Dissertation

# The role of flexibility in electricity systems with high shares of variable renewable energy

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*Hoffnung ist nicht die Überzeugung, dass etwas gut ausgeht, sondern die Gewissheit, dass etwas Sinn hat, egal wie es ausgeht. ~ Vaclav Havel*

*Der höchste Lohn für unsere Bemühungen ist nicht das, was wir dafür bekommen, sondern das, was wir dadurch werden. ~ John Ruskin*

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*Hope is not the conviction that something will turn out well but the certainty that something makes sense, regardless of how it turns out. ~ Vaclav Havel*

*The highest reward for a person's toil is not what they get for it but what they become by it. ~ John Ruskin*


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# Abstract

Decarbonizing the energy system is a key pillar of climate change mitigation, leading to higher electrification and increasing shares of variable renewable energy in the electricity system (VRE). Flexibility options are needed to balance demand and supply in the electricity system to ensure the security of supply. The core objective of this thesis is to show in detail how VRE generation increases the electricity system's variability, quantify the flexibility needs that arise through that, and analyze different flexibility options that can cover those needs.

Two analytical methods are combined to answer these research questions. First, empirical data is analyzed econometrically to show the historical impact of VRE on flexibility needs in Europe by using spot price variance as an indicator. Secondly, energy system modeling is applied to analyze the role of different short- and long-term flexibility options in the future electricity system. As a first application of the energy system modeling, case studies are conducted to explore two flexibility options in more detail: dispatchable solar power and demand response by decentral heat pumps. Finally, the integrated energy system and its main flexibility options are analyzed holistically on a country level: Flexibility needs and coverage are quantified on different time scales for a 100% renewable electricity system using the example of Austria and its planned electricity system transformation by 2030.

Generally, flexibility needs are expected to increase on all timescales in decarbonized electricity systems which is shown for Austria. However, results also show that short-term flexibility needs can be even reduced with increasing VRE shares due to flattening effects in the residual load curve. The highest increase in flexibility needs is observed annually due to the seasonal mismatch of electricity demand and supply. Regional differences in flexibility needs are significant and primarily depend on the degree of transmission interconnection and the electricity generation mix.

The techno-economic characteristics of the different components of electricity systems can be combined, causing synergistic effects as exemplified by the two case studies: First, a mix of wind and solar generation leads to lower short-term fluctuations than resource-concentrated systems. Second, dispatchable solar options are more cost-effective when combining different generation and storage technologies rather than using one single technology for night-time generation. The demand-side option heat pumps is found to provide mainly short-term flexibility and to be most helpful for wind integration by increasing market values for VRE during the winter. Antagonistic effects are also possible since the results show competing effects between batteries and thermal power plants, demand-side management in the household and service sector, and pumped hydropower (in the short term). Transmission has an ambiguous role as a flexibility option: On the one hand, exports and imports are seen as the main flexibility option on the annual timescale for Austria. On the other hand, they even increase short-term flexibility needs in the country because Austria exports (short-term)

flexibility provided by (pumped) hydro storage to the neighboring countries, according to the modeling.

The electricity system design, i.e., the availability of the flexibility options like export and import capacities, flexible power plants, and hydro (pump) storage, is more critical for a country's ability to balance fluctuations than the level and variance of the renewable infeed itself. The most robust coverage of flexibility needs is shown for technologically and geographically resource-diverse electricity systems in terms of generation technologies and flexibility options. The importance of long-term flexibility options to cover seasonal and interannual fluctuations is expected to grow with the increasing decarbonization of energy systems. These findings call for policies targeted at the coordinated and rapid take-up of flexibility options to safeguard the energy transition in Europe. Technological and geographical resource diversity in the mix of flexibility options is crucial here to use synergistic effects.

# Kurzfassung

Die Dekarbonisierung des Energiesystems ist eine wichtige Säule des Klimaschutzes und führt zu einer erhöhten Elektrifizierung und steigenden Anteilen variabler erneuerbarer Energien im Stromsystem (VRE). Um Angebot und Nachfrage im Stromsystem auszugleichen und die Versorgungssicherheit zu gewährleisten, bedarf es Flexibilitätsoptionen. Das Ziel dieser Arbeit ist es, im Detail aufzuzeigen, inwieweit fluktuierende erneuerbare Stromerzeugung die Variabilität des Stromsystems erhöht. Zusätzlich wird der daraus resultierende Flexibilitätsbedarf quantifiziert und es werden die verschiedenen Flexibilitätsoptionen analysiert, welche diesen Bedarf decken können. Zur Beantwortung der Forschungsfragen werden zwei analytische Methoden kombiniert. Zunächst werden empirische Daten ökonometrisch analysiert, um die historischen Auswirkungen von VRE auf den Flexibilitätsbedarf in Europa aufzuzeigen, wobei die Varianz des Börsenstrompreises als Indikator dient. Zweitens wird mittels Energiesystemmodellierung beleuchtet, welche unterschiedlichen Rollen verschiedenen kurz- und langfristigen Flexibilitätsoptionen im zukünftigen Stromsystem zukommen. Als erste Anwendung der Energiesystemmodellierung werden in zwei Fallstudien die beiden konkreten Flexibilitätsoptionen i) steuerbare solare Erzeugung und ii) flexible dezentrale Wärmepumpen näher untersucht. Den Abschluss bildet eine ganzheitliche Analyse des integrierten Energiesystem und seiner wichtigsten Flexibilitätsoptionen auf Länderebene. Am Beispiel Österreichs und seiner geplanten Stromsystemtransformation bis 2030 werden der Flexibilitätsbedarf und seine Deckung auf verschiedenen Zeitskalen für ein 100 % erneuerbares Stromsystem quantifiziert.

Generell wird erwartet, dass der Flexibilitätsbedarf in dekarbonisierten Stromsystemen auf allen Zeitskalen steigen wird. Dies kann für Österreich gezeigt werden. Die Ergebnisse zeigen jedoch ebenfalls, dass kurzfristige Flexibilitätsbedarfe mit steigenden VRE-Anteilen aufgrund von Glättungseffekten in der Residuallastkurve sogar reduziert werden können. Der höchste Anstieg des Flexibilitätsbedarfs wird in Österreich aufgrund des saisonalen Ungleichgewichtes von Stromnachfrage und -angebot auf der jährlichen Zeitskala beobachtet. Die regionalen Unterschiede im Flexibilitätsbedarf sind erheblich und hängen in erster Linie vom Grad der Vernetztheit und dem Stromerzeugungsmix im System ab. In Stromsystemen können die techno-ökonomischen Eigenschaften der verschiedenen Komponenten kombiniert und Synergieeffekte erzielt werden. Die zwei Fallstudien veranschaulichen diesen Effekt: Erstens führt ein Mix aus Wind- und Solarenergie zu geringeren kurzfristigen Schwankungen als ressourcenkonzentrierte Systeme. Zweitens sind regelbare Solaroptionen kostengünstiger, wenn sie verschiedene Erzeugungs- und Speichertechnologien kombinieren, anstatt eine einzige Technologie für die Erzeugung während der Nacht zu verwenden. Die bedarfsseitige Option Wärmepumpen bietet hauptsächlich kurzfristige Flexibilität und ist am hilfreichsten für die Windintegration, da sie die Marktwerte für VRE im Winter erhöht. Allerdings sind auch antagonistische Effekte möglich: Die Modellergebnisse zeigen

konkurrierende Effekte zwischen Batterien und thermischen Kraftwerken, Demand-Side Management im Haushalts- und Dienstleistungssektor und Pumpwasserkraft (kurzfristig). Das Übertragungsnetz als Möglichkeit des räumlichen Ausgleichs hat eine vielschichtige Rolle: Exporte und Importe werden einerseits auf der jährlichen Zeitskala für Österreich als wichtigste Flexibilitätsoption angesehen, andererseits erhöhen sie den kurzfristigen Flexibilitätsbedarf im Land sogar, da Österreich laut der Modellierung (kurzfristige) Flexibilität aus (Pump-)Speichern in die Nachbarländer exportiert.

Das Stromsystemdesign ist für die Fähigkeit eines Stromsystems, Schwankungen auszugleichen, relevanter als die Höhe und Varianz der erneuerbaren Einspeisung selbst. Zentrale Charakteristika dieses Designs sind die Verfügbarkeit von Flexibilitätsoptionen wie Export- und Importkapazitäten, flexible Kraftwerke und (Pump-)Speicherkraftwerke. Die robusteste Deckung des Flexibilitätsbedarfs zeigt sich für technologisch und geografisch ressourcendiverse Stromsysteme in Bezug auf deren Erzeugungstechnologien und Flexibilitätsoptionen. Die Bedeutung langfristiger Flexibilitätsoptionen zur Deckung saisonaler und interannueller Schwankungen wird mit steigender Dekarbonisierung der Energiesysteme zunehmen. Die Ergebnisse dieser Arbeit zeigen die Notwendigkeit von politischen Maßnahmen auf, welche auf eine koordinierte und zielgerichtete Nutzung von Flexibilitätsoptionen abzielen, um die Energiewende in Europa zu sichern. Dabei ist eine technologische und geografische Ressourcenvielfalt im Mix der Flexibilitätsoptionen entscheidend, um Synergieeffekte zu nutzen.

# Contents

# Abbreviations

| | |
|---|---|
| AC | Alternating current |
| BESS | Battery energy storage system |
| CC | Combined cycle |
| CHP | Combined heat and power |
| COP | Coefficient of performance |
| CSP | Concentrating solar thermal power |
| DC | Direct current |
| DNI | Direct normal irradiation |
| DSM | Demand-side management |
| E/P | Energy-to-power |
| EENS | Expected Energy Not Supplied |
| EEU | Expected Energy Unserved |
| ETS | Emissions Trading Scheme |
| EU | European Union |
| GARCH | Generalized autoregressive conditional heteroscedasticity |
| GHG | Greenhouse gas emissions |
| GHI | Global horizontal irradiation |
| HAC | Heteroscedasticity and autocorrelation consistent |
| HP | Heat pumps |
| HTF | Heat transfer fluid |
| ILR | Inverter loading ratio |
| LOLE | Loss-of-load expectation |
| NECP | National Energy and Climate Plans |
| NT | National Trends |
| NTC | Net transfer capacities |
| O&M | Operation and maintenance |
| P2G | Power-to-gas |
| P2H | Power-to-heat |
| PGP | Power-to-gas-to-power |
| PHS | Pumped hydropower storage |
| PV | Photovoltaics |
| PVS | Photovoltaics with storage |
| R&D | Research and development |
| RES | Renewable energy sources |
| RL | Residual load |

| | |
|---|---|
| RoR | Run-of-river |
| RQ | Research question |
| TES | Thermal energy storage |
| TYNDP | Ten-Year Network Development Plan |
| VRE | Variable renewable electricity |

# 1 Introduction

## 1.1 Motivation

Decarbonizing our energy system is a profound transition requiring rising shares of generation by variable renewable electricity (VRE) sources like wind, solar, and run-of-river (RoR) hydropower. At the same time, former fossil-fueled processes in all sectors will be electrified, leading to a higher electricity demand caused by new demands like e-mobility or power-to-heat (P2H). Renewable electricity generation throughout Europe has seen significant growth over the past decade. In 2021, 14.0% of gross electricity consumption was covered by wind energy and 5.7% by solar energy in the European Union (EU)[1], doubling its wind and solar electricity generation between 2013 and 2021 (Eurostat 2023). In the next years, rapidly growing capacities of renewable energy will be needed for the EU's contribution to staying within the 1.5°C limit of the Paris Agreement (United Nations Climate Change 2015). As part of the European Green Deal (European Commission 2019), the EU aims at full climate neutrality by 2050 and a 55% reduction of greenhouse gas emissions (GHG) by 2030 compared to 1990 levels (EC 2020b). The majority of newly added electricity-generating technologies will be fluctuating and non-dispatchable (EC 2020a). Since they are deployed mainly decentrally and have essentially different production patterns than conventional power plants, the uptake of VRE generation has to go hand in hand with their integration into the overall energy system. In addition to the rate of renewable expansion, safeguarding system stability and preserving security of supply are major challenges that need to be tackled in the coming years. The high proportion of VRE, including hydro, wind power, and PV, is expected to lead to massive weather-related fluctuations in power supply, while flexible thermal power plant capacity is expected to decrase. System flexibility is needed to compensate differences between generation and consumption both in the short (e.g., hourly fluctuations in both demand and supply) and in the long term (i.e., seasonal differences driven by high demand during the winter period, and an oversupply during summer months). This can be achieved by a wide range of flexibility options that ensure a stable and secure operation of all components of the electricity system. The use of these flexibility options may consequently contribute to i) the avoidance of VRE curtailment and increase of VRE share (Kirkerud, Nagel, and Bolkesjø 2021; Olkkonen et al. 2018), ii) system integration of VRE and an increased market value of VRE generation (Härtel and Korpås 2021), and iii) the reduction of residual peak

[1] EU27

loads which would alternatively have to be covered by additional power generation capacities and grid expansion (Kiviluoma, Rinne, and Helistö 2018; Nagel, Kirkerud, and Bolkesjø 2022).

It is important to understand the drivers of flexibility needs to develop and deploy appropriate flexibility options to cover them. Certain insights can be gained from past experiences since flexibility has always played its role in the electricity system due to the fundamental requirement to balance supply and demand at all times. However, the historical role of flexibility has been focused on times of unplanned generation or transmission outages, unexpected contingencies, and long-term adequacy planning (IEA 2020a). With increasing shares of VRE and decreasing shares of thermal power plants, flexibility needs at all timescales between real-time operations and long-term system planning are affected. While the majority of scientific literature in the field expects increasing flexibility needs with rising shares of VRE in electricity systems, many aspects of the underlying dynamics are not fully understood yet and require further differentiation. A central question is how much flexibility will be required on which timescales and how it can be best provided from a system perspective. A further unknown factor is that new options like sector coupling pose new challenges but, at the same time, have a great potential for providing flexibility to decarbonized electricity systems. Understanding these developments is a crucial precondition to fostering decarbonization and integration of VRE into the energy system.

Generally, flexibility options can be categorized into demand-side and supply-side solutions and their provided storage durations. The main flexibility options in the power system are

- dispatchable generation (e.g., flexible generation technologies or curtailment of VRE),
- storage (e.g., mechanical, electrical, electrochemical, or thermal),
- trade and transmission (incl. smart grids), and
- demand response (incl. advanced sector coupling) (Lund et al. 2015).

Interactions and dependencies between different flexibility options increase the complexity in the analysis of flexibility needs and options. While some of these options can be seen as substitutes with competing effects, others complement each other's characteristics and lead to synergistic effects. The research field of flexibility touches a wide span of challenges in the electricity system, ranging from technical to economical as well as regulatory and policy aspects. The analyses thereof consequently need to consider different perspectives (e.g., investor vs. central planner) and transform the findings into recommendations for policies and market design to safeguard the reliability and economic efficiency of decarbonized energy systems.

## 1.2 Core objective and research questions

The core objective of this thesis is to evaluate how variable renewable electricity generation increases the variability of the electricity system, to quantify the flexibility need that arises through that, and to analyze different flexibility options that can cover those needs. This is achieved by answering four specific research questions (RQ) defined in this section and answered in the respective chapters containing the related contributions that this thesis is based on.[2]

**Research Question 1:** *How has the need for flexibility evolved in recent years, and what development is expected for decarbonized electricity systems?*

The first RQ aims at a deeper understanding of flexibility needs and deals with their historical development. The first contribution (Schöniger and Morawetz 2022) shows the historical effect of VRE on electricity price fluctuation in Europe and how flexibility options (export/import, flexible power plants, and hydro storage) helped to balance it. The analysis provides an understanding of spatial components of flexibility needs and different phases of VRE integration that electricity systems go through. The method of approach is an econometric analysis using empirical electricity system data for several European countries, allowing for comparison between different electricity systems.

RQs 2-4 deal with the different flexibility options that can cover flexibility needs in future electricity systems using energy system modeling. RQ 2 and RQ 3 focus on specific solutions and analyze two flexibility options in greater detail – dispatchable solar power on the generation side and heat pump flexibility on the demand side of the electricity system. The two case studies were chosen to illustrate the wide range of technological solutions for flexibility provision. The two modeled energy systems – a solar-rich country in Southern Europe and a central European country with expected significant electric heating demand in the future – show the impact of regional differences in resource availability and generation patterns on flexibility options' operation. Consequently, RQ 2 and RQ 3 foster a detailed evaluation of different aspects, e.g., techno-economic details and economic potential, of the two chosen flexibility options. However, interactions with other flexibility options are not covered by RQ 2 and RQ 3. Therefore, RQ 4 comprehensively analyzes the whole spectrum of flexibility options and analyzes their interactions in a decarbonized electricity system. However, when modeling several flexibility options in an integrated manner in energy system models, certain simplifications have to be made. The analyses of RQ 2 and RQ 3, therefore, also provide valuable

[2] Parts of the four contributions are also used as the basis for Chapter 1, Chapter 2, and Chapter 7.

insights into the effects of chosen simplified assumptions regarding heat pump flexibility or solar power with storage.

