalvageValueTrade}_{r,rr,f,y}}{(1 + \text{DiscountRate}_r)^{1 + \text{EndYear} - \text{StartYear}}} \quad (\text{TRC9})$$

$$\forall_{r,rr,f,y} \quad \text{TotalDiscountedTradeCost}_{r,rr,f,y} = \text{DiscountedCapitalInvestmentTrade}_{r,rr,f,y} - \text{DiscountedSalvageValueTrade}_{r,rr,f,y} \quad (\text{TRC10})$$

Investment in new trade capacity is limited by a parameter expressed in GW instead of a growth rate, allowing the construction of new interconnectors between regions that don't initially have any (see equation TRC4). The aforementioned nomenclature issues within the GENeSYS-MOD transport module were also corrected in order to match that of OSeMOSYS and reduce the chances of error in the setup of a case study.

Note that this remains a fairly simple approach to power flow modelling, enforcing only Kirchhoff's current law at a rough geographical granularity. As reviewed in Lumbreras *et al.* [169], much more complex power flow modelling can be applied to studies where the case study scope allows it, e.g. when performing transmission system expansion planning.

4.3.3 Description of the modelled system and the input data

The case study to which the methodologies developed in this Chapter and in Chapter 5 is applied was built to meet the requirements of the H2020 European project OSMOSE⁷ (see PhD scope in Section 1.4).

As shown in Figure 4.2, the modelled system covers 33 European countries aggregated to 17 OSeMOSYS regions. In terms of temporal resolution, the investment period ranges from 2015 to 2050, in 5-year steps. The nature and relations between the considered technologies and fuels composing each region of the modelled system are described in Figure 4.3. It should be noted that the modelling is limited to the power system and does not consider links to the hydrogen or natural gas systems beyond CCGT and OCGT power plants. This simplification is likely to have an impact on results, missing potential synergies between energy vectors, it should therefore be the focus of further work.

The parameter values were determined by OSMOSE project partner TUB, and are to be made public on the downloads page of the OSMOSE website [45] (e.g. annual demand, technology costs, operational lives, initial capacities, renewable potentials, emission limits, CO₂ costs, renewable share targets...). While TUB developed three long-term scenarios, we only used the input data set corresponding to the central scenario, entitled "current goals achieved". A brownfield modelling approach has been adopted, *i.e.* the planning exercise does not propose a system built from scratch but builds upon existing infrastructure. Note that coal capacity is disallowed from 2035 onwards, and that transmission capacities up to 2025 are set at values determined by ENTSO-E in their latest MAF and TYNDP reports. Investment in additional transmission capacity is allowed from 2030 onwards.

Among the many functionalities proposed in OSeMOSYS, a few are worth discussing briefly as they have a significant impact on model outcomes and some of them have been used differently in the various model runs performed in this Chapter and in Chapter 5.

- **CO₂ budgets.** They are defined per region and per investment time step, and gradually decrease over the investment period (see Figure E.1 in the Appendix).
- **VRE share targets.** Also defined per region and per investment time step, they follow a step function (see Figure E.2 in the Appendix).
- **Timeslices.** As made clear in the literature review (Section 4.2), this is a key parameter that needs careful attention to express a degree of flexibility requirement suitable for a specific case study. The remainder of this Chapter

⁷No relation to OSeMOSYS.

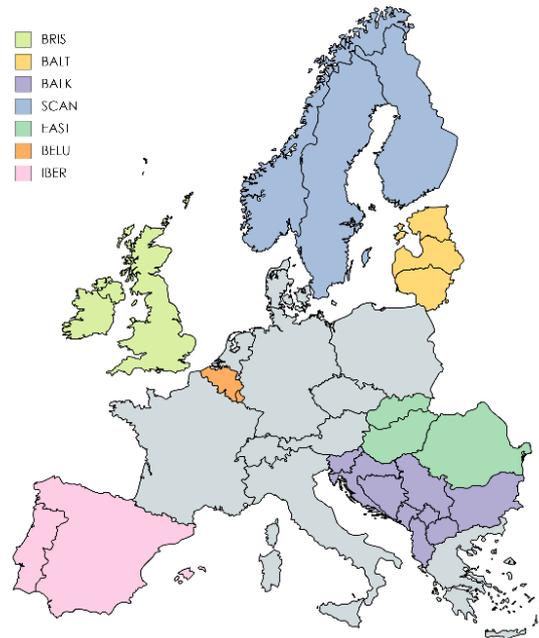


Figure 4.2: Geographical description of the OSeMOSYS European system. Grey countries are modelled as their own region, other countries are aggregated according to the colour code.

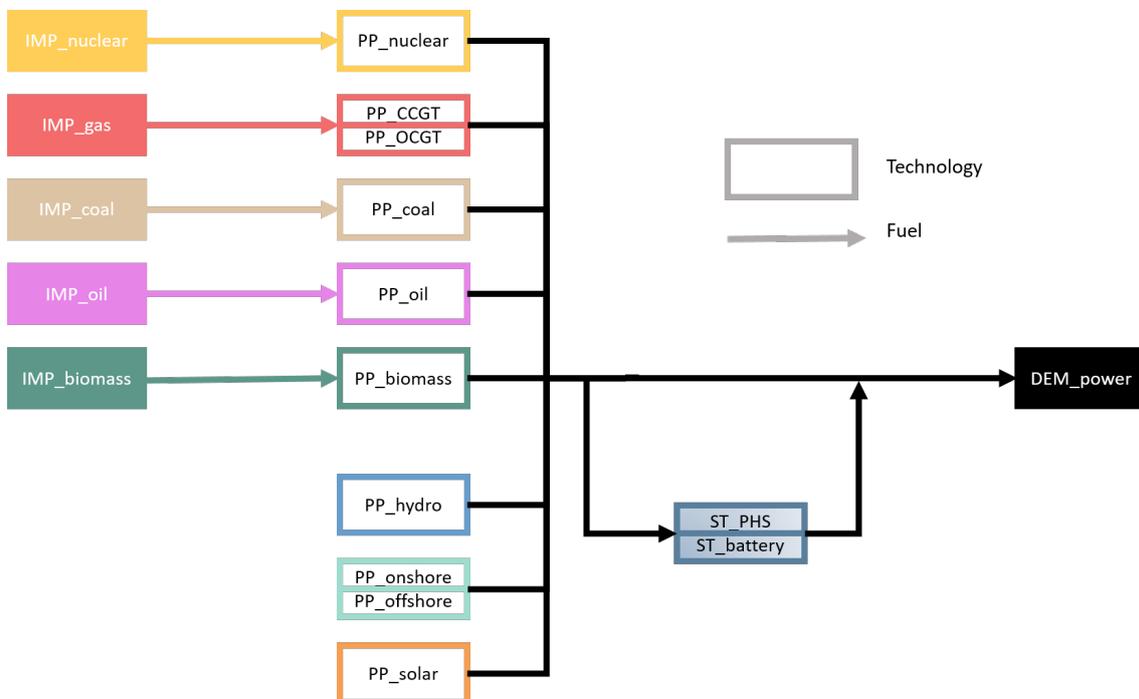


Figure 4.3: Description of the technologies and fuels considered in the OSeMOSYS European system.

will focus on the investigation of the impact of timeslice choice on CExM outcomes, testing many possible definition methods. The lessons learnt from this exercise will allow us to choose a single timeslice structure which will be used throughout Chapter 5.

- **Reserve Margin.** This functionality can be used to compensate for the fact that an investment pathway built on a timeslice-based operational understanding may be incapable of ensuring an acceptable reliability level when simulated with more operational detail (e.g. using a PCM). Each technology’s ability to contribute to a so-called reserve margin is, in the original OSeMOSYS formulation, expressed using a binary value. The aim of this Chapter being to study the impact of timeslice definition on model outcomes, this functionality was not used so as to not pollute the analysis. In Chapter 5, this functionality is used and extended upon.
- **Total annual max investment.** This parameter puts an upper bound on the investment in each investment step, each region and each technology, defined in GW terms. This parameter’s values were set by observing maximum development rates for French nuclear in the seventies and eighties, and for German VRE during the twenty-tens. A value of 25 GW per technology per 5-year investment step was thus obtained for Germany, applied uniformly over all technologies. Values were derived for each region, ratio-ed down according to each region’s annual demand. In this Chapter, the sensitivity of model outcomes to this parameter’s values is briefly examined. In Chapter 5, these values mentioned above are used for all model runs.

4.3.4 Timeslice definition methods

While production cost models will typically consider hourly time series of load and VRE behaviour in their unit-commitment and economic dispatch, the size of the problem solved by capacity expansion models prevents them from doing so. To reduce problem size, load and VRE time series are expressed in condensed form, using timeslices.

Different CExMs may consider these timeslices in different ways. In OSeMOSYS, they are structured as shown in Figure 4.4: each investment year is composed of a set of seasons, which are each composed of a set of day-types, themselves composed of a set of dailytimebrackets. The model user can specify their number, size and order; these must however remain the same in each subdivision. Note that this hierarchical structure was not included in the initial OSeMOSYS formulation proposed in [165], to the best of our knowledge, it was added later for the needs of the storage module (see up-to-date online documentation [170]).

VRE and load timeslice values were obtained based on a set of 35 years of hourly time series data, derived from reanalysis historical weather data. These time series express geographical, temporal and inter-variable correlations between load, wind, solar and run-of-river hydro; they are expected to be made public at the end of the OSMOSE H2020 project. The process applied to derive timeslice values from hourly values is shown in Equation 4.1. All hourly time steps corresponding to the

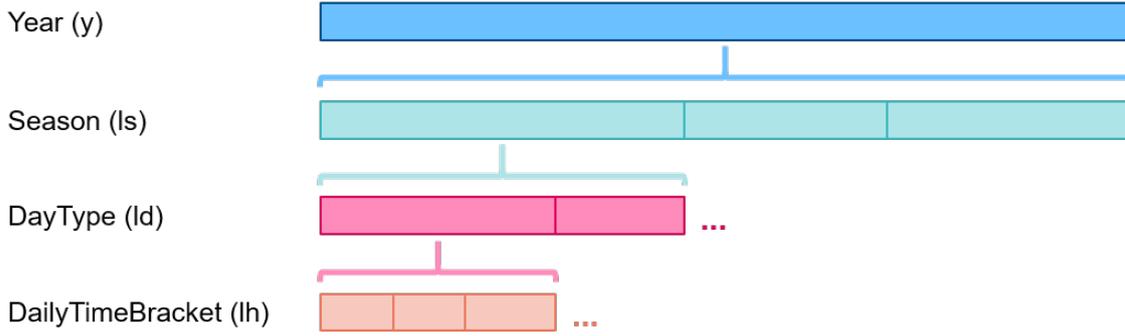


Figure 4.4: Hierarchical structure of OSeMOSYS timeslices. Lh specifies the number and order of the fractions of ld, ld those of the fractions of ls, and ls those of the fractions of lh.

intersection of a given set of season, day-type and daily-time-bracket are grouped together. The associated capacity factor timeslice value is set as the average power output relative to installed capacity on this group of hourly time steps. The principle for load timeslice values is the same.

$$\forall_{r,t,y,l} \text{CapacityFactor}_{r,t,y,l} = \text{mean}_{h_l \in h} (\text{CapacityFactorTimeSeries}_{r,t,wy,h}) \quad (4.1)$$

where: wy 35 weather years.
 h 8760 hours of a weather year.
 h_l Set of hours corresponding to the intersection of a season, a day-type and a daily-time-bracket matching the definition of timeslice l.

Timeslices must be defined uniformly over investment years and regions. As sunrise time differences can reach up to 4 hours between Finland and Portugal, fine-tuning timeslices to express precise features of load or VRE behaviour on a Europe-wide study is not a conceivable option. Instead, many timeslice structures were implemented, and these structures were tested for several 1 hour phase shifts in daily-time-bracket bins. The tested timeslice structures are detailed in Table 4.3.

Solar generation curves frequency spectra have three vastly dominating frequency components: annual, daily and half daily (see Figure A.3 in the Appendix). As a result, expressing solar variability using timeslices can be reasonably well achieved through seasons and daily-time-brackets. To study the impact of improving the representation of solar variability, the timeslice structures A to F were used.

Wind generation curves, on the other hand, have much more irregular frequency spectra (see Figure A.3 in the Appendix). They tend to have a significant annual component, a daily component in certain geographical locations, and many sporadic low frequency components which are different year on year. As a result, expressing wind variability using timeslices is much less straightforward than it is for solar. Timeslice structures G to I are an attempt at this, defining several day-types with different levels of wind power output.

Table 4.3: Different implementations of timeslice structures.

Reference (number of timeslices)	Seasons	Day-types	Daily-time-brackets	Variations
A (6)	Summer, Winter, Inter	1	Night, Day	4 different hourly phase shifts of daily-time-brackets
B (12)	Summer, Autumn, Winter, Spring	1	Night, Morning, Evening	4 different hourly phase shifts of daily-time-brackets
C (16)	Summer, Autumn, Winter, Spring	1	Night, Morning, Afternoon, Evening	3 different hourly phase shifts of daily-time-brackets
D (20)	Summer, Autumn, Winter, Spring	1	Night, Morning, Midday, Afternoon, Evening	3 different hourly phase shifts of daily-time-brackets
E (24)	Summer, Autumn, Winter, Spring	1	Night, Morning, Midday, Afternoon, Peak, Evening	3 different hourly phase shifts of daily-time-brackets
F (32)	Summer, Autumn, Winter, Spring	1	1, 2, 3, 4, 5, 6, 7, 8	3 different hourly phase shifts of daily-time-brackets
G (32)	Summer, Autumn, Winter, Spring	High wind, Low wind	Night, Morning, Afternoon, Evening	
H (48)	Summer, Autumn, Winter, Spring	High wind, Mid wind, Low wind	Night, Morning, Afternoon, Evening	
I (64)	Summer, Autumn, Winter, Spring	High wind, Mid-high wind, Mid-low wind, Low wind	Night, Morning, Afternoon, Evening	

Day-types are defined in such a way as to represent the same number of days, e.g. in timeslice structure G, summer-high wind timeslice values are evaluated on the half of summer days that have the highest daily mean wind power output. The limit between what is considered to be high and low wind power output is hence different for each season. There are several issues with this approach, inherent to the limitations of timeslices. The separation of day types is based on geographically

aggregated capacity factors (sum of onshore and offshore time series); it may be the case that the regions that are the most influential in determining whether a day ends up in a certain day-type will experience no wind investment. Also, we are enforcing an arbitrary chronology between day-types which is in no way an accurate representation of reality; this will affect storage behaviour and investment.

4.4 Impact of timeslice number and structure on capacity expansion outcomes

The results presented here are based on many model runs of the case study described in Section 4.3.3, using the different timeslice structures proposed in Table 4.3. We will start by investigating the impact of timeslice number and structure on computation time, TOTEX and investment in various technologies on a reference case, before looking at two other case studies to evaluate the extent to which this impact depends on other modelling decisions.

4.4.1 Reference case

A first important point to make when investigating the impact of timeslice definition on CExMs is that of computation time. As seen in Figure 4.5, it increases slightly super-linearly with respect to the number of timeslices.

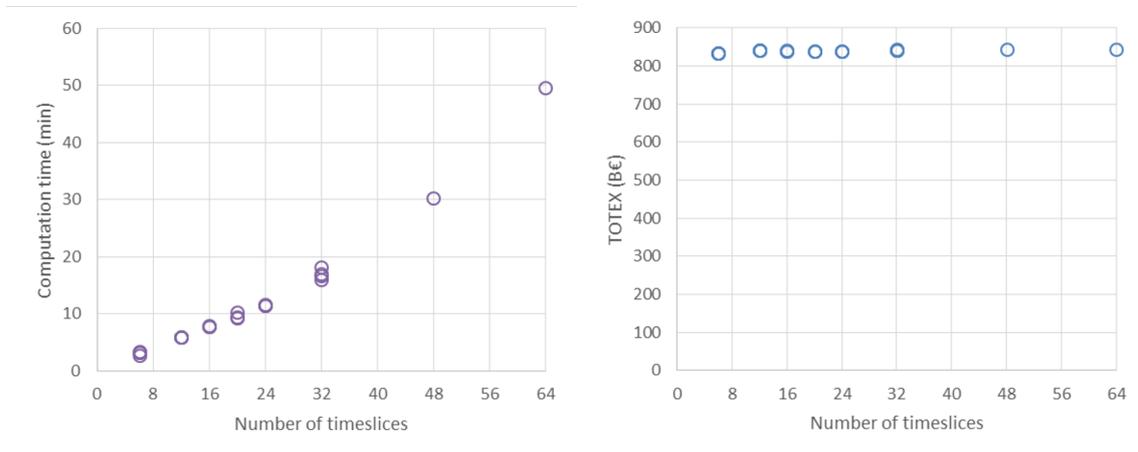


Figure 4.5: Impact of the number of timeslices on OSeMOSYS computation time (left) and TOTEX (right). Each dot corresponds to one of the variations of the 9 timeslice structures described in Table 4.3.

The graph on the right of Figure 4.5 shows limited change in TOTEX as the number of timeslices is increased: there is but a 1.3% increase between the average of A-runs and the I-run. As was made clear in the literature review however (see Section 4.2.2), limiting the analysis of timeslice impact to TOTEX is insufficient, more output variables need to be analysed.

While the overall trends match those mentioned in literature, Figure 4.6 shows that improving the representation of solar and wind variability through an increased

number of timeslices has a limited effect on VRE capacities. While solar capacity remains identical in all model runs, wind capacity increases by 1.3% with improved solar variability representation (gap between the average of A-runs and the average of F-runs), and decreases by 0.6% with improved wind variability representation (gap between the average of C-runs with the I-run). Closer inspection of investment plans reveals why that is: in many regions and investment years, respecting the VRE share targets and CO₂ budget constraints requires the saturation of solar and, occasionally, wind development rates imposed by the total annual max investment parameter.

The impact of improved representation of variability on other technologies' capacities is more significant, as their development is less directly impacted by modelled political constraints of VRE share targets or CO₂ budgets. Note that their maximum development rates are never reached. Between the average of A-runs and the I-run, base load generation capacity decreases: -0.5% in nuclear capacity; on the other hand, flexibility solution capacity increases: +3% in CCGT and interconnection, +4% in OCGT, +26% in batteries. The results for batteries should be taken with a grain of salt: their capacity is much higher for model runs with differentiated day-types expressing various levels of daily mean wind power output (average capacity of 65 GW, versus 11 GW for model runs with a single day type). The sensitivity of this result to chronology between day-types should be investigated for this result to hold (see Section 4.3.4).

4.4.2 Sensitivity analysis

Considering the extent to which these results seem to be impacted by political and industrial capacity constraints, some sensitivity analyses are required. We will look at two additional situations: “case Inv2” where the values of the total annual max investment parameter are doubled, and “case NoInvC” where this constraint is removed altogether along with the VRE minimum share constraint, and the annual CO₂ budget pathway is changed to one that decreases more slowly (Figure E.1 in the Appendix).

We will start by investigating whether the impact of timeslice number and structure is more important in these two cases, before comparing the mean model outcomes obtained in the reference case to “case Inv2” and “case NoInvC”.

Impact of timeslice number and structure

In “case Inv2”, increasing the number of timeslices still has a limited effect on VRE capacities, though it is more important than in the reference case (see Figure A.4 in the Appendix). Solar capacity remains identical in all model runs as, again, respecting VRE share targets and CO₂ budget constraints leads to a saturation of solar development rates. Wind development rates are no longer saturated however, and wind capacity increases with improved representation of solar variability: the gap between the averages of wind capacity in A-runs and F-runs reaches 5%.

For most FS's, the observations related to the impact of timeslices on their capacity are much starker in “case Inv2” than in the reference case (see Figure A.5 in the Appendix). Between the average of A-runs and the I-run, nuclear capacity

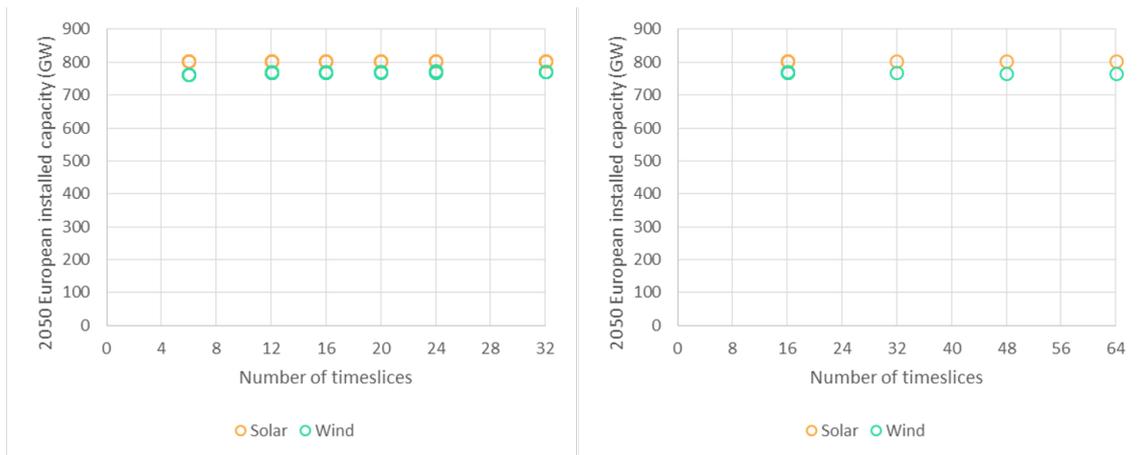


Figure 4.6: Left: impact of improved representation of solar variability on VRE capacity, through an increase in the number of seasons and daily-time-brackets. Each dot corresponds to one of the variations of timeslice structures A to F described in Table 4.3. Right: impact of improved representation of wind variability on VRE capacity, through an increase in the number of day-types. Each dot corresponds to one of the variations of timeslice structures C, G, H and I. Note that variations of the same structure lead to barely distinguishable results, and that wind capacity corresponds to the sum of onshore and offshore capacities.

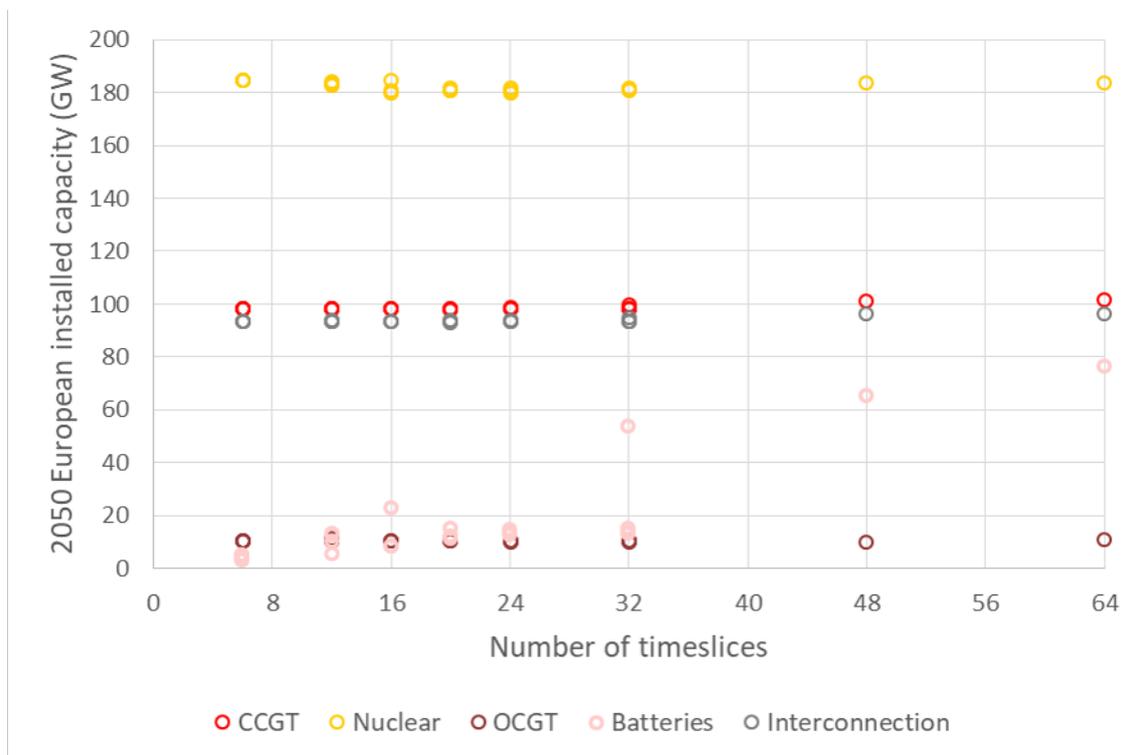


Figure 4.7: Impact of the number of timeslices on flexibility solutions 2050 European capacities. Each dot corresponds to one of the variations of one of the 9 timeslice structures described in Table 4.3.

decreases by 21% (0.5% previously), and OCGT and battery capacities increase by 67% and 236% respectively (4% and 26% previously). CCGT capacity only increases by 0.4% and interconnection capacity decreases by 11% (+3% and +3% previously).

“Case NoInvC” provides further evidence of increased impact of timeslice number and structure on model outcomes when OSeMOSYS is given more freedom in its investment plan. In terms of impact on VRE capacities (see Figure A.6 in the Appendix), results now match those found in literature: improving the representation of solar variability reduces its capacity by 1.1%, while it increases wind capacity by 1.1% (comparing the averages of A-runs and F-runs). Similarly, improving the representation of wind variability reduces its capacity by 4.6%, but it also reduces solar capacity by 0.4% (comparing the average of C-runs with the I-run).

In terms of FS’s, “case NoInvC” also mostly confirms previously made observations (see Figure A.7). Between the average of A-runs and the I-run, nuclear, CCGT and interconnection capacities decrease by 65%, 3% and 0.6% respectively, while battery capacity increases by 58%.

Impact of political and industrial capacity constraints

It is also worth exploring the impact of the political and industrial capacity considerations on direct model outcomes, not only their impact on the effect of timeslice number and structure. Comparing various energy mixes of pairs of reference case, “case Inv2” and “case NoInvC” model runs, Figure 4.8 clearly shows that the impact of the representation of flexibility requirement is much less significant than that of development rate, VRE share and CO₂ budget constraints.

This should by no means lead us to believe that the representation of flexibility in CExMs is not a problem. As made clear from the literature review in Section 4.2, the use of timeslices is but one of many flexibility-affecting simplifications used to keep capacity expansion problems tractable. Also, a significant problem pointed out in literature and that our approach cannot touch upon is that of technical feasibility. Solutions proposed by CExMs have been shown to be at significant risk of leading to unacceptably high levels of LOLE; the relevance of such solutions to power system planners is therefore questionable. This issue will be covered in extensive detail in Chapter 5.

Beyond these methodological considerations, an interesting policy message can be taken from Figure 4.8: if CO₂ emission reduction pledges are to be fulfilled, the inability of our industry to develop onshore wind and solar capacity fast enough will force us to massively develop low-carbon technologies with higher long-term marginal cost, notably nuclear and offshore wind generation.

4.5 Conclusion

In this Chapter, we have provided a broad overview of the chain of model types used in power system planning. We focussed on one of these, capacity expansion models, whose task it is to determine where, when, how much and what technology type to build or retire, and are therefore the model type that should be used to propose an optimal mix of flexibility solutions. Through a review of existing work, we showed

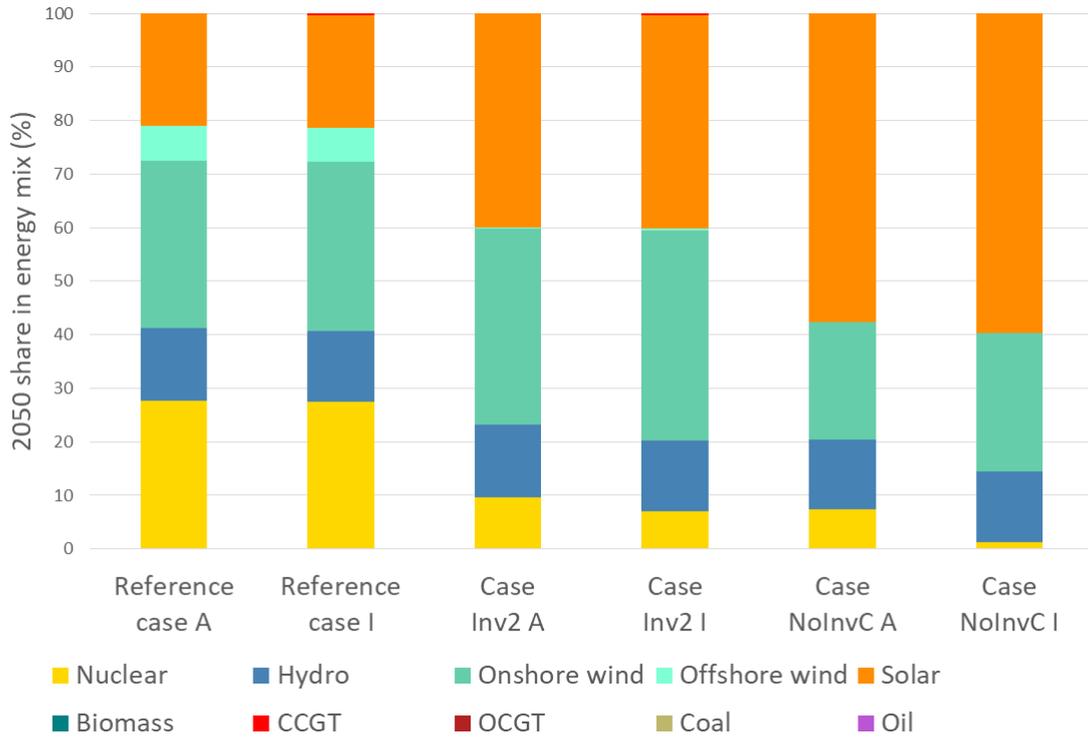


Figure 4.8: Annual contribution of considered generation technologies to total load, aggregated at the European level. For each case, the results are shown for the A and the I timeslice structures shown in Table 4.3.

that the representation of flexibility requirement and provision in CExMs is very rough, and that though this might have been acceptable in systems without VRE, it is no longer the case considering current and expected VRE development. Indeed, these simplifications may cause significant errors in key model outputs for system planning: TOTEX, emissions and capacity investment in various technologies.

We then tried to reproduce this literature result, focussing on a particular aspect of flexibility representation in CExMs: timeslices, the condensed time step used in these models to express operational aspects of power system. We thus used the open-source modelling framework OSeMOSYS to set up a case study designed for the needs of the H2020 European project OSMOSE. Considering the extent of network interconnection in the European power system and the significance of its contribution to flexibility provision (see Chapter 2), not being able to represent power flows nor to invest in cross-border capacity was not deemed to be acceptable; we hence proposed a power transmission module which we added to the OSeMOSYS framework.

Using this set-up, many model runs were performed, varying the number and structure of timeslices to study the impact of separately improving the representation of solar and wind variability.

The results obtained in our study of timeslice impact on model outcomes complement rather than confirm the findings of existing literature. We show that the reported impacts of poor flexibility representation of model outcomes do not neces-

sarily materialise when the degree of freedom of the model is reduced. This freedom is limited when a brownfield approach is adopted instead of a greenfield one, when investment is optimised over a pathway instead of for a single target year, and most importantly by taking political and industrial capacity constraints into account, e.g. maximum technology investment rates. This conclusion highlights (i) the extent to which our hope of success in reducing our CO₂ emissions holds on our industries' ability to roll-out new infrastructure fast enough, and (ii) the importance of taking this limiting factor into account in power system planning, something which is rarely done in academic settings.

In this chapter, we have focussed on evaluating the impact of a few CExM input parameters on model outcomes. However, we have not evaluated the suitability of the solutions such models propose. We are hence unable to guarantee that the derived power systems are technically able to ensure adequacy, stability or inertia. A typical and effective way of testing this consists in feeding the proposed solutions to models further down the line of the power system planning process. Using a production cost model, ensuring that CExM solutions are able to meet a user-defined adequacy criterion is the focus of the following chapter.

4.6 Résumé en français

Nous avons défini la flexibilité comme la capacité du système électrique à s'adapter à des variations et des incertitudes (voir Section 1.2.2), et avons spécifié que celle-ci peut être fournie par de la production flexible, de la consommation flexible, le stockage ou l'interconnexion (voir Section 1.3). Puisque tout composant d'un système électrique peut être considéré comme un levier de flexibilité, nous n'estimons pas que le mix optimal de leviers de flexibilité soit différent d'un mix optimal. Le problème d'optimisation que nous nous proposons de résoudre est donc une minimisation de la somme des coûts d'investissement et opérationnels d'un système, sous contrainte d'investissement et d'opération.

Ce chapitre commence par une analyse large de la littérature existante portant sur la planification du système électrique, décrivant la chaîne de modèles que ce processus implique. Nous nous concentrons particulièrement sur les modèles d'expansion de capacité (CExM), les plus à même de répondre à la question du mix optimal de leviers de flexibilité, leur rôle étant de déterminer où, quand, combien et dans quelles technologies l'on devrait investir pour minimiser les coûts totaux tout en assurant l'équilibre offre-demande.

De nombreuses études montrent que ces modèles peinent à représenter la flexibilité, tant en termes de son besoin que de sa fourniture. Si cela n'était pas problématique dans des systèmes sans EnRV, ça l'est aujourd'hui bien plus compte tenu du développement actuel et prévu de ces technologies. En effet, des simplifications historiquement acceptables conduisent désormais à des erreurs très significatives dans les sorties clés du processus de planification : les coûts totaux (sous-évalués), les émissions (sur- ou sous-évaluées selon les cas d'étude), et l'investissement dans les différents leviers de flexibilité (sur-investissement dans les technologies peu flexibles, telles que la production nucléaire, l'éolien ou le solaire, et sous-investissement dans les technologies plus flexibles, telles que les groupes thermiques

au gaz, les interconnexion ou le stockage).

Dans ce chapitre, nous avons cherché à reproduire ce résultat, en nous concentrant sur un aspect particulier de la représentation de la flexibilité dans les CExM : les *timeslices*, des pas de temps condensés sensés exprimer les aspects opérationnels du système électrique. Pour ce faire, nous avons utilisé le modèle open source OSeMOSYS pour construire un cas d'étude répondant aux besoins du projet européen H2020 OSMOSE. Compte tenu du degré d'interconnexion sur le système européen et de l'importance de sa contribution à la flexibilité (voir Chapitre 2), nous avons considéré qu'il était primordial de pouvoir modéliser les flux d'électricité et l'investissement dans la capacité d'interconnexion. Aussi, nous avons ajouté un module de transport d'électricité au modèle OSeMOSYS.

Sur la base de ce cas d'étude, de nombreuses exécutions du modèle ont été effectuées, en faisant varier le nombre et la structure des *timeslices*, afin d'évaluer l'impact séparé de l'amélioration de la représentation de la variabilité de l'éolien et du solaire.