**Research Question 2:** *What are the economics of different dispatchable solar power technologies, and how do storage time requirements impact technology choices for flexibility options?*
The second RQ examines the role of VRE in combination with utility-scale storage as a flexibility option for a renewable-based electricity system. The case study focuses on dispatchable solar power in Spain, compares three different technological options, and identifies niches for these solar and storage combinations. It examines the question of what impact the storage time requirements from the electricity system perspective – besides economic competitiveness – have on technology choices. The method of the second contribution (Schöniger et al. 2021) is a techno-economic analysis of the different technology options in a cost-minimizing linear programming approach. Parts of the elaborations on RQ 2 are also based on Schöniger, Resch, et al. (2022).

**Research Question 3:** *What is the potential of decentral heat pumps for providing flexibility to the future electricity system?*

The third RQ aims to identify the role of the demand side in providing flexibility in future electricity systems, exemplified in the specific case study of decentral heat pumps in Austria. The contribution Schöniger, Mascherbauer, et al. (2023) combines a detailed building model and energy system modeling to capture interactions between the heating and electricity sectors. RQ 2 and RQ 3 look at two specific flexibility options, allowing insights with a high level of techno-economic detail but without considering the interactions with other flexibility options in the system. Therefore, the last RQ aims at a holistic system-wide flexibility analysis which – on the downside – requires certain simplifications in the assumptions of a wide range of available flexibility options.

**Research Question 4:** H*ow high are the expected flexibility needs of the Austrian electricity system in 2030, acting as a role model for a (strongly) VRE-based power system, and which flexibility options are pertinent to meet the flexibility needs?*

The fourth RQ combines all aspects of the former RQs in an integrated manner and applies them to the specific case of Austria, which aims at having a 100% renewable electricity supply in 2030 (annual, national balance). The last contribution (Suna et al. 2022) assesses the short-to long-term flexibility needs of the Austrian electricity system by 2030 and the different flexibility options for meeting those needs. For this purpose, a high-resolution power and district heating model is used. A specific focus of the last contribution is the approach of quantifying flexibility needs and coverage for different timescales. This allows for a detailed evaluation of the interactions and complementarity of the different flexibility options to balance daily, weekly, monthly, and annual fluctuations of demand and supply.

In this thesis, two main analytical methods are applied. First, an econometrical approach combines a conceptual and an empirical model. They are used to analyze the development of flexibility needs in the past and identify the impact of single flexibility options like export and import capacity and (pumped) hydro storage. Since these capacities are rather static within one country, the method allows for the analysis of factors that hardly vary within one country and for conclusions derived from the cross-country comparison. By using the conceptual model, conclusions can be drawn on the development of short-term flexibility needs in future power systems. The findings derived from the econometrical approach are accompanied by the energy system modeling using a cost minimalization approach. Energy system modeling allows for the calculation of sensitivities that can not be observed in the empirical data. In this way, the methods complement each other in deriving robust findings on the role of flexibility in electricity systems with high shares of VRE.

Figure 1 shows the four research question of this thesis and their interrelations in a schematic way.

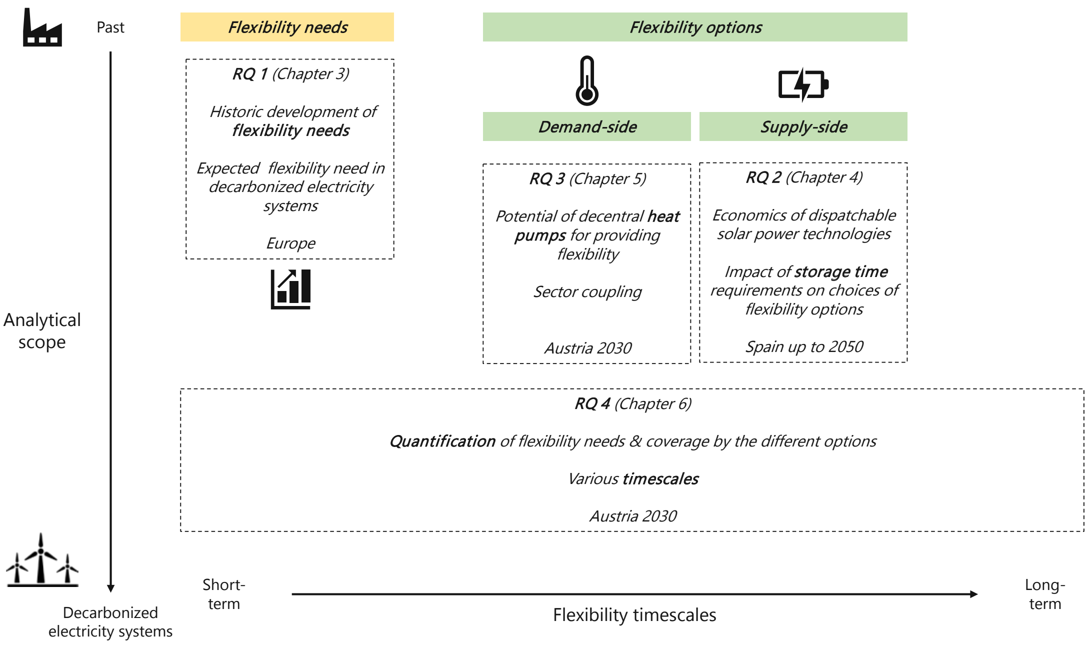


Figure 1: Overview of the four research questions of this thesis and their interrelations

## 1.3 Structure of the thesis

The remainder of this thesis is structured as follows: **Chapter 2** presents the state of the art of flexibility analysis in electricity systems and describes the novelty of this thesis' contribution. It

presents the current literature regarding flexibility needs and options in electricity systems, including a review of definitions, conventions, and approaches to measure flexibility.
**Chapter 3** investigates the question of what flexibility need can be expected in future electricity systems by analyzing electricity spot price variance as an indicator to measure short-term variability in the system. It shows the historical effect of VRE on electricity price fluctuation in Europe and how flexibility options helped to balance them. This allows for conclusions on expected developments of flexibility needs with increasing shares of VRE in the future.

Chapter 4 and Chapter 5 take a closer look at solutions that can provide flexibility in two case studies. The chosen case studies show the range of technological solutions for flexibility provision and illustrate the impact of regional differences in resource availability and generation patterns. **Chapter 4** (case study 1) analyzes a supply-side flexibility option: dispatchable solar power. Spain serves as one example of a southern European country that has the highest solar resources in the EU. The purpose of this case study is also to show how storage time requirements for flexibility provision impact the choice of technology options. **Chapter 5** (case study 2) presents a demand-side flexibility option: demand response by decentral heat pumps. Austria serves as a showcase here for a central European country with significant heating demand, which will be increasingly electrified with decarbonizing the energy system.

In **Chapter 6**, flexibility needs and options are analyzed together in a holistic approach for Austria in 2030. In this context, the flexibility needs and their coverage by different options are presented on different timescales.

The methodological approach of each contribution is described in the respective Chapters 3-6.
**Chapter 7** synthesizes and discusses the results of the analyses, presents the key findings, and derives policy recommendations for covering flexibility needs in future electricity systems. **Chapter 8** concludes this thesis and provides an outlook on required action and future research.

# 2 State of the art and progress beyond

This chapter describes the state of the art of flexibility assessment in electricity systems. It presents the current literature regarding approaches to i) define power system flexibility, ii) analyze the systems' flexibility needs, and iii) evaluate flexibility options to cover those needs, including a review of definitions and conventions as well as of approaches to measure flexibility. While this chapter deals with the state of the art of flexibility in electricity systems in general, more specific state of the art and research gap descriptions of dispatchable solar power and heat pump flexibility are presented in Section 4.2 and Section 5.2.

Globally and within Europe, the combat against climate change is a key driver for a rapid transformation process towards decarbonized energy systems and strong VRE uptake, which have been the object of a wide range of studies. Apart from analyses of corresponding policy needs (see BMNT & BMVIT (2018), EC (2020a), or IEA (2021)) as well as economic and environmental impacts (e.g., EC (2020a)), more technically oriented assessments of system flexibility needs have gained special attention in scientific literature. Below, I present a literature review on

i) definitions of power system flexibility to mark out the chosen definition in this thesis,

ii) flexibility needs to describe the broader context of the analyzed flexibility needs in this thesis (and what is not analyzed), and

iii) flexibility options to provide an overview of the analyzed flexibility options in this thesis.

## 2.1 Definitions of power system flexibility

Flexibility in power systems has been defined in different ways that depend on the focus of the study and the research question. Most definitions of flexibility describe the ability of an electricity system to balance supply and demand. According to IEA (2020a), flexibility is the "capability of a power system to maintain continuous service in the face of rapid and large swings in supply or demand, whatever the cause". Babatunde, Munda, and Hamam (2020) describe flexibility as the "degree to which a power system can adjust the electricity demand or generation in reaction to both anticipated and unanticipated variability" as well as "sustain supply during transient and large imbalances". Explicitly including security and economic aspects, Müller (2014) defines flexibility as "the extent to which a power system can adapt the patterns of electricity generation and consumption in a cost-effective manner while maintaining balance and security". While most definitions are more general, IRENA (2018) refers in its definition specifically to VRE. It includes the temporal dimensions and one specific flexibility option (curtailment) when it defines flexibility as "the capability of a power system to cope with the variability and uncertainty that VRE generation introduces into the system in different time scales, from the very short to the long term, avoiding curtailment of VRE and reliably supplying all the demanded energy to customers". Lannoye, Flynn, and O'Malley (2011) describe flexibility as the ability of a system to deploy its resources to respond to changes in net load. The net load or residual load is, thereby, according to the commonly applied convention, defined as the gap between [default] demand [without consideration of flexibility options] and non-dispatchable generation. The non-dispatchable generation mainly consists of VRE production but can, depending on the definition, also include must-run generation from inflexible thermal power producers (Schill 2014).

Flexibility can be analyzed on different spatial and temporal aggregation levels. On the spatial level, flexibility can be considered from an overall system perspective (e.g., frequency control, security of supply) or a more local perspective (e.g., bus voltage maintenance, local grid stabilization) (Hillberg et al. 2019). While flexibility has to be always implemented in real-time, its provision covers different time ranges: On the one hand, there are several activities related to flexibility provision in the medium- so short-term, e.g., fuel acquisition, management of hydro resources, and provision of operation reserves (primary to tertiary, or even cold). On the other hand, e.g., planning new investments in flexibility options takes several years (Batlle et al. 2007). A distinction of flexibility needs and options for different timescales, ranging from short to long term, is of high relevance to better identify appropriate options to cope with the respective needs, see Heggarty et al. (2019) or European Commission (2019). It can be differentiated between timescales from fractions of a second (e.g., stability and frequency support) to minutes and hours (e.g., thermal loadings and generation dispatch) to months and years (e.g., planning for seasonal resource adequacy and new investments). Hillberg et al. (2019) classify flexibility into four categories (power, energy, transfer capacity, and voltage) and describe their temporal (activation time) dimensions: While flexibility for power and voltage is necessary for the short-term (fractions of a second up to an hour) balance between electricity demand and supply and for maintaining frequency stability, flexibility for energy and transfer capacity ensures the long-term (hours to several years) equilibrium.

## 2.2 Evaluation of flexibility needs

Similarly to flexibility definitions, flexibility needs depend on the aspect of electricity system reliability they are targeted at. They can be analyzed from a planning or operational point of view. Flexibility assessments often address two dimensions of power system reliability: *security* and *adequacy* (Batlle et al. 2007). In scientific literature, *security* is mostly defined as the reliability of electricity regimes, i.e., the readiness of existing installed capacities to cover current electricity demand in a stable operational state (IEA 2020b; Aizenberg and Perzhabinsky 2019). This includes voltage and frequency control by reserves (short-term, seconds to minutes) managed by the system operator. *Adequacy* means balance reliability, i.e., that available and expected electricity capacity is sufficient to meet aggregate demands at all times (European Commission 2023). This applies to the generation and transmission of electricity under normal operating conditions, while the definition of "normal conditions" is key to adequacy assessments (IEA 2020b; Aizenberg and Perzhabinsky 2019). *Adequacy* concerns the planning of available capacities on various timescales from day-ahead to decades, including new installations of generation, storage, and transmission capacity (Gaudard and Romerio 2014). While in the past, *adequacy* has been mainly ensured by thermal fossil generation units, new flexibility options have to be implemented in decarbonized electricity systems. In this context, the relevance of *firmness* is increasing, i.e., the short-term generation availability of existing capacities which results from operation planning and, in the case of VRE, on resource availability (Batlle et al. 2007). In electricity systems, the need for flexibility is either expressed implicitly, i.e., by price signals derived from the supply and demand balance in an energy-only market, or explicitly through separate market mechanisms (e.g., balancing and reserve markets). Figure 2 summarizes the different definitions for flexibility from Section 2.1 and locates them in the context of their spatio-temporal need dimensions and system reliability aspect they are targeted at.

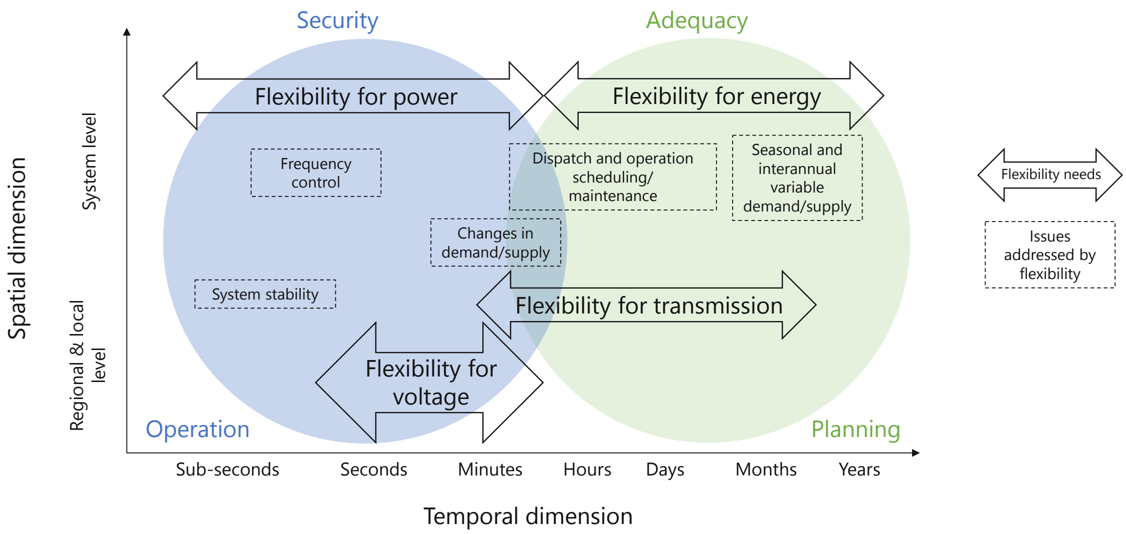


Figure 2: Interrelation of flexibility needs in the context of their spatiotemporal dimensions and system reliability (security or adequacy) (Own illustration based on Hillberg et al. (2019) and IEA (2020a))

Flexibility needs for power and voltage are short-term flexibility needs (sub-seconds to an hour) addressed at the issues of frequency control, system stability, and short-term changes in demand and supply, e.g., caused by the outage of large power plants or random fluctuations in power demand (IEA 2020a). These flexibility needs are mainly targeted at the operational security of the electricity system. The main drivers for these flexibility needs in decarbonized electricity systems are expected to be the massive increase of decentral VRE with fluctuation generation patterns. The energy and transmission flexibility needs are medium- to long-term flexibility needs (minutes to several years) tackled by planning processes and resource adequacy assessments. Here, the main challenges in decarbonized electricity systems are expected to be increased peaks of positive and negative residual load as well as the decrease of fuel storage-based energy supply (Hillberg et al. 2019).

For the analysis of flexibility needs according to the definitions described in Section 2.1, metrics are necessary that are able to measure shortage as well as surplus of electricity supply requiring the system to react flexibly. Lund et al. (2015) state that metrics for defining flexibility can be derived from grid frequency and voltage control, delivery uncertainty and variability, or power ramping rates and that they depend on the different aspects of the energy system they address. Hillberg et al. (2019) list as possible quantifiable dimensions of power system flexibility: Power (physical capability to deliver), response time, delivery speed, duration, energy (merging the power and duration dimensions), and recovery period. In the following, three categories of metrics from the literature are presented in greater detail, namely, i) residual load as an indicator, ii) economic indicators, and iii) technical indicators.

In many model-based approaches assessing the electricity system flexibility needs, the residual load has been used as an indicator. Kondziella and Bruckner (2016) argue that residual load and, accordingly, the technical potential of flexibility options to meet corresponding needs is determined by matching the time series of VRE generation with the spatially equivalent electricity demand. For the estimation of the economic potential of corresponding flexibility options, modeling approaches come into play. Brunner et al. (2020) analyze the impact of weather-dependent VRE on the residual load for an exemplary German energy system with 80% VRE. They evaluate three different indicators: residual load range, cumulated negative residual load over the year (surplus energy), or number of hours with negative residual load during a year (surplus energy). They show how the chosen flexibility indicator can impact the results of the cost optimization problem: While the scenario with increased offshore wind minimizes the range of the residual load, the scenario with increased photovoltaics (PV) plus offshore minimizes the surplus energy. The daily pattern of electricity generation for very high PV shares minimizes the surplus time but strongly increases the hourly gradients as well as the quantity of surplus energy. Heggarty et al. (2019) evaluate annual, weekly, and daily flexibility requirements for the future French electricity system through a set of frequency spectrum analysis-based metrics. The proposed methodology examines these flexibility requirements as sensitivity to five variables – namely, the degree of network interconnection and the penetration of wind power, solar power, and electric heating and cooling. They find increasing daily flexibility needs primarily due to PV and increasing weekly flexibility needs almost exclusively due to wind. Further, flexibility for energy on the annual timescale is decreased by electric heating reduction, wind power development, and network interconnection on the one side and increased by PV generation on the other side. EC (2019) defines flexibility needs at a daily, weekly, and annual level by analyzing the dynamics of residual load on several timescales. The authors state that hourly flexibility needs are mostly driven by renewable energy sources (RES) forecasting errors, while the daily pattern of demand and solar generation drives the daily level. At the annual level, it is argued that the required flexibility is determined by the (seasonal) match between demand and solar and wind generation patterns. That seasonal (mis-)match between VRE supply and overall demand appears of key relevance for countries in the Nordic hemisphere, where demand is generally higher during winter.

Another possible spectrum of metrics is derived from the financial or economic parameters of electricity markets, i.e., price signals. Metrics found in the literature are, e.g., the range of observable electricity prices, the frequency of price spikes (see, e.g., Doering et al. (2021)), volatility (see, e.g., Mauritzen (2010)), or price variance (see, e.g., Wozabal, Graf, and Hirschmann (2016)). While electricity spot price variance is not problematic in itself, a low variance is an indicator of an electricity system's desired ability to react on time to short-term demand- or supply-side fluctuations. On the other hand, many flexibility options used for balancing, such as storage or demand-side management (DSM), depend exactly on these price fluctuations since their business case is based on arbitrage between low and high electricity price levels. Similarly to DSM and storage solutions, some conventional power plants are dependent on intermittently rare but very high price peaks in the current market setting so that they can compensate for long periods of low power prices due to increased VRE production.

In the context of more technical resource adequacy assessments, there are common specific risk-related metrics that can also be used to analyze flexibility needs in electricity systems. The most common indicators are the loss-of-load expectation (LOLE) which measures the shortfall risk of an electricity system in different timeframes, and Expected Energy Unserved (EEU)/Expected Energy Not Supplied (EENS) (Stephen et al. 2022; Sheehy et al. 2016). Since these indicators provide point estimates lacking information on the variability of the outcome, their explanatory power for flexibility assessments for decarbonized electricity systems with high shares of VRE is questionable. For adequately capturing strong short- and long-term variability in these electricity systems, these indicators should be used in sequential modeling approaches, including Monte Carlo simulation (Sheehy et al. 2016).

## 2.3 Evaluation of flexibility options

In the previous section, flexibility needs in the electricity system were characterized by their temporal and spatial components. Flexibility options to cover those needs are consequently measures that can shift electricity in space (e.g., cross-border export and import of electricity) or time (e.g., storage). Additionally, and more recently, cross-sectoral shifts of energy via sector coupling can also offer flexibility (Härtel and Korpås 2021). In several studies, demand for storage is used as an equivalent to flexibility needs – although flexibility could be covered by several options (Kondziella 2017).

In general, power system flexibility options can be differentiated (IRENA 2018; Lund et al. 2015) into

- dispatchable generation on the supply-side (i.e., flexible generation capacities or VRE feed-in management),
- dispatchable demand (DSM, i.e., household, commercial, and industrial demand shifting or shedding or flexible sector coupling),
- infrastructure (i.e., transmission and distribution systems), and
- energy storage.

Some of the options above can also be used for flexibility provided in the form of grid ancillary services. Not being a flexibility option per se, regulation, market design, policy, and forecast quality also play central roles in creating the technical and economic framework conditions that flexibility can be provided in the electricity system.

On the supply side, flexible operation of dispatchable power plants and curtailment of VRE generation are the main options. Possible measures to increase this potential are increasing the flexibility in the operation (e.g., improved ramping capabilities and load gradients) and reduction of must-run capacities. To what extent the curtailment of VRE generation is a possible or needed flexibility option is mainly dependent on the support scheme design (Chaves-Avila, Banez-Chicharro, and Ramos 2017) and transmission expansion (Jorgensen, Mai, and Brinkman 2017). VRE infeed can also be made dispatchable to a certain degree by coupling different technologies in co-generation plants, by designing power plants accordingly (e.g., wind turbine types with higher full-load hours), or by combining decentral VRE generation with storage units. The specific example of dispatchable solar power and its state of the art is described in detail in Chapter 4.2.

The demand side of the electricity system has increasingly gotten in the focus of flexibility analyses (Schill 2020) because sector coupling and electrification of heating and industrial processes increase the flexibility potential to provide flexibility also on the demand side. Sector coupling is seen as one big opportunity for decarbonization by decoupling final energy from electricity demand. This is achieved by electric vehicles, electric boilers & heat pumps, and electrolyzers that a) adjust their demand profile based on price signals and b) make any integrated storage a source of energy storage for the power system (IRENA 2018). Sector coupling mainly takes up surplus VRE generation and only in some cases is able to provide electricity back to the grid in times of high loads (e.g., electricity generation fueled by hydrogen) (Schill 2020). Smart energy systems, where the electricity, heating, and transport sectors are coupled, are expected to play a crucial role in mobilizing the provision of flexibility (Mathiesen et al. 2015). DSM covers a wide range of targeted measures to flexibilize end-use electricity consumption profiles to achieve an increased correlation between VRE generation and consumption. The different means of DSM can be differentiated into three categories: i) Reducing (peak shaving, conservation), ii) increasing (valley filling, load growth), and iii) rescheduling (load shifting) electricity demand (Lund et al. 2015). The flexibility option DSM by decentral heat pumps is analyzed in detail in Chapter 5. In the residential sector, the DSM potential of e-mobility and power-to-heat is found to be higher than the potential from wet appliances in most studies (see, e.g., Rinaldi et al. (2022) or D'hulst et al. (2015)).

Transmission of electricity allows for the spatial shifting of energy and is one of the most important and best-established flexibility options in Europe. Depending on the size of the balancing area and generation mix in the connected regions, the grid also allows for temporally balancing seasonal mismatch of demand and supply in a single region (Schill 2020). Further development of transfer capacities between regions and countries is seen as a central enabler of a decarbonized electricity system. Maeder, Weiss, and Boulouchos (2021) quantify the need for flexibility technologies in central Europe for different transmission capacity scenarios up to 2050 and find that interconnections reduce carbon equivalent emissions by up to 9%.

Electricity storage technologies shift energy in time, mainly in a power-to-power mode. Storage options differ in their energy-to-power (E/P) ratios which mainly depend on their energy- and power-related costs and round-trip efficiencies (Schill 2020). The technological options can be categorized as i) electrochemical (e.g., Li-Ion batteries), ii) mechanical (e.g., pumped hydro storage), iii) thermal, or iv) chemical (e.g., hydrogen) storage) (MIT 2022). Electricity storage options cover a wide spectrum of power and energy flexibility needs, ranging from short-term (e.g., flywheel, lithium-ion batteries) to long-term (e.g., power-to-gas-to-power (PGP) with hydrogen-based storage). Thermal and battery storage technologies are described in detail in Chapter 4. Figure 3 shows the most common storage technology options and their power- and energy-related costs.

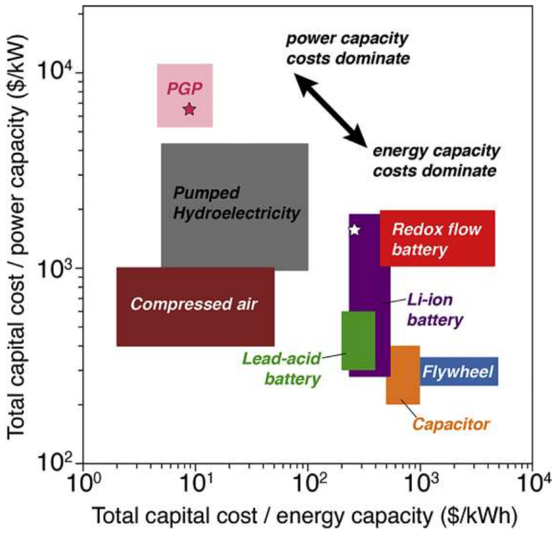


Figure 3: Storage options for short-term (right) and long-term (left) flexibility needs (Source: Dowling et al. (2020))

On the deployment path towards decarbonized energy systems, PGP linked to long-term (underground) storage can serve as a flexibility option for the seasonal mismatch of demand and supply or high interannual fluctuations in systems with high shares of VRE. Modeling of the future energy systems shows that they emerge relatively late but are an enabler for the last steps towards full decarbonization. Victoria et al. (2019) find that significant storage capacities only emerge for $CO_2$ reductions higher than 80% of the 1990 level in the electricity sector.

Whereas some of these flexibility options have been in the system for a long time (e.g., conventional generation capacities and transmission) and face changes in their operations due to the system transformation, other options are only starting to be part of the system at a large scale (e.g., sector coupling via hydrogen production). With the increasing decentralization of the system, a main challenge for the demand-side flexibility options is the management, aggregation, and automatization of decentral entities.

## 2.4 Novelty and contribution to the progress beyond the state of the art

This section describes the novelty of the contributions that answer the four research questions defined in section 1.2. Flexibility in this thesis is modeled as implicit flexibility, i.e., as a reaction to price signals. The analyses focus on flexibility for power (short-term equilibrium between power supply and power demand) and energy (medium- to long-term equilibrium between energy supply and energy demand) from the system perspective. Transmission connections to neighboring systems are also part of the power balancing capabilities considered in Chapter 3, Chapter 5, and Chapter 6. The other two categories – flexibility for voltage and (distributional) transfer capacity – are usually modeled by detailed grid models with high spatial and temporal resolution considering, e.g., voltage levels, infrastructure bottlenecks, and ancillary services, and are not part of this thesis. The temporal resolution of the applied models in Chapters 3-6 is hourly. This implies the assumption that the potential of the assessed flexibility options is the potential flexibility that can be delivered within one hour. Balancing and ancillary service in shorter time frames are not within the scope of this study, while weekly, monthly, and annual flexibility dynamics in the power system are covered. Additionally, Chapter 6 analyzes interannual fluctuations by considering two different weather years.

The first contribution (Schöniger and Morawetz 2022) in Chapter 3 analyzes electricity spot price variance as an indicator of short-term flexibility needs in Europe. Since VRE generation reduces the spot price and shows fluctuating characteristics, one could conclude that spot price fluctuations increase in the same way with increasing VRE generation. However, while the literature is largely unanimous concerning the reducing effect of VRE generation on spot price levels, the question of spot price variance triggers different opinions. Some studies argue that price variance is dependent on the type and amount of VRE generation and can even reduce price variability (see, e.g., Tveten et al. (2013) and Wozabal, Graf, and Hirschmann (2016)). Others see a higher share of renewable energy as definitely linked to increased price variance (see, e.g., Ketterer (2014), Klinge Jacobsen and Zvingilaite (2010), or Woo et al. (2011)). Most of the studies that have been conducted thus far focus on single countries or single technologies. The first contribution primarily adds to the literature by explaining how the – at first glance – contradictory findings from the literature relate to each other. Second, building on the work of Wozabal, Graf, and Hirschmann (2016), the impact of VRE on electricity spot price variance is assessed in a conceptual and an empirical model. The conceptual model builds on the two basic factors (shape of the supply curve and variance of VRE) influencing significant price variance (Green and Vasilakos 2010). Third, this is the first time such empirical analysis has been applied to nine European countries. This allows for comparing the effects and patterns for a broad range of different countries, which identifies the impacts of the availability of different flexibility options that show little variation within a single country, such as flexible power plants and export/import capacities. The analysis in Chapter 3 covers 78% of wind generation and 79% of solar generation in the current EU's electricity market (Eurostat 2021)[3].

Chapter 4, based on the second contribution (Schöniger et al. 2021), mainly adds to the literature by explicitly analyzing the impact of storage time requirements on the choice of flexibility options. Also, the evaluated combinations of the four solar technology components PV, battery energy storage systems (BESS), concentrating solar thermal power (CSP), and thermal energy storage (TES) add to the recent literature in this field. To my knowledge, no thorough peer-reviewed analysis of the expected comparative development of these three technologies (CSP+TES, PV+BESS, and PV+TES) exists that considers current expected technological and corresponding cost developments and includes the explicit technology combination PV+TES. Lovegrove et al. (2018) compare various technology combinations with storage at a more general level, looking at the dispatchability of renewables from an integrated system perspective using generic learning rates. Payaro, Naik, Guedez, & Laumert (2018) compare PV+BESS and CSP+TES for different capacity factor objectives taking into account also cost projections, while Jorgenson, Mehos, and Denholm (2016) additionally evaluate the option PV + gas turbine and Zurita et al. (2018) include a hybrid configuration of CSP+TES and PV+BESS in their studies. The detailed specific literature on dispatchable solar power is further described in Section 4.2.

As stated above (Section 2.3), sector coupling and related demand-side flexibility have gained increasing interest in scientific literature. The third contribution (Schöniger, Mascherbauer, et al. 2023) in Chapter 5 explores decentral heat pump flexibility and adds to the literature in this field in

[3] Renewable shares in EU28's electricity generation for the year 2019.

three ways[4]. First, it couples a detailed building-sector model and an energy system model to represent heat pump characteristics in the overall electricity system adequately. Second, it provides insights into possible flexibility provision for the Austrian electricity sector by decentral heat pumps and shows their system-wide effects in high temporal resolution for an entire year. And third, it sheds light on the impact of the choice of assumptions on the results. On the one hand, this serves as a deterministic sensitivity analysis for the results derived from the Austrian electricity sector. On the other hand, the modeling approach taken and the lessons learned may provide useful insights for other modelers that strive to enhance energy system modeling capabilities in accordance with recent energy sector trends.

Härtel and Korpås (2021) stress how important it is to adequately capture cross-sectoral interactions and a variety of technology combinations in a high spatiotemporal solution when analyzing electricity price formation effects in future low-carbon energy systems. Therefore, all flexibility options that have been identified as relevant in the presented literature above (see Section 2.3) are included in the analysis of Chapter 6. It evaluates the flexibility needs and coverage on different time scales for Austria in 2030. This is the first time that flexibility needs and options for Austria's future electricity system have been analyzed in such a grade of detail and in line with the most recent scientific methodological approaches. Findings and conclusions from this study can be highly relevant to the scientific community since Austria is expected to be one of the first countries in Europe to reach a 100% renewable share in the electricity sector. Austria serves here as a case study in this respect. The assessment of the flexibility needs for the Austrian power system builds upon the underlying approach of the European Commission (2019) described in Section 2.2, i.e., analyzing dynamics of residual load at distinct time scales, and extends the timely distinction by use of an additional period (i.e., monthly) as well as by consideration of the yearly balance of residual load (see Section 6.3). By modeling two different weather years for Austria, we additionally consider the weather dependency of VRE generation and resulting residual load dynamics.

[4] The specific state of the art of decentral heat pump flexibility is described in detail in Section 5.2.

# 3 Understanding flexibility needs

This chapter analyzes the third research question: *"How has the need for flexibility evolved in recent years, and what flexibility need is expected for decarbonized electricity systems?"* and is mainly based on Schöniger and Morawetz (2022). As described in Section 2.2, different indicators can be used to quantify flexibility needs. In this chapter, electricity spot price variance is used as an indicator to measure short-term variability in the system, partly caused by fluctuations in VRE generation. It analyzes how this generation behavior of VRE influences spot price variance in Europe since the identified short-term fluctuations are important market signals for incentivizing investments in (short-term) flexibility options. The empirical analysis of several European electricity markets allows for the identification of various spatiotemporal components of flexibility needs. It shows the historical effect of VRE on electricity price fluctuation in Europe and how flexibility options (export/import, dispatchable power plants, and hydro storage) helped to balance them. This allows for conclusions on expected developments of flexibility needs with increasing shares of VRE in the future.

## 3.1 Background

On the one hand, electricity price variance is seen as one of the main triggers for investments in flexibility options, such as storage facilities, flexible power plants, and DSM (Varghese and Sioshansi 2020). With the share of VRE in the grid becoming larger, the establishment of flexibility options ensuring supply security continues to gain importance and is a central determinant of the success of the transformation and decarbonization of the electricity sector. However, the competitiveness of these technologies depends mainly on the spread between low and high electricity prices, as their business model incentivizes buying electricity at times of low prices and selling at times of high prices. A high price variance in the current market setting is a major precondition for investments in electricity storage facilities and infrastructures, which increase the flexibility of the demand side of the market. On the other hand, electricity spot price variance is a measure of the system's ability to react to changes in demand and supply levels.