Nos résultats complètent plus qu'ils ne confirment les résultats de la littérature. Nous montrons que les impacts de la représentation limitée de la flexibilité observés dans les travaux existants ne se matérialisent pas forcément lorsque l'on réduit le degré de liberté accordé au modèle. Celui-ci est réduit quand on adopte une approche *brownfield* plutôt que *greenfield*, quand l'investissement est optimisé sur une trajectoire plutôt que sur une année cible, et surtout quand on modélise des contraintes politiques ou de capacité industrielle, telles qu'un rythme maximal de déploiement d'une technologie. Ces résultats soulignent (i) à quel point nos espoirs de réduction des émissions de CO₂ dépendent de la vitesse à laquelle nos industries seront capables de construire de nouvelles infrastructures, et (ii) l'importance de considérer cette contrainte dans la planification du système électrique, ce qui est très rarement fait dans les études académiques.

Dans ce chapitre, nous nous sommes concentrés sur l'évaluation de l'impact de quelques paramètres d'entrée sur les sorties des modèles d'expansion de capacité. Cependant, nous n'avons pas examiné la pertinence des solutions proposées. Nous ne sommes donc pas en mesure de garantir que les stratégies d'investissement sont capables d'assurer l'équilibre offre-demande, la stabilité ou l'inertie du système électrique. Une méthode efficace pour le valider consiste à simuler le fonctionnement des systèmes électriques proposés à l'aide d'outils plus détaillés. Dans le prochain chapitre, grâce à un modèle de simulation du dispatch, nous proposons une méthode permettant de garantir que la solution proposée par un CExM respecte un critère de sécurité d'approvisionnement défini par l'utilisateur.

Chapter 5

Soft-linking OSeMOSYS with Antares

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5.1 Introduction

As seen in Chapter 4, it is well established that capacity expansion models struggle to express flexibility, both in terms of its requirement and in its provision. It is also well established that this deficiency can significantly impact the accuracy and relevance of model results when considering case studies with high penetrations of variable renewable energy. Much effort has been made to solve this issue in recent years, with authors employing various modelling strategies. This Chapter will start by discussing some of this work, categorising strategies from the point of view of the model user (Section 5.2).

To directly build upon years of work invested into developing trustworthy models, we chose to address the flexibility in capacity expansion planning issue by building a bi-directional soft-link between a CExM with a Production Cost Model (PCM). Despite having been identified as an interesting path in literature, the few existing studies performing a bi-directional soft-linking exercise have often suffered from a lack of transparency, particularly when it comes to the most crucial element: the way information is fed back from the PCM to the CExM. We help close this gap by providing a detailed comparison of three different feedback techniques, eventually implementing a methodology able to propose investment pathways simultaneously considering generation, interconnection and storage.

A general overview of the soft-linking process is provided, laying out the common features of the three feedback techniques which have been tested (Section 5.3). Each technique is then covered in extensive detail, describing its methodology, justifying modelling decisions and discussing potential issues. The first technique (Section 5.4) is a re-application of the methodology developed by Alimou *et al.* [153], adapted to consider an investment pathway instead of a target year. The second technique (Section 5.5) is inspired by the first one, but changes its nature to solve its multiple structural problems, and adapts it so as to invest not only in generation capacity, but also in interconnection and storage. The third technique (Section 5.6) blends the general philosophy of the second one with the flexibility provision metrics proposed in Chapter 2.

This soft-linking exercise has raised many questions and generated many ideas worth investigating, which are discussed in a “further work” section (Section 6.2).

5.2 Improving the representation of flexibility in capacity expansion planning

Solving flexibility related accuracy issues in CExMs has been the focus of much recent work. There are many different possible approaches which a few review exercises have attempted to classify [128, 129, 159]. Here, we will take inspiration from Helistö *et al.* [159] and categorise them from the point of view of the model user. If one wants to perform a capacity expansion study with high VRE shares, one can

either (i) use existing CExMs and marginally adapt them to improve the consideration of flexibility, (ii) make use of PCMs' better representation of power system operation by linking one to a CExM (using a uni-directional or a bi-directional iterative link), or (iii) build a new model specifically designed to simultaneously solve both an investment and a unit commitment problem. Note that from a modelling methodology point of view, the limit between these three approaches may be fairly vague, particularly between options 2 and 3.

It is crucial to keep in mind that the ambition of all three of these approaches are limited by computation time. Depending on a user's experience with different models, the type of study they aim to perform and even the characteristics of the modelled system [159], one option may be a better choice than the other two. Also note that flexibility is not the only challenge facing CExMs: improving the representation of cross-sectoral links, adequacy, transmission capacity and stability are other issues that researchers are attempting to address (see IRENA report for a review of such work [129]).

5.2.1 Adapting existing capacity expansion models

An intuitive and commonly found improvement consists in increasing the number of timeslices. However, as discussed in Chapter 4, more timeslices is not necessarily better: it increases computation time superlinearly and, if not chosen with care, does not necessarily carry useful information. To allow the modelling of storage, some CExM have changed the structure of their timeslices to allow the user to build chronology between them (e.g. OSeMOSYS [137], see Chapter 4). This may constrain timeslice definition, making the use of unusual timeslices such as super-peak or rare low-wind/high-load periods more complicated.

Using representative days or weeks is a convenient way of keeping temporal resolution low while expressing chronology within these timescales. To determine how many of them should be used, Nahmacher *et al.* [147] select different numbers of representative days using hierarchical clustering and study the impact on model outcomes. They proposed that 6 representative days, each composed of 8 timeslices, were sufficient to reflect fluctuations in net load. However, Merrick [162], who performed a very similar study, argues that one cannot make that claim based only on VRE share and total system cost compared on a single scenario¹, and that 8 timeslices per day is insufficient to capture variations. In his own study, he concluded that 300 representative days or 50 representative weeks at hourly resolution are required to fully reflect variations in net load. Both papers do highlight that it is a matter of trade-off between computation time and model accuracy; the correct modelling decision always depends on the research question. One should keep in mind that, as with timeslices, choosing relevant representative days or weeks will become more challenging as geographical scale is extended. These techniques will also struggle to express chronology beyond the daily or weekly timescales, and hence may be unable to fully consider power system operation challenges such as long periods of wind drought, annual patterns in solar and load, etc.

¹Other studies corroborate this claim: capacity and energy mix are other important outputs that need to be examined [144, 151, 158, 164].

Another commonly found option consists in adding sets of constraints to express a proxy for flexibility, effectively approximating flexibility requirement and provision simultaneously. One example could be the “residual load² duration curves” method, which obtains a balance between VRE, base-load, mid-merit, peak generation and storage [150, 171]. Another could be the “flexibility balancing” constraint, which assigns flexibility coefficients to load, generation and storage technologies [171, 172]. Flexibility sources have positive coefficient values, flexibility sinks negative ones, and their weighted sums must exceed zero. This may be appropriate for studies with a wide ranging scope, e.g. studies of the interactions between global climate and the whole energy system. However, these methods are not accurate enough for power system expansion studies, as they fail to convey the fact that power system components can be both a flexibility source and sink, depending on the considered timescale, on its own capacity and on the behaviour of the rest of the power system at a particular point in time (see Chapter 2).

5.2.2 Linking capacity expansion models with production cost models

Another way of improving the representation of flexibility in capacity expansion planning consists in combining CExMs and PCMs³ by soft-linking two such models, obtaining an investment strategy built upon a detailed consideration of operational costs. The link may be uni-directional, in which case its purpose is typically to validate the feasibility of a given power system and to provide insight on its detailed operation [85, 144, 145, 173, 174], or to quantify the cost implications of various flexibility constraints [81]. The principle, illustrated in Figure 5.1, is the following: the CExM proposes an optimal system or an optimal investment trajectory, and the PCM takes the resulting installed capacities as an input, simulating its hourly operation. The link may also be bi-directional, in which case its purpose is to improve the consideration of flexibility in the capacity expansion problem, gradually converging to an approximation of an optimal point [153, 155, 157, 175–178] (note: there is no guarantee of optimality). The principle starts in the same way as previously, but the outputs of the PCM are then used to decide whether the system is acceptable and, if this is not the case, to tell the CExM how it should adjust.

Some soft-linking studies’ aim is to show the value of their approach, quantifying the impact on model outputs [144, 145, 153, 157]. In all of these mentioned cases, the methodology is appropriately detailed and reproducible, but their scopes are limited to a simple, single-node system. More commonly, soft-linking is simply a tool, the main focus of the paper being the case study. The methodology’s description is hence vague, or even non-existent when it comes to the crucial element: the process through which information is fed back from the PCM to the CExM [155, 175–177, 179]. This lack of transparency, raised repeatedly by literature [128, 180], is particularly problematic as this is where the value of a bi-directional soft-linking approach lies, and, as will be seen in following sections, is a non-trivial task.

²Interchangeable term for net load: load minus VRE generation.

³See Table 4.1 for an overview of these model types’ characteristics.

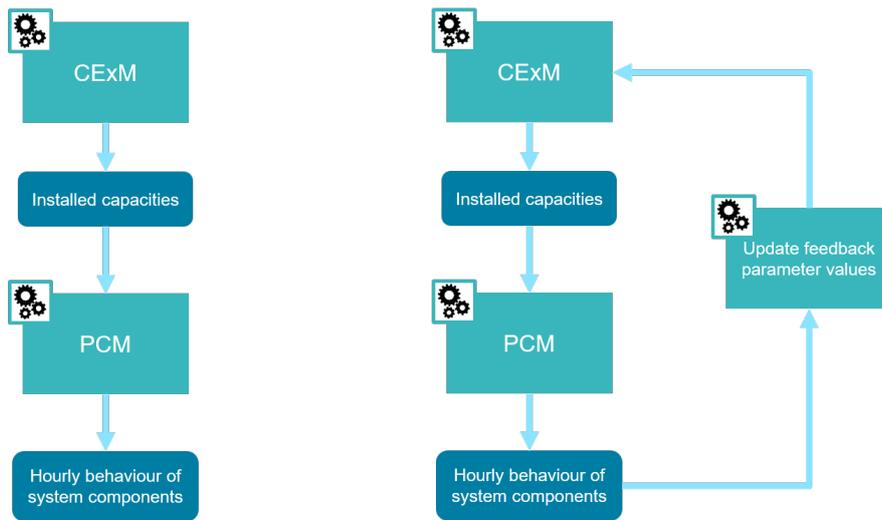


Figure 5.1: Relations between Capacity Expansion Models and Production Cost Models in a uni-directional (left) and bi-directional (right) soft-linking exercise.

A few studies do provide some more detailed information regarding the feedback process:

- In their study soft-linking TIMES with EnergyPLAN, Pina *et al.* [157] base their approach on the observation that CExMs underestimate curtailment. Their process is therefore the following: while the EnergyPLAN-derived curtailment exceeds 10% of potential VRE generation, VRE capacity limits in TIMES are gradually reduced. Note that each investment step is validated independently and successively.
- In their study soft-linking TIMES with Antares, Alimou *et al.* [153] use the fact that CExM-derived power systems may lead to loss-of-load. While the Antares-derived loss-of-load-expectation (LOLE)⁴ exceeds 3 hours per year, the capacity credits of certain generation technologies are updated based on Antares hourly outputs. These capacity credit values then determine how TIMES will adjust its investment strategy to respect its peaking reserve constraint. Note that while TIMES runs for a period ranging from 2013 till 2050, the link with Antares is only built for 2030.
- In their study building an investment loop around Continental, Lopez-Botet *et al.* [178] also base the suitability of a system on the expected value of LOLD not exceeding 3h. The investment module adjusts its plan by comparing generating unit costs to Continental-derived generating unit revenues (full details are not made very clear).

Note that soft-linking has been applied to other aspects of energy system planning, examples include (i) Deane *et al.* [181], who link the CExM TIMES to a

⁴On the basis of many Monte-Carlo years, the expected number of hours where loss-of-load occurs in a given year.

housing stock model, providing a detailed understanding of the implications of heat electrification, (ii) Krook-Riekkola *et al.* [182], who link TIMES to a Computable General Equilibrium model, capturing competition for energy resources, capital and labour in a low-carbon economy.

Performing such a study can be challenging, not least due to the fact that expertise in two models is required. Differences in model resolutions and input parameters may lead to hidden data inconsistencies [127], and crucially, feeding information from the PCM back to the CExM is based on the modeller’s experience [128]. Literature is missing a systematic comparison of eligible criteria.

5.2.3 Optimising investment and economic dispatch simultaneously

From the model-user perspective, a third option to perform a capacity expansion study with high VRE shares is to build a new model specifically designed to simultaneously solve the investment and the dispatch problems. Note that from a modelling methodology perspective, this is in some cases quite similar to the two approaches discussed previously.

There are many examples of such work, a brief review of which can be found in Helistö *et al.* [159]. Due to the size of the formulated problem, many simplifications must be made to ensure tractability. Examples of such simplifications are as follows: single-node system only [20, 149], no consideration of storage assets [20, 149, 152, 183], economic dispatch without unit commitment or relaxation of integer constraints [154, 184, 185], or solving the dispatch problem on a low number of representative days [152, 183] with the caveats mentioned in Chapter 4. When modelling approaches do solve the dispatch problem on full time series, this is done over a single weather year [154, 186], despite this having been shown to have a significant impact on model outcomes [173, 185]. Note that decomposition techniques such as Benders decomposition are occasionally implemented to reduce computation time [152, 154, 184], opening the door to parallel computing.

The referenced models vary greatly in terms of maturity and complexity, ranging from a theoretical model proposing a target year, green field investment while considering only generation investment [20], to a seasoned model proposing brown-field investment pathways simultaneously considering generation, network and storage, while also solving a unit-commitment problem on a full year at hourly resolution [186, 187].

5.3 Overview of the soft-linking process

This section provides the preliminary information required to understand the modelling work carried out to improve the representation of flexibility in power system planning. It starts by justifying our decision to implement a soft-linking approach between a CExM and a PCM, before briefly describing the chosen PCM, Antares, and specifying its study set-up. We then give a broad overview of the proposed soft-linking process, laying out the common features of the three implemented feedback techniques and defining their two key roles.

5.3.1 Proposal

Building a model destined for the formulation of policy recommendations is a very lengthy process. As well as the time required to formulate the problem, gather the data, choose scenarios, validate the approach by peers etc, researchers, companies and institutions must also be given the chance to build trust in the model. Only then can it become applicable and relevant, *i.e.* useful [188].

Therefore, rather than further bloat an abundant list of existing models (see Chapter 4) and to directly build upon years of trust-generating work and knowledge, we propose to improve the representation of flexibility in capacity expansion planning by soft-linking a Capacity Expansion Model (OSeMOSYS) with a Production Cost Model (Antares). Despite the soft-linking approach having been identified as an interesting path in literature, existing studies have mostly either not discussed their methodology, or limited their scope to a uni-directional quantification of CExM errors. Here, we aim to provide a formal and transparent discussion on bi-directional soft-linking, comparing different feedback techniques able to propose investment pathways considering generation, interconnection and storage simultaneously.

OSeMOSYS was chosen due to its open source and modular nature, the clarity and conciseness of its documentation and our ability to interact with experienced model users. Antares was chosen due to its open source nature, our possession of the required input data and our ability to interact with both experienced model users and model developers.

Note that when soft-linking a CExM with a PCM, the solution provided is by no means guaranteed to be optimal. For a capacity expansion problem, this is arguably a vain and irrelevant question, considering the modelling simplifications, the input data uncertainties, and the limited ability to factor in non-technical yet essential constraints (e.g. social or environmental). The solution proposed is however more guaranteed to be operationally adequate than in the other 2 discussed approaches, in the sense that its ability to match supply and demand with acceptable LOLE levels has been validated on full hourly resolution for many weather years.

5.3.2 OSeMOSYS study setup

The OSeMOSYS set up is essentially the same as the one described in Section 4.3.3, though some of the parameters which were varied in Chapter 4 are kept constant here. A single timeslice structure is used throughout this Chapter, composed of 4 seasons, 1 day-type and 4 daily-time-brackets. This was deemed an appropriate trade-off between computation time and precision, as Antares will be providing a much more detailed understanding of operational aspects. The reserve margin functionality is not only used, but a core component of 2 of the 3 feedback techniques which were applied. As for the the total annual max investment parameter, the initial reference set of values is used (see Section 4.3.3).

5.3.3 Description of Antares

Antares is an open-source software designed to produce a least-cost hydro-thermal unit commitment and economic dispatch, for several Monte-Carlo years at hourly

resolution, over a large interconnected system. Originally designed as a production cost model, its functionality has since been extended to perform generation and/or transmission expansion for a target year, though this functionality has not been used here. The version of Antares that was used is the V7.0.1.

First developed by the French TSO RTE, it is now a core element of several institutions' both short-term and long-term prospective studies (e.g. RTE [40, 97], Elia [41], ENTSO-E [43]), as well as a tool routinely used in academic studies [153, 189, 190].

Antares has three simulation modes with different trade-offs between accuracy and computation time. The most accurate simulation was used (“Economy” mode), which includes unit-commitment variables, minimum stable power, minimum up and down times, start-up costs and no-load heat costs (see [191] for the full optimisation problem formulation). A year is split into weekly problems solved independently but coupled to some degree using various heuristics. Each problem consists in a minimisation of operational costs, defined as the sum of:

- Thermal costs, which include a CO₂ penalty. Note that thermal generation is grouped into clusters of units with similar characteristics (as performed by [139]).
- Hydro costs, derived from water values.
- Transmission costs, a small hurdle cost proportional to power flow. Simple asymmetric Net Transfer Capacities (NTC) values were used to model power flows, though Antares is able to model them more accurately.
- Unsupplied energy cost, set at €10,000/MWh.
- Curtailed energy cost, set at €0/MWh.

The technologies considered in Antares simulations are the same as those considered in OSeMOSYS (see Figure 4.3), except onshore and offshore wind which are considered as a single technology, and hydro which is split into run-of-river and storage. The behaviour of nuclear, CCGT, OCGT, coal and oil power plants as well as hydro storage, PHS and batteries is optimised by Antares. Their parameter values are shown in Table E.1 in the Appendix. Biomass, run-of-river hydro, wind and solar are modelled as must-run (but curtailable) generation using 11 years' worth of hourly time series data⁵, derived from reanalysis historical weather data. These time series express geographical, temporal and inter-variable correlations between load, wind, solar and run-of-river hydro; they are expected to be made public at the end of the OSMOSE H2020 project⁶, along with their associated load time series.

Reserves must be accounted for within each hour of the unit-commitment schedule. The contracted reserve volume, constant throughout the year, is defined separately in each region, reflecting the size of its annual load.

⁵These 11 years are a subset of the 35 years used in Chapter 4 (see Section 4.3.3).

⁶April 2022.

5.3.4 Common features in implemented soft-linking techniques

The general overview of the soft-linking process is presented in Figure 5.2. After having given feedback parameter a set of initial values, OSeMOSYS can be run, proposing a first investment pathway from 2015 to 2050 in five year investment steps. Installed capacities for generation, interconnection and storage are thus obtained. The translation of these capacities to Antares inputs is then fairly straightforward.

For assets which do not require individual unit modelling to express operational constraints (non-thermal generation, interconnection and storage), capacities are taken as they are. The economic dispatch and unit commitment of thermal generation assets is significantly influenced by the size and number of units, another approach is hence required. To avoid the non-convexities⁷ that would be caused by a simple rounding to the closest multiple of a nominal capacity, the following approach is adopted. OSeMOSYS capacity is divided by a nominal capacity specific to each technology⁸, the result of which is rounded up to the closest greater integer to obtain a number of units to be modelled in Antares. These units' individual capacity is then defined as OSeMOSYS total capacity divided by the number of units, implicitly adjusting the default nominal capacity. Minimum stable power output is adjusted accordingly to represent the same proportion of nominal capacity as its default value⁹.

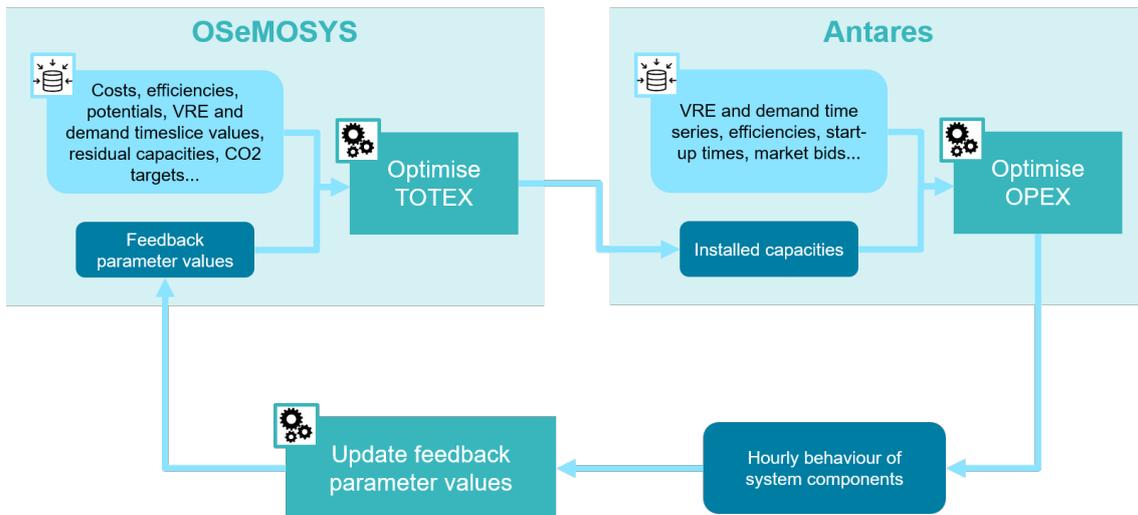


Figure 5.2: General overview of the bi-directional soft-linking process.

Next, an Antares simulation is run for every decade in the investment pathway

⁷In small systems, the resulting rounding error can represent a significant proportion of total system capacity, impacting the stability of the soft-linking process.

⁸See Table E.1 in the Appendix.

⁹For example: say OSeMOSYS has decided there should be 5664 MW of CCGT in region r for soft-linked year sy , and CCGT has a nominal capacity of 500 MW. Antares will therefore model 12 CCGT units ($5664/500=11.328$), which will each have a unit size of 472 MW ($5664/12=472$). The default value of CCGT's minimum power output being 150 MW, the units' minimum power output will therefore be set to 141.6 MW ($150/500*472=141.6$). Note that this means that generating units may have different name-plate capacities in different soft-linked years.

(soft-linked years, sy , 2020, 2030, 2040 and 2050, to reduce computation burden), each considering 11 weather years, wy (see Table 5.1). These hourly time series are based on reanalysis weather data, and express geographical, temporal and inter-variable correlations between load, wind, solar and run-of-river hydro.

For each soft-linked year, Antares thus outputs hourly time series describing the behaviour of all system components (generation, interconnection and storage). These outputs are then used to calculate new values for the feedback parameters¹⁰, the nature of which is different in each attempted feedback technique. The process is then repeated for a new iteration, with OSeMOSYS proposing a new investment pathway based on the new feedback parameter values. Note that this means all soft-linked years are soft-linked simultaneously, assuming perfect vision in the investment problem, not successively validated independently (e.g. as implemented by Pina *et al.* [157] or Després *et al.* [179]).

Table 5.1: There are three different year types referenced throughout this Chapter; being able to distinguish them is important to understand the work presented in the following sections.

Symbol	Name	Description
y	Investment year	OSeMOSYS investment step. Range from 2015 to 2050 in 5-year steps.
sy	Soft-linked year	Subset of investment year for which Antares simulations are run. Range from 2020 to 2050 in 10-year steps.
wy	Weather year	11 Antares realisations of the same soft-linked year

A typical way of exiting this feedback loop would be to check whether a security-of-supply criterion has been reached (e.g. 3 hours of LOLE, the recommended practice in French power system studies [40, 97, 153, 178] and in several other countries [192]). This ensures feasibility, but since the solution proposed by a soft-linking exercise cannot guarantee to be optimal, it can potentially lead to vastly over-invested systems (*i.e.* a system with an unreasonably high level of reliability). For all the tested feedback techniques, when possible, we thus ran 10 iterations and, within solutions leading to LOLE below 3h, kept the one with the lowest TOTEX. In most cases, 10 iterations were enough to observe a significant decrease in marginal TOTEX change. In some cases however, the soft-linking process's behaviour in subsequent was unclear. In these cases, a few iterations were added.

5.3.5 The two roles of the soft-linking process

The feedback process has two key roles: signalling under- and over-investment to OSeMOSYS, and instructing OSeMOSYS as to how the investment pathway should be adjusted in the next iteration. The principle for the first role is the same in all

¹⁰Parameters calculated based on soft-linked year 2020 are also applied to OSeMOSYS investment time steps 2015 and 2025, those on soft-linked year 2030 to OSeMOSYS investment time step 2035 etc.

three feedback techniques: a system is considered to be under-invested if it leads to more than 3 hours of LOLE, and over-invested if it leads to less than 2.5h of LOLE. The details of how this signal is effectively sent and the way the second role is fulfilled differs in each feedback technique.

5.4 Capacity credit based feedback

5.4.1 Methodology

As previously mentioned, this first technique is a re-application of the methodology developed by Alimou *et al.* [153], who soft-linked the CExM TIMES to the PCM Antares, on a single-node representation of the French power system, for a single target year and considering investment only in generation. Here, it was slightly adapted to derive investment pathways, which revealed structural problems with this feedback technique.

Adequacy constraint

The feedback technique is built around a constraint (see Equation 5.1 below) defined in TIMES which imposes that the sum of installed capacities weighted by their capacity credits must exceed a reserve margin multiplied by peak timeslice demand. For the definition of set indices, see Table 4.2.

$$\forall_{r,f=Power,y} \text{ReserveMargin}_{r,y} * \max(\text{RateOfDemand}_{r,f,y,l}) \leq \sum_t \text{TotalCapacityAnnual}_{r,t,y} * \text{CapacityCredit}_{r,t,y} \quad (5.1)$$

This equation is effectively an adequacy proxy, correcting for the fact that a power system sized on timeslices may be unable to meet peak demand. Through capacity credits, each generation technology is given a chance to contribute to this peak demand, defined as a reserve margin multiplied by the maximum timeslice demand. Alimou *et al.* keep the reserve margin set to 1.28 throughout the soft-linking process, while capacity credit values are updated after each iteration on the basis of Antares outputs (see Equation 5.2 below).

In OSeMOSYS, this same functionality is expressed by constraints RM1, RM2 and RM3, with subtle differences compared to the TIMES formulation. In OSeMOSYS, the capacity credit is referred to as ReserveMarginTagTechnology and is a binary parameter tagging the technologies able to contribute to the reserve margin (See OSeMOSYS documentation [168]). This parameter was changed to a float, and will henceforth be referred to as capacity credit to avoid confusion, defined over sets *region*, *technology* and *year*. A second subtlety lies in the way the reserve requirement is defined (*i.e.* the left side of Equation 5.1): while in TIMES it relates to peak demand, in OSeMOSYS, it relates to peak production. Since we have added a electricity transport module to allow for multi-node modelling¹¹, constraint RM2 was modified to relate to peak demand, in line with Alimou *et al.*

¹¹See Chapter 4.

Capacity credit calculation

A unit's capacity credit represents its contribution to the generation adequacy of a power system [193]. As discussed by Amelin [193] and Söder *et al.* [192], it can be calculated using many different approaches leading to significantly different values, with use cases ranging from capacity markets to capacity expansion planning.

With the latter application in mind, the IEA [194] proposed a methodology to calculate VRE capacity credits which has been implemented by Alimou *et al.* using the formulation in Equation 5.2. Note that in this implementation, *NetDemand* doesn't refer to the traditional object of demand minus non-dispatchable generation, but is an object calculated for each technology, equal to demand minus this technology's production.

$$\forall_{r,t,y} \text{CapacityCredit}_{r,t,y} = \text{median}_{wy \in \text{WeatherYear}} \left(\frac{\max_{h \in H} (\text{Demand}_{r,y,wy,h}) - \max_{h \in H} (\text{NetDemand}_{r,t,y,wy,h})}{\text{TotalCapacityAnnual}_{r,t,y}} \right) \quad (5.2)$$

where: wy 11 weather years
 h hours, ranging from 1 to 8760
 $\text{NetDemand}_{r,t,y,wy,h} = \text{Demand}_{r,y,wy,h} - \text{Production}_{r,t,y,wy,h}$

While the usual practice is to use Equation 5.2 to calculate the capacity credit values of VRE generation, in Alimou *et al.*, it is also used to find that of dispatchable generation. This changes the nature of the parameter and the information it carries, causing problems in the feedback process, as will be discussed in Section 5.4.2.

In accordance with Alimou *et al.*, for the first iteration, technologies were given initial capacity credit values based on the modeller's experience; here, 0 for solar, 0.2 for onshore and offshore wind and 1 for all other technologies. Alimou *et al.* considered neither storage nor interconnection in their study. Here, Equation 5.2 was also used to calculate the capacity credit values of storage (batteries and PHS); interconnection was however not considered as single-node studies revealed several structural issues with the feedback technique, as will now be seen. Note that capacity credits were bounded to the [0,1] interval.

5.4.2 Results and discussion

In order to fully understand the feedback technique's behaviour, it was first applied to a single-node study of the German power system. Germany was chosen due to its relatively important size (reducing the potential impact of nominal power induced non-convexities¹²) and its diversified initial technology mix (reducing the risk of validating the technique on a specific, single-technology dominated system). Germany being a system with high interconnection relative to peak load, this does mean the

¹²As stated in Section 5.3.4, when feeding thermal generation capacities from OSeMOSYS to Antares, capacities are rounded to the closest multiple of technology nominal power. In small systems, the resulting rounding error can represent a significant proportion of total system capacity.

initial system may be inadequate and its hourly dispatch a poor representation of reality.

Our results do corroborate the main conclusion from Alimou *et al.*'s study: due to poor operational detail, a generation mix provided by a CExM can lead to unacceptably high levels of LOLE. However, the feedback technique is ineffective in reliably providing an adequate investment pathway, as it fails to differentiate under- and over-invested situations, generating positive feedback as iterations progress. We will start by providing empirical evidence for this failure, before analysing the feedback equations to explain the issue from a theoretical perspective.

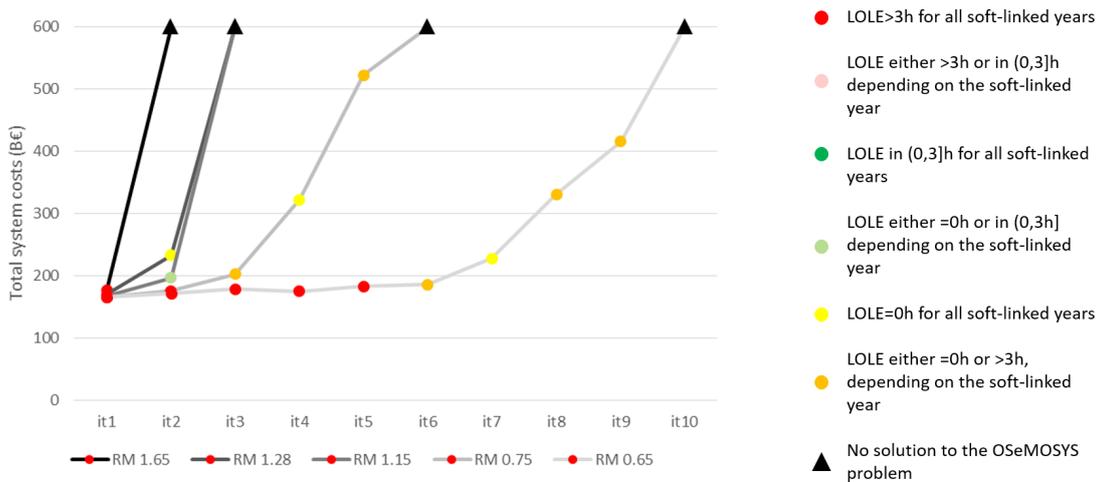


Figure 5.3: Evolution of OSeMOSYS total system costs over iterations, for different reserve margin (RM) sizes ranging from 0.65 to 1.65. Soft-linked years refer to investment pathway years 2020, 2030, 2040 and 2050, not to the different weather years, which are multiple realisations of the same soft-linked year. Black triangles at €600B show cases where OSeMOSYS was unable to find a solution that respected both the reserve margin constraint due to low capacity credits (see equation RM1) and the maximum annual capacity investment constraint (see equation NCC1).

As can be seen in Figure 5.3, investment pathways leading to more than 3 hours of LOLE (red and, for some soft-linked years, pink and orange dots) mostly tend to be adjusted as desired: investment is increased in the subsequent iteration. Symmetrically, investment pathways leading to less than 3 hours of LOLE (yellow, green and, for some soft-linked years, pink and orange dots) should be adjusted by reducing investment in the subsequent iteration; however, the opposite is true: investment is systematically increased, until the required increase is so important that it cannot respect the maximum annual capacity investment constraint (see equation NCC1)¹³. The feedback technique therefore fails to fulfil the first of its two roles: it is unable to signal both under- and over-investment to OSeMOSYS. Increased investment does not necessarily reduce LOLE levels, the second role is therefore not fulfilled either.

¹³Note that this no-solution issue could be avoided by modelling equation NCC1 as a “soft” constraint rather than a “hard” constraint, by penalising it in the objective function. This would however not prevent the positive feedback behaviour and hence not be of any use.

Looking back at Equation 5.1, the left terms being constant over iterations, a change in investment implies a change in capacity credits. Signalling over-investment would hence require an overall increase in capacity credit values when LOLE drops below 3 hours. We can see in Figure 5.4 that on the contrary, dropping LOLE levels lead to an overall collapse in capacity credit values, which will cause investment to increase in an already over-invested system.

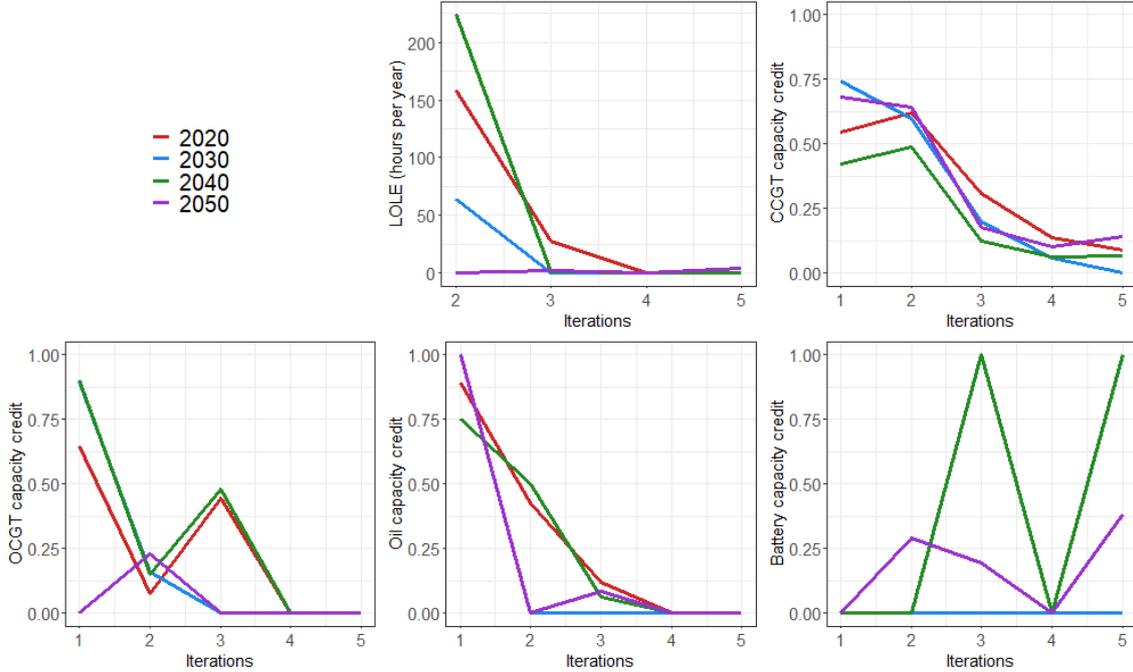


Figure 5.4: Evolution of loss-of-load-expectation and capacity credit values of CCGT, OCGT, oil power plants and batteries over iterations, for a reserve margin size of 0.75. Variations in capacity credit values suggest that they are not fulfilling their intended role: for dispatchable generation, the proportion of capacity that can be reliably expected to generate electricity during times of peak demand should be largely independent of system structure, and hence remain fairly constant.