Understanding electricity price variance is important for at least two reasons. First, storage and other flexibility options are exactly those needed to balance fluctuating generation and to enable the integration of large shares of wind and solar PV (Panos, Kober, and Wokaun 2019). Increased shares of renewable electricity generation are expected to lead to higher price fluctuations that could then make investments in flexibility options more competitive. Nevertheless, as long as the relationship between the VRE infeed and price variance is unclear, the investment-driving mechanisms of these market-based incentives are rather questionable.

Second, extreme prices are avoided mainly for political reasons. Electricity consumers in the EU should be protected from excessive price fluctuations and extremely high prices, which could occur from time to time. Thus, policy-makers and investors alike are interested in understanding the mechanisms driving price variance in a time of increasing renewable electricity generation in European electricity markets.

This chapter analyzes two major factors driving price variance: the shape of the supply function and the distribution of the residual load (i.e., the electricity demand reduced by VRE generation) in an electricity market. It adds new evidence to the controversy regarding how electricity spot price variance is influenced by different levels of wind and solar penetration in Europe. The question of primary interest is as follows: Does a higher share of renewable generation in the electricity grid necessarily lead to higher price variance (i.e., indicating short-term flexibility need) in Europe?

Electricity spot prices are determined by demand and supply levels and are able to react quickly to changes on both sides. The increased share of VRE generation, such as wind and solar, has led to remarkable changes in European electricity spot markets. There has been a consensus in the literature that VRE infeed has a price-reducing effect on electricity spot prices, known as the merit order effect (see, e.g., Bublitz, Keles, and Fichtner et al. (2017), Clò, Cataldi, and Zoppoli (2015), Cludius et al. (2014), Di Cosmo and Malaguzzi Valeri (2012), Dillig, Jung, and Karl (2016), EWEA (2010), Jónsson, Pinson, and Madsen (2010), Ketterer (2014), Martinez-Anido, Brinkman, and Hodge (2016), Neubarth et al. (2006), Nicholson, Rogers, and Porter (2010), Nicolosi (2010), Praktiknjo and Erdmann (2016), Welisch, Ortner, and Resch (2016), and Zipp (2017)). While the literature is more or less univocal regarding the price-dampening effect of renewables on the electricity market, i.e., the merit order effect, the findings regarding their influence on price variance are much more diverse.

Several papers support the hypothesis that increased renewable electricity generation increases price variance. Ketterer (2014) looks at the German market using a generalized autoregressive conditional heteroscedasticity (GARCH) model and finds that wind generation increases price variance, whereas load decreases it. Woo et al. (2011) analyze historical spot prices in Texas in a linear regression model. They conclude that increased wind energy generation leads to increased price variance in that geographic area. A higher fluctuation of prices as a result of increased renewable generation is presented by Klinge Jacobsen and Zvingilaite (2010) in their analysis of the market in Denmark. However, they also state that an increase in renewable generation lowers peak price frequency. Milstein and Tishler (2011) construct a two-stage game for electricity producers (with the possibility of building up VRE generation), finding that VRE generation can increase price volatility. In their study for Ghana, Adom et al. (2017) find that increased shares of VRE increase electricity price variance in the short and long run. The United Kingdom (UK) market in 2020 is modeled by Green and Vasilakos (2010), who evaluate monthly price distributions in a numerical supply function equilibrium model using wind generation as input (using real-world wind data and information on existing and planned wind farms) and including factors, such as the variation in the wind production, demand, and the competitiveness of the market. Based on their analysis, they expect increasing price volatility in the UK electricity market in the future. Martinez-Anido, Brinkman, and Hodge et al. (2016) model the power system in New England and find that electricity price volatility increases with wind penetration. Additionally, they identify a stronger effect of wind generation on short-term volatility than on longer term volatility (a 5-minute instead of an hourly time resolution).

The papers mentioned above conclude that increased fluctuating renewable electricity generation leads to increased price volatility. However, other papers do not support that hypothesis in general. Wozabal, Graf, and Hirschmann (2016) show that increasing shares of VRE can increase or decrease electricity price variance. Their argument is supported by the analysis of the Austrian-German market zone for the years 2007-2013. Jónsson, Pinson, and Madsen (2010) show in their study for Denmark that an increased share of forecasted wind generation in the total load even lowers intraday price variance. They find that the probability of extremely high prices is reduced for high wind shares, which translates into a reduction in price volatility. Another example is the analysis of Tveten et al. (2013), who look at historical data and conclude that PV generation in Germany reduced price variance between 2009 and 2011. A possible explanation for this phenomenon is the fact that times of high PV production usually coincide with times of low power prices. PV plants and other renewable technologies with low short-term marginal costs push plants, such as natural gas plants, out of the merit order; therefore, peak prices are less frequent at those times. Möbius and Müsgens (2015) state that increasing shares of VRE can increase and decrease price variance. They analyze the effect of an increasing share of wind on price variance not in an empirical model but through a full-cost approach using an investment and dispatch model. They find that in a stylized electricity system with three generation technologies, at low shares of wind generation, additional wind decreases electricity price variance, whereas, at higher shares, price variance increases with additional wind. In this general setting, they conclude that curtailment and ramping constraints of conventional power plants are the main reasons for this pattern. Rintamäki, Siddiqui, and Salo (2017) show that wind energy has a lessening effect on daily price volatility in Denmark, while it increases daily price volatility in Germany and weekly price volatility in both countries.

Most of the studies that have been conducted thus far focus on single countries or single technologies. One reason why the analysis of price variance is more diverse than that dealing with price levels is that there are several definitions for price variance or variability. The choice of conceptual models, time horizon, and empirical estimation additionally contributes to divergences in the results.

Our conceptual model builds on the two basic factors (shape of the supply curve and variance of VRE) influencing significant price variance (Green and Vasilakos 2010). Our study is more general than most of the literature discussed above. We apply our analysis to very different European countries and include two different sources of VRE (wind and solar[5]). The analysis of multiple countries enables us to identify in a statistically sound way the impact of factors that show little variation within a single country, e.g., the share of flexible generation capacities in the power mix and transmission lines allowing for balancing of the VRE infeed.

## 3.2 Method

### 3.2.1 Conceptual model

The studies presented above identify VRE production (wind and solar), the variance of VRE production, demand, prices of primary energy sources, temperature, the competitiveness of the market, weather fluctuations in wind speed or solar radiation, or daylight hours as drivers of electricity price variance. Green and Vasilakos (2010) argue that significant price variance is dependent on two major factors: 1) sufficient changes in renewable infeed, i.e., the distribution of residual load, and 2) the relationship between net demand for thermal generation and price, i.e., the supply function covering the residual load. Möbius and Müsgens (2015) state that the generation capacity mix that determines the merit order has an impact on electricity price variance, and they see the need for an analysis closer to an empirical market setting. Wozabal et al. (2016) reformulate the findings of Green and Vasilakos (2010) and Möbius and Müsgens (2015) and identify two pivotal factors impacting electricity prices in Germany: the shape of the supply function and the distribution of the residual load in an electricity market. Figure 4 shows their conceptual model, which is based on a standard static market model with a given inelastic demand for electricity. We use this model as a basis for our analysis of the influence of VRE generation on price variance in nine European countries.

[5] "Solar"comprises PV and CSP generation, but the share of the latter is negligible (ENTSO-E 2021a).

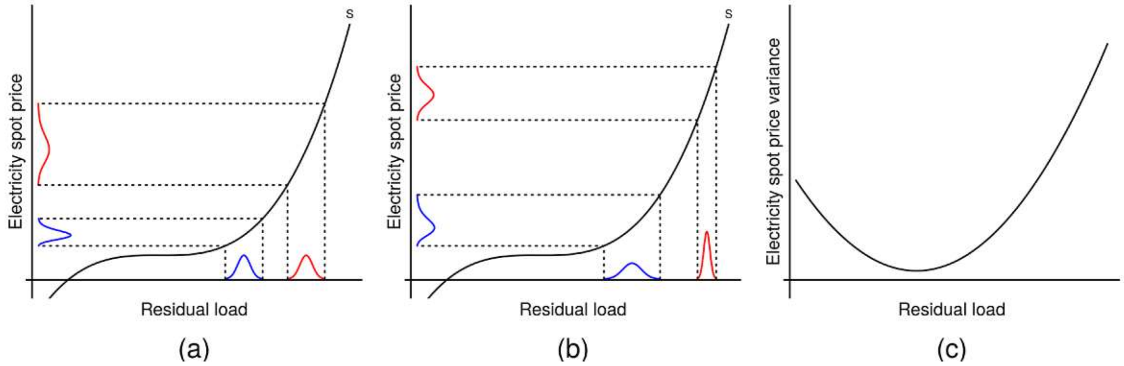


Figure 4: The two pivotal influencing factors on electricity price variance – the shape of the supply curve (illustrated in Panel (a)) and distribution of the residual load (illustrated in Panel (b)). Panel (c) shows the price variance for the supply curve in Panels (a) and (b) at a given distribution of residual load.
Source: Illustration based on Wozabal, Graf, and Hirschmann (2016)

The x-axis shows the residual load, defined as $X = Q - I$, where $Q$ is the aggregate electricity demand (i.e., load) and $I$ is VRE production (in this chapter, wind and solar are considered as VRE generation[6]). The intersection of the residual load $X$ and the black, static supply curve $S$ (aggregate marginal cost function without VRE) determines the electricity spot price. The concave-convex shape of the supply curve was found to approximate the real supply curve best (see Fanone, Gamba, and Prokopczuk (2013), He et al. (2013), and Wozabal, Graf, and Hirschmann (2016)). The low and even negative prices toward the left end of the supply curve are a consequence of the dispatch decision of conventional power plants, which accept very low prices rather than switch off their plants due to ramping constraints. The blue and red distributions located above the x-axis represent the stochastically varying residual loads, whereas the densities of the stochastic prices are located to the right of the y-axis. The distribution of the residual load creates the price distributions according to the slope of the static supply curve in a given time frame. In flat areas of the curve, fluctuating renewable infeed (i.e., alternating residual load levels) causes smaller price changes than in areas with a steeper slope.

In Figure 4a and Figure 4b, two time frames with different levels of VRE infeed are compared. In Figure 4a, one time frame with high prices (red) is compared with a time frame with lower prices (blue). The distribution of the residual load stays the same for both cases. When the increasing VRE share shifts the residual load to the left, two effects can be observed. First, the price level decreases; i.e., the merit order effect of renewables occurs. Second, the intersection with the black static supply

[6] As described in Section 2.1, there are different definitions of *Residual Load* in literature (Schill 2014). In contrast to this chapter (high-level analysis covering several countries in Europe), in Chapter 6, the analyzed residual load *RL* is defined as the inflexible demand minus wind, solar, and hydro RoR generation, since the latter is of high relevance for Austria.

curve moves to a flatter area, which indicates that the same distribution of residual load creates a different, narrower price distribution and leads to a decreasing price variance in that case.

In Figure 4b, the intersection shifts to the flat area of the supply curve as well, but its residual load distribution also changes (e.g., because the share of VRE has a higher variance than the non-VRE increases). We observe two opposing effects in addition to the decreasing price level here. On the one hand, the shift from a steep to a flat area of the supply curve causes a decrease in price variance, as already seen before. On the other hand, the change from a narrow to a broader residual load distribution broadens the price distribution and therefore increases the price variance. In sum, depending on the relative size of those two effects, an increased share of renewable production can either increase or decrease price variance in this conceptual model. Panel c in Figure 4 shows the price variance as a function of the mean *residual load X* for a given distribution of the residual load. For low and high residual loads, high variance can be observed, whereas, for medium residual load, lower price variance occurs.

In this conceptual model, DSM, storage, and the export and import to or from other electricity markets change the residual load and, therefore, have an impact on the point where the supply curve intersects with the load curve (see again Figure 4). At low prices, the residual load is increased (shifting to the right on the supply curve), and at high prices, the residual load is reduced (shifting to the left on the supply curve). This indicates that the flat, middle part of the supply curve determines the price more often, resulting in lower price variance in such a system than in a system without storage and export/import. The formal description of the model can be found in Appendix A1.

### 3.2.2 Empirical Model

In the empirical model, we consider two renewable electricity technologies as VRE: wind and solar. All other renewable sources, such as hydropower or geothermal energy, are assigned to conventional sources. This is the prevalent choice in the literature cited above because of the high share of wind and solar in renewable generation and their characteristic fluctuating, non-dispatchable production patterns. Other renewable energy technologies (e.g., hydropower or biomass plants) are dispatchable to a greater extent and, therefore, do not rely on highly fluctuating resources.

Using regression models, we test whether the variance of the electricity price is caused by the variance of the VRE and how this is related to the shape of the supply function for several countries in Europe. The explained variable in the regression is price variance per day. As a measure of variance, we use the variance of past prices, which is the most straightforward definition typically used in economics. Volatility, instead, is a concept from finance, and price ranges or spikes require decisions about the appropriate thresholds to use, which can be difficult to choose in cross-country comparisons.

To test the influence of the shape of the supply function and the variance of electricity generation on price variance, we model shape and variance as additive terms. The shape is modeled with a linear and a squared term of the daily mean residual load to allow for a U-shaped relation between the residual load and price variance (see Figure 4c).

Our Basic Model (based on Wozabal, Graf, and Hirschmann (2016)) is specified as

$$\boldsymbol{Var(Price)_{it} = \alpha + R_{it}\,\beta' + K_{it}\,\gamma' + \theta_t + \rho_t + C_i\,\delta' + u_{it},} \tag{1}$$

where α is the intercept and $R_{it}$ is an *Nx3* matrix containing the variables of interest for all *N* observations: residual load ("*Residual Load*"), residual load squared ("*Residual Load²*"), and variance of residual load ("*Residual Load var*") for country *i* at Day *t*. The vector $\beta'$ contains the respective coefficients. $K_{it}$ is a matrix containing the control variables natural gas price and three months lagged natural gas price, $\theta_t$ is an *Nx6* matrix containing day-fixed effects, and $\rho_t$ is an *Nx11* matrix containing month-fixed effects. $C_i$ is an *Nx3* matrix containing variables constant over time: export/import capacities, the share of oil and gas power plants[7] in installed capacities, and the share of hydro (pump) storage plants in installed capacities. Finally, $u_{it}$ is an error term that consists of a time-constant part $\nu_i$ and an idiosyncratic part $\epsilon_{it}$ such that $u_{it} = \nu_i + \epsilon_{it}$.
The explanatory variable "*Residual Load var*" in the Basic Model in Equation (1) is determined not only by the variance of VRE but also by any other shifts in the residual load. To identify the influence of VRE variance, an alternative specification is to divide residual load *X* into its two components: load *Q* and VRE production *I*. The squared term *X* results then in

$$\boldsymbol{X^2 = (Q - I)^2 = Q^2 - 2QI - I^2} \tag{2}$$

and for the variance

$$\boldsymbol{Var(X) = Var(Q - I) = Var(Q) - 2Cov(Q, I) + Var(I)} \tag{3}$$

This results in the Extended Model:

$$\boldsymbol{Var(Price)_{it} = \alpha + M_{it}\,\beta' + K_{it}\,\gamma' + \theta_t + \rho_t + C_i\,\delta' + u_{it},} \tag{4}$$

where $M_{it}$ is an *Nx8* matrix containing the variables of interest: load ("*Load*"), load squared ("*Load²*"), variable renewable electricity production ("*VRE*"), variable production squared ("*VRE²*"), variance of load ("*Load var*"), variance of variable renewable electricity production ("*VRE var*"), covariance

[7] Other power plants are also able to provide dispatchable power; however, oil & gas technology was taken because of their flexible generation characteristics and high share in historic power plant fleets. Nevertheless, other decarbonized flexible power plants will be needed in the future.

between variable renewable production and load ("*VRE Load cov*"), and an interaction term of load and variable renewable production ("*Load * VRE*").
Further splitting VRE into electricity generated from wind and solar results in the Wind & Solar Model

$$\boldsymbol{Var(Price)_{it} = \alpha + W_{it}\,\beta' + K_{it}\,\gamma' + \theta_t + \rho_t + C_i\,\delta' + u_{it}}\,, \tag{5}$$

where $W_{it}$ is an *Nx12* matrix containing load ("*Load*"), load squared ("*Load²*"), wind ("*Wind*"), wind squared ("*Wind²*"), Solar ("*Solar*"), Solar ("*Solar²*"), variance of load ("*Load var*"), variance of VRE ("*VRE var*"), covariance VRE and load ("*VRE Load cov*"), and the corresponding interaction terms ("*Load * Wind*", "*Load * Solar*", "*Wind * Solar*").

The countries included in the analysis vary substantially in the total load. We, therefore, transform all explanatory variables to relative values (except for dummies): We first calculate the country-specific maximum average load (i.e., the maximum of the daily loads of a country). We then express load, residual load, VRE, and wind and solar generation as a percentage of this maximum load (i.e., a value of 15 for wind means that wind on that day was 15% of the maximum load of this country). Based on these relative values, we then derive squared terms, variances, and covariances. The explained variable "*Price var*" is left unchanged because it is the absolute value of the price variance, which is of concern for consumers or investors.

The exogeneity of our variables of interest (i.e., no correlation of explanatory variables with the error term ($u_t$)) is necessary for the estimated coefficients to be interpreted as causal effects. The variance of wind and solar (and therefore also the variance of VRE and the residual load) is determined by the weather, making it unlikely that there are unobserved time-varying confounders influencing VRE and the price variance of a country. For load and residual load to be exogenous, it must also be assumed that there are no unobserved confounding variables between the variance of price and residual load. Industries (or households) might consider price variance when deciding how much electricity to consume. Our weekday- and month-fixed effects control for reoccurring patterns of price variance. These time-fixed effects thus likely control for most unobserved time-varying confounders related to electricity demand.
To address the potential influence of (unobservable) time-constant variables that differ across countries, we analyze the three models (Basic, Extended, and Wind & Solar Model) in four different ways. The first approach (pooled model) is pooling data from all countries and running a linear regression with the relative variables (as defined in the paragraph above). In the second approach (fixed effects model), we also use relative variables from all countries but transform all variables by subtracting the country-specific mean; e.g., $\ddot{x}_{it} = x_{it} - N_i^{-1}\sum_{it}^{N_i} x_{it}$, where $N_i$ is the number of observations of country *i*. In the third approach (first difference model), we transform all relative

variables by subtracting the observation from the previous day; e.g., $\Delta x_{it} = x_{it} - x_{it-1}$, which means losing the first observation of each country. The fourth approach is analyzing all countries separately without transforming the variables (this can be done with relative or absolute variables leading to different coefficients but identical standard errors). See, e.g., Wooldridge (2010) for a detailed treatment of the four approaches.

The advantage of the pooled model (our first approach) lies in being able to include observed time-constant variables $C_i$ explicitly. The disadvantage is that unobserved time-constant variables ($\nu_i$) cannot be included. This will result in biased estimated coefficients if the unobserved variables are correlated with explanatory variables. The fixed effects (second approach) and the first difference (third approach) models solve this problem by allowing us to control for unobserved time-constant effects. Due to the transformations of variables, all time-constant variables are swept out (the intercept ($\alpha$), observed ($C_i$), and unobserved ($\nu_i$) time-constant variables). The identification of the causal effect of linear terms thus hinges on variation over time only.[8] The interpretation of the estimated coefficients of the fixed effects and the first difference model is still the effect of the untransformed relative variable on the price variance (i.e., as in Equ. (1), (4), and (5)) even though the estimation has been run with transformed relative variables. The $R^2$, however, is typically much lower because it is reported in terms of the transformed relative variables.

A fixed effects estimator can be subject to spurious regression if the variables have unit roots (i.e., if they follow a random walk). We, therefore, check our variables for unit roots using the Maddala and Wu panel unit root test procedure (Maddala and Wu 1999; Croissant and Millo 2018). We find that none of our variables except the (lagged) gas price have a unit root (see Appendix A1, Table A.10). Given that we do not face the problem of spurious regression, we report fixed effects and first difference models.[9] To address serial correlation, we use White standard errors clustered by countries for the fixed effects estimator (White 1980; Croissant and Millo 2018) and Newey West standard errors for the first difference estimator (Newey and West 1987; Croissant and Millo 2018). We do likewise for all joint significance tests.

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[8] For squared terms, the identification is slightly more complex, since cross-section variation still matters to the extent that when squaring the variables before demeaning or differencing them, the original level still matters (and not just differences over time); see McIntosh and Schlenker (2006) for details.

[9] The choice of fixed effects vs. first difference hinges on the assumption about the idiosyncratic errors $\epsilon_{it}$. The fixed effects estimator is more efficient if the $\epsilon_{it}$ are serially uncorrelated, while the first difference estimator is more efficient if the $\epsilon_{it}$ follow a random walk. Applying a test proposed by Wooldridge (Wooldridge 2010; Croissant and Millo 2018), we reject the hypothesis of no serial correlation of the differenced errors for the first difference model and reject the hypothesis of no serial correlation in the original errors for the fixed effects model. We find these results for all three model variants estimated (Basic, Extended, and Wind & Solar Model). Since in this case, these tests provide no guidance, we report results for fixed effects and first difference estimators. The results of the test are available from the authors and as part of the code and data supplementary material.

While time-constant country-specific variables cannot be included in the fixed effects and first difference models, their interaction terms can. We, therefore, estimate an additional set of models where we interact the variables of interest ($R_{it}$, $M_{it}$, and $W_{it}$) with the time-constant observable variables $C_i$.

The appeal of fixed effects and first difference models is the ability to control for unobserved time-constant heterogeneity. However, pooling countries means that the estimated coefficients are weighted averages across all countries. For example, the estimated effect of a 1%-point increase in load is the weighted average across all countries (i.e., a weighted average of the effect of the shape of different merit order curves on price variance). While this is interesting in itself, a complementary approach is analyzing countries separately. We run all models (Basic, Extended, and Wind & Solar Model) for all countries.

In the fixed effects and first difference models, we can control for confounders constant over the observational period, but in the single country models, we cannot. Most prominently, flexibility options, such as DSM, storage facilities, and transmission capacity to neighboring electricity markets, are mostly constant for the time period we observe. The availability of those flexibility options is expected to result in a lower influence of the shape of the supply curve on the price variance. This will contribute to differences between the estimated coefficients of the countries analyzed. Standard errors of the single country models (and joint significance tests) are heteroscedasticity and autocorrelation consistent (HAC) since Durbin-Watson tests suggest significant autocorrelation of residuals. The modeling is conducted in MATLAB R2019b (MathWorks 2019) and R 3.6.3 (R Core Team 2020).

### 3.2.3 Data

The analysis is based on data for 2015-2019 and covers nine countries[10] with the highest share of wind and solar generation in the EU during the period considered (Eurostat 2021). These countries had a share of wind and solar generation in their overall electricity generation of at least 12% in the considered period 2015-2019.

Most variables (load, residual load, VRE, etc.) are originally available at an hourly resolution and enter the models at a daily resolution. This resolution is appropriate for two reasons. First, it is long enough that varying the VRE infeed can have an effect on the spot price. If we only looked at an hourly time window, certain factors, e.g., changes in the weather conditions and, consequently, changes in the VRE infeed, could not be appropriately captured. Second, a lower time resolution would lead to a loss of information since VRE production would become too aggregated.

[10] Originally, the ten countries with the highest VRE share were chosen but Ireland could not be analyzed because of insufficient electricity price data (ENTSO-E 2021a). Luxembourg and Austria were not among these countries with the highest share of VRE but are included in the analysis as part of the common market zone together with Germany.

The explained variable in the regressions is the daily spot price variance. Therefore, the day-ahead spot prices [Euro/MWh] are first standardized to an hourly resolution for all countries, and then, the variance per day is computed from these 24 observations. The daily values of the explanatory variables are derived from the day-ahead load [GW] and the day-ahead generation forecast for wind and solar [GW] (all from ENTSO-E (2021a)). The natural gas price considered is the Dutch TTF day-ahead spot price [Euro/MWh] and was standardized to have a zero mean and a standard deviation of 1 for data availability reasons (Trading Hub Europe 2022; Intercontinental Exchange 2022; EEX 2022). Export and import capacities are modeled values from the national transmission operators for 2020 (ENTSO-E, 2019a). However, since transmission capacity build-up is an inert process and this share is relatively constant for all countries, the value for 2020 is seen as an acceptable proxy for the considered period of 2015-2019 as well. Electricity generation capacities are annual values and derived from ENTSO-E (2021a).

There are some particularities regarding the price data for several countries: German data were aggregated with data from Austria and Luxembourg (referred to as "Austria/Germany" in the following) since these countries formed one market zone until September 30, 2018. In the regression model for Germany, we added a market split dummy to account for the structural change and used the data for Germany-Luxembourg after the split since it is the larger part of the market zone and accounts for the majority of wind and solar generation. Where necessary, national currencies were transformed into euros using historical exchange rates (ÖNB 2021). Exchange rates are available only for working days; therefore, the figures used for the days in between were interpolated between the two framing days available. Load and price data for some countries are divided into different bidding zones. For Denmark, Sweden, and Italy, the respective weighted average values were considered. Some installed generation capacities were missing for Austria-Germany in 2015, so these technologies have been assumed to have the same installed capacities as in 2016. For the UK, only the bidding zone Great Britain (GB) was considered because of insufficient data for the Irish part of the zone.

### 3.2.4 Descriptive statistics

Table 1 presents the descriptive statistics for all countries analyzed for 2015-2019. The values are means calculated from the hourly primary data; the price is the day-ahead price; price variance is the daily price variance.

Table 1: Descriptive statistics for all countries examined for 2015-2019. Means of electricity spot price, electricity load, and VRE generation (separated into wind onshore, wind offshore, and solar). The calculated means and VRE share in the load are based on hourly values. Source: ENTSO-E (2021a)

| Mean values | Price | Daily price variance | Load | VRE | VRE share | Wind onshore | Wind offshore | Solar |
|---|---|---|---|---|---|---|---|---|
| Unit | Euro/MWh | (Euro/MWh)² | GW | GW | | GW | GW | GW |
| Austria/Germany | 35.44 | 97.90 | 60.9 | 15.9 | 26.14% | 9.7 | 1.8 | 4.4 |
| Denmark | 33.20 | 64.29 | 3.8 | 1.7 | 44.68% | 1.0 | 0.5 | 0.1 |
| GB | 54.01 | 363.01 | 33.9 | 6.4 | 18.87% | 3.1 | 2.2 | 1.1 |
| Greece | 54.73 | 81.15 | 5.9 | 0.9 | 15.91% | 0.6 | - | 0.4 |
| Italy | 52.34 | 98.50 | 33.4 | 3.8 | 11.45% | 1.7 | - | 2.1 |
| Portugal | 49.54 | 43.70 | 5.7 | 1.5 | 25.88% | 1.4 | - | 0.1 |
| Romania | 42.89 | 187.33 | 6.8 | 1.0 | 14.18% | 0.8 | - | 0.1 |
| Spain | 49.43 | 47.86 | 28.7 | 7.1 | 24.65% | 5.6 | - | 1.5 |
| Sweden | 33.21 | 42.02 | 15.7 | 1.9 | 12.02% | 1.9 | - | - |

Mean electricity day-ahead prices range between 33.2 Euro/MWh in Denmark and more than 54 Euro/MWh in Greece and GB. The German-Austrian market zone is the largest zone, with an average hourly load of 60.9 GW. The highest relative share of VRE is found in Denmark, with an average hourly share of 45% of the load produced by VRE. In terms of absolute numbers, Austria/Germany produced the highest amount of VRE, with an average VRE generation of 15.9 GW in 2015-2019. The daily price variance is exceptionally high in GB (363.01 (Euro/MWh)²). This is on account of a few days in the second half of 2016, where five days show a daily price variance of more than 20,000 (Euro/MWh)²; without these five days, the mean price variance would be 216.08 (Euro/MWh)². The panel model presented in the next section is based on all countries other than GB, which we excluded due to the exceptionally high price variance in 2016.[11] Table 2 shows the share of flexible production capacities[12], hydro (pump) storage capacities, and transmission capabilities to other countries. All these variables differ considerably between countries.

[11] Estimated coefficients and standard errors are similar when GB is included, but the $R^2$ is very small. The results are available from the authors and can be generated easily from the code in the supplementary material.

[12] As an approximation, oil and gas plants were considered here.

Table 2: Share of flexible power plants in installed capacities for all countries examined, means for 2015-2019. Export/import capacities for 2020 compared to the maximal load observed in 2015-2019. When different, the mean of export and import capacity was taken. Source: Generation capacities and load (ENTSO-E 2021a); Ex-/import capacities (ENTSO-E 2019b)

| | Hydro (pump) storage capacities | Oil & gas | Export/import capacities |
|---|---|---|---|
| | % of all installed generation capacities | | % of max. load in 2015-2019 |
| Austria/Germany | 6.7% | 17.7% | 11.7% |
| Denmark | - | 23.2% | 138.9% |
| GB | 3.1% | 32.8% | 10.4% |
| Greece | 18.0% | 30.6% | 34.5% |
| Italy | 11.7% | 42.8% | 18.9% |
| Portugal | 19.6% | 24.8% | 54.0% |
| Romania | 17.0% | 20.6% | 25.7% |
| Spain | 23.3% | 29.7% | 18.6% |
| Sweden | 41.3% | - | 42.7% |

To render the variables comparable, the countries are additionally analyzed in relative terms. Table 3 contains the statistics of the relative variables of the whole panel without GB.

Table 3: Summary statistics for relative variables (excluding Great Britain).

| | Mean | 1st Qu. | Median | 3rd Qu. | NA's |
|---|---|---|---|---|---|
| Residual Load | 58.41 | 50.63 | 60.04 | 68.58 | 302 |
| Residual Load² | 3631.09 | 2563.83 | 3605.14 | 4703.54 | 302 |
| Residual Load var | 118.61 | 51.68 | 82.40 | 141.50 | 331 |
| Load | 75.26 | 68.03 | 76.59 | 82.54 | 30 |
| Load² | 5777.06 | 4627.58 | 5866.55 | 6813.00 | 30 |
| VRE | 16.82 | 8.19 | 12.71 | 20.77 | 277 |
| VRE² | 458.99 | 67.12 | 161.65 | 431.45 | 277 |
| Wind | 13.75 | 4.89 | 9.36 | 17.28 | 237 |
| Wind² | 374.17 | 23.93 | 87.54 | 298.71 | 237 |
| Solar | 3.03 | 0.94 | 2.17 | 4.95 | 204 |
| Solar² | 16.31 | 0.89 | 4.69 | 24.49 | 204 |
| Load var | 117.33 | 57.77 | 103.31 | 160.72 | 46 |
| VRE var | 48.71 | 9.46 | 26.72 | 60.53 | 291 |
| VRE Load cov | 23.46 | -0.17 | 18.39 | 45.25 | 331 |

## 3.3 Results

### 3.3.1 Results of the panel model

Table 4 shows the estimated coefficients and hypothesis tests of the fixed effects model for the Basic, Extended, and Wind & Solar Models. The explanatory variables are measured in relative terms (between 0 and 100, except for the gas price). The estimates are based on all 14,266 observations of eight countries (GB is excluded due to the exceptionally high price variance, see above). As is typical for fixed effects models with cross-section observations, the $R^2$ is rather small since it measures the share of explained variance over total variance after demeaning. The results for the pooled models and first difference models are comparable in conclusions and are shown in Appendix A1 (see Table A.1 - Table A.3).

Table 4: Regression results for the fixed effects panel model for the Basic, Extended, and Wind & Solar Models.

| | Model | | |
|---|---|---|---|
| | Basic | Extended | Wind & Solar |
| Residual Load | -5.19 (.000) | | |
| Residual Load$^2$ | 0.05 (.000) | | |
| Residual Load var | 0.19 (.000) | | |
| Load | | -20.47 (.000) | -18.06 (.000) |
| Load$^2$ | | 0.17 (.000) | 0.16 (.000) |
| VRE | | 13.47 (.000) | |
| VRE$^2$ | | 0.02 (.000) | |
| Wind | | | 9.69 (.000) |
| Wind$^2$ | | | 0.03 (.000) |
| Solar | | | 32.55 (.000) |
| Solar$^2$ | | | 0.75 (.007) |
| Load var | | 0.08 (.235) | 0.12 (.050) |
| VRE var | | 0.11 (.000) | 0.09 (.000) |
| VRE Load cov | | -0.43 (.000) | -0.41 (.000) |
| Load*VRE | | -0.18 (.000) | |
| Load*Wind | | | -0.15 (.000) |
| Load*Solar | | | -0.64 (.000) |
| Wind*Solar | | | 0.65 (.000) |
| Gas Price | 15.82 (.000) | 14.63 (.000) | 14.67 (.000) |
| Lagged Gas Price | -8.02 (.017) | -6.96 (.034) | -6.76 (.036) |
| Observations | 14266 | 14266 | 14266 |
| $R^2$ | 0.088 | 0.102 | 0.113 |
| Joint Significances | | | |
| Residual Load and Residual Load$^2$ | 47.03 (.000) | | |
| Load, Load$^2$ | | 45.85 (.000) | 37.36 (.000) |
| VRE, VRE$^2$ | | 12.71 (.000) | |
| Load, Load$^2$, VRE, VRE$^2$ | | 78.53 (.000) | |
| Load var, VRE var, VRE Load cov, Load*VRE | | 209.63 (.000) | |
| Wind, Wind$^2$, Load*Wind, Wind*Solar | | | 91.52 (.000) |
| Solar, Solar$^2$, Load*Solar, Wind*Solar | | | 65.09 (.000) |
| Load, Load$^2$, Wind, Wind$^2$, Solar, Solar$^2$, Load*Wind, Load*Solar, VRE Load cov | | | 292.42 (.000) |
| Load var, VRE var | | | 31.66 (.000) |

Note: p values in parenthesis based on clustered standard errors. Joint significances report the F-statistics with clustered standard errors in parenthesis. Dummies for weekdays and months are included in all models but not shown.