This brings us to the core of the problem: the gap between what we intuitively expect of capacity credits and what they actually express. The formulation proposed in Equation 5.2 roughly expresses the degree to which a technology is actually used to meet peak net load¹⁴, while the information we are seeking in this particular application is the degree to which a technology could be used to meet peak net load if required.

While these two notions are equivalent for VRE, they are not for dispatchable generation. Equation 5.2 is hence suitable to evaluate the capacity credits of the former, but not the latter, as can be understood through a simple example. If we take a system where peak load occurs at a time of significant VRE output, there is no reason to expect peaking generation to be online. The maximum of $(Demand_{r,y,w,h} - Production_{r,t,y,w,h})$ will hence be equal to the maximum of $Demand_{r,y,w,h}$, causing

¹⁴Hence the low capacity credit values in over-invested systems with very low LOLE levels, especially for dispatchable technologies.

the capacity credit value to equal 0. There are a few other problems with Equation 5.2, e.g. had capacity credit values not been bounded to the $[0,1]$ interval, it would often have led to negative capacity credit values for storage assets, providing a poor indication of these technologies' ability to contribute to peak net load. Also, this equation implies that if in iteration i , a technology had no installed capacity in a certain soft-linked year, this technology will have no capacity credit value in iteration $i+1$ and hence no way of valuing its ability to contribute to the reserve margin.

Note that the number of iterations required for this positive feedback behaviour to materialise depends on the chosen reserve margin value, and that a lucky guess may potentially lead to adequate solutions before reaching no-solution territory (see Figure 5.3). Also, in studies optimising investment for a target year instead of a pathway (as is the case in Alimou *et al.*), the structural issues of this feedback technique will not necessarily be made apparent: if the first iteration leads to an under-invested system, subsequent iterations may neatly converge to a 3h-LOLE system, at which point the model user may decide to stop the process. However, in an investment pathway study, a soft-linked year is very likely to reach 3h-LOLE while others are still well off, causing its capacity credits to drop and making the loop diverge before the other soft-linked years get a chance of being adjusted.

5.4.3 Conclusion

Due to all the described structural issues with this feedback technique, it is not considered fit for purpose, and it was hence not applied to multi-node case studies. However, there is significant value in the general idea behind the feedback technique. After lengthy explorations, testing the introduction of inertia in capacity credit updates, changing the methodology used to calculate capacity credits, allowing the reserve margin to take values other than 1.28 (see Figure 5.3), a new feedback technique was derived, which is described in the following section.

5.5 Reserve margin based feedback

This section starts by describing the methodology, justifying modelling decisions based on the lessons learned from the capacity credit based feedback technique (Section 5.4). Results are then presented, both for single-node and multi-node case studies.

5.5.1 Methodology

Signalling under- and over-investment

The reserve margin balancing equation used in the capacity credit based feedback technique (Equation 5.1) was taken as a basis, adding a term to also allow interconnectors to contribute to the reserve margin¹⁵.

¹⁵See equations RM1, RM2 and RM3 for the exact formulation used in our model runs.

$$\begin{aligned}
\forall_{r,f=Power,y} \text{ReserveMargin}_{r,y} * \max(\text{RateOfDemand}_{r,f,y,l}) \leq \\
\sum_t \text{TotalCapacityAnnual}_{r,t,y} * \text{CapacityCredit}_{r,t,y} + \\
\sum_{rr} \text{TotalTradeCapacityAnnual}_{r,rr,f,y} * \text{TradeCapacityCredit}_{r,rr,f,y}
\end{aligned}
\tag{5.3}$$

The reserve margin parameter's role is to express the degree to which a generation mix sized on timeslices is unable to ensure adequacy, potentially forcing OSeMOSYS to invest in additional capacity. This proxy has no direct link to power system physical quantities, and a reserve margin value derived for a given system has no reason to be appropriate for another. Therefore, there is no reason not to update this parameter over iterations based on Antares outputs, and it also happens to be a very appropriate tool to signal under- and over-investment: if LOLE levels are too high, the reserve margin can be increased; if LOLE levels are too low, the reserve margin can be decreased (see Figure 5.5).

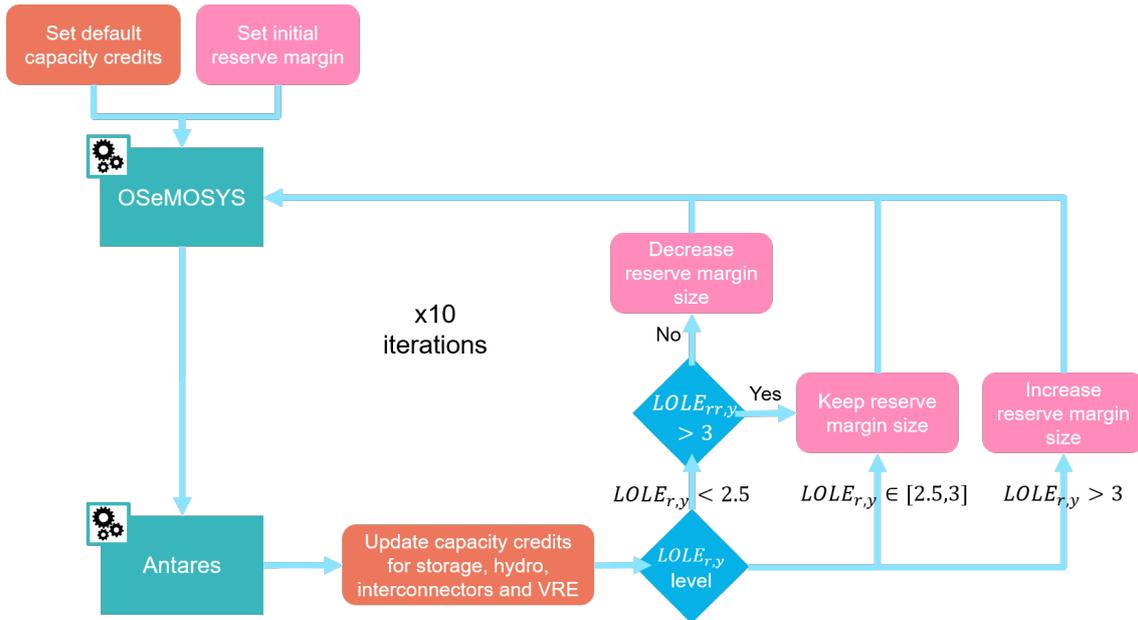


Figure 5.5: Overview of the reserve margin based feedback technique. In multi-node case studies, the reserve margin size of region r can only be reduced if LOLE levels in region r are below 2.5h and none of its neighbouring regions rr have a LOLE level above 3h.

There are many potential ways of implementing the details of this adjustment principle; Figure 5.6 shows three examples. Extensive testing showed that, to ensure that an adequate¹⁶ investment pathway is proposed in under 10 iterations, it was preferable to have a reserve margin adjustment approach that aimed to first obtain an adequate solution and then reduce investment, hence the step at 3 hours of

¹⁶*I.e.* LOLE below 3 hours for all soft-linked years.

LOLE. The “conservative” strategy aims to ensure that an adequate solution is found in a relatively low number of iterations, though this may lead to higher TOTEX investment pathways than required (see Figure 5.8). The “risky” strategy is likely to cause more erratic behaviour over iterations, but it might be lucky and find an adequate investment pathway with lower TOTEX (also see Figure 5.8). As will be seen in the results section, these functions may be more or less suited to a particular case study, and redefining their parameters when applying the soft-linking framework to a new case study can potentially lead to better results.

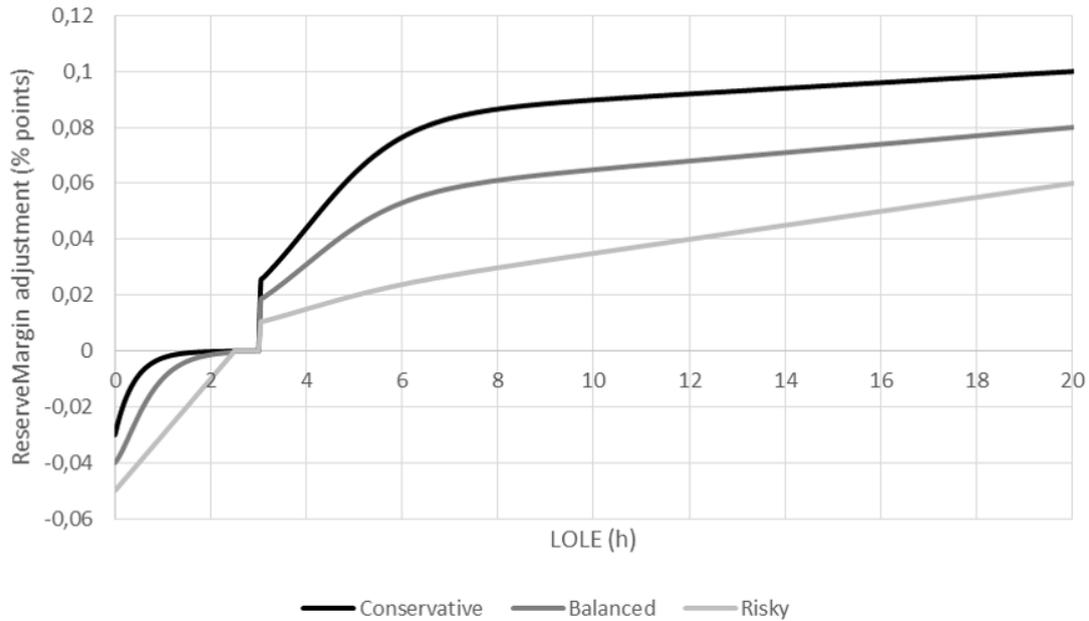


Figure 5.6: Three examples of reserve margin adjustment functions, showing incremental change in reserve margin value in terms of the LOLE level of a given region and soft-linked year.

As will be discussed, in multi-node case studies, ensuring the stability of the soft-linking process is not an easy task. This is why in multi-node situations, as illustrated in Figure 5.5, the reserve margin adjustment defined above has an additional rule: a region’s reserve margin can only be reduced if, for the same soft-linked year, none of its neighbouring regions have a LOLE level above 3h.

Instructing how the investment pathway should be adjusted

As discussed in Section 5.4.2, we argue the information required by OSeMOSYS from a capacity credit is the degree to which a technology could be used to meet peak net load if required, not the degree to which a technology is actually used to meet it. For assets such as storage, hydro generation and interconnection, this ability is influenced by the installed capacities and behaviours of the rest of the power system. Their capacity credit value should hence be updated over iterations. This should also be done for VRE generation, since the degree to which they could be used to meet peak net load if required depends on their own capacity. For thermal generation

assets however, this ability is dictated by their own technical parameters, and is hence mostly independent from the rest of the power system. Therefore, updating generation capacity credit value in successive iterations is irrelevant, and, as seen in Section 5.4.2, is likely to express unrelated and undesired information.

To ensure that capacity credit values fulfil their intended role, a new method was used to derive them. As previously mentioned, there are many ways of expressing the idea behind a capacity credit. Our needs are quite specific: we need one that is suitable not only for VRE, but also for dispatchable generation, storage and interconnection. To this end, Equation 5.4 calculates the mean production of a technology on the 100 hours of highest net load, relative to installed capacity.

$$\forall_{r,t,y} \text{ CapacityCredit}_{r,t,y} = \text{median}_{wy \in \text{WeatherYear}} \left(\text{mean}_{hnl \in \text{HighNetLoad}} \left(\frac{\text{Production}_{r,t,y,wy,h}}{\text{TotalCapacityAnnual}_{r,t,y}} \right) \right) \quad (5.4)$$

where: wy 11 weather years.
 hnl Set of 100 hours where net load is highest.

The same principle applies for interconnectors: each link is assigned a pair of capacity credit values, based on the mean flow during the 100 hours of highest net load in each of the two connected regions. Note that this may lead to a negative value.

$$\forall_{r,rr,f=\text{Power},y} \text{ TradeCapacityCredit}_{r,rr,f,y} = \text{median}_{wy \in \text{WeatherYear}} \left(\text{mean}_{hnl \in \text{HighNetLoad}} \left(\frac{\text{InterconnectorFlow}_{r,rr,f,y,wy,h}}{\text{TotalTradeCapacityAnnual}_{r,rr,f,y}} \right) \right) \quad (5.5)$$

Note that many aspects of these equations are fairly arbitrary: their very structure, the fact that they consider a set of 100 hours, that they take the mean over these 100 hours, the median over the 11 weather years... The implications of these choices will be discussed in the further work Section 6.2.

These equations are used at the end of each iteration to update capacity credit values for storage, hydro, interconnectors and VRE. Prior to 10-iteration runs, they were also used to derive a set of default capacity credit values, which are used both in the first iteration and in iteration $i + 1$ for technologies with no installed capacity in iteration i . The process applied to derive these default values is the following: to ensure that what they measure is indeed an asset's ability to be online when it is really needed, OSeMOSSYS proposes an investment pathway designed for a load 25% lower than the one fed to Antares, with a non-binding reserve margin constraint. In Antares, residual capacity¹⁷ may be sufficient to ensure adequacy at the start of the model period, but this process will lead to high levels of LOLE at the end of it, and will hence provide asset behaviour under tense conditions.

¹⁷Remaining available capacity from before the modelling period, see Appendix D.4.

This process was applied to several single-node systems; on the basis of their results for late soft-linked years, a set of default values was derived (see Table E.2 in the Appendix). These values are assigned uniformly across soft-linked years and regions, and, for assets whose capacity credits are updated, are deliberately on the lower end of typical values, to avoid investment bouncing back and forth over iterations¹⁸.

5.5.2 Validation of feedback technique behaviour

Single-node case study

As was done in Section 5.4.2, the reserve margin based feedback technique was first tested on a single-node case study of the German power system to validate the methodology's behaviour.

The TOTEX trajectories in figures 5.7 and 5.8 suggest that both roles of the soft-linking process are successfully fulfilled. In terms of the first role: LOLE levels over 3 hours in iteration i leads to increased investment in iteration $i + 1$; LOLE levels below 2.5h in iteration i leads to reduced investment in iteration $i + 1$. In terms of the second role: the fact that increased investment does indeed reduce LOLE levels (and reduced investment does increase LOLE levels) suggests that capacity credits are sending an effective signal as to how OSeMOSYS should adjust its investment pathway.

Updating capacity credit values over iterations brings limited value to the process, however. The comparison of TOTEX trajectories presented in Figure 5.8 shows that successively updating capacity credits leads to more instability, particularly in the first few iterations, while the cheapest adequate systems proposed have TOTEX cheaper by 0.1% at most. Part of this being due to instability, it could reasonably be expected that adding inertia to the capacity credit updating process may increase its value. Also, in this particular case study, the iterative changes made to the power system structure are fairly limited, the added value of expressing the changing role of technologies cannot be expected to be that important (see evolution in installed capacities over iterations in Figure A.8, and evolutions in capacity credits in Figure A.9 in the Appendix).

From Figure 5.7, we can see that the TOTEX of the cheapest adequate solutions proposed by each 10-iteration run is unaffected by the choice of initial reserve margin value, though this choice does affect the path taken to get there. These cheapest adequate solutions have identical installed capacities for most technologies, confirming their robustness; the main discrepancy is usually a difference of a few dozen MW in OCGT and CCGT investment, or in the balance between OCGT and CCGT and batteries. Looking at the capacity credits and reserve margins in the iterations prior to these best solutions, differences are minimal and there is no clear evidence to suggest that one or the other plays a more important role in investment differences.

¹⁸Example of such a situation: default value is high so invest in iteration i , asset turns out not to be as useful as planned, so, in iteration $i + 1$, low capacity credit value and hence no investment, repeat.

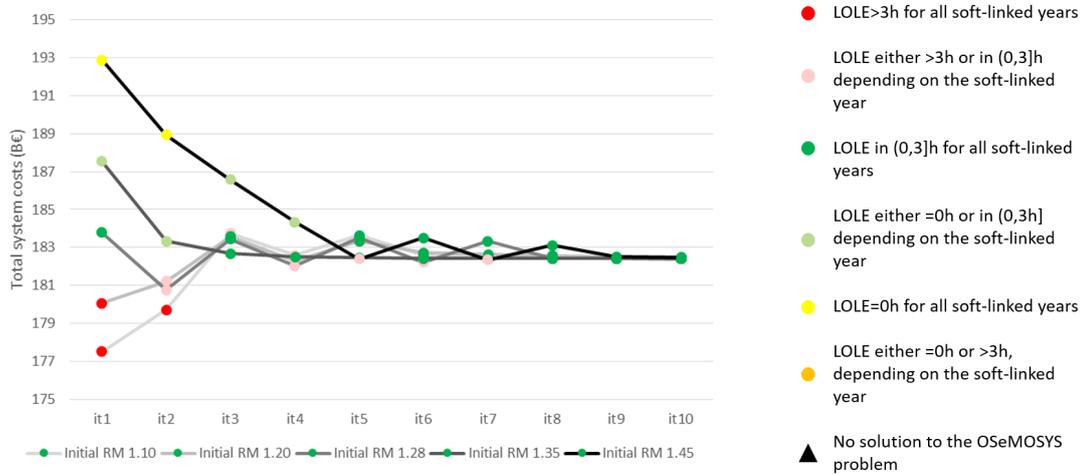


Figure 5.7: Evolution of OSeMOSYS total system costs over 10-iteration runs for the single-node German system, using the “balanced” reserve margin adjustment strategy, for different initial reserve margin (RM) sizes ranging from 1.10 to 1.45.

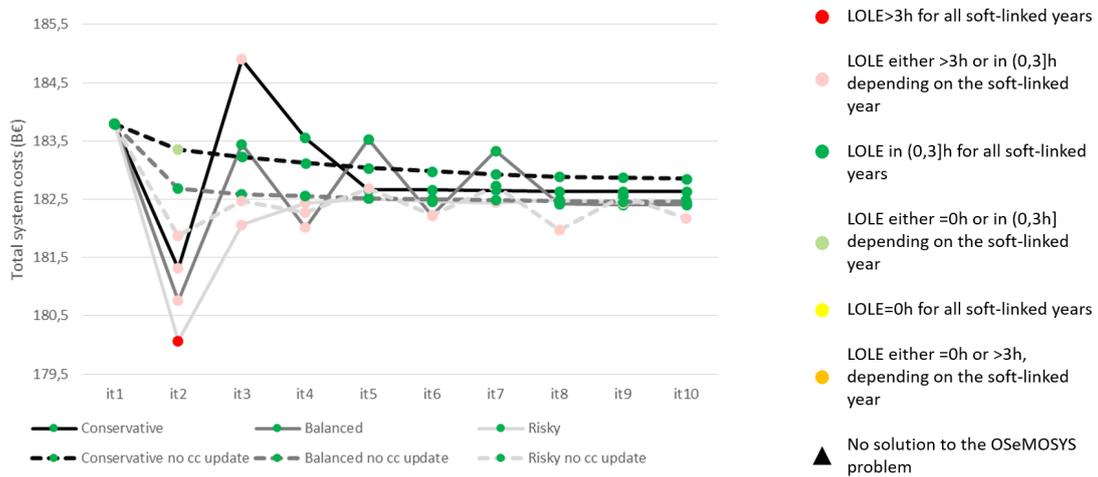


Figure 5.8: Evolution of OSeMOSYS total system costs over 10-iteration runs for the single-node German system, for different reserve margin adjustment functions with an initial reserve margin size of 1.28. Full lines show results for runs with capacity credit (cc) updates, dashed lines for runs without capacity credit updates.

The cheapest adequate solution proposed by each 10-iteration run is influenced by the choice of reserve margin adjustment function, as is made clear by Figure 5.8. As was to be expected considering the way each function was designed, more of the solutions proposed by the “conservative” strategy are adequate (*i.e.* LOLE below 3 hours for all soft-linked years), but they tend to be more expensive. In this particular case study, the “risky” strategy provided a cheaper adequate solution despite fairly unstable behaviour, but the cheapest adequate solution was proposed by the “balanced” strategy.

The reserve margin based feedback technique’s behaviour having been validated on a single-node system, it can now be tested on more complex, multi-node case studies.

Multi-node case study

The soft-linking framework was applied to the European power system described in Chapter 4, which aggregates some countries together to build a 17-node model (see Figure 4.2). The OSeMOSYS trade module proposed in this same Chapter 4 was used to model power flows and investment in interconnection capacity. Note that, as expressed in Equation 5.3, the reserve margin functionality is applied to each node separately, with different reserve margins and capacity factors for each.

The first thing to note in these results is the difference with the TOTEX values obtained in OSeMOSYS model runs performed in Chapter 4, which did not include the adequacy constraint. While these were, for the same values of maximum technology development rates, in the €833B to €844B range depending on timeslice structure, no adequate solution could be found under €918B using the soft-linking approach, *i.e.* an increase of up to 10%.

The next important point to make is that without the inclusion of the rule preventing the reserve margin size of a region to be reduced if a neighbouring region has a LOLE level over 3 hours (see Section 5.5.1), the feedback technique fails to propose a multi-node investment pathway that respects the 3h-LOLE criterion for every region and every soft-linked year. Over iterations, the location of new generation investment may switch between neighbouring regions, failing to bring LOLE levels below 3 hours in both regions simultaneously.

Even with the inclusion of this neighbouring region reserve margin adjustment rule, the feedback technique struggles to find adequate investment pathways, as is apparent from Figure 5.9. When capacity credits for storage, hydro, interconnectors and VRE are updated over iterations, only one adequate investment pathway is proposed, after 14 iterations using the “conservative” reserve margin adjustment strategy. If no capacity credits are updated, there are more adequate solutions among the proposed investment pathways, and some of them are cheaper than the best adequate solution proposed by runs with capacity credit updates.

Figure 5.9 provides a geographically aggregated vision of results, which is too imprecise to investigate investment adjustment behaviour over iterations. To improve on that, Figure 5.10 provides more detailed insight into the evolution of LOLE, and explains why investment decreases in iteration $i + 1$ despite there being cases of LOLE exceeding 3 hours in iteration i : in the vast majority of combinations of regions and soft-linked years, LOLE is below 3 hours. With decreasing investment

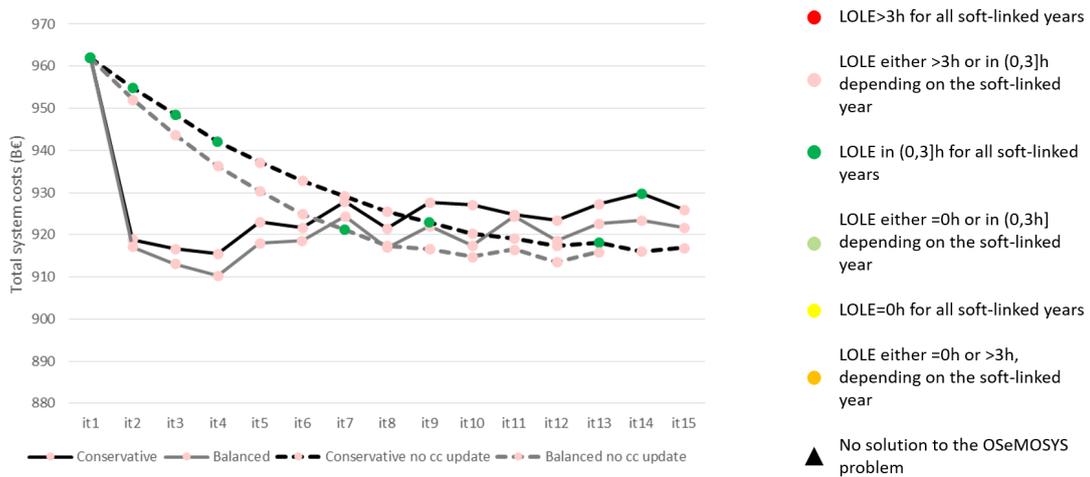


Figure 5.9: Evolution of OSeMOSYS total system costs over 10-iteration runs for the 17-node European system, for different reserve margin adjustment functions with an initial reserve margin size of 1.28. Full lines show results for runs with capacity credit (cc) updates, dashed lines for runs without capacity credit updates.

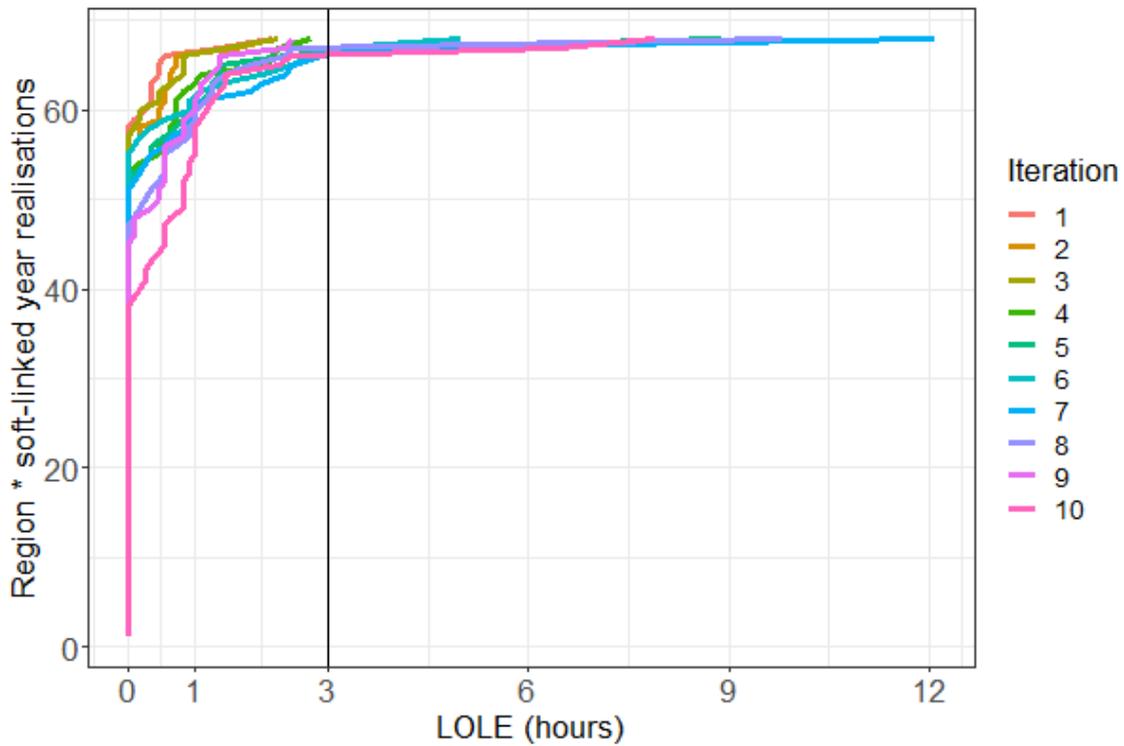


Figure 5.10: Evolution of LOLE over iterations for the “balanced” reserve margin update strategy, without capacity credit update. This graph should be read in the following way: out of the 68 LOLE values obtained in iteration 10 (one value for each of the 17 regions and each of the 4 soft-linked years), 47 were smaller or equal to 0.55 hours.

as iterations go by, there are fewer situations with 0h of LOLE and more situations with LOLE levels in the (0,3] hours interval, suggesting the soft-linking process is successfully reducing investment in over-invested region and soft-linked years combinations. However, it struggles to keep all LOLE values below 3 hours, and the process seems rather unstable. It should be noted that LOLE in excess of 3 hours remains at reasonable low levels. Closer inspection of situations in which LOLE exceeds 3 hours reveals that they are geographically spread out, and that they often repeatedly affect the same regions, reappearing in iteration $i + 2$ after having being corrected in iteration $i + 1$, potentially in another soft-linked year.

There is another important point to note regarding the reserve margin based feedback technique: the three reserve margin adjustment functions that were used were defined with the single-node German power system in mind. If we were to try to adapt them to the new, 17-node case study, we might find new adequate investment paths with potentially lower TOTEX. Lastly, performing further iterations during a soft-linking run is of course likely to lead to more interesting results.

5.6 Flexibility contribution based feedback

By looking only at a technology's ability to contribute to peak net load, capacity credits are unable to express the value this technology may have for different purposes, notably flexibility. As discussed in detail in Chapter 2 and made evident here in the FSCD shown in Figure 5.18, the value brought by a FS varies significantly with the considered timescale, and being able to express this information in the soft-linking framework may help us find adequate investment plans at lower TOTEX. This intuition has led to the flexibility contribution based feedback technique, which we will cover in this section.

5.6.1 Methodology

Overview of the methodology's structure

The flexibility contribution based feedback technique was designed in such a way as to build upon lessons learnt from the experience with the previous two feedback techniques. It follows a similar general structure to that of the adequacy constraint used previously (Equation 5.3): in OSeMOSYS, a flexibility target, defined for a region and an investment year, must be met by a sum of installed FS capacity, weighted by a parameter expressing the ability of each solution to provide flexibility, whose value is determined based on Antares outputs. As discussed above, due to the contrasting nature of the flexibility challenge over annual, weekly and daily timescales, this "flexibility balancing" is individually imposed on each of these timescales, as expressed in Equation 5.6¹⁹.

$$\mathbf{FlexibilityTarget}_{r,y,tl} \leq \sum_t \mathbf{TotalCapacityAnnual}_{r,t,y} * \mathbf{FlexibilityProxy}_{r,t,y,tl} \quad (5.6)$$

¹⁹See equations FP1, FP2 and FP3 for the exact formulation used in our model runs.

where: tl Timescale, which takes the values “annual”, “weekly” and “daily”.

An early structural design decision had to be made: should these flexibility constraints be a replacement or an addition to the adequacy constraint proposed in Section 5.5? Had the optimisation problem been limited to OSeMOSYS, adding a constraint could only have degraded the solution, but this is not necessarily the case in a soft-linking exercise: the validity of a solution is confirmed exogenously based on Antares outputs, which is also how parameter values are derived. An additive approach was likely to make the analysis of the feedback technique’s behaviour more complex: identifying the constraint responsible for an adjustment of the investment pathway could be a delicate task, and adequacy or flexibility constraints could occasionally become non-binding and hence unable to signal anything. To simplify the validation of the feedback technique’s behaviour, flexibility constraints were therefore treated as a replacement for the adequacy constraint.

Flexibility proxy derivation

Another thorny design issue to be dealt with is that of the nature of the information carried by flexibility proxies, which play a role analogous to that of capacity credits in the adequacy constraint. To put it in the terms used in the previous sections, should the flexibility proxies express the degree to which a FS is actually used to provide flexibility, or the degree to which a FS could be used to provide flexibility if required?

- Option 1: degree to which a FS is actually used to provide flexibility. Considering the results presented in Chapter 2, this sounds like the most obvious choice: the contribution of a FS to total system modulation is highly dependent on the structure of the rest of the power system. The capacity credit based feedback technique implemented in Section 5.4 warns us of the risks related to this approach: as LOLD levels drop, the degree to which a FS is actually used to provide flexibility may completely change, causing positive feedback and eventually leading to an unsolvable problem²⁰. There is an important difference in this case however: as LOLE levels fall, all technologies will be of less use overall, hence all capacity credits can be expected to drop, leading to positive feedback. If flexibility proxies are to be based on the FSCD proposed in Chapter 2, as LOLE levels fall, the flexibility provided by certain FSs may drop but another will fill in the gap. Though stability issues may occur, positive feedback should hence not be a worry.
- Option 2: degree to which a FS could be used to provide flexibility if required. As shown with the reserve margin based feedback technique, this has the significant advantage of providing a more stable signal, which helps with the convergence of the soft-linking process. However, the review of flexibility metrics in Chapter 2 suggests that while this information could be expressed

²⁰The investment required to respect the adequacy constraint is so significant that it cannot respect annual investment constraints.

with reasonable ease for timescales ranging from minutes to hours, it would be much more complicated to evaluate on longer timescales. Constraints affecting FS would move away from technical considerations (e.g. start-up and shut-down times, minimum power output) to economic considerations (e.g. number of annual operating hours required to recover investment), which are directly linked to the structure of the power system. This would hence require all flexibility proxies to be updated after each iteration, leading to the same stability worries as the first option.

The second option was not considered to be a feasible option, the first one was hence selected, despite the stability issues it could cause. The information provided by the Flexibility Solution Contribution Distribution (FSCD) proposed in Chapter 2 is close to the idea expressed in option 2, but it requires some adaptation. As stated in Equation 2.2, the FSCD tool evaluates a FS's modulation relative to total flexibility mix modulation. It does so separately for the annual, weekly and daily timescales, on time steps where the absolute value of total system modulation is larger than 20% of its maximum²¹.

A first adaptation is related to the dimension of the resulting object: while the FSCD tool provides a distribution per timescale, OSeMOSYS requires a single value per timescale. A quantile of each distribution is therefore taken. The impact of quantile choice on soft-linking behaviour is discussed in the results section.

The second adaptation is related to the nature of the FSCD. As it evaluates each FS's contribution to total system modulation, a high contribution may simply be due to a high installed capacity. If the flexibility proxy is based on this information, iteration after iteration, it will reward technologies with high installed capacity and ignore the flexibility value of technologies with low installed capacity. To obtain the flexibility proxy value of a FS, its flexibility contribution is hence divided by its relative capacity share in the system, as described in Equation 5.7.

$$\forall_{r,y,tl,FS} \quad FlexibilityProxy_{r,y,tl,FS} = median_{wy \in WeatherYear} \left(quantile_{ts_{tl} \in ts} \left(\frac{Modulation_{tl,FS,ts}}{\sum_{FS} Modulation_{tl,FS,ts}} \right) * \frac{\sum_{FS} Capacity_{FS}}{Capacity_{FS}} \right) \quad (5.7)$$

where:	<i>FS</i>	Set of flexible solutions, which includes interconnection and all technologies save VRE
	<i>wy</i>	11 weather years
	<i>tl</i>	Timescale, which takes the values "annual", "weekly" and "daily"
	<i>ts</i>	Time steps of a weather year, from 1 to 8760 hours
	<i>ts_{tl}</i>	Set of time steps where the absolute value of total system modulation on the tl timescale is larger than 20% of its maximum

²¹To avoid spurious behaviour, see Section 2.3.3.