### Basic Model

The results of the Basic Model, which only includes the terms of the residual load, are displayed in the first column of Table 4. All coefficients are statistically significant (p value <0.05). The results show that the residual load has a convex quadratic influence on the price variance as anticipated in the conceptual model (see Figure 4) since the coefficients of $Residual\ Load$ (-5.19) and $Residual\ Load^2$ (0.05) are statistically significant (jointly and individually). According to Table 3, the third quartile of the residual load is 68.58% residual load. At this point, a decrease of 10%-points in residual load causes the price variance to decrease by 17.38 (Euro/MWh)². At the median, a decrease of 10%-points in the residual load reduces the price variance by 8.84 (Euro/MWh)², and at the first quartile, it increases the price variance by 0.57 (Euro/MWh)². This is expected due to the U-shaped relationship between price variance and the residual load. The minimum price variance is estimated to be reached if the residual load is 51.2% of the load (or when the VRE is 48.8% of the load). The variance of the residual load increases the price variance as expected and has a marginal effect of 0.19. At the mean of the variance of the residual load (118.61%²), the effect on the price variance is thus 22.54 (Euro/MWh)². At the third quartile (141.50%²), the effect is 26.89 (Euro/MWh)². Thus, at Q3 of the residual load, the shape-induced effect from a 10% reduction in the residual load (17.38 (Euro/MWh)²) partly compensates for the effect from the residual load variance (26.89 (Euro/MWh)²). At Q1 of the residual load, this is not the case.

**Extended Model**

In the Extended Model, the influence of the residual load is divided into its two components, namely, $Load$ and $VRE$ production. The results confirm the hypothesis from the conceptual model that the shape of the residual load, i.e., the distributions of the load and VRE production, influence price variance: *Load, Load², VRE, VRE²,* and *Load*VRE* are all individually statistically significant. Figure 5 illustrates the effects of load and VRE on the price variance (shifted to start at zero) by setting all variables except load, VRE, and the interaction term to their means (or zero for the time dummies). The price variance is highest at low levels of load combined with high levels of VRE (low prices). Similarly, the price variance is relatively high at high levels of load combined with low levels of VRE (high prices). These peaks are driven by the negative interaction term of load and VRE. Consequently, we find a U-shaped effect of load only at a low level of VRE, and we find a U-shaped effect of VRE only at high levels of load. Thus, the interaction term is key to understanding whether a U-shape is found.

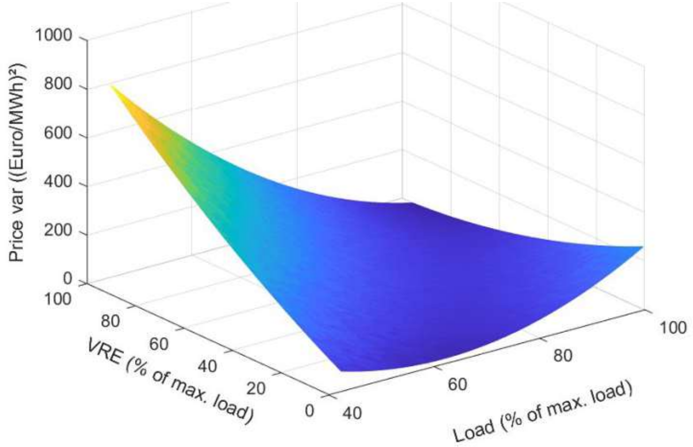
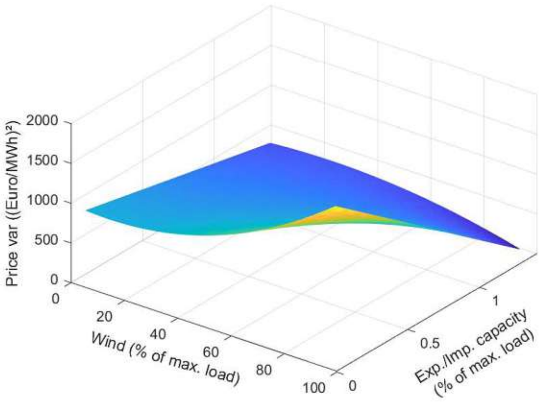



Figure 5: Impact of load and VRE on electricity price variance based on fixed effects estimates. Load and VRE are depicted in % of maximal load.

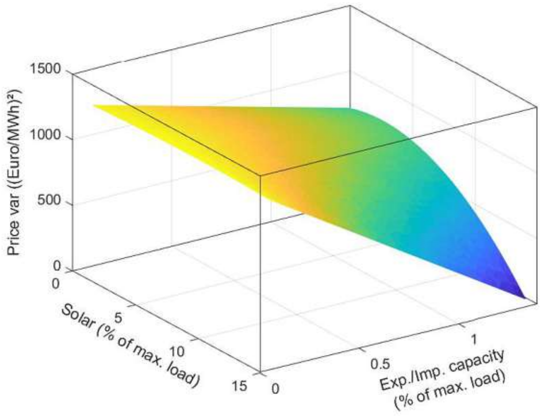
The effect of the variance of the load and the variance of VRE are jointly statistically significant, while the marginal effect of VRE (0.11) is also individually significant. The covariance (-0.43) of VRE and load, in contrast, has a negative effect on price variance since a higher load increases and a higher VRE infeed decreases the price level. If load and VRE vary jointly within a day, this reduces price variance. This is similar to the negative interaction term (-0.18), which measures the effect between days.

**Wind & Solar Model**

The Wind & Solar Model was introduced to analyze the impact of wind and solar generation on price variance separately. From Table 4 (Column 3), it can be seen that the estimated coefficients are very similar to those from the Extended Model (Column 2) for variables other than wind-related and solar-related variables. We, therefore, discuss a variant of the Wind & Solar Model that includes interactions with shares of flexible electricity generation and export/import capacities (see Appendix A1). Using the figures shown below, the model in the Appendix allows for the analysis of the influence of flexible power plants and export/import on price variance. The shapes of wind and solar are statistically significant, as are the interaction terms of the flexible generation and export/import capacities (see Table A.6 in Appendix A1). To interpret the sign and magnitude of the coefficients, the results are depicted in Figure 6.




*(a)*

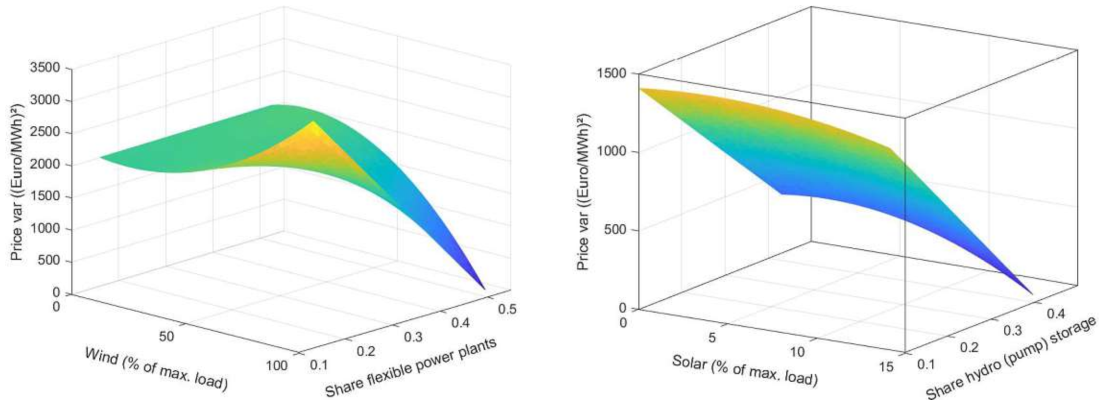



**(b)**

Figure 6: Impact of wind (Panel (a)) and solar generation (Panel (b)) and export/import capacity on electricity price variance based on fixed effects estimates. Wind and solar generation and transmission capacities are depicted in % of maximal load.

We observe a U-shaped impact of wind infeed on the electricity price variance, which is not observable for solar generation. However, much higher shares of wind infeed (up to 93.9%) than solar infeed (up to 14.1%) are present in the analyzed data sample covering the years 2015-2019, making the effect of solar much harder to elicit. The share of transmission capacities allowing the countries to balance the VRE infeed through exports/imports has a much higher impact on the price variance than the VRE infeed itself: The better a country is interconnected to its neighboring markets, the lower the effect of VRE infeed on the price variance. The same effect can be observed for the share of flexible power plants in the system (see Figure 7): The higher the capabilities of flexible power plants (Panel (a)) and hydro (pump) storage (Panel (b)) are, the less distinct the impact of the VRE infeed on price variance. The higher the share of wind in the system is, the higher – the more important – the impact of export/import capacity (see Figure 7, Panel (a)) and flexible power plants (see Figure 7, Panel (a)), as shown by the steeper slope of the dependency.

The effect of the availability of those flexibility options has a greater impact than the level and variance of VRE generation for the observed wind and solar shares. Figures for all possible combinations of flexibility options and technology types can be found in Appendix A1 (see Figure A 1).




*(a)* **(b)**

Figure 7: Impact of wind generation and share of flexible power plants (oil and gas, Panel (a)), and solar generation and share of hydro (pump) storage (Panel (b)) on electricity price variance based on fixed effects estimates. Wind and solar generation and transmission capacities are depicted in % of maximal load, and flexible generation capacities are depicted in % of overall generation capacity.

These results show that flexible generation capacity and interconnections with neighboring markets are able to balance VRE infeed very well so that its impact on price variance is kept at a low level.

## 3.3.2 Country-specific results

The analysis of multiple countries in Europe allows us to derive country-specific findings subject to different electricity systems. All explanatory variables are expressed in relative terms (i.e., as % of maximum load) to render them comparable between countries (results for the absolute variables lead to the same conclusions and can be found in Appendix A1; see Table A.7 - Table A.9).

**Basic Model**

Table 5 shows the results of the Basic Model for individual countries.

Table 5: Regression results for individual countries in the Basic Model.

| Basic Model | Austria/ Germany | Denmark | GB | Greece | Italy | Portugal | Romania | Spain | Sweden |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | 929.12 (.000) | 87.29 (.000) | 42.27 (.982) | 930.14 (.007) | 565.57 (.000) | 74.82 (.000) | 393.38 (.170) | 106.19 (.000) | 1036.15 (.015) |
| Residual Load | -30.19 (.000) | -3.22 (.000) | -39.09 (.504) | -31.81 (.004) | -18.60 (.000) | 1.01 (.055) | -10.22 (.214) | -0.57 (.574) | -41.60 (.011) |
| Residual Load² | 0.25 (.000) | 0.05 (.000) | 0.59 (.190) | 0.27 (.004) | 0.15 (.000) | -0.01 (.002) | 0.11 (.119) | -0.01 (.152) | 0.39 (.010) |
| Residual Load var | 0.95 (.000) | 0.12 (.000) | 1.69 (.089) | 1.08 (.001) | 0.62 (.000) | 0.08 (.000) | 1.25 (.000) | 0.52 (.000) | 0.48 (.005) |
| Gas Price | 28.91 (.000) | 13.30 (.017) | -115.76 (.466) | 25.54 (.058) | 10.81 (.026) | 5.74 (.006) | 25.85 (.055) | 6.07 (.018) | 11.20 (.558) |
| Lagged Gas Price | -11.50 (.043) | 6.36 (.233) | -44.10 (.599) | -34.68 (.044) | -1.80 (.762) | -0.18 (.943) | -8.53 (.561) | -0.87 (.762) | -10.52 (.431) |
| Market split dummy | 3.16 (.795) | | | | | | | | |
| Observations | 1785 | 1818 | 1820 | 1786 | 1779 | 1698 | 1815 | 1826 | 1759 |
| R² | 0.43 | 0.19 | 0.03 | 0.11 | 0.26 | 0.40 | 0.26 | 0.54 | 0.17 |
| Joint significance of Residual Load and Residual Load² | 25.39 (.000) | 15.82 (.000) | 3.98 (.019) | 4.27 (.014) | 13.99 (.000) | 26.39 (.000) | 4.85 (.008) | 52.72 (.000) | 4.08 (.017) |

Note: p values in parenthesis based on HAC robust standard errors. Joint significances report the F-statistics with clustered standard errors in parenthesis. Dummies for weekdays and months are included in all models but not shown.

The results show that for the majority of countries analyzed – Austria/Germany, Denmark, GB, Greece, Italy, Romania, and Sweden – the hypothesis of a convex quadratic influence of the residual load on the price variance can be supported (see negative coefficient of *Residual Load*, positive coefficient of *Residual Load$^2$*, and joint significance); i.e., the price variance is higher for low and high average residual loads. The coefficients for Portugal and Spain are (jointly) significant, but the signs are different, resulting in an inverse U-shape or a flat line (see Figure 8), suggesting that there is limited influence of the shape in these two countries. Furthermore, the variance of the residual load – which is significant for eight out of nine countries in the Basic Model – can be said to increase price variance significantly in Europe. Hence, both the shift to steep parts of the supply curve due to low or high residual load and the distribution of the residual load itself have a significant influence on the price variance in the majority of the countries under study.

Based on the regression results of the Basic Model, we can depict the partial effect of the residual load on price variance by calculating the amount of residual load that leads to the minimal price variance in each country (see Figure 8). The variance of the residual load is fixed at its daily mean for the years 2015-2019 for each country. This means that on the deployment path toward more VRE in the electricity system, the countries move from the right to the left. For Austria/Germany, Greece, Italy, Romania, and Sweden, we find that the minimal price variance is reached when VRE covers approximately 10-40% of the average load level for 2015-2019. Assuming that VRE production will increase, this result implies that the point of minimal price variance for these countries was reached in the later years of the period considered or lies in the future. For Denmark, we can see a very weak dependence of the price variance on the residual load level. As explained above, Portugal and Spain show a different pattern[13].

[13] The influence of Denmark, Portugal and Spain likely causes the minimum of the panel model (48.8%) to be comparably high.

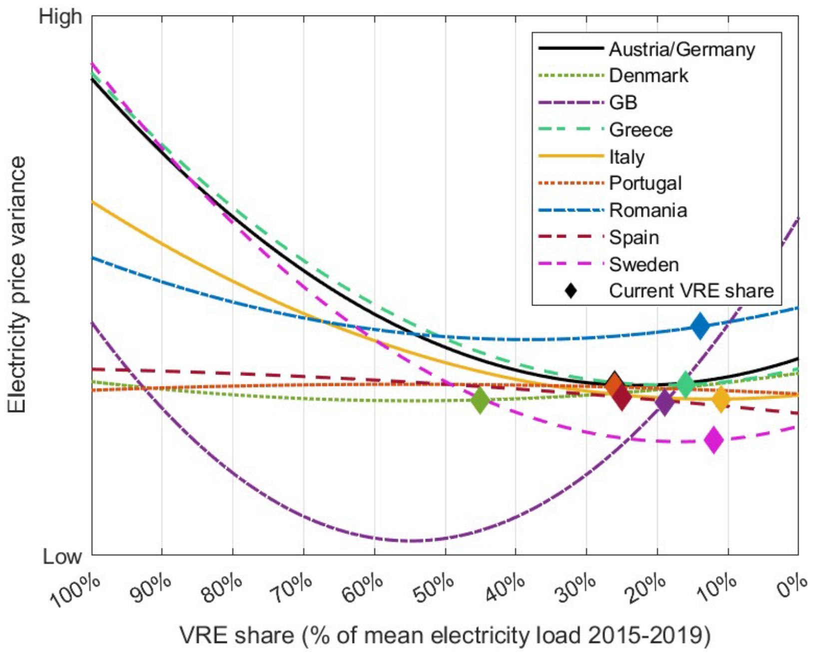



Figure 8: Electricity price variance depending on the share of VRE in the electricity load (mean of the load 2015-2019) for several European countries. The current VRE share depicted is the average VRE infeed during the study period 2015-2019.

The variance of the residual load increases the electricity spot price variance in all countries. However, there are differences in the extent to which a country is impacted by a fluctuating residual load. Figure 9 shows the coefficient of the variance of the residual load from the country regression models (see Table 5) with respect to the dependence of the residual load variance on their share of flexible power plants and export/import capacities in the system (see Table 2).