Flexibility target definition

Another design decision had to be made regarding the way flexibility targets were to be defined. Should they be defined based on net load variability, as was done in Chapter 3, or should they take abstract, arbitrary initial values, and be updated iteration on iteration, as was done in the reserve margin based feedback technique? Considering that load does not vary over iterations, and that, in the previous two feedback techniques, neither did VRE capacity²², a net load based flexibility target could not be expected to send much of a signal. Flexibility targets were hence treated in a similar way to the reserve margin, increased or decreased from one iteration to the next depending on LOLE levels.

This LOLE-dependent update considers the fact that loss-of-load may have more to do with one timescale than another. To express this idea, LOLE is first characterised on the annual, weekly and daily timescales. As described in Equation 5.8, for all time steps where loss-of-load occurs, the extent of total system modulation relative to its maximum value is recorded, for each timescale. The resulting set of values is then averaged over these time steps and over the 11 weather years, providing an indication of the timescales that are challenging to manage from an adequacy perspective.

$$\forall_{r,y,tl} \quad LOLECharacterisation_{r,y,tl} = mean_{wy \in WeatherYear} \left(mean_{ts \in ts_{LOL}} \left(\frac{\sum_{FS} Modulation_{tl,FS,ts}}{\max_{ts} (\sum_{FS} Modulation_{tl,FS,ts})} \right) \right) \quad (5.8)$$

where: ts Time steps of a weather year, from 1 to 8760 hours
 ts_{LOL} Set of time steps where loss-of-load occurs

An adjustment budget is then defined based on LOLE levels, just as was done for the reserve margin in Section 5.5. Several adjustment functions, described in Figure 5.11, were implemented, giving different soft-linking behaviours.

The adjustment budget derived using these functions can then be shared among the annual, weekly and daily timescales according to the previously defined LOLE characterisation, as expressed by Equation 5.9.

²²Investment in VRE capacity is mostly affected by VRE share and CO₂ constraints. VRE capacity credit value remained unchanged over iterations, hence so did their adequacy role.

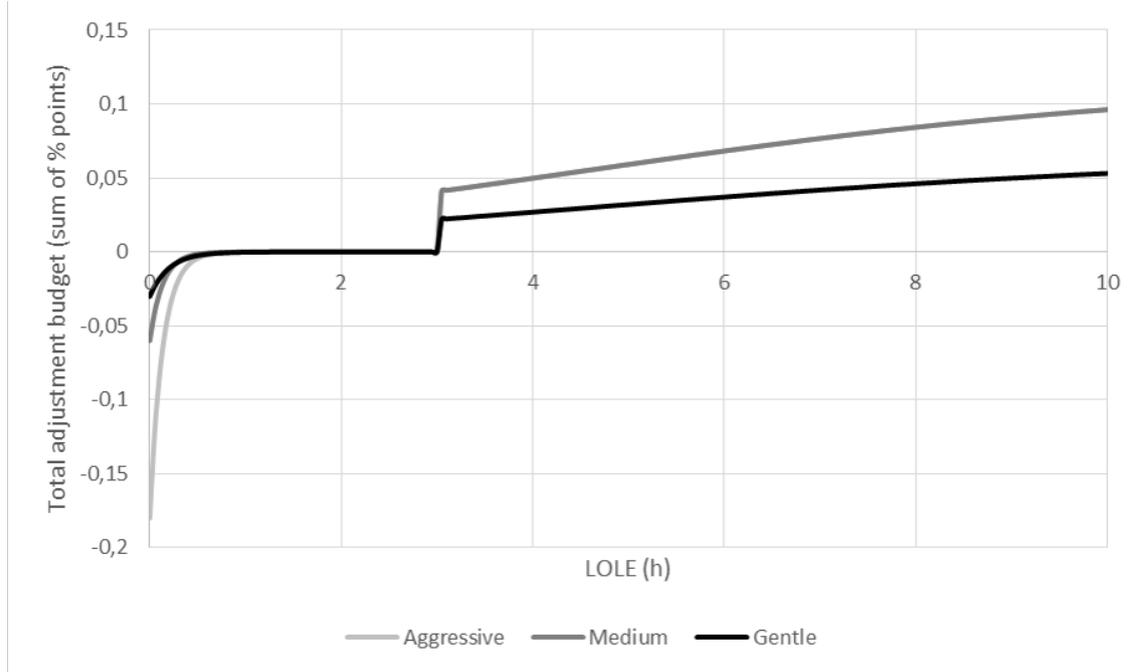


Figure 5.11: Three examples of flexibility target adjustment budget functions, showing incremental change in flexibility target value in terms of the LOLE level of a given region and soft-linked year. These three functions were empirically designed to work better with different inertia values (see below): “aggressive” for an inertia set to 1, “medium” for an inertia set to 0.66 and “gentle” for an inertia set to 0.33. Note that for LOLE levels exceeding 3 hours, the “aggressive” and “medium” functions are identical.

$$\begin{aligned}
 & \text{if } LOLE > 3h : \\
 & \quad FlexibilityTarget_{r,y,tl,i+1} = FlexibilityTarget_{r,y,tl,i} * \\
 & \quad \quad \left(1 + AdjustmentBudget * \frac{LOLECharacterisation_{r,y,tl}}{\sum_{tl} LOLECharacterisation_{r,y,tl}} \right) \\
 & \text{if } LOLE < 2.5h : \\
 & \quad FlexibilityTarget_{r,y,tl,i+1} = FlexibilityTarget_{r,y,tl,i} * \\
 & \quad \quad (1 - AdjustmentBudget * \\
 & \quad \quad \frac{(\sum_{tl} LOLECharacterisation_{r,y,tl}) - LOLECharacterisation_{r,y,tl}}{\sum_{tl} LOLECharacterisation_{r,y,tl}}) \\
 & \text{if } LOLE = 0h : \\
 & \quad FlexibilityTarget_{r,y,tl,i+1} = FlexibilityTarget_{r,y,tl,i} * (1 - AdjustmentBudget/3)
 \end{aligned} \tag{5.9}$$

where: i Iteration

Ensuring stability in the soft-linking process

As will be made clear in the results section (Section 5.6.2), the key to ensuring the effectiveness of the flexibility contribution based feedback technique is maintaining its stability. The values derived from the flexibility proxy equation described above can vary significantly from one iteration to the next, and as flexibility targets are also updated to signal under- and over-investment, this can cause a “push and pull” effect: updates in proxies and targets can send conflicting signals to OSeMOSYS, impeding on feedback convergence. If not managed appropriately, it can lead to positive feedback and to an OSeMOSYS problem with no solution, as was observed in Section 5.4. The stability of the soft-linking process was managed through careful feedback parameter initialisation and updating, as will now be discussed.

One possible approach to the soft-linking process could be to choose non-binding initial feedback parameter values and let the soft-linking framework work it out. In the first iteration of this feedback technique, this can lead to LOLE levels in excess of 1000 hours, requiring abrupt updates of feedback parameter values to have a reasonable hope of reaching an adequate²³ investment pathway in 10 iterations. These abrupt updates are likely to lead to instability. If the soft-linking framework is given a head start using educated guesses for initial flexibility targets and flexibility proxies, the updates required to reach an adequate solution within 10 iterations will be much more gentle, reducing the risk of instability.

Flexibility targets were given very easily derived initialisation values: that of the maximum hourly demand for a given region and soft-linked year. A more sophisticated approach could certainly be implemented, potentially taking inspiration from the work presented in Chapter 3, but this choice has the merit of simplicity and the possibility of being defined exogenously. Note that a different initialisation method would likely require the adjustment budget functions of Figure 5.11 to be adapted, since they were empirically built with this initialisation approach in mind. As for initial flexibility proxy values, a similar approach was used to that of capacity credits in Section 5.5. Model runs were launched for several systems, providing a range of possible flexibility proxy values for all FSs. A set of values on the lower side of these distributions was defined (see Table E.3 in the Appendix), to avoid investment bouncing back and forth over iterations. In model runs, these values were assigned uniformly across soft-linked years and regions, and used both for initialisation in the first iteration and as default values in cases where a FS’s capacity in previous iteration was 0.

Giving the soft-linking process a head start using carefully chosen initial feedback parameter values meant that these parameters could be updated more gently over iterations. For flexibility targets, this translates to lower extremes in adjustment budget functions. For flexibility proxies, this was done by introducing inertia in the updating process, as expressed by Equation 5.10.

$$\forall_{r,y,tl,FS} \quad FlexibilityProxy_{r,y,tl,i+1} = FlexibilityProxy_{r,y,tl,i} + (1 - inertia) * (RawFlexibilityProxy_{r,y,tl,i} - FlexibilityProxy_{r,y,tl,i}) \quad (5.10)$$

²³*I.e.* LOLE below 3 hours for all soft-linked years and regions.

where:	i	Iteration
	$inertia$	Parameter which can take a value in the $[0,1]$ range
	$RawFlexibilityProxy$	Value derived from Antares outputs according to Equation 5.7

An inertia set to 1 effectively means flexibility proxies aren't updated at all, sticking to default values, whereas an inertia set to 0 means that the updating process carries no memory of past iterations. The impact of the inertia parameter value on model outcomes will be explored in the results section.

Note that to avoid the “push and pull” effect, the model user can choose to give more leeway either to flexibility targets (choose the “aggressive” adjustment function, and a high inertia value for flexibility proxy updates) or to flexibility proxies (choose the “gentle” adjustment function, and a low inertia value for flexibility proxy updates). Simultaneously giving leeway to both will lead to unstable feedback behaviour.

5.6.2 Validation of feedback technique behaviour

Single-node case study

As was done in previous sections, the flexibility contribution based feedback technique was first tested on a single-node case study of the German power system to validate the methodology's behaviour.

Figures 5.12, 5.13 and 5.14 show the results of 10-iteration runs with flexibility proxies calculated based on the 80th percentile of FSCD (see Equation 5.7), comparing results for different flexibility target adjustment budget functions and different flexibility proxy update inertia values. These graphs confirm that, for all 10-iteration runs where inertia is not set to 0, both roles of the soft-linking process are successfully fulfilled. In terms of the first role: LOLE levels over 3h²⁴ in iteration i leads to increased investment in iteration $i + 1$; LOLE levels below 2.5h²⁵ in iteration i leads to reduced investment in iteration $i + 1$. In terms of the second role: the fact that increased investment does indeed reduce LOLE levels (and reduced investment does increase LOLE levels) suggests that flexibility proxies are sending an effective signal as to how OSeMOSYS should adjust its investment pathway. When inertia is set to 0 however, these two roles are not fulfilled, leading to unstable behaviour. For the “medium” and “gentle” flexibility target adjustment functions, this eventually led to an OSeMOSYS problem with no solution, for the 10th and 8th iterations respectively.

The behaviour of the flexibility contribution based feedback technique having been validated, the next crucial observation to make is that it has proposed cheaper adequate investment pathways than the reserve margin based feedback technique, albeit not by much (0.8%). This is true for all three flexibility target adjustment functions.

²⁴Red and, for some soft-linked years, pink and orange dots.

²⁵Yellow, green and, for some soft-linked years, pink and orange dots.

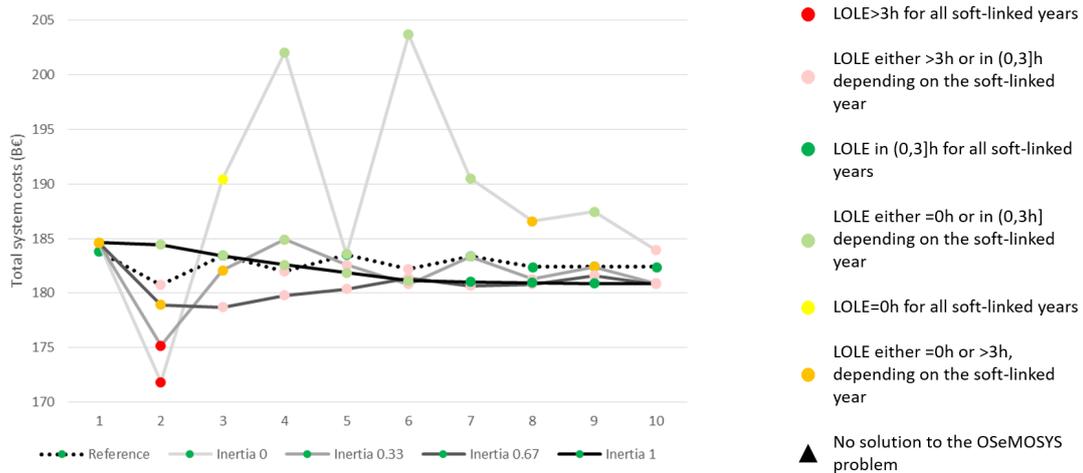


Figure 5.12: Evolution of OSeMOSYS total system costs over 10-iteration runs for the single-node German system, using the “aggressive” flexibility target adjustment budget function, flexibility proxies based on the 80th percentile of FSCD, for different inertia values ranging from 0 to 1. Note that this “aggressive” function was empirically designed to work best with an inertia set to 1. The 10-iteration run leading to the cheapest adequate investment path using the reserve margin based feedback technique is marked in dotted line for reference.

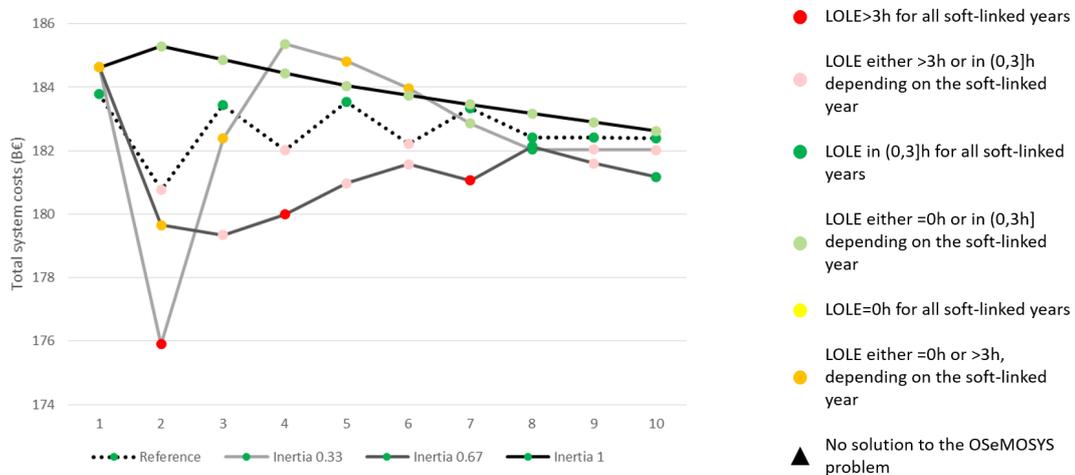


Figure 5.13: Evolution of OSeMOSYS total system costs over 10-iteration runs for the single-node German system, using the “medium” flexibility target adjustment budget function, flexibility proxies based on the 80th percentile of FSCD, for different inertia values ranging from 0.33 to 1. Note that this “medium” function was empirically designed to work best with an inertia set to 0.67. The run with inertia set to 0 led to positive feedback, and was hence not represented to ensure the readability of other results. The run leading to the cheapest adequate investment path using the reserve margin based feedback technique is marked in dotted line for reference.

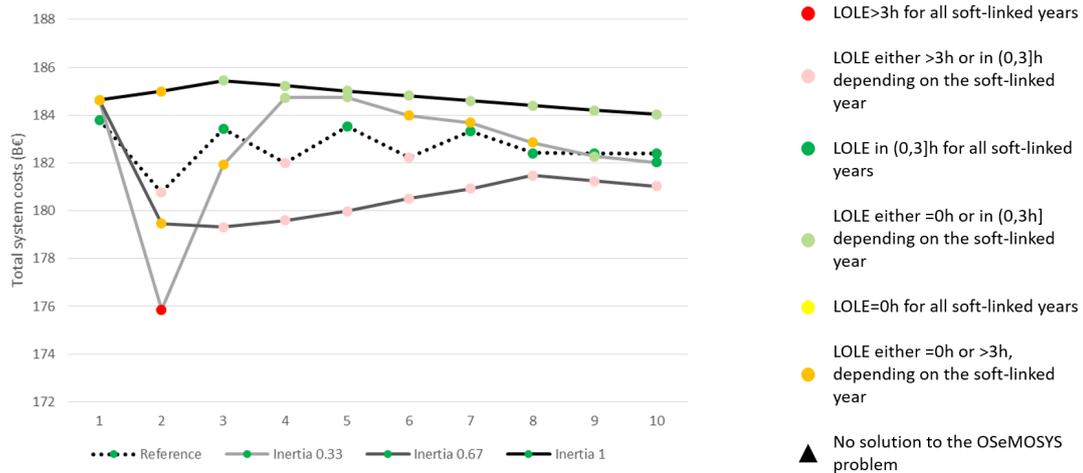


Figure 5.14: Evolution of OSeMOSYS total system costs over 10-iteration runs for the single-node German system, using the “gentle” flexibility target adjustment budget function, flexibility proxies based on the 80th percentile of FSCD, for different inertia values ranging from 0.33 to 1. Note that this “gentle” function was empirically designed to work best with an inertia set to 0.33. The run with inertia set to 0 led to positive feedback, and was hence not represented to ensure the readability of other results. The run leading to the cheapest adequate investment path using the reserve margin based feedback technique is marked in dotted line for reference.

The three graphs highlight the balance that must be found between providing too much leeway in feedback parameter updates which will lead to instability, and providing too little which will generate solutions with higher TOTEX. Comparing these graphs, it can also be seen that sharing this leeway differently between either flexibility target updates or flexibility proxy updates leads to solutions with fairly equivalent TOTEX: gap of 0.2% between the cheapest adequate solutions of “aggressive-inertia-1” and “medium-inertia-0.67”, gap of 0.6% between the cheapest adequate solutions of “aggressive-inertia-1” and “gentle-inertia-0.33” (hereafter Agg-in-1, Med-in-0.67 and Gen-in-0.33). While the cheapest adequate Agg-in-1 solution is reached by keeping flexibility proxies constant and reducing flexibility targets, those of Med-in-0.67 and Gen-in-0.33 are obtained through a general increase in both flexibility targets and proxies (see figures A.10 to A.14 in the Appendix for a few examples of feedback parameter evolutions). Most technologies show negligible differences in installed capacities, however for CCGT, OCGT and batteries these differences can be quite significant, reaching 15 GW for certain investment years (roughly 15% of that technology’s capacity).

From figures A.10 and A.11 (see Appendix), it can be seen that flexibility targets have very similar values on each timescale, even after 10 iterations. This raises the question of the added value of the whole LOLE characterisation process. Additional runs of Agg-in-1, Med-in-0.67 and Gen-in-0.33 were therefore made, sharing the flexibility target adjustment equally over timescales instead of according to the process described in Equation 5.9, the results of which can be seen in Figure 5.15. Unsurprisingly, introducing a timescale characterisation of LOLE in the flexibility target

adjustment process brings more value in the Agg-in-1 case, which gives more leeway to the flexibility target update. In the Gen-in-0.33 case however, where more leeway is given to the flexibility proxy update, not performing this timescale characterisation of LOLE leads to a cheaper adequate solution, suggesting that the timescale related information is being sent through flexibility proxy updates instead.

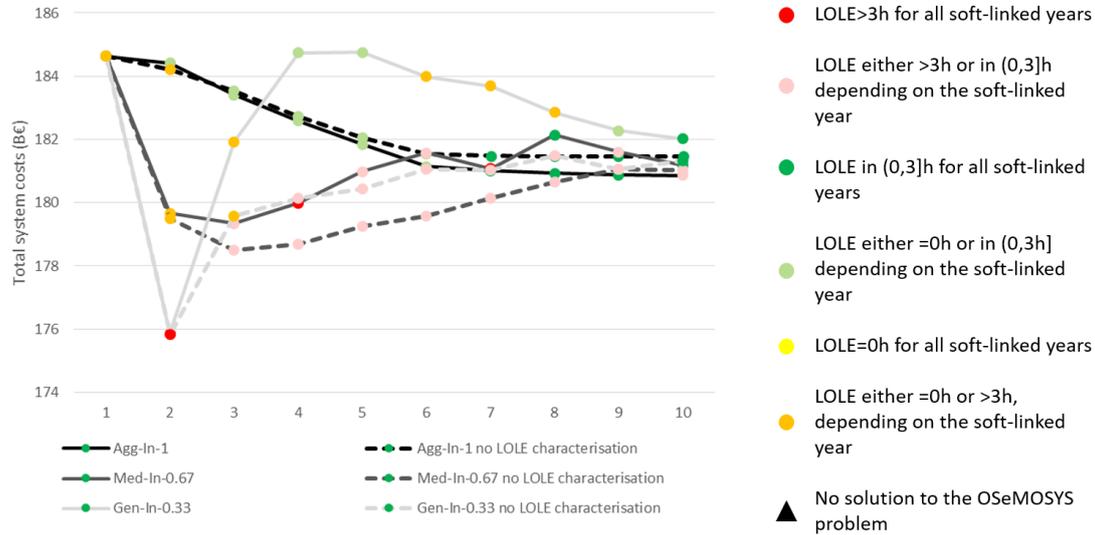


Figure 5.15: Evolution of OSeMOSYS total system costs over 10-iteration runs for the single-node German system, with (full lines) and without (dashed lines) LOLE characterisation. Flexibility proxies are based on the 80th percentile of FSCD.

It is also worth exploring the impact of another modelling decision on model outcomes: that of the quantile used in the flexibility proxy derivation (see Equation 5.7). For the comparison to be fair, this implies defining new default values for flexibility proxies, new initial values for flexibility targets, new flexibility target adjustment budget functions empirically designed to work better with different inertia values. This whole process was carried out to launch new 10-iteration runs with flexibility proxies based on the 90% percentile of FSCD, with mixed results. While these new runs provided a better solution for 0.90-Med-in-0.67²⁶, the cheapest adequate solutions proposed for 0.90-Agg-in-1 and 0.90-Gen-in-0.33 had higher TOTEX than their 80th percentile counterparts (see Figure A.15 in the Appendix).

The fact that all these arbitrary modelling decisions cannot be validated without resorting to lengthy and cumbersome trial and error is a key weakness of all three of the feedback techniques implemented. The implications of such limitations and potential solutions are discussed in the concluding Chapter 6.

Multi-node case study

Due to time constraints, the flexibility contribution based feedback method was not applied to multi-node case studies. If we were to speculate, we would expect setting

²⁶Note that the “0.90-medium” adjustment function is different to the one used previously for model runs using flexibility proxies based on the 80% percentile of FSCD.

this up to require a re-calibration of a few modelling decisions, and that just as it was for the reserve margin based feedback method, it would be a struggle to ensure our adequacy criterion is respected in every region and every soft-linked year. The results would likely be in the same ball-park as those obtained with the second feedback method, potentially providing better solutions as flexibility contributions could be expected to provide a better indication of the value of interconnection than capacity credits.

5.7 Impact of soft-linking on proposed solutions

In the last two sections, we have shown that after a few iterations, a soft-linking framework between a CExM and a PCM is able to propose long-term investment pathways guaranteed to meet a user-defined adequacy criterion by simulating its operation at full hourly resolution. Having analysed the soft-linking framework's behaviour, it is also worth investigating its impact on model outcomes.

To this end, for the single-node case study, Figure 5.16 compares a selection of outputs from three different model runs: a reference case corresponding to a uni-directional link of OSeMOSYS and Antares, where neither of the feedback constraints were used (*i.e.* neither Equation 5.3 nor Equation 5.6), and two others corresponding to the cheapest adequate solutions obtained using the second and third feedback techniques.

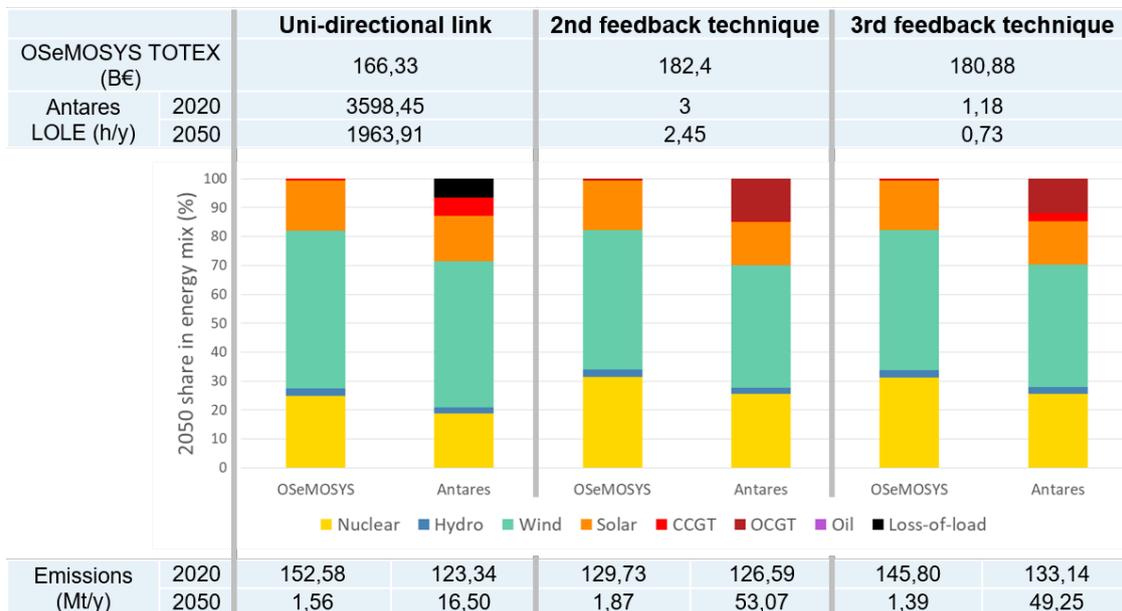


Figure 5.16: Comparison of a selection of OSeMOSYS and Antares outputs, for a uni-directional soft link and for the best adequate solutions proposed by the second and third feedback technique.

First of all, we note that the soft-linking framework leads to a 10% increase in the TOTEX calculated by OSeMOSYS. This increase should not come as a surprise,

as we have added constraints to an optimisation problem. If we look at Antares-derived LOLE, we get a clear explanation of why that is: while the best adequate solutions from the second and third feedback technique meet our adequacy criterion of 3 hours of LOLE per year, the reference case very noticeably does not, with LOLE reaching a few thousand hours per year. From a system operator point of view, the soft-linking is therefore not only a success but also a crucial step: it ensures that a capacity expansion planning tool does not end up with a vastly inadequate investment pathway.

Now looking at each 2050 energy mix: in the uni-directional case, we see that OSeMOSYS has overestimated the generation output of nuclear, wind and solar, while vastly underestimating the need to operate gas plants to meet demand, which could not be fully met for nearly 2000 of the 8760 hours of the year. Comparing the OSeMOSYS and Antares energy mixes of the best solutions resulting from the soft-linking framework, the shares of nuclear, wind and solar have again been overestimated. We can also see that while OSeMOSYS did not see much dispatch value for gas plants, it still invested in enough OCGT and CCGT capacity for Antares to meet the adequacy criterion, in order to respect feedback constraints.

This severe underestimation of gas plant use has significant implications for system emissions. While for the 2020 simulation, OSeMOSYS and Antares give reasonably similar values, in 2050, OSeMOSYS estimates are way off, and its investment pathways are well over their carbon budget (around 17 MT in 2050 for this single-node study).

This issue of OSeMOSYS not seeing any “dispatch use” for the FSs it has invested in can be seen in more detail by comparing Figure 5.17 with Figure 5.18. These two figures describe, for the same region of the same system, the dispatch as seen by OSeMOSYS and Antares respectively. In this particular example based on the second feedback technique, OSeMOSYS has built more than 60 GW of gas generation capacity purely to respect the adequacy constraint. In Antares however, this fossil fuel based generation capacity has a significant role to play to provide annual flexibility and ensure adequacy.

OSeMOSYS’s inability to accurately evaluate a system’s reliability, TOTEX and emissions raise severe doubt as to the relevance of investment pathways proposed by CExMs.

5.8 Conclusion

This chapter started by reviewing potential strategies used to improve the representation of flexibility in capacity expansion planning, classifying them from the point of view of the model user. This literature review (Section 5.2) hinted the soft-linking of a CExM with a PCM to be an interesting approach, but also highlighted the limited scope or lack of transparency of past attempts.

Implementing a soft-linking of the CExM OSeMOSYS with the PCM Antares, the work presented in this chapter aimed to shed light on the core aspect of such a soft-linking exercise: the way information is fed from the PCM back to the CExM. Three different feedback techniques were implemented, building on existing work and finding a new practical use for the flexibility provision metrics presented in

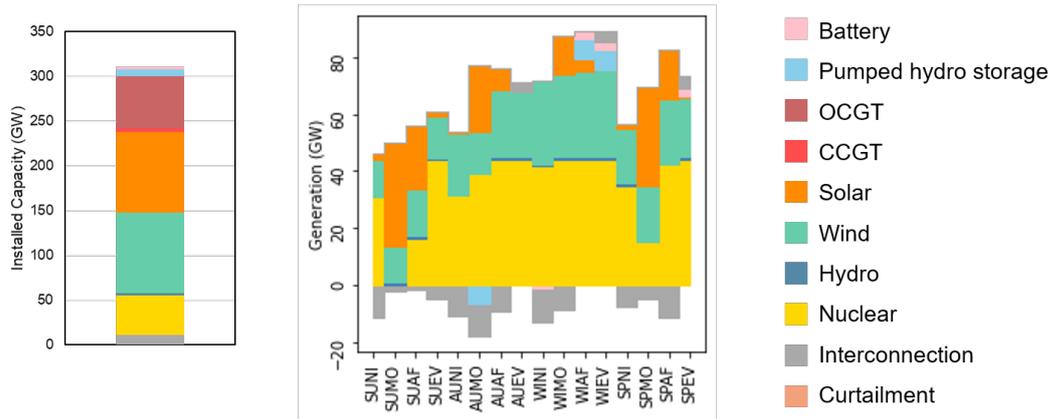


Figure 5.17: For the reserve margin feedback method applied to the 17 node case study, OSeMOSYS 2050 dispatch for the British Isles region over 16 timeslices. These results are those obtained for the cheapest adequate investment path proposed by the soft-linking framework (“balanced” reserve margin update, no capacity credit update, iteration 7). Note that while timeslice bars are given equal widths, they do not represent the same time duration (SUNI: summer night, AUMO: autumn morning etc.).

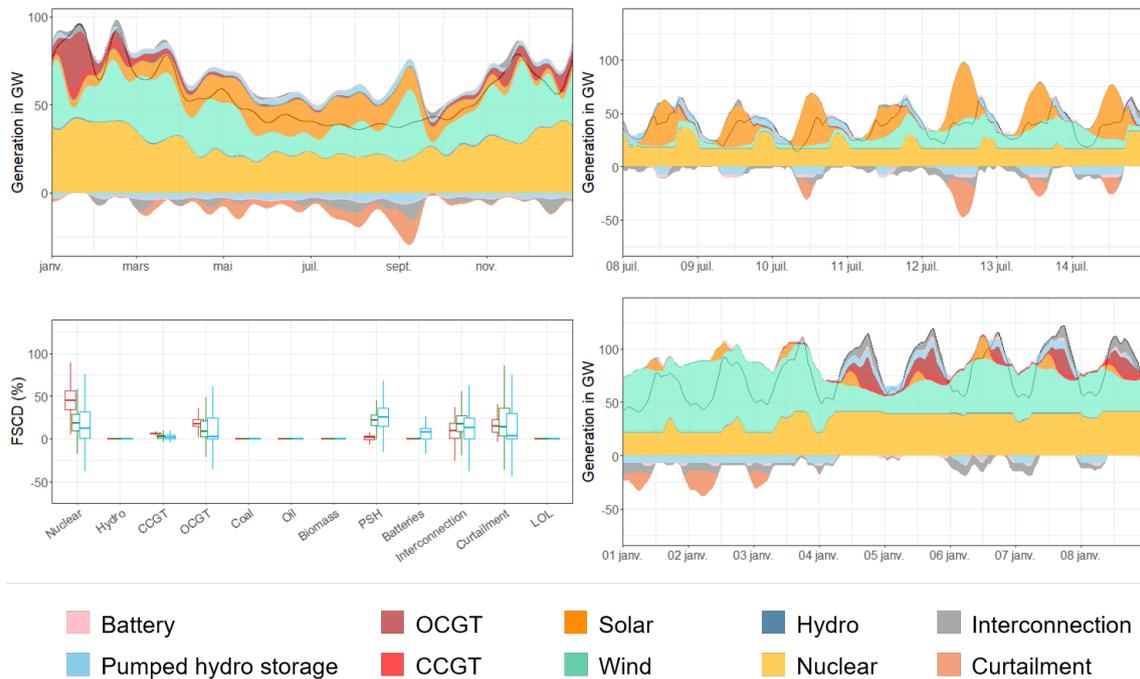


Figure 5.18: For the reserve margin feedback method applied to the 17 node case study, Antares 2050 results for a single weather year for the British Isles region. These results are those obtained for the cheapest adequate investment path proposed by the soft-linking framework (“balanced” reserve margin update, no capacity credit update, iteration 7). Top left: low frequency components of the annual dispatch to ease readability. Top right: full signal generation stack zoomed into a summer week. Bottom right: full signal generation stack zoomed into a winter year. Bottom left: FSCD (see Chapter 2). Generation stacks show generation before curtailment.

Chapter 2.

The first one, based on existing work, failed to perform correctly, but understanding the reasons behind this failure led to many learning points that were crucial for the development of the further two techniques. Through the reserve margin based feedback method, we were successful in building a soft-linking framework able to propose long-term investment pathways on a large, multi-node system considering not only investment in generation, but storage and interconnection also. The third feedback technique, based on the flexibility contribution metrics proposed in Chapter 2, was shown to propose better solutions, but was only tested on a single-node study. This improved result further demonstrates the flexibility contribution metrics' ability to extract the key information concerning the way a system manages variability and uncertainty on annual, weekly and daily timescales.

On the single-node case study, comparing the best adequate solutions produced by the second and third feedback techniques to the one proposed by a uni-directional link underlines how crucial it is to simulate the detailed operation of a power system proposed by a CExM before it can be taken seriously: doing so reveals that LOLE can reach a few thousand hours per year, while a typical target for power system planners is 3 hours per year. By using the second or the third feedback technique, this can be corrected and we can derive investment pathways demonstrated to lead to sub-3-hour LOLE when simulated on 11 weather years at hourly resolution. While this may be considered a low number of weather years from an adequacy study perspective, it is a rare feat in capacity expansion studies. Note that this correction leads to a 10% increase in TOTEX and notable changes to the generation mix, and that the corrected investment pathway does not respect the CO₂ budget allocated in OSeMOSYS.

Though this is a significant improvement compared to standard CExM outcomes, it does not mean proposed investment pathways can be considered as definite: many crucial power system constraints require yet more detailed modelling (stability, inertia, internal network congestion...). Also note that while the second and third feedback techniques are designed in such a way as to avoid over-investment, they do not guarantee the derived investment pathways will be optimal.