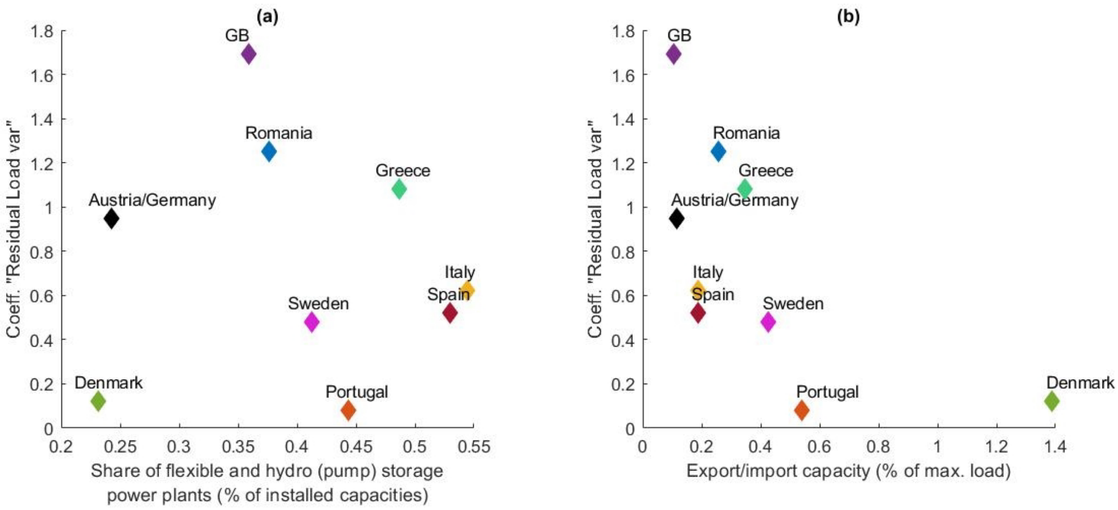



Figure 9: The coefficient of the variance of the residual load for all analyzed countries with respect to the dependence of the residual variance on their share of flexible power plants (Panel (a)) and export/import capacities (Panel (b)). Capacities are based on Table 2. Flexible power plants include oil, gas, and (pump) hydro storage capacities.

The Iberian and the Nordic countries show the lowest impact of fluctuating residual load on electricity price variance. It becomes obvious that with increasing shares of flexible power plants or import/export capacities, the impact of a fluctuating residual load on the price variance decreases.

Spain and Portugal present a different picture than the other countries, with a very flat dependence of the price variance on VRE generation (see Figure 8). One reason could be that Portugal and Spain have the highest share of hydro (pump) storage capacity after Sweden (see Table 2). Additionally, Spain has a high share of (flexible) gas power plants. Since augmenting their interconnection capacities in 2014, these two national electricity markets remain closely coupled, which offers the advantages of spatial arbitrage without trading barriers, resulting in an improved geographical allocation of generation. Pereira da Silva and Horta (2019) find that the sensitivity of price volatility to wind generation decreased sharply after market coupling. Pereira, Pesquita, and Rodrigues (2017) also found that the high share of hydropower balancing options helps Spain to reduce electricity price volatility. These flexibility options may partly explain the flat curve for these two countries.

Denmark shows a very low impact of a fluctuating residual load on price variance (see Figure 8) but reflects almost no share of flexible power plants (see Figure 9). However, the highest share of export/impact capacity, i.e., balancing opportunities with neighboring countries – and other specifics of the power system that are not covered by our regression – lead to a low impact of a fluctuating residual load. Denmark has the highest share of VRE of all the countries examined (see Table 1) and may have gained experience integrating large amounts of VRE production into the electricity system so that the build-up of VRE capacities no longer has an impact on price variance.

Since the Nordic countries were among the first ones to liberalize their markets, compared with other countries, they may have more mature liberalized markets and may thus be better able to handle the factors influencing price variance. Additionally, flexibility due to large hydro reservoirs is exceptionally high in Sweden. In 2015-2019, 41% of the installed generation capacity was hydro storage plants (ENTSO-E 2019a), which offer a greatly enhanced ability to balance fluctuations from wind generation. The results indicate that for its current level of VRE production, Sweden has well-suited capabilities for achieving low levels of price variance. However, with increasing shares, this may change (see the steep increase in price variance in Figure 8). One aspect that was not explicitly analyzed in our regression is the demand side response. The Nordic countries show high shares of electric heating and energy-intensive industries, which result in a particularly high flexible load per inhabitant (Kirkerud, Nagel, and Bolkesjø 2021; Bergaentzlé, Skytte, and Gunkel 2020), giving those countries additional options to balance electricity demand more effectively.

Unobserved variables may account for why the price variance of GB is not well explained (see low $R^2$ in Table 5). Specifically, there are a few exceptionally high daily price variance values (up to 100,000 $(\text{Euro/MWh})^2$) in the second half of 2016 (see Section 3.2.4) that add substantial noise to the data. On these days, intraday price hikes were caused by fundamental changes (e.g., foreign exchange movements and fuel commodity price increases) after the referendum vote to leave the EU and a general tightness of capacity margins (severed by a shutdown of French nuclear reactors and damage to international transmission lines) during that time (Ward and Unwin 2017). Gissey et al. (2018) found that following these events, gas was subject to more price setting in GB than in other major European electricity markets (2-2.5 times greater than in Spain and Italy and almost five times greater than in Germany). The price hikes in the second half of 2016 are thus most likely unrelated to VRE production and the load and should not bias our estimates. Additional reasons for the differing results in GB may be that it was one of the first countries to introduce Contracts for Difference in their national renewable support strategy (UK Public General Acts 2013), as well as being a capacity market and among the assessed countries having by far the largest share of offshore wind in their generation mix (see Table 1), which is less variable than onshore wind (Stehly and Beiter 2019).

### Extended Model

In the Extended Model, the effects of the i) shape of the supply curve and ii) the variance of the residual load are divided into several components.

Table 6: Regression results for individual countries in the Extended Model.

| Extended Model | Austria/ Germany | Denmark | GB | Greece | Italy | Portugal | Romania | Spain | Sweden |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | 390.19 (.154) | 281.04 (.316) | -3259.20 (.406) | 146.77 (.789) | 455.01 (.004) | 210.63 (.026) | 602.84 (.287) | 11.68 (.924) | 1324.78 (.018) |
| Load | -13.39 (.075) | -9.75 (.232) | 78.95 (.529) | -12.26 (.420) | -15.57 (.002) | -2.45 (.304) | -20.98 (.170) | 2.00 (.555) | -49.69 (.013) |
| $Load^2$ | 0.15 (.013) | 0.12 (.054) | -0.29 (.742) | 0.16 (.143) | 0.14 (.001) | 0.01 (.340) | 0.21 (.072) | -0.03 (.196) | 0.44 (.010) |
| VRE | 21.85 (.000) | 3.02 (.076) | -118.73 (.478) | 39.29 (.008) | 15.23 (.023) | -0.94 (.314) | -4.04 (.659) | -0.26 (.879) | 22.21 (.063) |
| $VRE^2$ | 0.33 (.000) | 0.04 (.000) | 4.95 (.103) | 0.68 (.040) | 0.63 (.063) | -0.01 (.056) | 0.15 (.150) | 0.00 (.969) | 0.67 (.013) |
| Load var | 0.41 (.119) | -0.53 (.000) | 3.57 (.151) | 1.26 (.000) | 0.46 (.000) | -0.13 (.002) | 0.26 (.734) | 0.62 (.000) | 0.17 (.808) |
| VRE var | 1.32 (.000) | 0.10 (.000) | 5.88 (.062) | 0.70 (.035) | 1.12 (.000) | 0.05 (.028) | 1.44 (.000) | 0.61 (.000) | -0.41 (.451) |
| VRE Load cov | -1.95 (.000) | -0.27 (.000) | -3.30 (.068) | -2.10 (.013) | -1.51 (.000) | -0.20 (.000) | -2.22 (.000) | -1.02 (.000) | -1.52 (.000) |
| Load*VRE | -0.46 (.000) | -0.08 (.001) | -1.01 (.362) | -0.79 (.000) | -0.36 (.002) | 0.03 (.020) | -0.02 (.878) | 0.03 (.186) | -0.54 (.034) |
| Gas Price | 23.06 (.000) | 11.49 (.013) | -126.10 (.451) | 23.21 (.072) | 11.03 (.024) | 5.72 (.002) | 14.47 (.245) | 6.41 (.012) | 8.94 (.615) |
| Lagged Gas Price | -11.31 (.021) | 6.20 (.197) | -55.74 (.496) | -34.94 (.044) | -3.26 (.602) | 2.70 (.234) | -4.82 (.732) | -0.90 (.747) | -8.41 (.493) |
| Market split dummy | -3.87 (.787) | | | | | | | | |
| Observations | 1785 | 1818 | 1820 | 1786 | 1779 | 1698 | 1815 | 1826 | 1759 |
| $R^2$ | 0.43 | 0.23 | 0.04 | 0.11 | 0.27 | 0.42 | 0.28 | 0.54 | 0.18 |
| Joint Significances | | | | | | | | | |
| Load, $Load^2$ | 6.17 (.002) | 18.26 (.000) | 2.89 (.056) | 4.03 (.018) | 6.12 (.002) | 0.58 (.560) | 3.56 (.029) | 8.20 (.000) | 3.71 (.025) |
| VRE, $VRE^2$ | 20.19 (.000) | 23.65 (.000) | 3.24 (.039) | 7.55 (.001) | 5.41 (.005) | 2.78 (.062) | 1.04 (.354) | 0.02 (.984) | 3.11 (.045) |
| Load, $Load^2$, VRE, $VRE^2$, VRE Load cov, Load*VRE | 11.27 (.000) | 16.30 (.000) | 2.07 (.082) | 4.89 (.001) | 4.77 (.001) | 1.75 (.136) | 4.87 (.001) | 6.87 (.000) | 3.25 (.011) |
| Load var, VRE var | 26.92 (.000) | 36.02 (.000) | 1.08 (.364) | 5.14 (.000) | 17.95 (.000) | 24.41 (.000) | 18.38 (.000) | 59.63 (.000) | 7.54 (.000) |

Note: p values in parenthesis based on HAC robust standard errors. Joint significances report the F-statistics with clustered standard errors in parenthesis. Dummies for weekdays and months are included in all models but not shown.

The shape of the supply curve (measured by the joint significance of *Load, Load², VRE, VRE², VRE Load cov, and Load*VRE*) has a significant impact on the price variance in seven out of nine countries in the Extended Model (see Table 6). Similarly to the results from the Basic Model, the variance of the residual load (measured by the joint significance of *Load var and VRE var*) is significant in all countries except GB. The covariance of VRE and load ($IRE\ Load\ cov$) is significant for eight out of nine countries. All countries show a significantly negative influence of this covariance on price variance (GB is significant only at the 10% level). The interaction term $Load * IRE$ shows a significantly negative impact on price variance for five out of nine countries. The Extended Model shows the important role of the interaction between load and VRE: the higher the timewise correlation of load and electricity generation is, the lower the price variance.

### Wind & Solar Model

The countries analyzed also show peculiarities in how wind and solar infeed impacts price variance. The countries differ greatly in terms of infeed levels: Wind infeed is highest in Denmark at certain times (up to 93.9% of the maximal load) and solar infeed in the Austrian-German market zone (up to 14.1% of the maximal load).

Table 7: Regression results for individual countries in the Wind & Solar Model.

| Wind & Solar Model | Austria/ Germany | Denmark | GB | Greece | Italy | Portugal | Romania | Spain | Sweden |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | 134.88 (.660) | 551.56 (.162) | -3537.62 (.404) | -438.20 (.427) | 490.72 (.006) | 146.13 (.205) | 1789.49 (.021) | 66.47 (.559) | 1324.78 (.018) |
| Load | -6.91 (.372) | -16.41 (.122) | 85.46 (.525) | -6.03 (.654) | -15.77 (.002) | -1.07 (.690) | -48.56 (.016) | 1.18 (.710) | -49.69 (.013) |
| $Load^2$ | 0.11 (.059) | 0.15 (.037) | -0.33 (.728) | 0.20 (.079) | 0.13 (.001) | 0.01 (.548) | 0.36 (.011) | -0.03 (.206) | 0.44 (.010) |
| Wind | 20.05 (.000) | 3.22 (.108) | -132.15 (.505) | 33.00 (.012) | 17.58 (.010) | -0.89 (.392) | 3.89 (.728) | 0.07 (.966) | 22.21 (.063) |
| $Wind^2$ | 0.33 (.000) | 0.04 (.000) | 4.95 (.111) | 0.65 (.080) | 0.96 (.002) | -0.01 (.030) | 0.11 (.310) | -0.01 (.657) | 0.67 (.013) |
| Solar | 38.71 (.000) | -18.98 (.510) | -59.64 (.894) | 170.64 (.032) | -2.85 (.886) | 11.11 (.620) | -245.91 (.015) | -12.77 (.108) | |
| $Solar^2$ | 0.19 (.561) | -0.67 (.673) | 6.55 (.840) | -0.04 (.990) | 1.40 (.187) | -0.37 (.902) | 5.16 (.706) | 0.19 (.625) | |
| Load var | 0.45 (.094) | -0.44 (.000) | 3.65 (.135) | 0.79 (.010) | 0.56 (.000) | -0.12 (.003) | 0.34 (.620) | 0.61 (.000) | 0.17 (.808) |
| VRE var | 1.24 (.000) | 0.10 (.000) | 3.93 (.149) | 1.31 (.025) | 0.59 (.159) | 0.05 (.064) | 1.29 (.001) | 0.64 (.000) | -0.41 (.451) |
| VRE Load cov | -1.89 (.000) | -0.27 (.000) | -3.25 (.061) | -1.71 (.030) | -1.85 (.000) | -0.22 (.000) | -2.49 (.000) | -1.03 (.000) | -1.52 (.000) |
| Load*Wind | -0.44 (.000) | -0.08 (.002) | -0.87 (.536) | -0.73 (.000) | -0.41 (.001) | 0.02 (.044) | -0.06 (.596) | 0.03 (.140) | -0.54 (.034) |
| Load*Solar | -0.68 (.000) | 0.37 (.288) | -1.46 (.614) | -2.84 (.029) | -0.02 (.949) | -0.36 (.162) | 3.53 (.021) | 0.16 (.039) | |
| Wind*Solar | 0.87 (.000) | 0.04 (.711) | 11.59 (.270) | 1.63 (.158) | 0.85 (.333) | 0.17 (.318) | -1.71 (.353) | -0.12 (.257) | |
| Gas Price | 25.10 (.000) | 11.83 (.010) | -127.47 (.453) | 21.84 (.081) | 11.97 (.015) | 4.81 (.010) | 17.93 (.154) | 6.08 (.019) | 8.94 (.615) |
| Lagged Gas Price | -11.88 (.021) | 5.94 (.219) | -53.07 (.516) | -36.06 (.037) | -3.75 (.543) | 2.27 (.305) | -9.42 (.519) | -0.78 (.777) | -8.41 (.493) |
| Market split dummy | -7.38 (.594) | | | | | | | | |
| Observations | 1785 | 1818 | 1820 | 1786 | 1779 | 1698 | 1815 | 1826 | 1759 |
| $R^2$ | 0.44 | 0.23 | 0.04 | 0.12 | 0.28 | 0.44 | 0.30 | 0.55 | 0.18 |
| Joint Significances | | | | | | | | | |
| Wind, $Wind^2$, Load*Wind, Wind*Solar | 11.59 (.000) | 11.90 (.000) | 1.67 (.154) | 5.17 (.000) | 8.35 (.000) | 10.82 (.000) | 0.98 (.415) | 33.71 (.000) | 2257.78 (.000) |
| Solar, $Solar^2$, Load*Solar, Wind*Solar | 5.96 (.000) | 1.59 (.173) | 1.16 (.324) | 1.61 (.170) | 1.06 (.374) | 8.42 (.000) | 2.40 (.048) | 1.45 (.215) | |
| Load, $Load^2$, Wind, $Wind^2$, Solar, $Solar^2$, Load*Wind, Load*Solar, VRE Load cov | 21.44 (.000) | 16.53 (.000) | 1.02 (.420) | 3.94 (.000) | 14.38 (.000) | 15.73 (.000) | 19.51 (.000) | 33.06 (.000) | 8359.11 (.000) |
| Load var, VRE var | 24.76 (.000) | 43.99 (.000) | 1.44 (.238) | 8.87 (.000) | 18.86 (.000) | 6.84 (.001) | 6.41 (.002) | 56.00 (.000) | 0.72 (.489) |

Note: p values in parenthesis based on HAC robust standard errors. Joint significances report the F-statistics with clustered standard errors in parenthesis. Dummies for weekdays and months are included in all models but not shown.

These differences are reflected in Table 7, which shows the estimated coefficients for the Wind & Solar Model: Wind is found to have a jointly significant influence on price variance in all countries other than GB and Romania. Solar, on the other hand, is found to have a jointly significant effect only in Austria/Germany, Portugal, and Romania. Sweden has negligible solar production, and the influence of solar is therefore not available in the data.