There is another important conclusion to draw from the work presented in the last few sections: finding appropriate ways of sending information from a production cost model to a capacity expansion model in order to improve the representation of flexibility in an expansion study is a complex and cumbersome task. Ensuring that feedback parameters behave the way we intuitively expect them to is a struggle, as is ensuring stability in the feedback process. Many arbitrary modelling decisions must be validated through trial and error: the equations used to derive feedback parameters, the set of time steps they are evaluated on, feedback parameter adjustment functions, the number of iterations performed etc. Furthermore, we cannot guarantee that these arbitrary modelling decisions will not have to be re-calibrated when the methodology is applied to a new case study. These difficulties are a significant limiting factor to the potential industrialisation of soft-linking approaches; potential workarounds will be discussed in the following closing chapter.

5.9 Résumé en français

Dans le Chapitre 4, nous avons vu que les outils d'expansion de capacité peinent à représenter la flexibilité de manière appropriée, et que cela pouvait introduire des biais importants dans les résultats lorsque le cas d'étude comprend une part importante d' EnRV. De nombreux travaux de recherche récents se sont focalisés sur ce problème. Du point de vue de l'utilisateur de ce type de modèle, leurs approches peuvent être rangées dans trois catégories : (i) l'amélioration d'un modèle existant à la marge, sans fondamentalement changer sa structure, (ii) le couplage d'un CExM avec un modèle de simulation du dispatch à la représentation de la flexibilité bien plus fine, et (iii) la construction d'un nouveau modèle spécifiquement conçu pour résoudre un problème de dispatch et un problème d'investissement simultanément.

Plutôt que d'ajouter un nouvel item à la longue liste de modèles existants, et afin de bénéficier au mieux des longues années de travail de la communauté scientifique, nous optons pour la deuxième option, mettant en place un couplage bidirectionnel entre le CExM OSeMOSYS et le modèle de simulation du dispatch Antares. Nous nous concentrons sur l'élément crucial d'un couplage bidirectionnel : la manière dont l'information est remontée depuis Antares vers OSeMOSYS. Trois différentes méthodes de remontée de l'information sont mises en place.

La première se base sur des travaux existants, et s'est avérée incapable de résoudre notre problème. L'identification des raisons de cet échec fut néanmoins très importante pour le développement des deux méthodes suivantes. Grâce à la deuxième méthode, nous sommes parvenus à proposer des plans d'investissement long-terme sur un système électrique multi-nœud, optimisant simultanément l'investissement dans la production, les interconnexions et le stockage, tout en respectant un critère de sécurité d'approvisionnement. La troisième méthode, basée sur les outils de quantification de la fourniture de flexibilité présentés dans le Chapitre 2, donna des meilleures solutions que la deuxième méthode, mais ne put être testée que sur un cas d'étude composé d'un seul nœud, faute de temps. Cette amélioration de la solution peut être vue comme une nouvelle preuve de la capacité de nos indicateurs à extraire l'information clé concernant la gestion de la variabilité et de l'incertitude aux horizons annuels, hebdomadaires et journaliers.

Sur le cas d'étude à un nœud, la comparaison des meilleures solutions proposées par les méthodes 2 et 3, respectant le critère d'approvisionnement retenu, avec celle proposée par un couplage unidirectionnel démontre à quel point il est crucial de simuler le fonctionnement détaillé d'un système proposé par un CExM avant de le prendre au sérieux. En effet, l'espérance de la défaillance peut atteindre plusieurs milliers d'heures par an. En utilisant les méthodes 2 ou 3, ce problème peut être corrigé et le couplage peut produire des trajectoires d'investissement garantissant une espérance de défaillance inférieure à 3 heures par an, par la simulation du dispatch sur 11 années météorologiques à granularité horaire. Cette correction induit une augmentation des coûts totaux de l'ordre de 10% et des changements notables du mix de production. De plus, la trajectoire d'investissement corrigée ne peut respecter le budget CO₂ alloué dans OSeMOSYS.

Ceci est une nette amélioration comparé aux sorties d'un CExM classique, mais les solutions proposées ne peuvent néanmoins pas être considérées comme définitives

: de nombreux autres phénomènes potentiellement dimensionnants nécessitent une modélisation plus fine encore (stabilité, inertie, congestion du réseau interne. . .). De plus, si les deux dernières méthodes de couplage sont conçues de manière à limiter le surinvestissement, on ne peut garantir que les trajectoires d'investissement soient optimales.

Il y a une autre conclusion importante à tirer du travail présenté dans ce chapitre : trouver des manières appropriées de faire remonter de l'information depuis un modèle de simulation de dispatch vers un CExM est une tâche lourde et complexe. Il est difficile de s'assurer que les paramètres de rétroaction expriment bien le message escompté et que la boucle de rétroaction reste stable. De nombreuses décisions de modélisations arbitraires doivent être validées par essai-erreur : les équations permettant de calculer les valeurs des paramètres de rétroaction, les pas de temps sur lesquels ils sont évalués, les fonctions d'ajustement des paramètres de rétroaction, le nombre d'itérations etc. De plus, il n'est pas à exclure que ces décisions de modélisation aient besoin d'être recalibrées quand la méthodologie est appliquée à un nouveau cas d'étude. Ces difficultés sont un frein important à l'industrialisation potentielle de ces techniques de couplage ; des solutions de contournement éventuelles font l'objet du chapitre de conclusion.

Chapter 6

General conclusion and further work

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6.1 Summary and PhD contributions

As discussed in the introduction to this thesis, the most widely accepted means of mitigating climate change is through stark reductions in energy related greenhouse gas emissions, made possible by significant structural changes in our energy system. This is generally expected to involve a replacement of carbon-intensive power generation by variable renewable energy sources. These changes are affecting power system flexibility, both in terms of its requirement (growing VRE penetration introduces more variability and uncertainty in the system) and its provision (historically dominant means of coping with variability and uncertainty are the carbon-intensive assets that are being replaced). Meanwhile, new flexibility solutions are experiencing falling prices. In such a changing context, a key question that power system planners must address is hence: what optimal mix of flexibility solutions should be used to provide flexibility in a power system with high penetrations of VRE?

As power systems are composed of capital intensive assets with lifetimes in the order of decades, costly lock-in effects are a significant risk which requires particular attention. Policy makers, investors and the general public must be well informed and given a chance to have a say, while power system planners must ground their intelligible policy recommendations in careful modelling, fed with appropriate data and based on study-specific trade-offs between accuracy and robustness. From this context: two key objectives were drawn for the work presented in this thesis: (i) improve our understanding and ability to communicate on power system flexibility, and (ii) improve the representation of flexibility in capacity expansion planning in order to propose an optimal mix of flexibility solutions.

Chapter 1 starts by covering the context and motivation for this PhD, before making a qualitative contribution to the first of these two objectives. By reviewing proposed definitions of power system flexibility over the past few decades, the meaning of the term was shown to have evolved with the changing context. Most notably, while flexibility was considered to be solely a short-term issue when VRE was first integrated into power systems, it is increasingly being explicitly defined as a multi-timescale issue. We then proposed our own understanding, broadly defining flexibility as a power system's ability to cope with variability and uncertainty. There are many reasons why each of these occur, which we discussed individually for different timescales, before providing a general description of the 4 categories of solutions that can be used to cope with them: flexible generation, flexible load, interconnection and storage. While flexibility is required both to match generation with demand and to ensure that power flows do not exceed network thermal and voltage limits, the work presented in this thesis focussed on the former. Chapter 1 also delimited the scope of the PhD, specifying the way it relates to the different tasks of the European H2020 project OSMOSE, and giving an overview of the different approaches used to consider uncertainties in our modelling work.

To understand and to be able to communicate on power system flexibility, the qualitative approach of Chapter 1 was complemented by quantitative analyses. Quantification of the different facets of flexibility has been the focus of much recent work, generally targeting two practical uses: (i) condensing large amounts of data to help the power system planner gain a quick understanding of a complex situation, and (ii) providing a clear and neutral basis on which discussions can be founded to explain policy recommendations. This was the focus of Chapters 2 and 3.

Chapter 2 started with an extensive review of flexibility quantification methods, classifying them depending on the question they address: (i) how much flexibility does my system need? (ii) how flexible is my flexibility solution? (iii) how flexible is my power system? and (iv) who is providing flexibility in my power system? Existing methods addressing this last question were shown to be limited in terms of their number, scope and relevance. A pair of novel tools were therefore developed to close this gap in literature: the Flexibility Solution Modulation Stack (FSMS) and the Flexibility Solution Contribution Distribution (FSCD). Their input consisting of flexibility solution time series, these frequency spectrum analysis based tools quantify flexibility provided by all 4 categories of flexibility solutions, separately considering their roles on the annual, weekly and daily timescales. Through example applications on several power systems with contrasting characteristics, FSMS and FSCD were shown to be able to support a wide range of narratives, from shedding light on interactions between flexibility solutions, ranking their contributions and analysing the roles of future solutions, to tracking the evolution of a flexibility solution's importance.

Chapter 3 expanded the state-of-the-art of flexibility requirement metrics, which the review of quantification methods showed to be heavily focussed on short-term phenomena. Making further use of frequency spectrum analysis, we proposed a set of metrics quantifying flexibility requirement on the annual, weekly and daily timescales, their input consisting of net load time series. These metrics constitute

the core element of our analysis of the potential evolution of flexibility requirements on the French power system, investigating their sensitivity to five variables: the degree of network interconnection and the penetration of wind power, solar power, electric heating and cooling. This analysis showed that the most impacting variables differ with the considered aspect of the flexibility problem. Considering expected evolutions of the 5 previously mentioned variables, flexibility requirement will significantly increase on the daily and weekly timescales, primarily due to increasing solar and wind penetrations respectively. In relative terms, the other studied variables should have a limited impact, and the changes in flexibility requirement should be less significant on the annual timescale. This does not mean that the annual timescale will be easy to manage however: the results exposed in Chapter 3 suggest that, on the contrary, the phase out of fossil fuel based generation is likely to be the most problematic on the annual timescale. One should however keep in mind that we have not considered very short-term issues such as stability and inertia. The developed framework was also used to evaluate the potential for network interconnection to reduce flexibility requirement by exploiting diversity in load and VRE generation profiles, this potential being shown to increase with VRE penetration.

The descriptive nature of the proposed quantification methods make them effective analysis and teaching tools. However, while descriptive statistics help us understand a known situation, they are of little use when searching for robust and effective ways of dealing with identified evolutions in power system flexibility requirement. Such a question calls for optimisation techniques, and brings us to the second objective of this PhD: improving the representation of flexibility in capacity expansion planning in order to propose an optimal mix of flexibility solutions. This is the focus of Chapters 4 and 5.

Chapter 4 starts by discussing the numerous model types used in power system planning, with a particular focus on capacity expansion models, which determine when, where, how much and what technology type to build or retire. To keep the problem tractable, these models' representation of flexibility is simplified. While this was historically acceptable, literature has made abundantly clear that in the face of growing uncertainty and variability, it can strongly affect the validity of results. Existing studies show that due to an underestimation of flexibility requirement and an overestimation of flexibility provision, capacity expansion models undervalue flexibility, leading to errors in key model outputs: total system costs, carbon emissions, capacity investment and energy mix to name a few. After having added a power transmission module to the open-source modelling framework OSeMOSYS, these literature results were confirmed and refined on a brownfield investment study ranging from 2015 to 2050, on a 17-node representation of the European power system. The impact of the representation of variability on model outcomes was shown to depend on the degree of freedom given to the CExM; it can be very limited if maximum infrastructure development rates are considered in the model. These results also highlighted the importance of taking this limiting factor into account in power system planning.

Chapter 5 worked to solve this issue of flexibility representation in capacity expansion models. A literature review identified several possible strategies, hinting at the value of soft-linking a capacity expansion model to a production cost model,

whose representation of flexibility is much more detailed. It also highlighted the limited scope or lack of transparency of previous soft-linking attempts, particularly when it comes to the core element: the way information is fed from the PCM back to the CExM. Shedding light on this key issue was the focal point of our soft-linking exercise between OSeMOSYS and Antares, applied to the case study described in Chapter 4. Three different feedback techniques were implemented. The first, based on existing work, failed to perform correctly, but understanding the reasons behind this failure led to many learning points crucial for the development of the further two, novel, techniques. The second feedback technique was successful in proposing investment pathways simultaneously considering generation, storage and interconnection. Based on the FSCD introduced in Chapter 2, the third feedback technique produced better results than the second (*i.e.* cheaper adequate solutions), providing further evidence that this quantification tool is able to capture the essence of flexibility provision in a given system. It was however only applied to a single-node case study due to time constraints.

The soft-linking results underline just how crucial it is to simulate the detailed operation of a system proposed by a CExM, as LOLE can reach a few thousand hours per year. This issue can be corrected using the second and third feedback technique, leading to a 10% increase in TOTEX and notable changes to the generation mix. This does not mean proposed investment pathways should be considered as definite: many crucial power system phenomena require yet more detailed modelling (stability, inertia, internal network congestion...). Proposing an effective feedback technique was shown to be a complex and cumbersome task, with many arbitrary modelling decisions having to be validated through trial and error. Making sure that feedback parameters behave the way we expect them to was a struggle, as was ensuring stable behaviour in the feedback process. These difficulties are a significant limiting factor to the potential industrialisation of soft-linking approaches; potential workarounds will be discussed in the further work section.

6.2 Further work

The PhD work presented in this thesis has opened up many new paths which may be worth exploring, some mere extensions, others broad new research questions. We will wrap up this thesis by mentioning a few of these.

Regarding flexibility quantification methods, the FSMS and FSCD proposed in Chapter 2 could be extended to consider additional energy vectors, providing a full energy system view of flexibility solution behaviour. The flexibility requirement metrics proposed in Chapter 3 could also be extended, and indeed have been. Building on our work, Olsen *et al.* [62] used the same approach to also look at additional, smaller timescales. Saarinen *et al.* [119] made another interesting extension to our metrics, splitting the flexibility power requirement into upwards and downwards regulation, easing their comparison with FS operational constraints. Elsewhere in flexibility metric territory, quantifying flexibility related to congestion management instead of matching generation with demand is a comparatively much less explored issue.

Regarding the soft-linking of CExMs with PCMs, more time could certainly be

spent on improving the effectiveness of proxies in mimicking flexibility solution behaviour. Extending the soft-linking process to include additional aspects could also be very useful: the reconciliation of OSeMOSYS and Antares OPEX and emissions could potentially bring much value to the exercise, as could explorations on the potential role of timeslice number and structure adjustment over iterations. Another interesting lead could be to adjust the investment pathway in the style of Lopez-Botet *et al.* [178], on the basis of a comparison of OSeMOSYS-derived asset investment costs with Antares-derived asset revenues, though this raises the question of the legitimacy of Antares revenues as an investment signal.

These potential options are unlikely to be effective in avoiding the lengthy process of validating arbitrary modelling decisions through trial and error. This issue was identified as a severe impediment to the potential industrialisation of such a modelling approach. An adjustment to the approach might help, however: bringing artificial intelligence tools into the equation. At least 2 potential strategies might be of interest:

- A first strategy would consist in deriving a function that would act as an Antares emulator, providing a quick evaluation of whether an OSeMOSYS investment pathway is likely to lead to acceptable LOLE levels. Only if the result is unclear would the system be fed to Antares for more detailed simulation. This function would have to be differentiable, to obtain gradients which could guide OSeMOSYS to more suitable investment pathways. However, results obtained in Section 5.5 suggest that this is not necessarily the task that requires the most computation time: LOLE levels quickly fall to the sub-10-hour zone, the more time-consuming task is then reducing TOTEX while maintaining acceptable sub-3-hour LOLE.
- A second promising strategy would consist in performing several dozens of uni-directional soft-links, and use black-box algorithms to do the “dirty work” of selecting which features are desirable and which are not. A new generation of uni-directional evaluations could then be proposed, eventually converging to a range of acceptable solutions. This strategy would be greedy in terms of computation time, but would allow parallel computing.

Considering the time investment required to make the soft-linking process work, computation time reduction is another aspect that has not been studied in much detail, though some low-hanging fruits are available¹.

Beyond methodological aspects, the scope of the framework should ideally be extended before it is able to feed expansion studies and provide useful policy advice. Though links with the hydrogen and methane systems were not included in the soft-linking exercise due to the way tasks were allocated between partners of the OSMOSE H2020 project, these technologies should be an integral part of a methodology used to propose an optimal mix of flexibility for a power system.

Lastly, attempting to bring together the two objectives of the PhD would be an idea worth pursuing, bringing much value to the public debate. With a fully functional soft-linking framework considering the links between the electricity, hydrogen

¹For the 17 node system optimised in Section 5.5, it took around 12 hours to go through all 10 iterations.

and methane system, an interesting case study could consist in fixing VRE capacities, investment dates and locations, while optimising the rest of the energy system. By performing evaluations on a large number of VRE input conditions, a sensitivity analysis would allow us to reveal trends in the flexibility solution mixes most suited to a particular balance or a particular geographical spread in VRE capacity. The flexibility requirement metrics proposed in Chapter 3 could also be used to establish links between flexibility requirement shape and associated optimal flexibility solution mix, leading to simple, easy to understand rules of thumb that would apply for any system.

6.3 Résumé en français

Ce chapitre propose une synthèse des travaux de thèse, résumant ses principales contributions. Il comprend également une discussion sur les poursuites de travaux éventuelles et sur les nouvelles pistes de recherche dévoilées, notamment autour du couplage d'OSeMOSYS et Antares. Après avoir proposé quelques nouvelles techniques de rétroaction qui vaudraient la peine d'être explorées, nous décrivons le rôle prometteur que pourrait jouer l'intelligence artificielle. Cette option permettrait de limiter le recours à la validation de décisions de modélisation par essai-erreur, facilitant une industrialisation éventuelle d'un couplage de ce type. Nous mentionnons enfin quelques idées d'études que cette méthodologie permettrait d'effectuer.

Appendix A

Additional figures

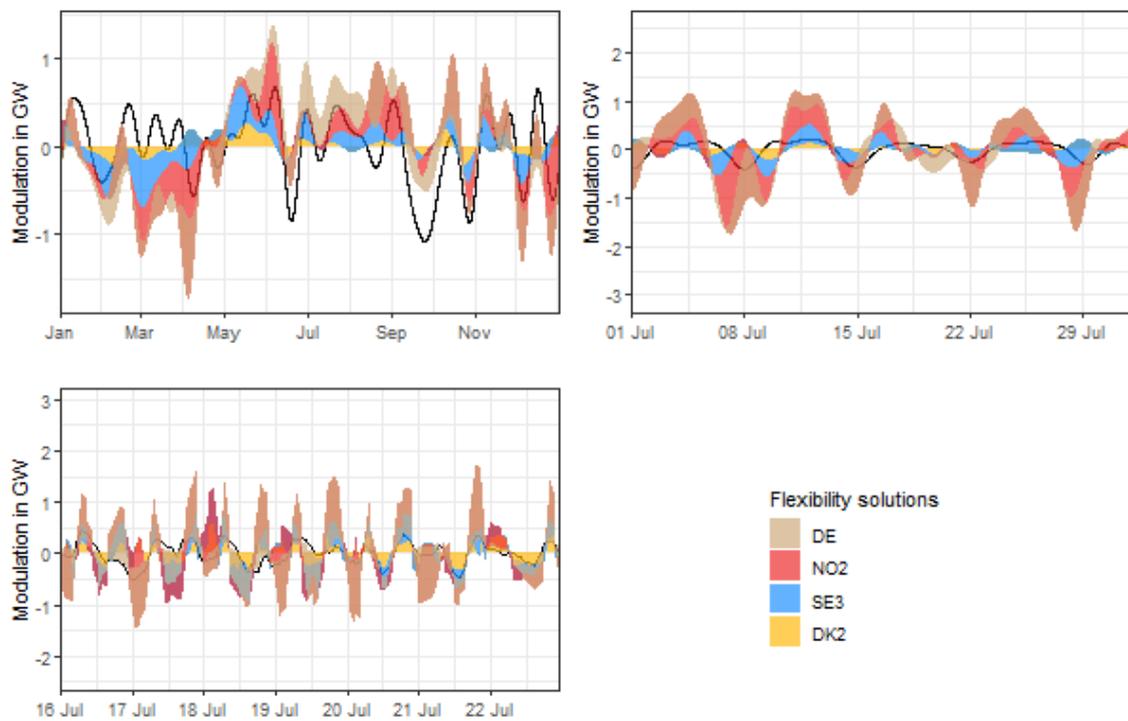


Figure A.1: Section 2.4.3: How do interconnectors contribute to flexibility in highly interconnected systems? Flexibility solution modulation stack on annual, weekly and daily timescales, for the western Denmark power system in 2018 (data from [88]). Note that the sum of the interconnector modulations do not sum up to total system modulation (black line), as, to ensure readability, other flexibility solution modulations have not been represented.

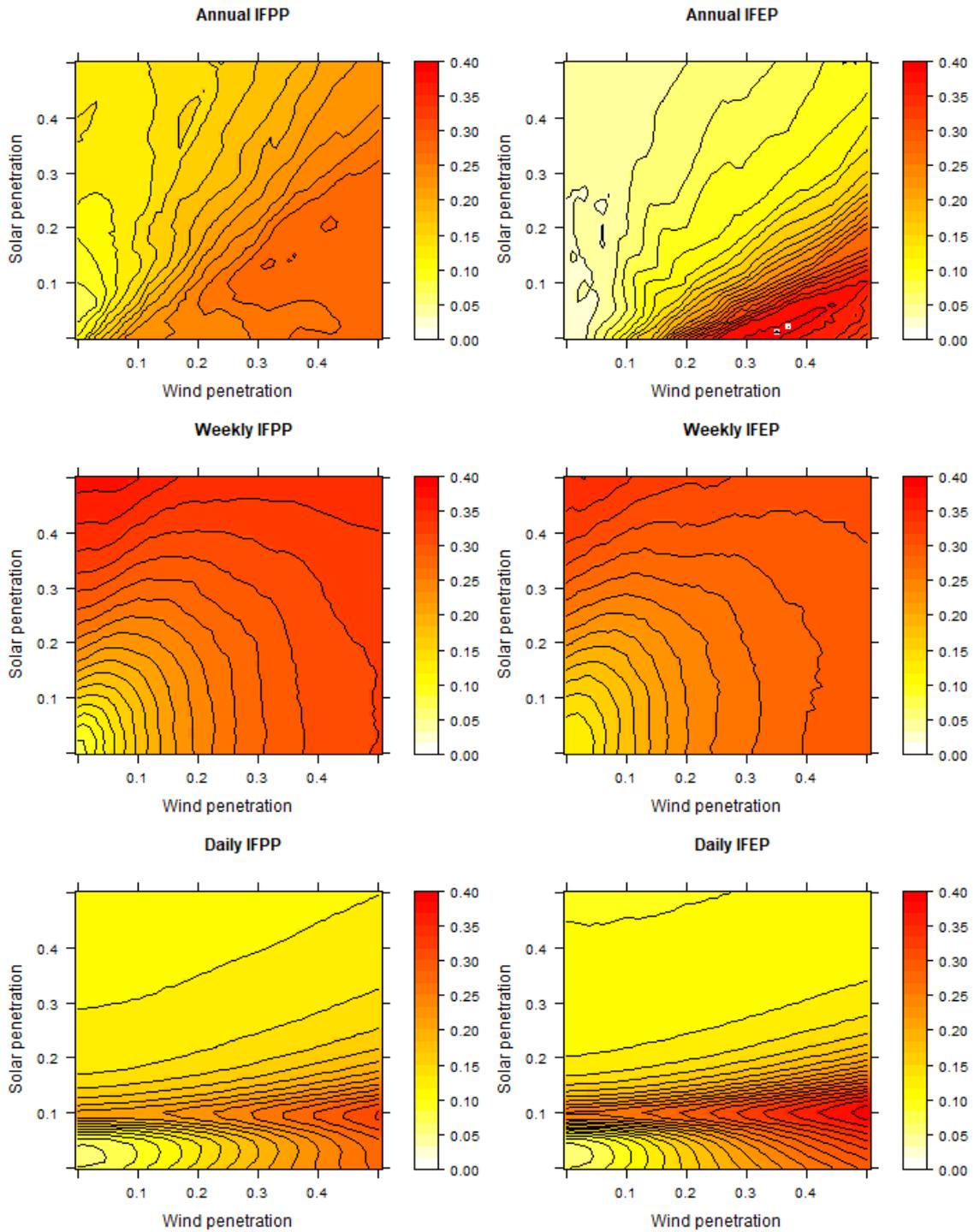


Figure A.2: Section 3.5.2: Based on the 95th percentiles of FPR and FER , interconnection flexible power potential ($IFPP$) expressed in terms of percentage of $\sum_c FPR$ (left) and energy potential ($IFEP$) expressed in terms of percentage of $\sum_c FER$ (right) in terms of wind and solar penetrations. Top, middle and bottom rows show results for the annual, weekly and daily timescales respectively.

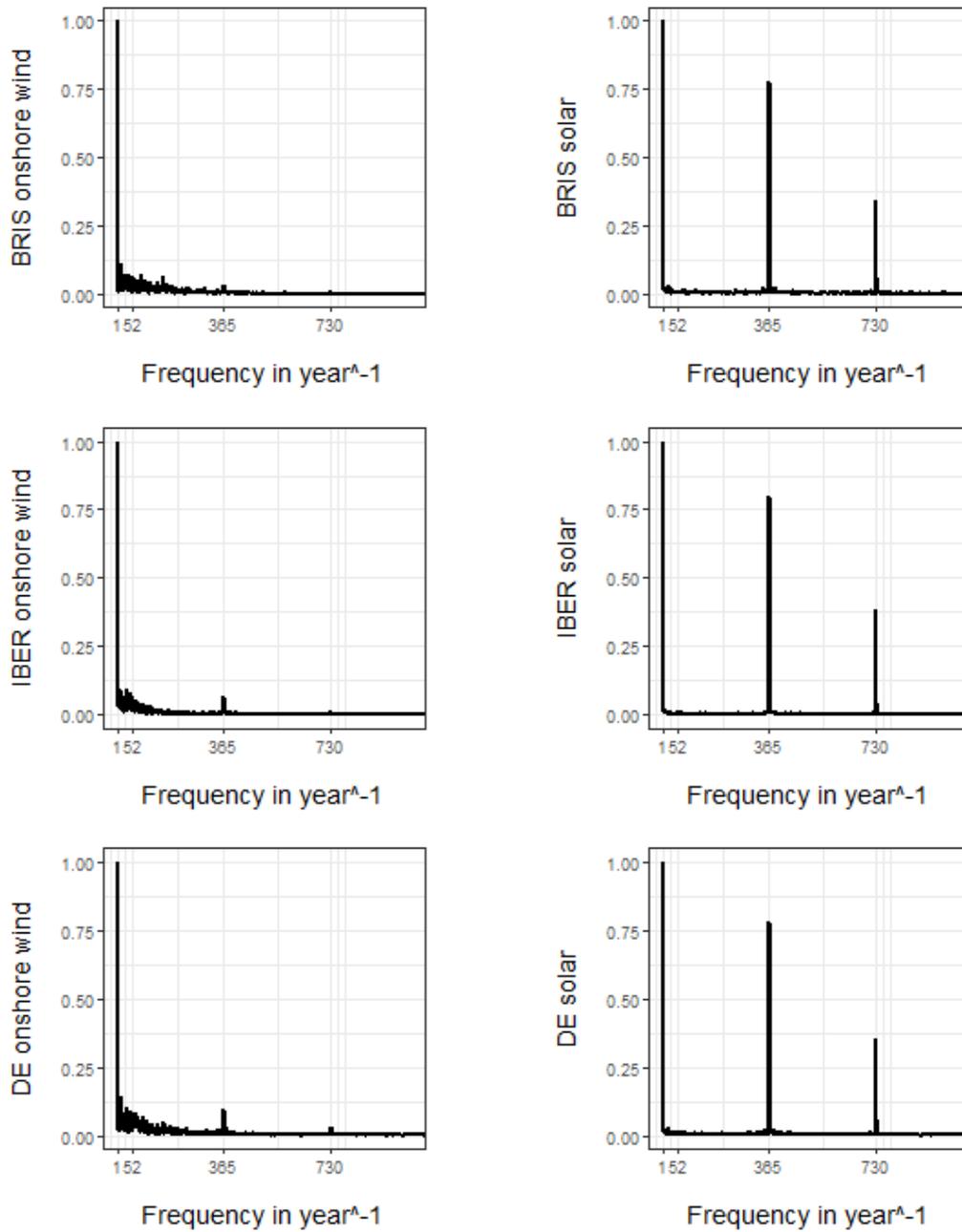


Figure A.3: Section 4.3.4: Normalised power spectral densities of onshore wind (left) and solar (right) hourly time series, for the British Isles (top row), Iberia (middle row) and Germany (bottom row). These were obtained based on 1 of the 35 weather years mentioned in section 4.3.4.

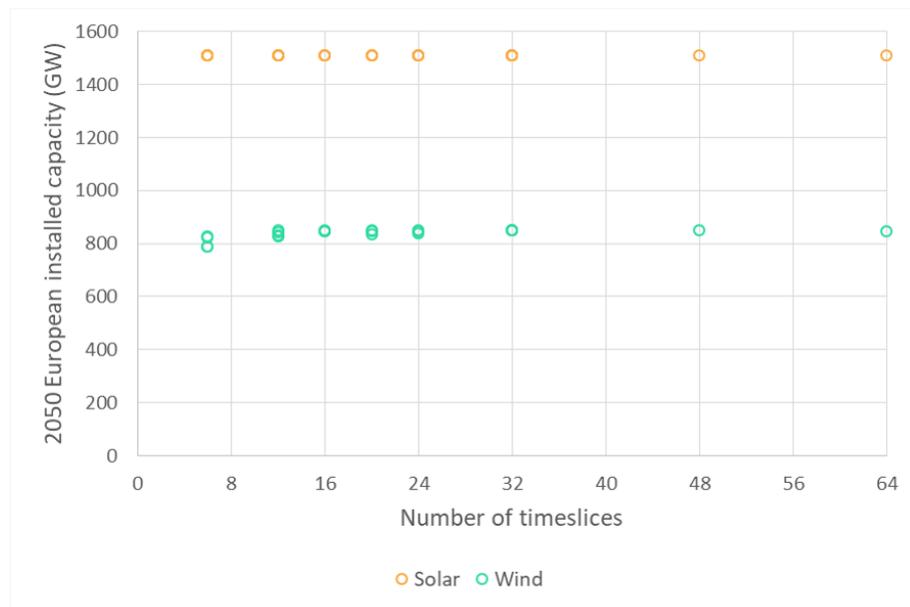


Figure A.4: Section 4.4.2: Impact of the number of timeslices on VRE 2050 European capacities in case A. Each dot corresponds to one of the variations of one of the 9 timeslice structures described in table 4.3.

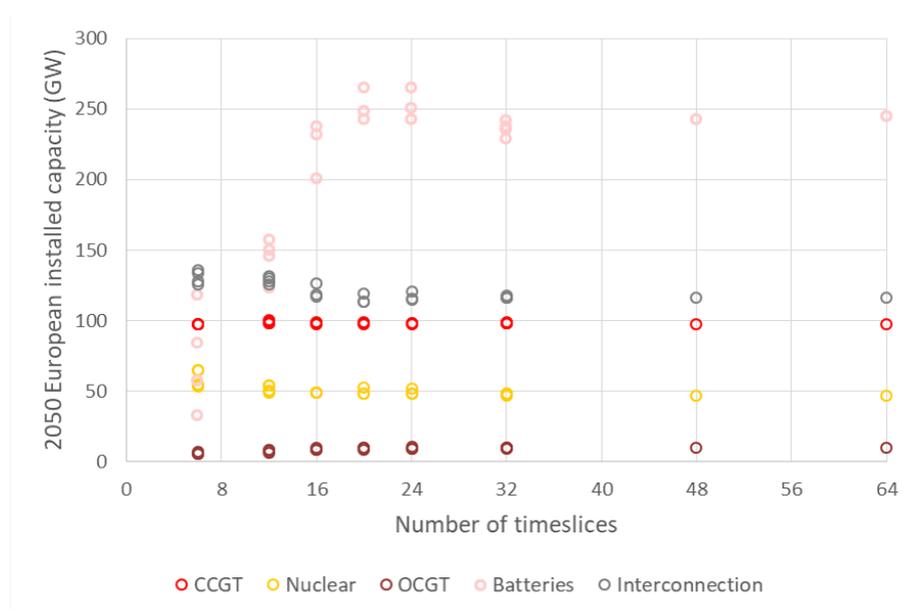


Figure A.5: Section 4.4.2: Impact of the number of timeslices on flexibility solutions 2050 European capacities in case A. Each dot corresponds to one of the variations of one of the 9 timeslice structures described in table 4.3.

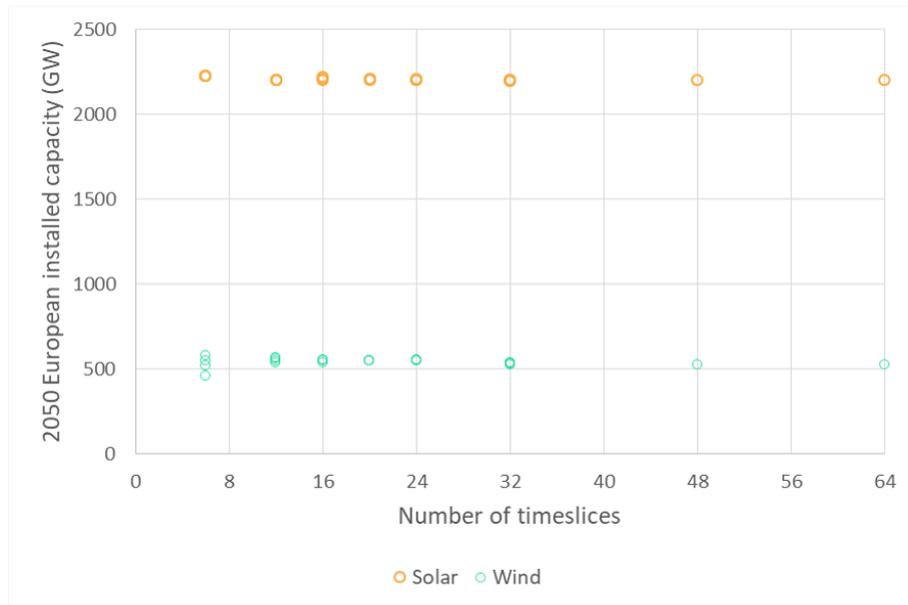


Figure A.6: Section 4.4.2: Impact of the number of timeslices on VRE 2050 European capacities in case B. Each dot corresponds to one of the variations of one of the 9 timeslice structures described in table 4.3.

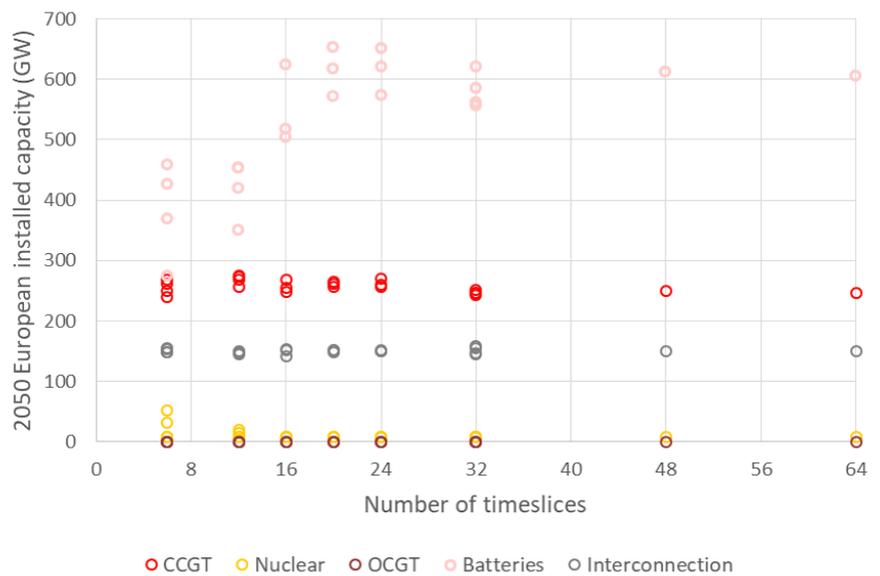


Figure A.7: Section 4.4.2: Impact of the number of timeslices on flexibility solutions 2050 European capacities in case B. Each dot corresponds to one of the variations of one of the 9 timeslice structures described in table 4.3.

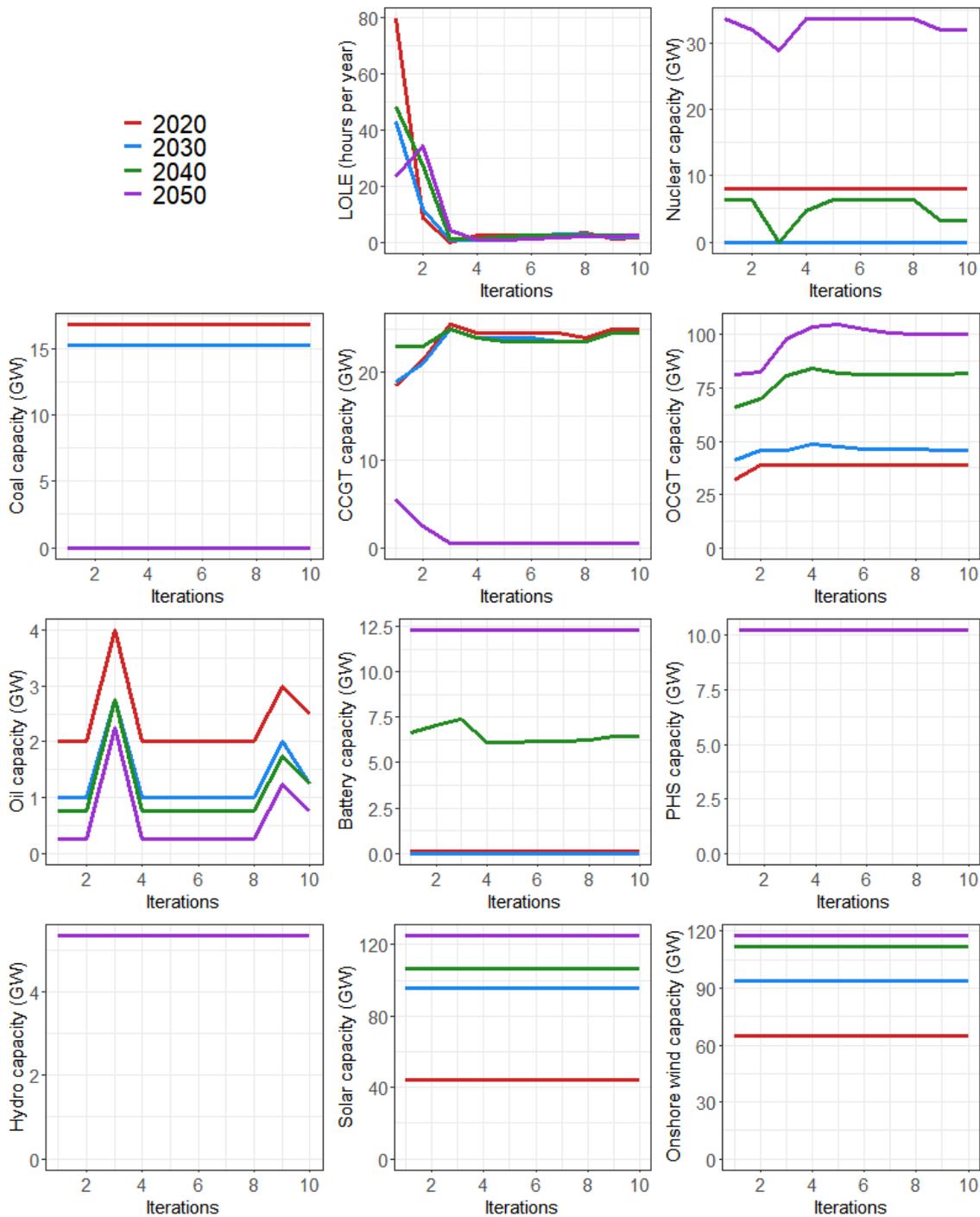


Figure A.8: Section 5.5.2: Evolution of loss-of-load-expectation and annual installed capacities of several technologies over iterations, for the model run of the single node German power system, with updated capacity credits and an initial reserve margin size of 1.10, adjusted using the "balanced" strategy. This model run was chosen so more substantial changes in power system structure could be observed. Note that iterations 1, 2, 3 and 4 lead to LOLE levels above 3 hours for at least one soft-linked year and that iteration 10 proposes the cheapest investment pathway leading to LOLE levels under 3 hours.

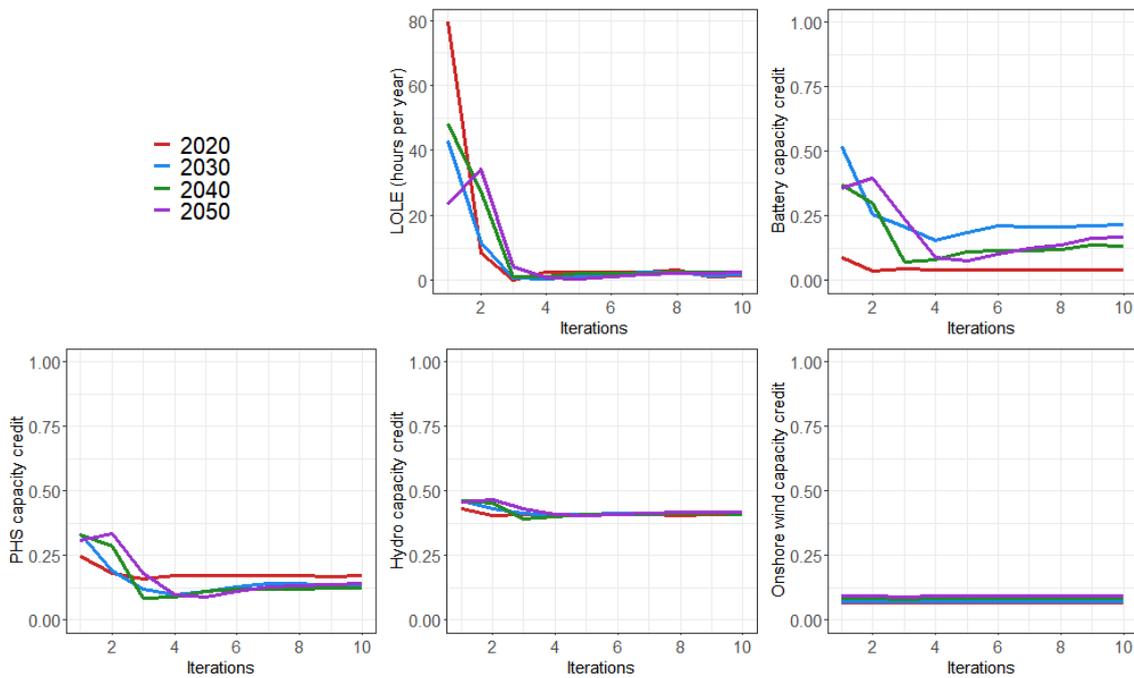


Figure A.9: Section 5.5.2: Evolution of loss-of-load-expectation and capacity credit values of batteries, pumped-hydro-storage, hydro and onshore wind over iterations, for the model run of the single node German power system, with updated capacity credits and an initial reserve margin size of 1.10, adjusted using the "balanced" strategy. This model run was chosen so more substantial changes in power system structure could be observed. Note that iterations 1, 2, 3 and 4 lead to LOLE levels above 3 hours for at least one soft-linked year and that iteration 10 proposes the cheapest investment pathway leading to LOLE levels under 3 hours.

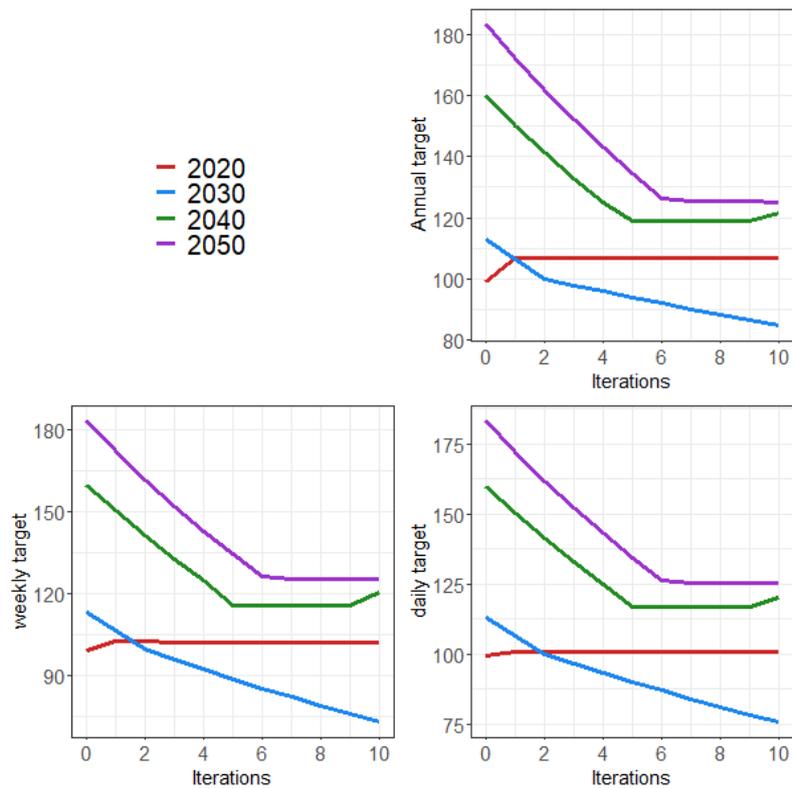


Figure A.10: Section 5.6.2: Evolution of flexibility proxy values for the model run of the single node German power system, an inertia set to 1 and flexibility targets adjusted using the "aggressive" strategy. Iterations 2 through 9 lead to LOLE levels under 3 hours.

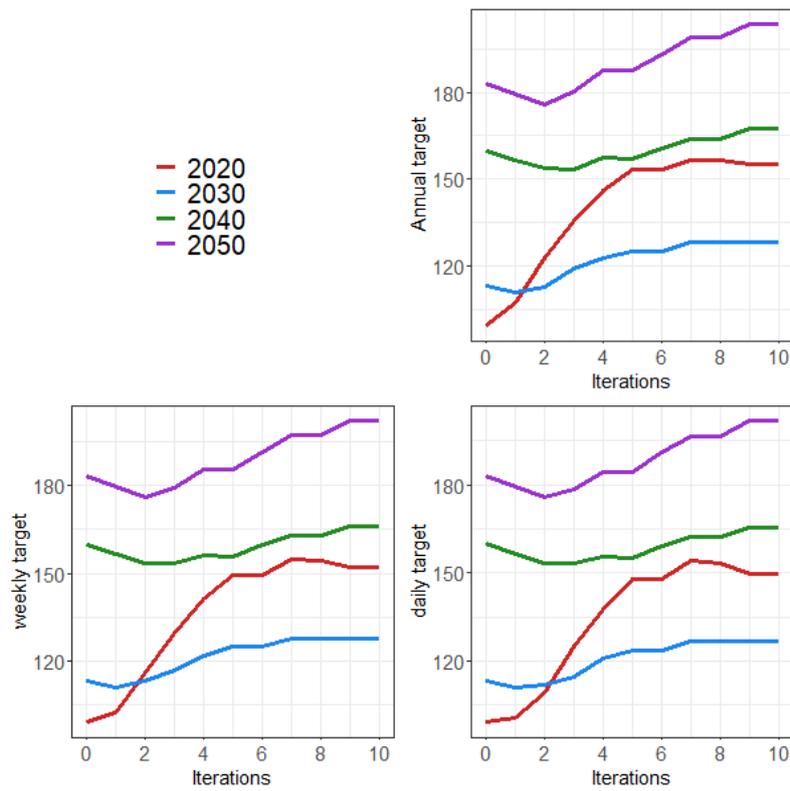


Figure A.11: Section 5.6.2: Evolution of flexibility target values for the model run of the single node German power system, an inertia set to 0.67 and flexibility targets adjusted using the "medium" strategy. Iterations 8 and 10 lead to LOLE levels under 3 hours. See Section 5.6.1 for information on how flexibility targets are defined and updated.

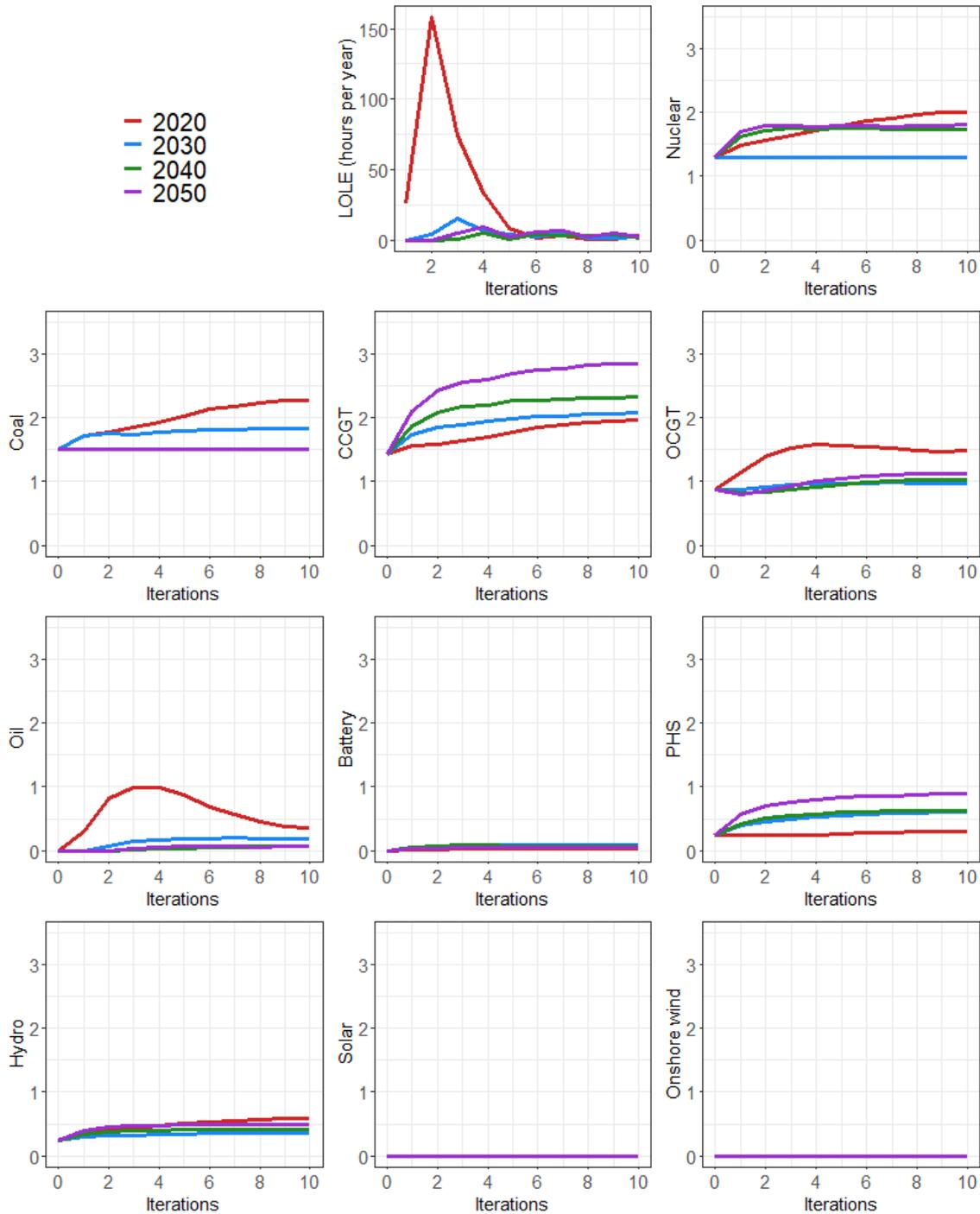


Figure A.12: Section 5.6.2: Evolution of loss-of-load-expectation and annual flexibility proxy values of nuclear, coal, CCGT, OCGT, oil power plant, batteries, pumped-hydro-storage, hydro and onshore wind over iterations, for the model run of the single node German power system, an inertia set to 0.67 and flexibility targets adjusted using the "medium" strategy. Iterations 8 and 10 lead to LOLE levels under 3 hours. See Section 5.6.1 for information on how flexibility proxies are defined and updated.

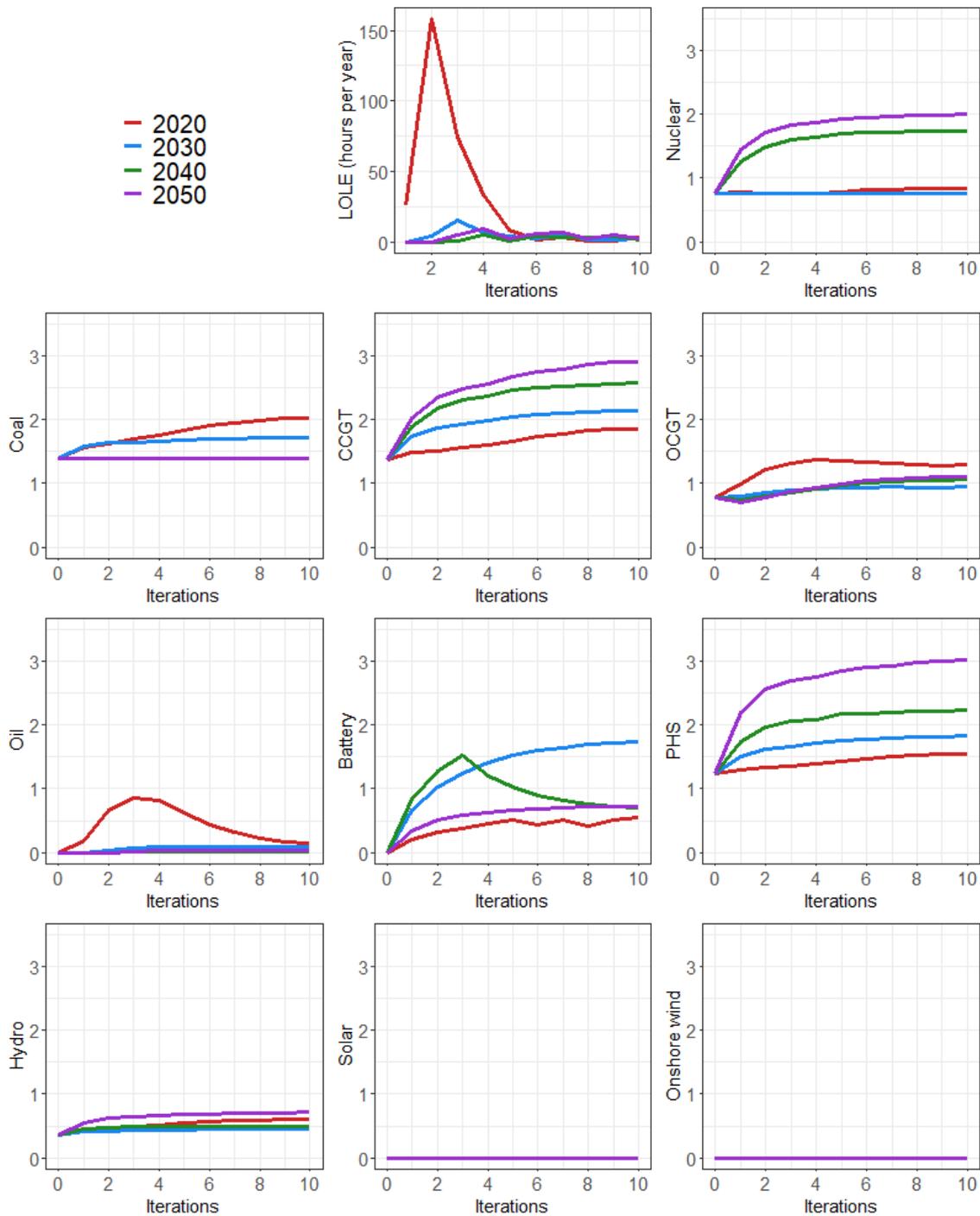


Figure A.13: Section 5.6.2: Evolution of loss-of-load-expectation and weekly flexibility proxy values of nuclear, coal, CCGT, OCGT, oil power plant, batteries, pumped-hydro-storage, hydro and onshore wind over iterations, for the model run of the single node German power system, an inertia set to 0.67 and flexibility targets adjusted using the "medium" strategy. Iterations 8 and 10 lead to LOLE levels under 3 hours. See Section 5.6.1 for information on how flexibility proxies are defined and updated.

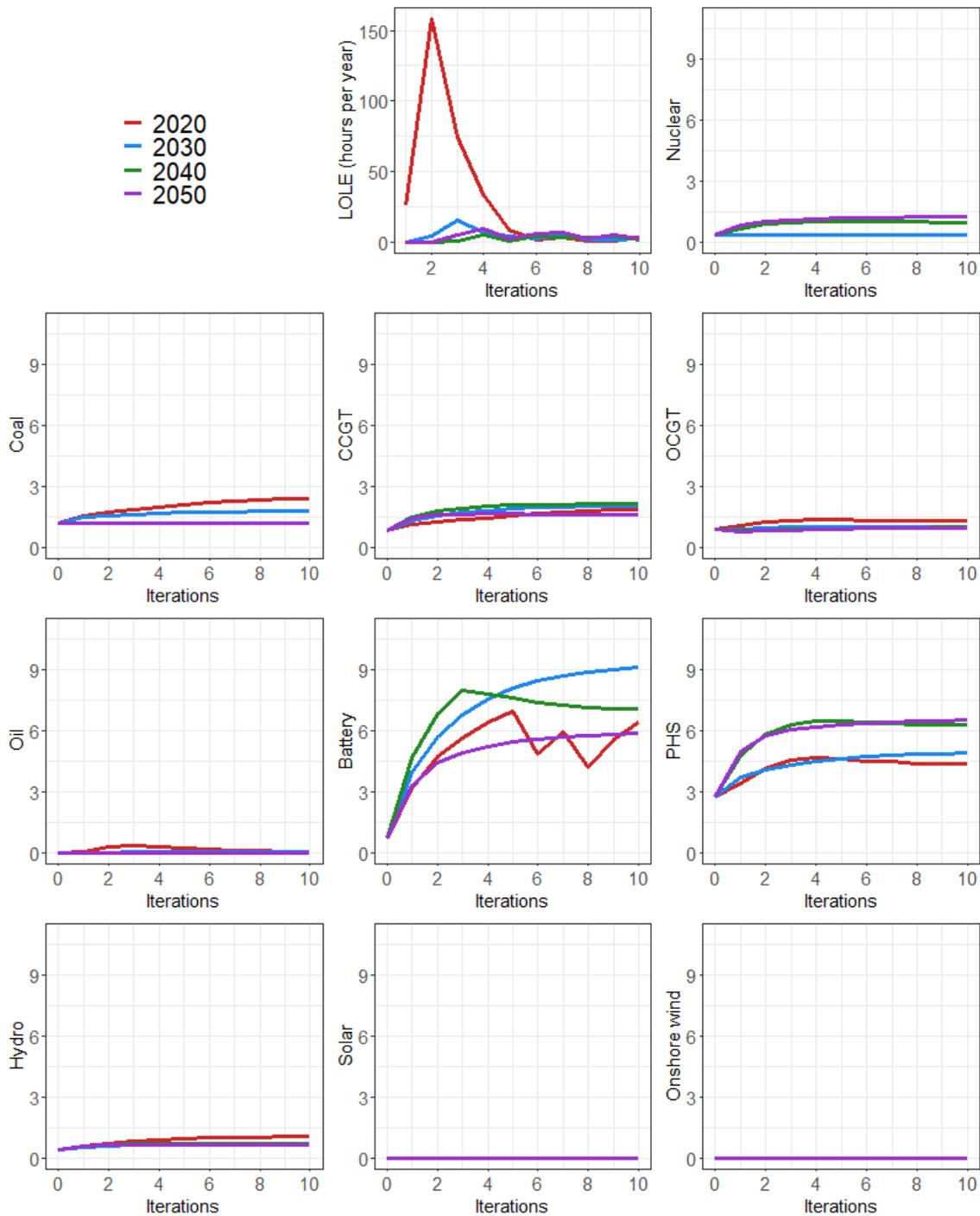


Figure A.14: Section 5.6.2: Evolution of loss-of-load-expectation and daily flexibility proxy values of nuclear, coal, CCGT, OCGT, oil power plant, batteries, pumped-hydro-storage, hydro and onshore wind over iterations, for the model run of the single node German power system, an inertia set to 0.67 and flexibility targets adjusted using the "medium" strategy. Iterations 8 and 10 lead to LOLE levels under 3 hours. See Section 5.6.1 for information on how flexibility proxies are defined and updated.

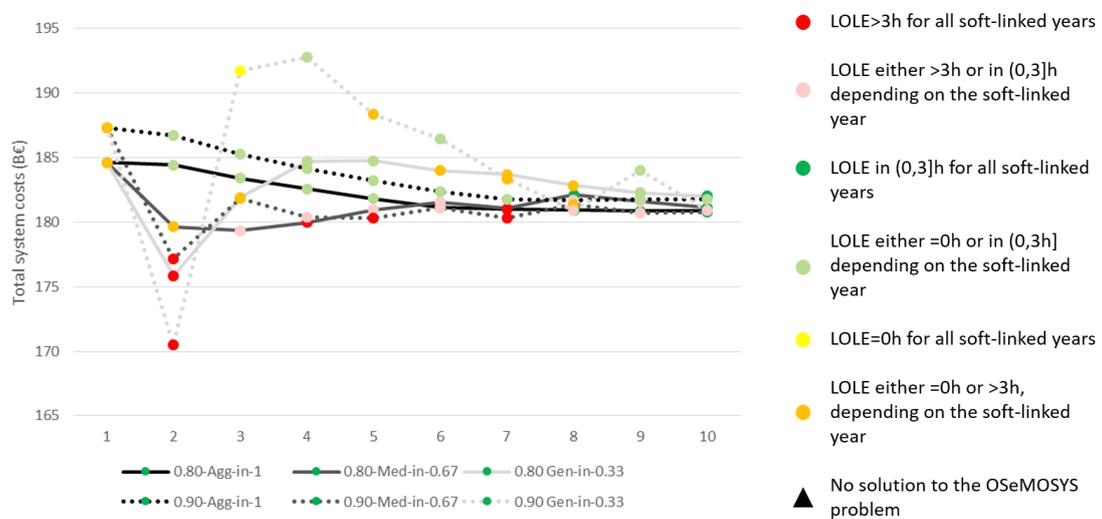


Figure A.15: Section 5.6.2: Evolution of OSeMOSYS total system costs over 10-iteration runs for the single-node German system, with flexibility proxy values based on the 80th (full lines) and 90th (dotted lines) percentiles. The cheapest adequate solutions are obtained for the 9th, 10th, 10th, 7th, 10th and 9th iterations for 0.80-Agg-in-1, 0.80-Med-in-0.67 and 0.80-Gen-in-0.33, 0.90-Agg-in-1, 0.90-Med-in-0.67 and 0.90-Gen-in-0.33 respectively.

Appendix B

Power system flexibility definitions

Table B.1: Power system flexibility definitions considered in section 1.2

Authors	Proposed definition	Reference
Van Greet <i>et al.</i> (1993)	The ability to adapt the system (both generation and transmission), quickly and at reasonable cost, to any change in the conditions that prevailed at the time it was planned.	[11]
Bresembi <i>et al.</i> (2003)	The attitude [ability?] of the transmission system to keep up a desired standard of reliability, at reasonable operation costs, when the generation scenarios change.	[12]
IEA (2011)	The capability of a power system to maintain reliable supply in the face of rapid and large imbalances, whatever the cause.	[17]
Bertsch <i>et al.</i> (2012)	The capability to balance rapid changes in renewable generation and forecast errors within a power system.	[13]
Holttinen <i>et al.</i> (2013)	Ability to accommodate the variability and uncertainty in the load-generation balance while maintaining satisfactory levels of performance for any timescale.	[19]
Ma <i>et al.</i> (2013)	The ability of a power system to cope with variability and uncertainty in both generation and demand, while maintaining a satisfactory level of reliability at a reasonable cost, over different time horizons.	[20]
Mandatova <i>et al.</i> (2014)	The modification of generation injection and/or consumption patterns in reaction to an external signal (price signal or activation) in order to provide a service within the energy system.	[23]
Huber <i>et al.</i> (2014)	The ability of a power system to respond to changes in power demand and generation.	[24]
Tuohy and Lannoye (2014)	The ability to adapt to changing conditions while providing electricity safely, reliably, affordably, and in an environmentally responsible manner.	[25]
ENTSO-E (2017)	The active management of an asset that can impact system balance or grid power flows on a short-term basis, i.e. from day-ahead to real-time.	[18]
Villavicencio (2018)	Ability to adjust to changing conditions over different timescales.	[21]
CEER (2018)	The capacity of the electricity system to respond to changes that may affect the balance of supply and demand at all times.	[22]
IEA (2018)	All relevant characteristics of a power system that facilitates the reliable and cost-effective management of variability and uncertainty in both supply and demand.	[8]
IRENA (2018)	The capability of a power system to cope with the variability and uncertainty that VRE generation introduces in to the system in different time scales, from the very short term to the long term, avoiding curtailment of VRE and reliably supplying all the demanded energy to customers.	[14]
Papaefthymiou <i>et al.</i> (2018)	The power system readiness for higher shares of variable renewables.	[15]

Appendix C

Power system flexibility quantification methods

Table C.1: How much flexibility does my system need? Papers considered in section 2.2.1

Authors	Brief description	Reference
Kondziella and Bruckner (2016)	Review and classification of methods quantifying short-term FS potential. FS theoretical potential can be equated to flexibility requirement.	[55]
Huber <i>et al.</i> (2014)	Study of the impact of wind and solar generation on short-term flexibility requirement by evaluating one and multiple hour ramp rate in net load.	[24]
Holttinen <i>et al.</i> (2010)	Study the impact of wind generation on net load variability by evaluating 10-60 minute ramp rates.	[57]
Deetjen <i>et al.</i> (2017)	Study the impact of VRE penetration on flexibility requirement through six indicators: 1 hour ramp-rate, 3 hour ramp rate, ramp factor, ramp acceleration, 1 hour volatility and 1 day volatility.	[58]
Lannoye <i>et al.</i> (2012)	Review of flexibility quantification methods. Proposed the basis for the classification used in this paper. Mention a few metrics that were used back then, such as standard deviation of VRE output and net load, or forecast error statistics.	[59]
Dvorkin <i>et al.</i> (2014)	Study the impact of wind generation on flexibility requirement, by evaluating the magnitude, ramp rate and ramp duration of deviations between scheduled and actual net load.	[60]
Nosair <i>et al.</i> (2015)	Present the "flexibility envelope" framework, which covers multiple facets of flexibility. Flexibility requirement is one of the framework's building blocks, and identified as 95% of the probability distribution function of VRE intra-hourly deviation from forecast.	[61]
Heggarty <i>et al.</i> (2019)	Present a set of metrics evaluating flexibility requirement on multiple timescales.	[49]
Olsen <i>et al.</i> (2020)	Extension of method presented by [49], looking at additional shorter timescales.	[62]
Makarov <i>et al.</i> (2012)	Present a methodology to quantify the storage capacity that would be required to manage the mismatch between hour-ahead net load forecast and reality.	[64]
Oh and Son (2018)	Explore the feasibility of sizing a storage device to reduce penalties from wind forecasting errors.	[65]
Belderbos <i>et al.</i> (2017)	Study the link between storage power and energy sizing and the shape of generation and load profiles.	[35]
Steinke <i>et al.</i> (2013)	Study the roles of storage and network in providing "backup" for 100% VRE systems.	[66]
Heide <i>et al.</i> (2010)	Study the wind/solar balance that minimises the need to store energy.	[67]
Denholm and Hand (2011)	Study how curtailment is impacted by VRE penetration, wind/solar balance and the introduction of storage.	[68]
Weitemeyer <i>et al.</i> (2015)	Study the role of VER curtailment-fed storage in maximising VRE integration.	[69]
Zerrahn and Schill (2017)	Among other things, review storage requirement quantification methods.	[70]
Jurasz <i>et al.</i> (2020)	Review metrics quantifying energy resource complementarity.	[71]

Table C.2: How flexible is my flexibility solution? Papers considered in section 2.2.2

Authors	Brief description	Reference
Ma <i>et al.</i> (2014)	Present a composite metric based on a generator's operational margin and ramp rate. Aggregation method is also proposed to express the metric at system level.	[20]
Oree and Hassen (2016)	An extension of [20], present a composite metric based on 8 indicators: operational range, minimum power output, up/down ramping capability, start-up and shut-down times, response time, and minimum up and down times. Aggregation method is also proposed to express the metric at system level.	[72]
Wu <i>et al.</i> (2020)	While analysing the link between flexibility and scheduling cost, calculate a flexibility index for generating units following a method close to [72]. Aggregation method is also proposed to express the metric at system level.	[73]
Ulbig <i>et al.</i> (2015)	Based on power system simulation, evaluate power capability for up/down regulation, energy storage capability, power ramping capability, power ramping duration. This is performed at both FS and system level.	[74]
Nosair <i>et al.</i> (2015)	Present the "flexibility envelope" framework, which covers multiple facets of flexibility. As part of this framework, they track upward and downward potential against a constant scheduled output, for both an individual solution and a system.	[61]
Lannoye <i>et al.</i> (2012)	Review of existing flexibility quantification methods. Proposed the basis for the classification used in this paper. Mention a few metrics that were used back then, such as ramp rate, energy available within a certain timescale, or the ability to provide reserve.	[59]

Table C.3: How flexible is my power system? Papers considered in section 2.2.3

Authors	Brief description	Reference
Nosair <i>et al.</i> (2015)	Present the "flexibility envelope" framework, which covers multiple facets of flexibility. As part of this framework, they track upward and downward potential against a constant scheduled output, for both an individual solution and a system.	[61]
Ma <i>et al.</i> (2014)	Present a composite metric based on a generator's operational margin and ramp rate. Aggregation method is also proposed to express the metric at system level.	[20]
Oree and Hassen (2016)	An extension of [20], present a composite metric based on 8 indicators: operational range, minimum power output, up/down ramping capability, start-up and shut-down times, response time, and minimum up and down times. Aggregation method is also proposed to express the metric at system level.	[72]
Wu <i>et al.</i> (2020)	While analysing the link between flexibility and scheduling cost, calculate a flexibility index for generating units following a method close to [72]. Aggregation method is also proposed to express the metric at system level.	[73]
Ulbig <i>et al.</i> (2015)	Based on power system simulation, evaluate power capability for up/down regulation, energy storage capability, power ramping capability, power ramping duration. This is performed at both FS and system level.	[74]
NERC (2016)	Among other things, discuss probabilistic adequacy metrics.	[75]
Bird <i>et al.</i> (2016)	Review of international experience with VRE curtailment.	[76]
Lannoye <i>et al.</i> (2015)	Propose two metrics identifying flexibility deficiency: Periods of Flexibility Deficits, Insufficient Ramping Resource Expectation.	[59]
Tuohy and Lannoye (2014)	Provide a broad overview of flexibility assessment methods, while also introducing the Expected Unserved Ramping metric.	[25]
Zhao <i>et al.</i> (2016)	Propose a versatile unified framework to define and measure flexibility, allowing the consideration of several of its facets. Among other things, they maximise the uncertainty that a system can accommodate for a given cost, and propose a Boolean metric indicating whether a system's largest variation range is within a target range.	[78]
Menemenlis <i>et al.</i> (2011)	Propose a methodology to evaluate the probability of a balancing reserve strategy satisfying various scenarios.	[79]
Deane <i>et al.</i> (2014)	In their analysis of the impact of sub-hourly modelling of a power system with high wind penetration, calculate the shadow price of ramping.	[80]
Vithayasrichareon <i>et al.</i> (2017)	Quantify the cost implications of various flexibility constraints e.g. ramping, Pmin, start-up costs.	[81]
Morales <i>et al.</i> (2013)	Addresses modelling challenges for VRE market integration.	[82]
Bresesti <i>et al.</i> (2013)	Propose an index comparing the flexibility of different network configurations, for use both in planning and operations.	[12]
Capasso <i>et al.</i> (2014)	From a network congestion point of view, propose a metric quantifying the additional generation that a transmission system can accommodate.	[83]
Papaefthymiou <i>et al.</i> (2018)	List 80 key performance indicators to assess a system's readiness for high shares of VRE.	[15]

Table C.4: Who is providing flexibility in my power system? Papers considered in section 2.2.4

Authors	Brief description	Reference
Yasuda <i>et al.</i> (2013)	Propose a "flexibility chart" to give an overview of a system's existing FS capacities.	[84]
Deane <i>et al.</i> (2014)	In their analysis of the impact of sub-hourly modelling of a power system with high wind penetration, track the number of generator start-ups.	[80]
Vithayasrichareon <i>et al.</i> (2017)	In their quantification of the cost implications of various flexibility constraints, track the number of generator start-ups.	[81]
Heggarty <i>et al.</i> (2020)	Propose a pair of tools (FSMS and FSCD) to quantify the flexibility provided by sets of flexibility solutions.	[50]

Appendix D

OSeMOSYS problem description

D.1 Sets

Table D.1: Sets

Name	Symbol	Description
REGION	r	Defines the regions to be modelled, e.g. different countries.
TECHNOLOGY	t	Defines the elements of the energy system that change a fuel from one form to another, use it or supply it.
FUEL	f	Defines the energy vectors, energy services or proxies entering or exiting technologies.
STORAGE	s	Defines the storage facilities in the model.
EMISSION	e	Defines the emission types that can potentially result from the operation of the defined technologies.
MODE_OF_OPERATION	m	Number of modes of operation that the technologies can have.
YEAR	y	Investment time frame of the model, it contains all the years to be considered in the study.
TIMESLICE	l	List of model time-steps within an investment year.
SEASON	ls	Defines the seasons that are accounted for and their order.
DAYTYPE	ld	Defines the day types that are accounted for and their order.
DAILYTIMEBRACKET	lh	Defines how many parts a day is split into and their order.

D.2 Parameters

Table D.2: Global parameters

Name	Defined on	Description
YearSplit	y,l	Duration of a modelled timeslice, expressed as a fraction of the year. The sum of each entry over one modelled year should equal 1.
DiscountRate	r	Region specific value for the discount rate, expressed in decimals (e.g. 0.05).
DaySplit	y, lh	Length of one daily time bracket in one specific day as a fraction of the year.
Conversionls	l, ls	Binary parameter linking one timeslice to a certain season.
Conversionld	l, ld	Binary parameter linking one timeslice to a certain day type.
Conversionlh	l, lh	Binary parameter linking one timeslice to a certain daily time bracket.
DaysInDayType	ls, ld, y	Number of days for each day type, within one week (natural number, ranging from 1 to 7).
DepreciationMethod	r	Binary parameter defining the type of depreciation to be applied. It has value 1 for sinking fund depreciation, value 2 for straight-line depreciation.

Table D.3: Demands

Name	Defined on	Description
SpecifiedAnnualDemand	r, f, y	Total specified demand for the year, linked to a specific 'time of use' during the year (chosen units: TWh).
SpecifiedDemandProfile	r, f, y, l	Annual fraction of fuel demand that is required in each timeslice. For each year, input values should sum up to 1.
AccumulatedAnnualDemand	r, f, y	Accumulated Demand for a certain fuel in one specific year. It cannot be defined for a fuel if its SpecifiedAnnualDemand for the same year is already defined and vice versa

Table D.4: Performance

Name	Defined on	Description
CapacityToActivityUnit	r, t	Conversion factor relating the energy that would be produced when one unit of capacity is fully used in one year.
CapacityFactor	r, t, y, l	Capacity available per each timeslice expressed as a fraction of the total installed capacity, with values ranging from 0 to 1. It gives the possibility to account for forced outages.
AvailabilityFactor	r, t, y	Maximum time a technology can run in the whole year, as a fraction of the year ranging from 0 to 1. It gives the possibility to account for planned outages.
OperationalLife	r, t	Useful lifetime of a technology (units: years).
ResidualCapacity	r, t, y	Remaining available capacity from before the modelling period (chosen units: GW).
InputActivityRatio	r, t, f, m, y	Rate of use of a fuel by a technology, as a ratio of the rate of activity.
OutputActivityRatio	r, t, f, m, y	Rate of fuel output from a technology, as a ratio of the rate of activity.

Table D.5: Technology costs

Name	Defined on	Description
CapitalCost	r, t, y	Capital investment cost of a technology, per unit of capacity (chosen units: M€/GW).
VariableCost	r, t, m, y	Cost of a technology for a given mode of operation (Variable O&M cost), per unit of activity (chosen units: M€/TWh).
FixedCost	r, t, y	Fixed O&M cost of a technology, per unit of capacity (chosen units: M€/GW).

Table D.6: Storage

Name	Defined on	Description
TechnologyToStorage	r, t, s, m	Binary parameter linking a technology to the storage facility it charges.
TechnologyFromStorage	r, t, s, m	Binary parameter linking a storage facility to the technology it feeds.
StorageLevelStart	r, s	Level of storage at the beginning of the first modelled year, in units of activity (chosen units: TWh).
StorageLeeway	s	Extent to which the level of storage can vary year on year, imposing an annual cycle. Expressed as a percentage of StorageLevelYearFinish.
StorageMaxChargeRate	r, s	Maximum charging rate for the storage, in units of activity per year.
StorageMaxDischargeRate	r, s	Maximum discharging rate for the storage, in units of activity per year.
MinStorageCharge	r, s, y	It sets a lower bound to the amount of energy stored, as a fraction of the maximum, ranging between 0 and 1.
OperationalLifeStorage	r, s	Useful lifetime of the storage facility.
CapitalCostStorage	r, s, y	Capital investment cost of a storage facility, per unit of energy capacity (chosen units: M€/TWh).
ResidualStorageCapacity	r, s, y	Remaining available energy capacity from before the modelling period (chosen units: TWh).

Table D.7: Capacity constraints

Name	Defined on	Description
CapacityOfOneTechnologyUnit	r, t, y	If this parameter is set, the related technology will be installed only in batches of the specified capacity and the problem will turn into a Mixed Integer Linear Problem.
TotalAnnualMaxCapacity	r, t, y	Total maximum existing (residual plus cumulatively installed) capacity allowed for a technology in a specified year (chosen units: GW).
TotalAnnualMinCapacity	r, t, y	Total minimum existing (residual plus cumulatively installed) capacity allowed for a technology in a specified year (chosen units: GW).
TotalAnnualMaxCapacityInvestment	r, t, y	Maximum annual capacity investment in a technology (chosen units: GW).
TotalAnnualMinCapacityInvestment	r, t, y	Minimum annual capacity investment in a technology (chosen units: GW).

Table D.8: Activity constraints

Name	Defined on	Description
TotalTechnologyAnnualActivityUpperLimit	r, t, y	Total maximum level of activity allowed for a technology in a year.
TotalTechnologyAnnualActivityLowerLimit	r, t, y	Total minimum level of activity allowed for a technology in a year.
TotalTechnologyModelPeriodActivityUpperLimit	r, t	Total maximum level of activity allowed for a technology in the entire modelled period.
TotalTechnologyModelPeriodActivityLowerLimit	r, t	Total minimum level of activity allowed for a technology in the entire modelled period.

Table D.9: Reserve margin

Name	Defined on	Description
CapacityCredit	r, t, y	Parameter expressing the contribution of technologies to the reserve margin.
TradeCapacityCredit	r, r, f, y	Parameter expressing the contribution of interconnectors to the reserve margin.
ReserveMarginTagFuel	r, f, y	Binary parameter tagging the fuels to which the reserve margin applies.
ReserveMargin	r, y	Minimum level of the reserve margin required to be provided for all the tagged commodities, by the tagged technologies. If, for instance, 20% reserve margin is required, the parameter will have value 1.2.

Table D.10: Flexibility balancing (not in the "original" OSeMOSYS formulation)

Name	Defined on	Description
AnnualFlexibilityProxy	r, t, y	Parameter expressing the ability of technologies to contribute to flexibility on the annual timescale (unitless).
WeeklyFlexibilityProxy	r, t, y	Parameter expressing the ability of technologies to contribute to flexibility on the weekly timescale (unitless).
DailyFlexibilityProxy	r, t, y	Parameter expressing the ability of technologies to contribute to flexibility on the daily timescale (unitless).
AnnualFlexibilityTarget	r, t, y	Minimum level of annual flexibility required, provided by technologies according to their capacity and their flexibility proxy value. Equivalent unit: GW.
WeeklyFlexibilityTarget	r, t, y	Minimum level of weekly flexibility required, provided by technologies according to their capacity and their flexibility proxy value. Equivalent unit: GW.
DailyFlexibilityTarget	r, t, y	Minimum level of daily flexibility required, provided by technologies according to their capacity and their flexibility proxy value. Equivalent unit: GW.

Table D.11: RE Generation target

Name	Defined on	Description
RETagTechnology	r, t, y	Binary parameter tagging the renewable technologies that contribute towards the target.
RETagFuel	r, f, y	Binary parameter tagging the fuels to which the renewable target applies.
REMinProductionTarget	r, y	Minimum ratio of all renewable commodities tagged in the RETagFuel parameter, to be produced by the technologies tagged with the RETagTechnology parameter.

Table D.12: Emissions

Name	Defined on	Description
EmissionActivityRatio	r, t, e, m, y	Emission factor of a technology per unit of activity, per mode of operation.
EmissionsPenalty	r, e, y	Penalty per unit of emission.
AnnualExogenousEmission	r, e, y	It allows the user to account for additional annual emissions, on top of those computed endogenously by the model.
AnnualEmissionLimit	r, e, y	Annual upper limit for a specific emission generated in the whole modelled region.
ModelPeriofExogenousEmission	r, e	It allows the user to account for additional emissions over the entire period, on top of those computed endogenously by the model.
ModelPeriodEmissionLimit	r, e	Upper limit for a specific emission generated in the whole modelled region over the entire period.

Table D.13: Trade (different to the "original" OSeMOSSYS formulation)

Name	Defined on	Description
TradeRoute	r, rr, f, y	Binary indicator linking regions to one another.
TradeCost	r, rr, f	Data not provided in Osmose runs, presumably variable cost associated with the trading of non-electricity fuels.
TradeLossBetweenRegions	r, rr, f, y	Data not provided in Osmose runs.
ResidualTradeCapacity	r, rr, f, y	Remaining trade capacity available from before the modelling period.
CapitalCostTrade	r, rr, f	Provides the cost of increasing a link's capacity (chosen unit: M€/GW).
TotalAnnualMaxTradeInvestment	r, rr, f, y	Upper limit to investment in trade capacity in a given year. Set to 0 in Osmose runs to prevent investment before 2030.
OperationalLifeTrade	r, rr, f, y	Useful life of an interconnector.

D.3 Variables

Table D.14: Demands

Name	Defined on	Unit	Description
RateOfDemand	r, f, y, l	TWh/year	It represents the energy that would be demanded in one timeslice l if the latter lasted the whole year. It is a function of the parameters SpecifiedAnnualDemand and SpecifiedDemandProfile (≥ 0).
Demand	r, f, y, l	TWh	Demand for one fuel in one timeslice (≥ 0).

Table D.15: Storage

Name	Defined on	Unit	Description
RateOfStorageCharge	r, s, y, ls, ld, lh	TWh/year	It represents the fuel that would be charged to the storage facility s in one timeslice if the latter lasted the whole year. It is a function of the parameters RateOfActivity and TechnologyToStorage.
RateOfStorageDischarge	r, s, y, ls, ld, lh	TWh/year	It represents the fuel that would be discharged to the storage facility s in one timeslice if the latter lasted the whole year. It is a function of the parameters RateOfActivity and TechnologyFromStorage.
NetChargeWithinYear	r, s, y, ls, ld, lh	TWh	Net quantity of fuel charged to storage facility s in year y. It is a function of the RateOfStorageCharge and the RateOfStorageDischarge and can be negative.
NetChargeWithinDay	r, s, y, ls, ld, lh	TWh	Net quantity of fuel charged to storage facility s in daytype ld. It is a function of the RateOfStorageCharge and the RateOfStorageDischarge and can be negative.
StorageLevelYearStart	r, s, y	TWh	Level of stored fuel in storage facility s in the first time step of year y (≥ 0).
StorageLevelYearFinish	r, s, y	TWh	Level of stored fuel in storage facility s in the last time step of year (≥ 0).
StorageLevelSeasonStart	r, s, y, ls	TWh	Level of stored fuel in storage facility s in the first time step of season ls (≥ 0).
StorageLevelDayTypeStart	r, s, y, ls, ld	TWh	Level of stored fuel in storage facility s in the first time step of daytype ld (≥ 0).
StorageLevelDayTypeFinish	r, s, y, ls, ld	TWh	Level of stored fuel in storage facility s in the last time step of daytype ld (≥ 0).
StorageLowerLimit	r, s, y	TWh	Minimum allowed level of stored fuel in storage facility s, as a function of the storage capacity and the user-defined MinStorageCharge ratio (≥ 0).
StorageUpperLimit	r, s, y	TWh	Maximum allowed level of stored fuel in storage facility s, as a function of the storage capacity and the user-defined MinStorageCharge ratio (≥ 0).
AccumulatedNewStorageCapacity	r, s, y	TWh(?)	Cumulative capacity of newly installed storage from the beginning of the time domain to year y (≥ 0).
NewStorageCapacity	r, s, y	TWh(?)	Capacity of newly installed storage in year y (≥ 0).
CapitalInvestmentStorage	r, s, y	M€	Undiscounted investment in new capacity for storage facility s. Derived from the NewStorageCapacity and the parameter CapitalCostStorage (≥ 0).
DiscountedCapitalInvestmentStorage	r, s, y	M€	Investment in new capacity for storage facility s, discounted through the DiscountRate (≥ 0).
SalvageValueStorage	r, s, y	M€	Salvage value of storage facility s in year y, as a function of the parameters OperationalLifeStorage and DepreciationMethod (≥ 0).
DiscountedSalvageValueStorage	r, s, y	M€	Salvage value of storage facility s, discounted through the parameter DiscountRate (≥ 0).
TotalDiscountedStorageCost	r, s, y	M€	Difference between the discounted capital investment in new storage facilities and the salvage value in year y (≥ 0).

Table D.16: Activity

Name	Defined on	Unit	Description
RateOfActivity	r, t, m, y, l	TWh/year	Activity of technology t in one mode of operation and in timeslice l, if the latter lasted the whole year (≥ 0).
RateOfTotalActivity	r, t, y, l	TWh	Sum of the RateOfActivity of a technology over the modes of operation (≥ 0).
TotalTechnologyAnnualActivity	r, t, y	TWh	Total annual activity of technology t (≥ 0).
TotalAnnualTechnologyActivityByMode	r, t, m, y	TWh	Annual activity of technology t in mode of operation m (≥ 0).
TotalTechnologyModelPeriodActivity	r, t	TWh	Sum of TotalTechnologyAnnualActivity over the years of the modelled period (≥ 0).
RateOfProductionByTechnologyByMode	r, t, f, m, y, l	TWh/year	Quantity of fuel f that technology t would produce in one mode of operation and in timeslice l, if the latter lasted the whole year. It is a function of RateOfActivity and OutputActivityRatio (≥ 0).
RateOfProductionByTechnology	r, t, f, y, l	TWh/year	RateOfProductionByTechnologyByMode summed over modes of operation (≥ 0).
ProductionByTechnology	r, t, f, y, l	TWh	Production of fuel f by technology t in timeslice l (≥ 0).
ProductionByTechnologyAnnual	r, t, f, y	TWh	Annual production of fuel f by technology t (≥ 0).
RateOfProduction	r, f, y, l	TWh	RateOfProductionByTechnology summed over technologies (≥ 0).
Production	r, f, y, l	TWh	Total production of fuel f in timeslice l. ProductionByTechnology summed over technologies (≥ 0).
RateOfUseByTechnologyByMode	r, t, f, m, y, l	TWh/year	Quantity of fuel f that technology t would use in one mode of operation and in timeslice l, if the latter lasted the whole year. Function of RateOfActivity and InputActivityRatio (≥ 0).
RateOfUseByTechnology	r, t, f, y, l	TWh/year	RateOfUseByTechnologyByMode summed over modes of operation (≥ 0).
UseByTechnologyAnnual	r, t, f, y	TWh	Annual use of fuel f by technology t (≥ 0).
UseByTechnology	r, t, f, y, l	TWh	Use of fuel f by technology t in timeslice l (≥ 0).
Use	r, f, y, l	TWh	Total use of fuel f in timeslice l. UseByTechnology summed over technologies (≥ 0).
ProductionAnnual	r, f, y	TWh	Total annual production of fuel f. Production summed over all technologies (≥ 0).
UseAnnual	r, f, y	TWh	Total annual use of fuel f. Use summed over all technologies (≥ 0).

Table D.17: Capacity

Name	Defined on	Unit	Description
NumberOfNewTechnologyUnits	r, t, y	-	Number of newly installed units of technology t in year y, as a function of the parameter CapacityOfOneTechnologyUnit (integer, ≥ 0).
NewCapacity	r, t, y	GW	Newly installed capacity of technology t in year y (≥ 0).
AccumulatedNewCapacity	r, t, y	GW	Cumulative newly installed capacity of technology t from the beginning of the time domain to year y (≥ 0).
TotalCapacityAnnual	r, t, y	GW	Total existing capacity of technology t in year y (sum of cumulative newly installed and residual capacity) (≥ 0).

Table D.18: Costing variables

Name	Defined on	Unit	Description
CapitalInvestment	r, t, y	M€	Undiscounted investment in new capacity of technology t. Function of NewCapacity and CapitalCost (≥ 0).
DiscountedCapitalInvestment	r, t, y	M€	Investment in new capacity of technology t, discounted through DiscountRate (≥ 0).
SalvageValue	r, t, y	M€	Salvage value of technology t in year y, function of OperationalLife and DepreciationMethod (≥ 0).
DiscountedSalvageValue	r, t, y	M€	Salvage value of technology t, discounted through DiscountRate (≥ 0).
OperatingCost	r, t, y	M€	Undiscounted sum of the annual variable and fixed operating costs of technology t (≥ 0).
DiscountedOperatingCost	r, t, y	M€	Annual OperatingCost of technology t, discounted through DiscountRate (≥ 0).
AnnualVariableOperatingCost	r, t, y	M€	Annual variable operating cost of technology t. Function of TotalAnnualTechnologyActivityByMode and VariableCost (≥ 0).
AnnualFixedOperatingCost	r, t, y	M€	Annual fixed operating cost of technology t. Function of TotalCapacityAnnual and FixedCost (≥ 0).
TotalDiscountedCostByTechnology	r, t, y	M€	Difference between the sum of discounted operating cost / capital cost / emission penalties and salvage value (≥ 0).
TotalDiscountedCost	r, y	M€	TotalDiscountedCostByTechnology summed over technologies (≥ 0).
ModelPeriodCostByRegion	r	M€	Sum of the TotalDiscountedCost over all modelled years. (≥ 0).

Table D.19: Reserve margin

Name	Defined on	Unit	Description
TotalCapacityInReserveMargin	r, y	TWh?	Total available capacity of the technologies required to provide reserve margin. Function of TotalCapacityAnnual and ReserveMarginTagTechnology (≥ 0).
DemandNeedingReserveMargin	r, y, l	TWh/year	Quantity of fuel produced that is assigned to a reserve margin. Function of RateOfProduction and ReserveMarginTagFuel (≥ 0).

Table D.20: RE Generation Target

Name	Defined on	Unit	Description
TotalREProductionAnnual	r, y	TWh	Annual production by technologies tagged as renewable in the model. Function of ProductionByTechnologyAnnual and RETagTechnology.
RETotalProductionOfTargetFuelAnnual	r, y	TWh	Annual production of fuels tagged as renewable in the model. Function of RateOfProduction and RETagFuel.

Table D.21: Emissions

Name	Defined on	Unit	Description
AnnualTechnologyEmissionByMode	r, t, e, m, y	MT CO ₂ eq	Annual emission of agent e by technology t in mode of operation m. Function of RateOfActivity and EmissionActivityRatio (≥ 0).
AnnualTechnologyEmission	r, t, e, y	MT CO ₂ eq	AnnualTechnologyEmissionByMode summed over the modes of operation (≥ 0).
AnnualTechnologyEmissionPenaltyByEmission	r, t, e, y	M€	Undiscounted annual cost of emission e by technology t. Function of AnnualTechnologyEmission and EmissionPenalty (≥ 0).
AnnualTechnologyEmissionsPenalty	r, t, y	M€	Total undiscounted annual cost of all emissions generated by technology t. AnnualTechnologyEmissionPenaltyByEmission summed over all emitted agents (≥ 0).
DiscountedTechnologyEmissionsPenalty	r, t, y	M€	Annual cost of emissions by technology t, discounted through DiscountRate (≥ 0).
AnnualEmissions	r, e, y	MT CO ₂ eq	AnnualTechnologyEmission summed over all technologies. (≥ 0).
ModelPeriodEmissions	r, e	MT CO ₂ eq	Total system emissions of agent e in the model period, accounting for both the emissions by technologies and the user defined ModelPeriodExogenousEmission (≥ 0).

Table D.22: Trade (different to the "original" OSeMOSSYS formulation)

Name	Defined on	Unit	Description
Import	r, rr, f, y, l	TWh	Quantity of fuel imported by region r from region rr in timeslice l (≥ 0).
Export	r, rr, f, y, l	TWh	Quantity of fuel exported by region r to region rr in timeslice l (≥ 0).
NewTradeCapacity	r, rr, f, y	GW	Newly installed trade capacity between regions r and rr in year y (≥ 0).
TotalTradeCapacityAnnual	r, rr, f, y	GW	Total trade capacity installed in year y (≥ 0).
AccumulatedNewTradeCapacity	r, rr, f, y	GW	Cumulative newly installed capacity of technology t from the beginning of the time domain to year y.
CapitalInvestmentTrade	r, rr, f, y	M€	Undiscounted investment in new trade capacity between regions r and rr (≥ 0).
DiscountedCapitalInvestmentTrade	r, rr, f, y	M€	Investment in new trade capacity discounted through DiscountRate (≥ 0).
SalvageValueTrade	r, rr, f, y	M€	Salvage value of an interconnector in year y, as a function of parameters OperationalLifeTrade and DepreciationMethod (≥ 0).
DiscountedSalvageValueTrade	r, rr, f, y	M€	Salvage value of an interconnector discounted through the parameter DiscountRate (≥ 0).
TotalDiscountedTradeCost	r, rr, f, y	M€	Difference between the discounted capital investment in new interconnection capacity and the salvage value in year y (≥ 0).
NetTrade	r, f, y, l	TWh	For region r and timeslice l, the sum of imports and exports to and from neighbouring regions.
NetTradeAnnual	r, f, y	TWh	For region r, annual sum of imports and exports to and from neighbouring regions.
TotalTradeCost	r, y, l	M€	Presumably cost of importing non-electricity fuels.
AnnualTotalTradeCost	r, y	M€	Annual cost of importing non-electricity fuels.
DiscountedAnnualTotalTradeCost	r, y	M€	Discounted annual cost of importing non-electricity fuels.

D.4 Equations

D.4.1 Objective function

$$\text{minimise } \sum_r \text{ModelPeriodCostByRegion}_r \quad (\text{OBJ})$$

D.4.2 Constraints

Rate of demand

$$\text{s.t. } \forall_{r,f,y,l} \text{RateOfDemand}_{r,f,y,l} = \frac{\text{SpecifiedAnnualDemand}_{r,f,y} * \text{SpecifiedDemandProfile}_{r,f,y,l}}{\text{YearSplit}_{y,1}} \quad (\text{EQ})$$

Capacity Adequacy A

$$\text{s.t. } \forall_{r,t,y} \text{AccumulatedNewCapacity}_{r,t,y} = \sum_{yy: y-yy < \text{OperationalLife}_{r,t} \ \&\& \ y-yy \geq 0} \text{NewCapacity}_{r,t,yy} \quad (\text{CAa1})$$

$$\text{s.t. } \forall_{r,t,y} \text{TotalCapacityAnnual}_{r,t,y} = \text{AccumulatedNewCapacity}_{r,t,y} + \text{ResidualCapacity}_{r,t,y} \quad (\text{CAa2})$$

$$\text{s.t. } \forall_{r,t,y,l} \text{RateOfTotalActivity}_{r,t,y,l} = \sum_m \text{RateOfActivity}_{r,t,m,y,l} \quad (\text{CAa3})$$

$$\text{s.t. } \forall_{r,t,y,l} \text{RateOfTotalActivity}_{r,t,y,l} \leq \text{TotalCapacityAnnual}_{r,t,y} * \text{CapacityFactor}_{r,t,y,1} * \text{CapacityToActivityUnit}_{r,t} \quad (\text{CAa4})$$

If values are provided for CapacityOfOneTechnologyUnit, turning OSeMOSYS into a mixed-integer-linear-problem:

$$\text{s.t. } \forall_{r,t,y} \text{NewCapacity}_{r,t,y} = \text{CapacityOfOneTechnologyUnit}_{r,t,y} * \text{NumberOfNewTechnologyUnits}_{r,t,y} \quad (\text{CAa5})$$

Capacity Adequacy B

$$\text{s.t. } \forall_{r,t,y} \sum_l \text{RateOfTotalActivity}_{r,t,y,l} * \text{YearSplit}_{y,1} \leq \sum_l (\text{TotalCapacityAnnual}_{r,t,y} * \text{CapacityFactor}_{r,t,y,1} * \text{YearSplit}_{y,1}) * \text{AvailabilityFactor}_{r,t,y} * \text{CapacityToActivityUnit}_{r,t} \quad (\text{CAb1})$$

Energy Balance A

$$s.t. \quad \forall_{r,t,f,m,y,l} \quad \text{RateOfProductionByTechnologyByMode}_{r,t,f,m,y,l} = \text{RateOfActivity}_{r,t,m,y,l} * \text{OutputActivityRatio}_{r,t,f,m,y} \quad (\text{EBa1})$$

$$s.t. \quad \forall_{r,t,f,y,l} \quad \text{RateOfProductionByTechnology}_{r,t,f,y,l} = \sum_m \text{RateOfProductionByTechnologyByMode}_{r,t,f,m,y,l} \quad (\text{EBa2})$$

$$s.t. \quad \forall_{r,f,y,l} \quad \text{RateOfProduction}_{r,f,y,l} = \sum_t \text{RateOfProductionByTechnology}_{r,t,f,y,l} \quad (\text{EBa3})$$

$$s.t. \quad \forall_{r,t,f,m,y,l} \quad \text{RateOfUseByTechnologyByMode}_{r,t,f,m,y,l} = \text{RateOfActivity}_{r,t,m,y,l} * \text{InputActivityRatio}_{r,t,f,m,y} \quad (\text{EBa4})$$

$$s.t. \quad \forall_{r,t,f,y,l} \quad \text{RateOfUseByTechnology}_{r,t,f,y,l} = \sum_m \text{RateOfUseByTechnologyByMode}_{r,t,f,m,y,l} \quad (\text{EBa5})$$

$$s.t. \quad \forall_{r,f,y,l} \quad \text{RateOfUse}_{r,f,y,l} = \sum_t \text{RateOfUseByTechnology}_{r,t,f,y,l} \quad (\text{EBa6})$$

$$s.t. \quad \forall_{r,f,y,l} \quad \text{Production}_{r,f,y,l} = \text{RateOfProduction}_{r,f,y,l} * \text{YearSplit}_{y,l} \quad (\text{EBa7})$$

$$s.t. \quad \forall_{r,f,y,l} \quad \text{Use}_{r,f,y,l} = \text{RateOfUse}_{r,f,y,l} * \text{YearSplit}_{y,l} \quad (\text{EBa8})$$

$$s.t. \quad \forall_{r,f,y,l} \quad \text{Demand}_{r,f,y,l} = \text{RateOfDemand}_{r,f,y,l} * \text{YearSplit}_{y,l} \quad (\text{EBa9})$$

$$s.t. \quad \forall_{r,f,y,l} \quad \text{Production}_{r,f,y,l} \geq \text{Demand}_{r,f,y,l} + \text{Use}_{y,l} \quad (\text{EBa9})$$

$$s.t. \quad \forall_{r,f,y,l} \quad \text{Production}_{r,f,y,l} \geq \text{Demand}_{r,f,y,l} + \text{Use}_{y,l} \quad (\text{EBa9})$$

$$s.t. \quad \forall_{r,rr,f,y,l} \quad \text{Export}_{r,rr,f,y,l} = \text{Import}_{rr,r,f,y,l} \quad (\text{EBa10})$$

$$s.t. \quad \forall_{r,f,y,l} \quad \text{Production}_{r,f,y,l} \geq \text{Demand}_{r,f,y,l} + \text{Use}_{r,f,y,l} + \text{NetTrade}_{r,f,y,l} \quad (\text{EBa11})$$

$$s.t. \quad \forall_{r,f,y,l} \quad \text{NetTrade}_{r,f,y,l} = \sum_{rr} (\text{Export}_{r,rr,f,y,l} * (1 + \text{TradeLossBetweenRegions}_{r,rr,f,y}) - \text{Import}_{r,rr,f,y,l}) \quad (\text{EBa12})$$

Energy Balance B

$$s.t. \quad \forall_{r,f,y} \quad \text{ProductionAnnual}_{r,f,y} = \sum_l \text{Production}_{r,f,y,l} \quad (\text{EBb1})$$

$$s.t. \quad \forall_{r,f,y} \quad \text{UseAnnual}_{r,f,y} = \sum_l \text{Use}_{r,f,y,l} \quad (\text{EBb2})$$

$$s.t. \quad \forall_{r,f,y} \quad \text{NetTradeAnnual}_{r,f,y} = \sum_l \text{NetTrade}_{r,f,y,l} \quad (\text{EBb3})$$

$$s.t. \quad \forall_{r,f,y} \quad \text{ProductionAnnual}_{r,f,y} \geq \text{UseAnnual}_{r,f,y} + \text{AccumulatedAnnualDemand}_{r,f,y} + \text{NetTradeAnnual}_{r,f,y} \quad (\text{EBb4})$$

Accounting Technology Production/Use

$$s.t. \quad \forall_{r,t,f,y,l} \quad \text{ProductionByTechnology}_{r,t,f,y,l} = \text{RateOfProductionByTechnology}_{r,t,f,y,l} * \text{YearSplit}_{y,l} \quad (\text{Acc1})$$

$$s.t. \quad \forall_{r,t,f,y,l} \quad \text{UseByTechnology}_{r,t,f,y,l} = \text{RateOfUseByTechnology}_{r,t,f,y,l} * \text{YearSplit}_{y,l} \quad (\text{Acc2})$$

$$s.t. \quad \forall_{r,t,f,y,l} \quad \text{TotalAnnualTechnologyActivityByMode}_{r,t,m,y} = \sum_l (\text{RateOfActivity}_{r,t,m,y,l} * \text{YearSplit}_{y,l}) \quad (\text{Acc3})$$

$$s.t. \quad \forall_r \quad \text{ModelPeriodCostByRegion}_r = \sum_y \text{TotalDiscountedCost}_{r,y} \quad (\text{Acc4})$$

Storage equations

$$s.t. \quad \forall_{r,t,s,m,y,ls,ld,lh} \quad \text{RateOfStorageCharge}_{r,s,y,ls,ld,lh} = \sum_m \sum_l \sum_t (\text{RateOfActivity}_{r,t,m,y,l} * \text{TechnologyToStorage}_{r,t,s,m} * \text{Conversionls}_{l,ls} * \text{Conversionld}_{l,ld} * \text{Conversionlh}_{l,lh}) \quad (\text{SE1})$$

$$s.t. \quad \forall_{r,t,s,m,y,ls,ld,lh} \quad \text{RateOfStorageDischarge}_{r,s,y,ls,ld,lh} = \sum_m \sum_l \sum_t (\text{RateOfActivity}_{r,t,m,y,l} * \text{TechnologyFromStorage}_{r,t,s,m} * \text{Conversionls}_{l,ls} * \text{Conversionld}_{l,ld} * \text{Conversionlh}_{l,lh}) \quad (\text{SE2})$$

$$\begin{aligned}
s.t. \quad \forall_{r,s,y,ls,ld,lh} \quad NetChargeWithinYear_{r,s,y,ls,ld,lh} &= \sum_l ((RateOfStorageCharge_{r,s,y,ls,ld,lh} - \\
&RateOfStorageDischarge_{r,s,y,ls,ld,lh}) * \\
&YearSplit_{y,1} * \\
&Conversionls_{1,ls} * \\
&Conversionld_{1,ld} * \\
&Conversionlh_{1,lh})
\end{aligned} \tag{SE3}$$

$$\begin{aligned}
s.t. \quad \forall_{r,s,y,ls,ld,lh} \quad NetChargeWithinDay_{r,s,y,ls,ld,lh} &= (RateOfStorageCharge_{r,s,y,ls,ld,lh} - \\
&RateOfStorageDischarge_{r,s,y,ls,ld,lh}) * \\
&DaySplit_{y,lh}
\end{aligned} \tag{SE4}$$

$$\begin{aligned}
s.t. \quad \forall_{r,s,y} \quad if \quad y = StartYear : \\
\quad StorageLevelYearStart_{r,s,y} &= StorageLevelStart_{r,s} \\
else : \\
\quad StorageLevelYearStart_{r,s,y} &= StorageLevelYearStart_{r,s,y-1} + \\
&\sum_{ls} \sum_{ld} \sum_{lh} NetChargeWithinYear_{r,s,y-1,ls,ld,lh}
\end{aligned} \tag{SE5a}$$

The following two constraints have been added to the "original" OSeMOSSYS formulation to avoid unwanted model behaviour for case studies with a significantly decreasing CO2 allowance, or significantly increasing CO2 cost. Their absence can lead to storage assets being charged up at the start of the investment period for energy release at the end of the period. The StorageLeeway parameter was set at 0.1.

$$s.t. \quad \forall_{r,s,y} \quad StorageLevelYearStart_{r,s,y} \geq StorageLevelFinish_{r,s} * (1 - StorageLeeway_s) \tag{SE5b}$$

$$s.t. \quad \forall_{r,s,y} \quad StorageLevelYearStart_{r,s,y} \leq StorageLevelFinish_{r,s} * (1 + StorageLeeway_s) \tag{SE5c}$$

$$\begin{aligned}
s.t. \quad \forall_{r,s,y} \quad if \quad y < EndYear : \\
\quad StorageLevelYearFinish_{r,s,y} &= StorageLevelYearStart_{r,s,y+1} \\
else : \\
\quad StorageLevelYearFinish_{r,s,y} &= StorageLevelYearStart_{r,s,y} + \\
&\sum_{ls} \sum_{ld} \sum_{lh} NetChargeWithinYear_{r,s,y,ls,ld,lh}
\end{aligned} \tag{SE6}$$

$$\begin{aligned}
s.t. \quad \forall_{r,s,y,ls} \quad if \quad ls = StartSeason : \\
\quad StorageLevelSeasonStart_{r,s,y,ls} &= StorageLevelYearStart_{r,s,y} \\
else : \\
\quad StorageLevelSeasonStart_{r,s,y,ls} &= StorageLevelSeasonStart_{r,s,y,ls-1} + \\
&\sum_{ld} \sum_{lh} NetChargeWithinYear_{r,s,y,ls-1,ld,lh}
\end{aligned} \tag{SE7}$$

$$\begin{aligned}
s.t. \quad & \forall_{r,s,y,ls} \quad \text{if } ld = \text{StartDayType} : \\
& \quad \text{StorageLevelDayTypeStart}_{r,s,y,ls,ld} = \text{StorageLevelSeasonStart}_{r,s,y,ls} \\
& \text{else} : \\
& \quad \text{StorageLevelDayTypeStart}_{r,s,y,ls,ld} = \text{StorageLevelDayTypeStart}_{r,s,y,ls,ld-1} + \\
& \quad \quad \sum_{lh} \text{NetChargeWithinDay}_{r,s,y,ls,ld-1,lh} * \text{DaysInDayType}_{y,ls,ld-1}
\end{aligned} \tag{SE8}$$

$$\begin{aligned}
s.t. \quad & \forall_{r,s,y,ls,ld} \quad \text{if } ld = \text{EndDayType} : \\
& \quad \text{if } ls = \text{EndSeason} : \\
& \quad \quad \text{StorageLevelDayTypeFinish}_{r,s,y,ls,ld} = \text{StorageLevelYearFinish}_{r,s,y} \\
& \quad \text{else} : \\
& \quad \quad \text{StorageLevelDayTypeFinish}_{r,s,y,ls,ld} = \text{StorageLevelSeasonStart}_{r,s,y,ls+1} \\
& \text{else} : \quad \text{StorageLevelDayTypeFinish}_{r,s,y,ls,ld} = \text{StorageLevelDayTypeFinish}_{r,s,y,ls,ld+1} - \\
& \quad \quad \sum_{lh} \text{NetChargeWithinDay}_{r,s,y,ls,ld+1,lh} * \text{DaysInDayType}_{y,ls,ld+1}
\end{aligned} \tag{SE9}$$

Storage constraints

$$\begin{aligned}
s.t. \quad & \forall_{r,s,y,ls,ld,lh} \quad \text{StorageLowerLimit}_{r,s,y} \leq \text{StorageLevelDayTypeStart}_{r,s,y,ls,ld} + \\
& \quad \sum_{lh:lh>0} \text{NetChargeWithinDay}_{r,s,y,ls,ld,lh}
\end{aligned} \tag{SC1}$$

$$\begin{aligned}
s.t. \quad & \forall_{r,s,y,ls,ld,lh} \quad \text{if } ld > \text{StartDayType} : \\
& \quad \text{StorageLowerLimit}_{r,s,y} \leq \text{StorageLevelDayTypeStart}_{r,s,y,ls,ld} - \\
& \quad \sum_{lh:lh<0} \text{NetChargeWithinDay}_{r,s,y,ls,ld-1,lh}
\end{aligned} \tag{SC2}$$

$$\begin{aligned}
s.t. \quad & \forall_{r,s,y,ls,ld,lh} \quad \text{StorageLowerLimit}_{r,s,y} \leq \text{StorageLevelDayTypeFinish}_{r,s,y,ls,ld} - \\
& \quad \sum_{lh:lh<0} \text{NetChargeWithinDay}_{r,s,y,ls,ld,lh}
\end{aligned} \tag{SC3}$$

$$\begin{aligned}
s.t. \quad & \forall_{r,s,y,ls,ld,lh} \quad \text{if } ld > \text{StartDayType} : \\
& \quad \text{StorageLowerLimit}_{r,s,y} \leq \text{StorageLevelDayTypeFinish}_{r,s,y,ls,ld-1} + \\
& \quad \sum_{lh:lh>0} \text{NetChargeWithinDay}_{r,s,y,ls,ld,lh}
\end{aligned} \tag{SC4}$$

$$\begin{aligned}
s.t. \quad & \forall_{r,s,y,ls,ld,lh} \quad \text{StorageUpperLimit}_{r,s,y} \geq \text{StorageLevelDayTypeStart}_{r,s,y,ls,ld} + \\
& \quad \sum_{lh:lh>0} \text{NetChargeWithinDay}_{r,s,y,ls,ld,lh}
\end{aligned} \tag{SC5}$$

$$\begin{aligned}
s.t. \quad \forall_{r,s,y,ls,ld,lh} \quad \text{if } ld > \text{StartDayType} : \\
\quad \text{StorageUpperLimit}_{r,s,y} \geq \text{StorageLevelDayTypeStart}_{r,s,y,ls,ld} - \\
\quad \sum_{lh: lh-lh < 0} \text{NetChargeWithinDay}_{r,s,y,ls,ld-1,lh}
\end{aligned} \tag{SC6}$$

$$\begin{aligned}
s.t. \quad \forall_{r,s,y,ls,ld,lh} \quad \text{StorageUpperLimit}_{r,s,y} \geq \text{StorageLevelDayTypeFinish}_{r,s,y,ls,ld} - \\
\quad \sum_{lh: lh-lh < 0} \text{NetChargeWithinDay}_{r,s,y,ls,ld,lh}
\end{aligned} \tag{SC7}$$

$$\begin{aligned}
s.t. \quad \forall_{r,s,y,ls,ld,lh} \quad \text{if } ld > \text{StartDayType} : \\
\quad \text{StorageUpperLimit}_{r,s,y} \geq \text{StorageLevelDayTypeFinish}_{r,s,y,ls,ld-1} + \\
\quad \sum_{lh: lh-lh > 0} \text{NetChargeWithinDay}_{r,s,y,ls,ld,lh}
\end{aligned} \tag{SC8}$$

$$s.t. \quad \forall_{r,s,y,ls,ld,lh} \quad \text{RateOfStorageCharge}_{r,s,y,ls,ld,lh} \leq \text{StorageMaxChargeRate}_{r,s} \tag{SC9}$$

$$s.t. \quad \forall_{r,s,y,ls,ld,lh} \quad \text{RateOfStorageDischarge}_{r,s,y,ls,ld,lh} \leq \text{StorageMaxDischargeRate}_{r,s} \tag{SC10}$$

Storage Investment

$$s.t. \quad \forall_{r,s,y} \quad \text{StorageUpperLimit}_{r,s,y} = \text{AccumulatedNewStorageCapacity}_{r,s,y} + \text{ResidualStorageCapacity}_{r,s,y} \tag{SI1}$$

$$s.t. \quad \forall_{r,s,y} \quad \text{StorageLowerLimit}_{r,s,y} = \text{MinStorageCharge}_{r,s,y} * \text{StorageUpperLimit}_{r,s,y} \tag{SI2}$$

$$\begin{aligned}
s.t. \quad \forall_{r,s,y} \quad \text{AccumulatedNewStorageCapacity}_{r,s,y} = \\
\quad \sum_{yy: y-yy < \text{OperationalLifeStorage}_{r,s} \ \&\& \ y-yy \geq 0} \text{NewStorageCapacity}_{r,s,yy}
\end{aligned} \tag{SI3}$$

$$s.t. \quad \forall_{r,s,y} \quad \text{CapitalInvestmentStorage}_{r,s,y} = \text{CapitalCostStorage}_{r,s,y} + \text{NewStorageCapacity}_{r,s,y} \tag{SI4}$$

$$s.t. \quad \forall_{r,s,y} \quad \text{DiscountedCapitalInvestmentStorage}_{r,s,y} = \frac{\text{CapitalInvestmentStorage}_{r,s,y}}{(1 + \text{DiscountRate}_r)^{y - \text{StartYear}}} \tag{SI5}$$

Assuming straight-line depreciation method:

$$\begin{aligned}
s.t. \quad \forall_{r,s,y} \quad & \text{if } (y + \text{OperationalLifeStorage}_{r,s} - 1) > \text{EndYear} : \\
& \text{SalvageValueStorage}_{r,s,y} = \text{CapitalInvestmentStorage}_{r,s,y} * \left(1 - \frac{\text{EndYear} - y + 1}{\text{OperationalLifeStorage}_{r,s}}\right) \\
& \text{else :} \\
& \text{SalvageValueStorage}_{r,s,y} = 0
\end{aligned} \tag{SI6}$$

$$s.t. \quad \forall_{r,s,y} \quad \text{DiscountedSalvageValueStorage}_{r,s,y} = \frac{\text{SalvageValueStorage}_{r,s,y}}{(1 + \text{DiscountRate}_r)^{1 + \text{EndYear} - \text{StartYear}}} \tag{SI7}$$

$$s.t. \quad \forall_{r,s,y} \quad \text{TotalDiscountedStorageCost}_{r,s,y} = \text{DiscountedCapitalInvestmentStorage}_{r,s,y} - \text{DiscountedSalvageValueStorage}_{r,s,y} \tag{SI8}$$

Capital Costs

$$s.t. \quad \forall_{r,t,y} \quad \text{CapitalInvestment}_{r,t,y} = \text{CapitalCost}_{r,t,y} * \text{NewCapacity}_{r,t,y} \tag{CC1}$$

$$s.t. \quad \forall_{r,t,y} \quad \text{DiscountedCapitalInvestment}_{r,t,y} = \frac{\text{CapitalInvestment}_{r,t,y}}{(1 + \text{DiscountRate}_r)^{y - \text{StartYear}}} \tag{CC2}$$

Operating Costs

$$\begin{aligned}
s.t. \quad \forall_{r,t,y,l} \quad \text{AnnualVariableOperatingCost}_{r,t,y} &= \sum_m (\text{TotalAnnualTechnologyActivityByMode}_{r,t,m,y} * \\
& \quad \text{VariableCost}_{r,t,m,y})
\end{aligned} \tag{OC1}$$

$$s.t. \quad \forall_{r,t,y} \quad \text{AnnualFixedOperatingCost}_{r,t,y} = \text{TotalCapacityAnnual}_{r,t,y} * \text{FixedCost}_{r,t,y} \tag{OC2}$$

$$s.t. \quad \forall_{r,t,y} \quad \text{OperatingCost}_{r,t,y} = \text{AnnualVariableOperatingCost}_{r,t,y} + \text{AnnualFixedOperatingCost}_{r,t,y} \tag{OC3}$$

$$s.t. \quad \forall_{r,t,y} \quad \text{DiscountedOperatingCost}_{r,t,y} = \frac{\text{OperatingCost}_{r,t,y}}{(1 + \text{DiscountRate}_r)^{y - \text{StartYear} + 0.5}} \tag{OC4}$$

Total Discounted Costs

$$\begin{aligned}
s.t. \quad \forall_{r,t,y} \quad \text{TotalDiscountedCostByTechnology}_{r,t,y} &= \text{DiscountedOperatingCost}_{r,t,y} + \\
& \text{DiscountedCapitalInvestment}_{r,t,y} + \\
& \text{DiscountedTechnologyEmissionsPenalty}_{r,t,y} - \\
& \text{DiscountedSalvageValue}_{r,t,y}
\end{aligned} \tag{TDC1}$$

$$\begin{aligned}
s.t. \quad \forall_{r,y} \quad \text{TotalDiscountedCost}_{r,y} &= \sum_t \text{TotalDiscountedCostByTechnology}_{r,t,y} + \\
& \sum_s \text{TotalDiscountedStorageCost}_{r,s,y} + \\
& \sum_f \sum_{rr} \text{TotalDiscountedTradeCost}_{r,rr,f,y} + \\
& \text{DiscountedAnnualTotalTradeCost}_{r,y}
\end{aligned} \tag{TDC2}$$

Total Capacity Constraints

$$s.t. \quad \forall_{r,t,y} \quad TotalCapacityAnnual_{r,t,y} \leq TotalAnnualMaxCapacity_{r,t,y} \quad (TCC1)$$

$$s.t. \quad \forall_{r,t,y} \quad TotalCapacityAnnual_{r,t,y} \geq TotalAnnualMinCapacity_{r,t,y} \quad (TCC2)$$

Salvage Value

Assuming straight-line depreciation method:

$$s.t. \quad \forall_{r,t,y} \quad \text{if } (y + OperationalLife_{r,t} - 1) > EndYear :$$

$$\quad \quad \quad SalvageValue_{r,t,y} = CapitalCost_{r,t,y} * NewCapacity_{r,t,y} * \left(1 - \frac{EndYear - y + 1}{OperationalLife_{r,t}}\right)$$

$$\quad \quad \quad \text{else :}$$

$$\quad \quad \quad SalvageValue_{r,t,y} = 0 \quad (SV1)$$

$$s.t. \quad \forall_{r,t,y} \quad DiscountedSalvageValue_{r,t,y} = \frac{SalvageValue_{r,t,y}}{(1 + DiscountRate_r)^{1+EndYear-StartYear}} \quad (SV2)$$

New Capacity Constraints

$$s.t. \quad \forall_{r,t,y} \quad NewCapacity_{r,t,y} \leq TotalAnnualMaxCapacityInvestment_{r,t,y} \quad (NCC1)$$

$$s.t. \quad \forall_{r,t,y} \quad NewCapacity_{r,t,y} \geq TotalAnnualMinCapacityInvestment_{r,t,y} \quad (NCC2)$$

Annual Activity Constraints

$$s.t. \quad \forall_{r,t,y} \quad TotalTechnologyAnnualActivity_{r,t,y} = \sum_l RateOfTotalActivity_{r,t,y,l} * YearSplit_{y,l} \quad (AAC1)$$

$$s.t. \quad \forall_{r,t,y} \quad TotalTechnologyAnnualActivity_{r,t,y} \leq TotalTechnologyAnnualActivityUpperLimit_{r,t,y} \quad (AAC2)$$

$$s.t. \quad \forall_{r,t,y} \quad TotalTechnologyAnnualActivity_{r,t,y} \geq TotalTechnologyAnnualActivityLowerLimit_{r,t,y} \quad (AAC3)$$

Total Activity Constraints

$$s.t. \quad \forall_{r,t} \quad TotalTechnologyModelPeriodActivity_{r,t} = \sum_y TotalTechnologyAnnualActivity_{r,t,y} \quad (TAC1)$$

$$s.t. \quad \forall_{r,t} \quad TotalTechnologyModelPeriodActivity_{r,t} \leq TotalTechnologyModelPeriodActivityUpperLimit_{r,t} \quad (TAC2)$$

$$s.t. \quad \forall_{r,t} \quad TotalTechnologyModelPeriodActivity_{r,t} \geq TotalTechnologyModelPeriodActivityLowerLimit_{r,t} \quad (TAC3)$$

Reserve Margin Constraints

The following set of constraints is the core of the soft-linking feedback techniques presented in sections 5.4 and 5.5. They were however not used in the work presented in Chapter 4 nor in the soft-linking feedback technique presented in section 5.6. Note that the constraints do not exactly match the "original" OSeMOSYS formulation as they were slightly adapted for the purpose of the soft-linking framework: the name of the parameter ReserveMarginTagTechnology was changed to CapacityCredit for clarity, and interconnectors were given a chance to contribute to TotalCapacityInReserveMargin.

$$s.t. \quad \forall_{r,f=Power,y} \quad TotalCapacityInReserveMargin_{r,y} = \sum_t (TotalCapacityAnnual_{r,t,y} * CapacityCredit_{r,t,y} * CapacityToActivityUnit_{r,t}) + \sum_{rr} (TotalTradeCapacityAnnual_{r,rr,f,y} * TradeCapacityCredit_{r,rr,f,y} * 8.76) \quad (RM1)$$

The 8.76 value corresponds to the CapacityToActivityUnit that was used in model runs. For simplicity, an additional parameter carrying the same information but not defined over the set *technology* was not added to the problem formulation. This is not a clean solution, as this value would need to be changed in the optimisation code if different reference units were used to express power and energy.

$$s.t. \quad \forall_{r,y,l} \quad DemandNeedingReserveMargin_{r,y,l} = \sum_f (RateOfProduction_{r,f,y,l} * ReserveMarginTagFuel_{r,f,y}) \quad (RM2)$$

$$s.t. \quad \forall_{r,y,l} \quad TotalCapacityInReserveMargin_{r,y} \geq DemandNeedingReserveMargin_{r,y,l} * ReserveMargin_{r,y} \quad (RM3)$$

Flexibility Proxy Constraints

The following set of constraints is the core of the soft-linking feedback technique presented in section 5.6. They were not used in any of the model runs presented elsewhere in this thesis. Due to lack of time, this feedback technique was only applied to single-node systems. If multi-node systems were to be modelled, these constraints would require an additional term allowing interconnection to contribute to the different flexibility targets.

$$s.t. \quad \forall_{r,y} \quad \text{AnnualFlexibilityTarget}_{r,y} \leq \text{TotalCapacityAnnual}_{r,t,y} * \text{AnnualFlexibilityProxy}_{r,t,y} \quad (\text{FP1})$$

$$s.t. \quad \forall_{r,y} \quad \text{WeeklyFlexibilityTarget}_{r,y} \leq \text{TotalCapacityAnnual}_{r,t,y} * \text{WeeklyFlexibilityProxy}_{r,t,y} \quad (\text{FP2})$$

$$s.t. \quad \forall_{r,y} \quad \text{DailyFlexibilityTarget}_{r,y} \leq \text{TotalCapacityAnnual}_{r,t,y} * \text{DailyFlexibilityProxy}_{r,t,y} \quad (\text{FP3})$$

RE Production targets

$$s.t. \quad \forall_{r,t,f,y} \quad \text{ProductionByTechnologyAnnual}_{r,t,f,y} = \sum_l \text{ProductionByTechnology}_{r,t,f,y,l} \quad (\text{RE1})$$

$$s.t. \quad \forall_{r,y} \quad \text{TotalREProductionAnnual}_{r,y} = \sum_t \sum_f \text{ProductionByTechnologyAnnual}_{r,t,f,y} * \text{RETagTechnology}_{r,t,y} \quad (\text{RE2})$$

$$s.t. \quad \forall_{r,y} \quad \text{RETotalProductionOfTargetFuelAnnual}_{r,y} = \sum_f \sum_l \text{RateOfProduction}_{r,f,y,l} * \text{RETagFuel}_{r,f,y} * \text{YearSplit}_{y,l} \quad (\text{RE3})$$

$$s.t. \quad \forall_{r,y} \quad \text{TotalREProductionAnnual}_{r,y} \geq \text{REMinProductionTarget}_{r,y} * \text{RETotalProductionOfTargetFuelAnnual}_{r,y} \quad (\text{RE4})$$

$$s.t. \quad \forall_{r,t,f,y} \quad \text{UseByTechnologyAnnual}_{r,t,f,y} = \sum_l (\text{RateOfUseByTechnology}_{r,t,f,y,l} * \text{YearSplit}_{y,l}) \quad (\text{RE5})$$

Emissions Accounting

$$s.t. \quad \forall_{r,t,e,m,y} \quad \text{AnnualTechnologyEmissionByMode}_{r,t,e,m,y} = \frac{\mathbf{EmissionActivityRatio}_{r,t,e,m,y} * \text{TotalAnnualTechnologyActivityByMode}_{r,t,m,y}}{\quad} \quad (\text{E1})$$

$$s.t. \quad \forall_{r,t,e,y} \quad \text{AnnualTechnologyEmission}_{r,t,e,y} = \sum_m \text{AnnualTechnologyEmissionByMode}_{r,t,e,m,y} \quad (\text{E2})$$

$$s.t. \quad \forall_{r,t,e,y} \quad \text{AnnualTechnologyEmissionPenaltyByEmission}_{r,t,e,y} = \text{AnnualTechnologyEmission}_{r,t,e,y} * \mathbf{EmissionsPenalty}_{r,e,y} \quad (\text{E3})$$

$$s.t. \quad \forall_{r,t,y} \quad \text{AnnualTechnologyEmissionsPenalty}_{r,t,y} = \sum_e \text{AnnualTechnologyEmissionPenaltyByEmission}_{r,t,e,y} \quad (\text{E4})$$

$$s.t. \quad \forall_{r,t,y} \quad \text{DiscountedTechnologyEmissionsPenalty}_{r,t,y} = \frac{\text{AnnualTechnologyEmissionsPenalty}_{r,t,y}}{(1 + \mathbf{DiscountRate}_r)^{y - \mathbf{StartYear} + 0.5}} \quad (\text{E5})$$

$$s.t. \quad \forall_{r,e,y} \quad \text{AnnualEmissions}_{r,e,y} = \sum_t \text{AnnualTechnologyEmission}_{r,t,e,y} \quad (\text{E6})$$

$$s.t. \quad \forall_{r,e} \quad \sum_y \text{AnnualEmissions}_{r,e,y} = \text{ModelPeriodEmissions}_{r,e} - \mathbf{ModelPeriodExogenousEmission}_{r,e} \quad (\text{E7})$$

$$s.t. \quad \forall_{r,e,y} \quad \mathbf{AnnualEmissionLimit}_{r,e,y} \geq \text{AnnualEmissions}_{r,e,y} + \text{AnnualExogenousEmission}_{r,e,y} \quad (\text{E8})$$

$$s.t. \quad \forall_{r,e} \quad \text{ModelPeriodEmissions}_{r,e} \leq \mathbf{ModelPeriodEmissionLimit}_{r,e} \quad (\text{E9})$$

Trade capacities and investments

The following set of constraints is not part of the "original" OSeMOSYS problem formulation. They have been added to allow the modelling of power trade between regions. For more information, see section 4.3.2.

$$s.t. \quad \forall_{r,rr,f=Power,y,l} \quad \text{TotalTradeCapacityAnnual}_{r,rr,f,y} * (1 + \mathbf{TradeLossBetweenRegions}_{r,rr,f,y}) \geq \frac{\text{Export}_{r,rr,f,y,l}}{\mathbf{CapacityToActivityUnit}_{r,t} * \text{YearSplit}_{y,l}} \quad (\text{TRC1a})$$

$$s.t. \quad \forall_{r,rr,f=Power,y,l} \quad TotalTradeCapacityAnnual_{r,rr,f,y} * (1 + TradeLossBetweenRegions_{r,rr,f,y}) \geq \frac{Import_{rr,r,f,y,l}}{CapacityToActivityUnit_{r,t} * YearSplit_{y,l}} \quad (TRC1b)$$

$$s.t. \quad \forall_{r,rr,f=Power,y} \quad TotalTradeCapacityAnnual_{r,rr,f,y} = AccumulatedNewTradeCapacity_{r,rr,f,y} + ResidualTradeCapacity_{r,rr,f,y} \quad (TRC2)$$

$$s.t. \quad \forall_{r,rr,f=Power,y} \quad AccumulatedNewTradeCapacity_{r,rr,f,y} = \sum_{yy: y-yy \geq 0} NewTradeCapacity_{r,rr,f,yy} \quad (TRC3)$$

$$s.t. \quad \forall_{r,rr,f=Power,y} \quad NewTradeCapacity_{r,rr,f,y} \leq \frac{TotalAnnualMaxTradeInvestment_{r,rr,f,y} * TradeRoute_{r,rr,f,y}}{TradeRoute_{r,rr,f,y}} \quad (TRC4)$$

$$s.t. \quad \forall_{r,rr,f=Power,y} \quad NewTradeCapacity_{r,rr,f,y} = NewTradeCapacity_{rr,r,f,y} \quad (TRC5)$$

$$s.t. \quad \forall_{r,rr,f=Power,y} \quad CapitalInvestmentTrade_{r,rr,f,y} = \frac{NewTradeCapacity_{r,rr,f,y} * CapitalCostTrade_{r,rr,f}}{CapitalCostTrade_{r,rr,f}} \quad (TRC6)$$

$$s.t. \quad \forall_{r,rr,f=Power,y} \quad DiscountedCapitalInvestmentTrade_{r,rr,f,y} = \frac{CapitalInvestmentTrade_{r,rr,f,y}}{(1 + DiscountRate_r)^{y-StartYear}} \quad (TRC7)$$

$$s.t. \quad \forall_{r,rr,f,y} \quad \text{if } (y + OperationalLifeTrade_{r,rr,f} - 1) > EndYear : \\ \quad \quad \quad SalvageValueTrade_{r,rr,f,y} = CapitalInvestmentTrade_{r,rr,f,y} * (1 - \frac{EndYear - y + 1}{OperationalLifeTrade_{r,rr,f}}) \\ \quad \quad \quad \text{else :} \\ \quad \quad \quad SalvageValueTrade_{r,rr,f,y} = 0 \quad (TRC8)$$

$$s.t. \quad \forall_{r,rr,f,y} \quad DiscountedSalvageValueTrade_{r,rr,f,y} = \frac{SalvageValueTrade_{r,rr,f,y}}{(1 + DiscountRate_r)^{1+EndYear-StartYear}} \quad (TRC9)$$

$$s.t. \quad \forall_{r,rr,f,y} \quad TotalDiscountedTradeCost_{r,rr,f,y} = DiscountedCapitalInvestmentTrade_{r,rr,f,y} - DiscountedSalvageValueTrade_{r,rr,f,y} \quad (TRC10)$$

Trading costs

The following set of constraints can be used to model variable costs associated with fuel exchanges between regions. Variable costs of power exchanges were considered to be zero. For other fuels, only imports were considered (i.e. no extraction), and it was assumed the variable costs of these imports already include transport costs. This functionality was hence not used in our model runs.

$$s.t. \quad \forall_{r,y,l} \quad TotalTradeCost_{r,y,l} = \sum_f \sum_{rr} (Import_{r,rr,f,y,l} * TradeCost_{r,rr,f}) \quad (TC1)$$

$$s.t. \quad \forall_{r,y} \quad AnnualTotalTradeCost_{r,y} = \sum_l TotalTradeCost_{r,y,l} \quad (TC2)$$

$$s.t. \quad \forall_{r,y} \quad DiscountedAnnualTotalTradeCost_{r,y} = \frac{AnnualTotalTradeCost_{r,y}}{(1 + DiscountRate_r)^{y-StartYear}} \quad (TC3)$$

Appendix E

Selection of capacity expansion study inputs

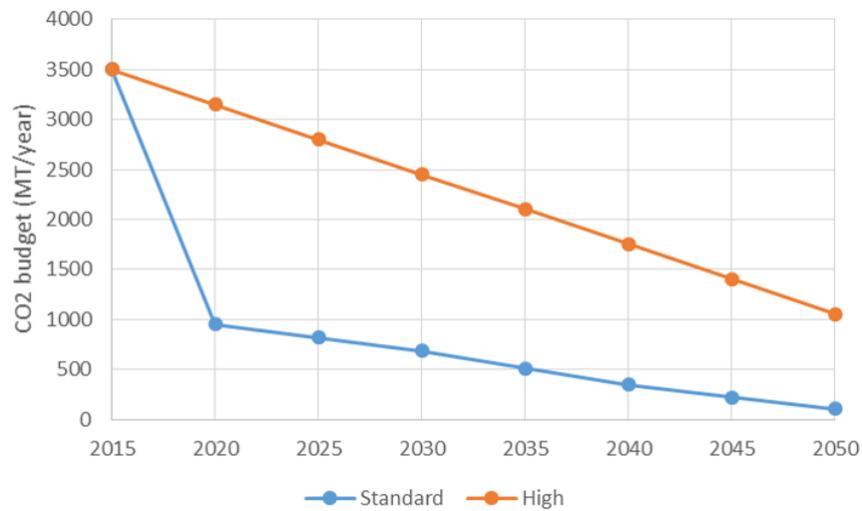


Figure E.1: CO₂ annual budgets aggregated at the European level. Budgets are allocated among regions according to their share in European annual demand. The "standard" budget, based on TUB OSMOSE scenario data, is used as a reference in Chapter 4 and for all model runs in Chapter 5; the "high" budget is used for the sensitivity study of section 4.4.2. Note that these carbon budgets are typically non-binding at the start of the model period.

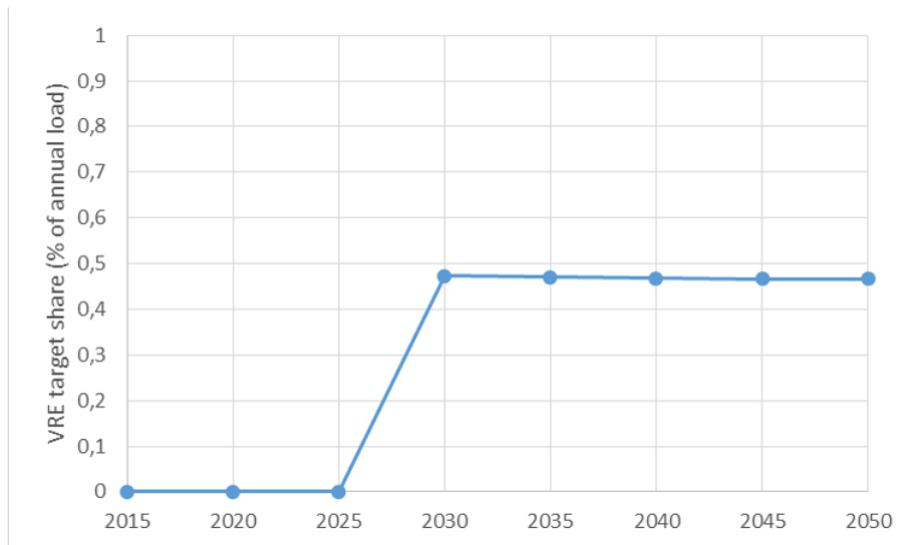


Figure E.2: Minimum VRE share target aggregated at the European level. Values at regional level were set by TUB in the OSMOSE scenario data.

Table E.1: Thermal generation Antares parameters (bio-energy modelled as must-run).

Technology	Pmax (MW)	Pmin (MW)	Min up time (h)	Min down time (h)	Market bid (€)	CO2 emissions (tCO2e/MWh)
Nuclear	1600	800	168	168	14	0
Coal	800	320	6	6	79	0.75
CCGT	500	150	3	3	118	0.327
OCGT	250	120	0	0	172	0.488
Oil	250	120	3	3	190	0.65

Table E.2: Default capacity credit values, assigned uniformly across soft-linked years and regions (note: in Antares, biomass is modelled as a must-run technology).

Technology	DefaultCapacityCredit
PP_biomass	0.47
PP_CCGT	0.92
PP_coal	0.92
PP_hydro	0.40
PP_nuclear	0.89
PP_OCGT	0.92
PP_offshore	0.07
PP_oil	0.92
PP_onshore	0.07
PP_solar	0
ST_battery	0.01
ST_PHS	0.10
Interconnectors	0

Table E.3: Default flexibility proxy values on the annual, weekly and daily timescales. These values are assigned uniformly across soft-linked years and regions (note: in Antares, biomass is modelled as a must-run technology).

Technology	Annual	Weekly	Daily
PP_biomass	0	0	0
PP_CCGT	1,43	1,37	0,82
PP_coal	1,51	1,4	1,17
PP_hydro	0,24	0,35	0,4
PP_nuclear	1,3	0,76	0,33
PP_OCGT	0,88	0,77	0,88
PP_offshore	0	0	0
PP_oil	0	0	0
PP_onshore	0	0	0
PP_solar	0	0	0
ST_battery	0	0	0,73
ST_PHS	0,24	1,23	2,77
Interconnector	0	0	0

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RÉSUMÉ

Dans le cadre de nos efforts pour atténuer le changement climatique, la production d'électricité à partir de combustibles fossiles est progressivement remplacée par des technologies bas carbone, principalement l'éolien et le solaire. Ce changement mène à une augmentation du besoin de flexibilité du système électrique, tout en retirant les leviers qui permettaient historiquement de la fournir. Une question clé est donc celle de la combinaison optimale de leviers de flexibilité capable d'assurer le bon fonctionnement d'un système à forte pénétration d'énergies renouvelables. Dans cette thèse, nous proposons de nouveaux indicateurs quantifiant différentes facettes de la flexibilité, améliorant notre compréhension et notre capacité à communiquer des recommandations à un public large. Nous nous concentrons ensuite sur l'amélioration de la prise en compte de la flexibilité dans la planification du système électrique, notamment à travers le couplage bidirectionnel de deux types d'outils, le modèle d'expansion de capacité OSeMOSYS et l'outil de simulation du dispatch Antares.

MOTS CLÉS

Flexibilité, Planification, Expansion de capacité, Equilibre offre demande, Optimisation, Métriques, Etudes prospectives.

ABSTRACT

In our attempt to mitigate climate change, fossil fuel based power generation is gradually being replaced by low-carbon technologies, primarily wind and solar. This is simultaneously increasing the need for power system flexibility and removing our historically dominant way of providing it. A key question to be addressed is hence that of the optimal combination of flexibility solutions able to operate a power system with high penetrations of variable renewables. In this PhD, we propose new metrics quantifying different facets of flexibility, improving our understanding and ability to communicate policy recommendations to wider audiences. We then concentrate on the improvement of the representation of flexibility in power system planning, through the bi-directional soft-linking of two different model types, the capacity expansion model OSeMOSYS and the production cost model Antares.

KEYWORDS

Flexibility, System planning, Capacity expansion, Electricity balancing, Optimisation, Metrics, Prospective studies