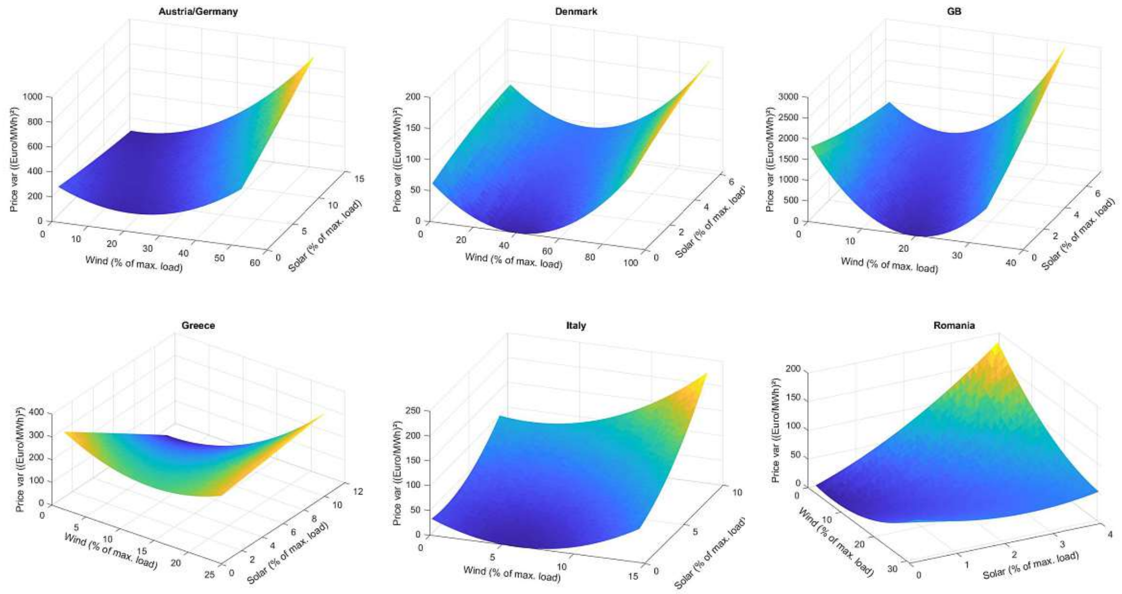



Figure 10: Electricity price variance depending on the share of wind and solar in the electricity load (mean of the load 2015-2019) for several European countries.

Figure 10 shows the effect of the percentage of wind and solar production on the fitted values of price variance for all countries except Sweden (where no solar data are available), Spain, and Portugal (which had an inverse U-shape for the residual curve). For better comparison, the price variance is shifted to zero at the origin. For the countries shown, high wind and high solar infeed at the same time lead to the highest price variance in all countries except for Romania. In the Austrian-German market zone, GB, and Greece, solar infeed increases price levels at high wind infeed, whereas solar production reduces price variance at low wind infeed. In times of high wind production, prices are often already low and defined by the steep part on the left end of the supply curve. The solar infeed in these hours pushes prices even lower and increases price variance. However, when there is no wind infeed, increasing solar production is able to reduce otherwise high electricity prices and push residual demand from the steep right part to the flatter part of the supply curve in the middle: Then, it decreases price variance. The combination of low wind and low solar infeed leading to increased price variance (and confirming the U-shaped impact of VRE infeed) is especially distinct for Greece but can also be observed in the Austrian-German market zone, Denmark, GB, and Italy. In Denmark, price variance is mainly impacted by wind infeed, while solar infeed shows very little effect.

## 3.4 Discussion and limitations

This chapter addresses the question of how VRE generation influences electricity spot price variance in Europe and what flexibility options help different countries cope with VRE infeed. Electricity spot price variance is used as an indicator for short-term flexibility need as it is a market signal for incentivizing short-term flexibility options. Our analysis covers nine[14] countries, encompassing 78% of the wind generation and 79% of the solar generation in the current EU's electricity market (Eurostat, 2021). The more the residual load (i.e., load minus VRE production) fluctuates, the higher the price variance. This can be confirmed for eight out of nine countries. Furthermore, our analysis confirms that in seven out of nine countries analyzed, low and high residual load levels lead to higher price variance than moderate levels. This indicates – depending on the current deployment level of VRE in a country – that an increased share of VRE does not necessarily increase price variance but can even lower it. These results confirm previous analyses (e.g., by Wozabal, Graf, and Hirschmann (2016)) for the first time for a wide range of countries. The minimum price variance is found to be between 10% and 40% of the VRE share for the countries that adhere to the described pattern. For these countries, given the increasing shares of VRE beyond this minimum in the future and static power system assumptions, increased price variance, i.e., short-term flexibility needs, can be expected. However, there are measures that dampen this effect, as shown by countries such as Denmark that already have a high share of VRE but where this nevertheless has a low impact on price variance.

Lower price variance in the medium to the long run is reached by different flexibility options that help to balance fluctuating VRE by 1) reducing the variance of the VRE infeed itself or 2) changing the shape of the supply curve – i.e., by export or import capacities. Furthermore, we find that the effect of wind and solar infeed on spot price variance is relatively low compared to the impact of certain electricity system characteristics of a country. More specifically, the availability of flexible power plants and export/import capacities are more important factors for a country's ability to balance VRE infeed than the extent and the variance of the VRE production itself. Since the extension of transmission capacities is a very inert process, countries should foster this early on in their VRE deployment.

The regression models cannot fully explain the price variance because factors such as supply shortages, policy shifts, and remuneration schemes are not explicitly covered. Such factors – even if not the focus of our analysis –can also have a great impact on price variance. We show for the case of GB that exceptionally high price variance over a few days due to the electricity supply shortages in 2016 caused a tremendous increase in the average price variance[15].

The comparison of multiple countries shows the lowest impact of VRE infeed on price variance in the Iberian and Nordic countries. They all are characterized by either high shares of flexible power plants, hydro (pump) storage or transmission capacities to the neighboring countries. Denmark, which has the highest share of VRE (41%)[16] among the countries analyzed, shows how these factors can support the successful integration of variable renewables in a power system, and our results suggest that these factors

[14] Austria/Germany/Luxembourg were analyzed as one country because of the common market zone.
[15] Since the causes for these supply shortages were uncorrelated to VRE production and load, the exogeneity of our variables of interest is maintained.
[16] Average VRE share in hourly load in 2015-2019

make a difference. For the support of VRE uptake, it is most important to minimize the price risk for VRE producers (Egli 2020). Therefore, in many European countries, VRE generators still receive incentives to generate electricity even if the spot price levels are negative for up to six hours. Denmark was one of the first countries to scrap this rule for new wind offshore generation (González and Kitzing 2019), which means that generators will avoid generation as soon as there are negative prices indicating a surplus of renewable generation and pushing demand toward the steep part of the supply curve to the left.

Our finding that increasing VRE can even lower price variance in a wide range of countries has important market and policy implications. The empirical analysis shows that a large volume of VRE increases price variance. However, we see that along the deployment path of rising VRE shares in a market, price variance may even be lowered by VRE. This indicates that during the current phase of moderate amounts of VRE and since most of the countries analyzed are still expected to see lower price variance with increasing VRE share, price variance alone cannot be the driver for investments in short-term flexibility facilities.

## 3.5 Nomenclature

| | |
|---|---|
| $\ddot{x}_{it}$ | Relative variable reduced by the country-specific mean (applied in the fixed effects model) |
| $\Delta x_{it}$ | Relative variable reduced by the observation from the previous day (applied in the first difference model) |
| $C_i$ | *Nx3* matrix containing variables constant over time: export/import capacities, the share of oil and gas power plants in installed capacities, and the share of hydro (pump) storage plants in installed capacities |
| $K_{it}$ | Matrix containing the control variables natural gas price and three months lagged natural gas price |
| $M_{it}$ | *Nx8* matrix containing the variables of interest: load ("*Load*"), load squared ("*Load²*"), variable renewable electricity production ("*VRE*"), variable production squared ("*VRE²*"), variance of load ("*Load var*"), variance of variable renewable electricity production ("*VRE var*"), covariance between variable renewable production and load ("*VRE Load cov*"), and an interaction term of load and variable renewable production ("*Load * VRE*") |
| $N_i$ | Number of observations of country *i* |
| $R_{it}$ | *Nx3* matrix containing the variables of interest for all *N* observations: residual load ("*Residual Load*"), residual load squared ("*Residual Load²*"), and variance of residual load ("*Residual Load var*") for country *i* at Day *t* |
| $W_{it}$ | *Nx12* matrix containing load ("*Load*"), load squared ("*Load²*"), wind ("*Wind*"), wind squared ("*Wind²*"), Solar ("*Solar*"), Solar ("*Solar²*"), variance of load ("*Load var*"), variance of VRE ("*VRE var*"), covariance VRE and load ("*VRE Load cov*"), and the corresponding interaction terms ("*Load * Wind*", "*Load * Solar*", "*Wind * Solar*") |
| $u_{it}$ | Error term |
| $\beta', \gamma', \delta'$ | Respective coefficients |
| $\theta_t$ | *Nx6* matrix containing day-fixed effects |
| $\nu_i$ | Time-constant part of the error term $u_{it}$ |
| $\rho_t$ | *Nx11* matrix containing month-fixed effects |
| $\epsilon_{it}$ | Idiosyncratic part of the error term $u_{it}$ |
| $\alpha$ | Intercept |
| $I$ | Wind and solar generation |
| $Q$ | Aggregate electricity demand (i.e., load) |
| $X$ | Residual load |

# 4 Flexible generation: Case study 1 - dispatchable solar power

After shedding light on the determinants of flexibility needs in the previous chapter, the following two chapters take a closer look at solutions that can provide flexibility. As elaborated on in Chapter 2.3, there are various types of flexibility options differing in their techno-economic characteristics, diffusion levels, and applicability to different timescales. In this chapter and Chapter 5, two case studies present two flexibility options in greater detail – before, in Chapter 6, flexibility needs and options are analyzed together. The chosen case studies show the range of technological solutions for flexibility provision and illustrate the impact of regional differences in resource availability and generation patterns. Case study 1 in this chapter analyzes a supply-side flexibility option that is of high relevance in solar-rich countries because of its diurnal and seasonal generation pattern: dispatchable solar power. Spain serves as one example of a southern European country with the highest solar resources in the EU. Since the timescale for flexibility provision is a key factor in differentiating between flexibility options (see Section 2.2), the following analysis identifies the impact of storage time on the competitiveness of flexibility options, exemplified by different technological options for dispatchable solar power in Spain. It answers the second research question *"What are the economics of different dispatchable solar power technologies, and how do storage time requirements impact technology choices for flexibility options?"* and is based on Schöniger et al. (2021) and Schöniger, Thonig, et al. (2022). Some aspects of this chapter were also covered in Schöniger, Resch, et al. (2022).

## 4.1 Background

With increasing shares of VRE, there is an increasing effort to develop solutions for making their generation more dispatchable. This leads to the question of how renewable technologies can be reduced in their fluctuations or even become dispatchable and what can be their different roles in the provision of flexibility.

Driven by dedicated support policies, electricity from solar PV and wind turbines has become much cheaper in the last decade and has reached grid parity in many electricity markets around the globe. The global weighted-average total installed cost of utility-scale solar PV projects commissioned in 2019 was USD 995/kW (IRENA 2020). The LCOE was USD 0.068/kWh, with an estimated learning rate of about 36% between 2010 and 2019 (IRENA 2020). With expected investment costs as low as, e.g., USD 350/kW for utility-scale PV installations in 2050 (NREL, 2019), cheap renewable electricity from solar and also wind power will play a big role in decarbonizing power systems (European Commission 2020) and will be the cheapest power source for new power generators in most places

(Nayak et al. 2019). These technologies are, however, not sufficient to assure that supply meets demand at all times as their power generation follows the fluctuating nature of its resource and not the demand profile. While the deployment of PV and wind is continuously growing, research now aims to understand and develop technologies to accompany VRE generation; making renewable electricity available in times when solar and wind resources are scarce. There are different technologies suggested to balance supply and demand on different time scales, from seconds to seasonal variations.

Power systems rich in PV generators typically have abundant power supply during the day. In such systems, the main challenge is to be able to meet supply in a cost-efficient way when there is no sunshine, e.g., during the night and during cloudy day-time conditions (Denholm, O'Connell, and Brinkman 2015). Finding solutions for this is a central solar power problem for the future, and there are several options. First, adding a battery energy storage system (BESS) extends the operating time of a PV system and thus also increases both the dispatchability and market value of PV installations (Denholm, Margolis, and Eichman 2017). Second, concentrating solar thermal power (CSP) has the inherent capability to make its power output dispatchable and offers a fully developed and commercialized solution to supply solar power at night by including thermal energy storage (TES) (Lunz et al. 2016; Yagi, Sioshansi, and Denholm 2019). Third, it is also possible to connect PV with TES, as is now implemented at the utility scale in the 800 MW solar hybrid Midelt project in Morocco (SolarPACES, 2020) and the 400 MW SolarReserve Australia II project (1414 degrees, 2019).

This leaves us with three apparent technological solutions for providing (in principle) solar electricity during times when no or little sunlight is available for several hours, especially at night. The question is which technology combination will provide the least-cost solutions for this solar power niche in times of no sunshine today and towards the 2050 horizon when power systems need to become fully decarbonized.

In this chapter, we compare these three technology configurations: CSP with TES (two-tank molten-salt TES) and PV combined either with BESS (Li-Ion batteries) or with a TES using an electric heater. As previous analyses suggest, one of the key parameters that determine competitiveness between these options is the required storage time (i.e., hours of electricity output from storage at nameplate capacity) (Lovegrove et al. 2018). We investigate the relative competitiveness of each of the three options as a function of current and future investment costs and the desired storage duration. We show how the break-even between CSP+TES, PV+BESS, and PV+TES changes as technology costs shift.

In our analysis, we assume that a continuous load of 100 MW has to be delivered from storage for a certain pre-specified period, varying from 1 to 24 hours after sunset (with no additional solar energy collection, i.e., 0.1 GWh to 2.4 GWh of electricity storage) within a simplified model environment representing a location with Spanish solar radiation profile. We conduct a model-based investment and dispatch optimization to calculate the necessary electricity generation (solar field and power block for CSP and PV modules) and storage capacities (TES and utility-scale BESS). This enables us to evaluate the specific cost for demand coverage under the given assumptions and to compare the resulting annualized costs for the three technology combinations CSP+TES, PV+BESS, and PV+TES.

## 4.2 Recent developments of PV, CSP, and storage

Recently, PV with storage (PVS) has seen increasing adaptation in residential and utility-scale applications. In the US, 2.6 $GW_{ac}$ battery capacity with a storage duration of between 2-5 hours was built in 2018 (Bolinger, Seel, and Robson 2019). As with PV, the cost of battery storage exhibits a strong downward trend, especially for lithium-ion batteries that are projected to reach investment costs below USD 100 per kWh before 2050 (Lazard 2018). The literature offers quite different assessments of the cost to be expected in the next decade as different factors, from spending on research and development (R&D) resulting in material and manufacturing improvements to the costs of resources, all impact the expected cost in the future (Kittner, Lill, and Kammen 2017; Schmidt et al. 2019). With the ongoing development of battery-electric vehicles and consumer electronics, further spill-overs decreasing the cost not only for mobility applications but also for grid-scale battery storage in the power sector are expected (Malhotra, Schmidt, and Huenteler 2019; Stephan et al. 2019).

In the case of CSP technology, thermal storage capacities have been a central part of the technology already for a longer time. However, a trend toward increasing storage sizes is observable. In the last five years (2016-2020), most CSP stations are either parabolic trough power plants (10 of 22) or solar towers (9). Almost all new stations (19 of 22) employ two-tank TES with molten salt, usually a mixture of 60% sodium nitrate and 40% potassium nitrate; these stations have, on average, 9.3 hours of TES, allowing these stations to resume power generation also after sundown or during adverse weather for at least this number of hours (CSP.guru 2020). The biggest storage yet - totaling 1.9 GWh - will be commissioned in the Cerro Dominador project in Chile, scheduled for completion in 2020. It will be able to generate 110 MW of electricity for up to 17.5 hours from stored heat and together with the co-located 100 MW PV plant. The complex is designed to provide around-the-clock solar energy.

Currently, deployed TES systems are much larger than deployed battery systems; for example, the TES of Cerro Dominador is 15 times larger than the world's largest lithium-ion battery system, the 100 MW/129 MWh storage system at Hornsdale, Australia (Hornsdale Power Reserve 2020). Hence, the addition of TES can make CSP fully dispatchable, allowing it to shift the generation to the night hours (Mehos et al. 2016; Murphy et al. 2019; Pfenninger et al. 2014). Because storage increases the utilization of components, especially the power block, the Levelized cost of CSP electricity decreases with larger storage as long as the load factor increases (Wang 2019a).

Deployment policies have significantly reduced the cost of CSP in the last decade, with further decreases expected if further investments in new power plant capacities are undertaken (Lilliestam et al. 2018; 2017; CSP.guru 2020).

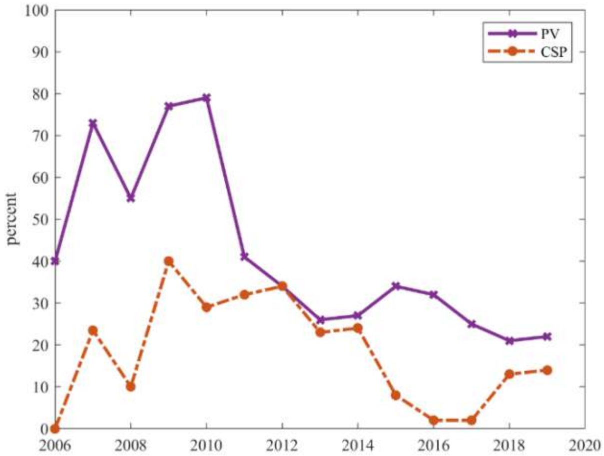



Figure 11: Yearly growth of cumulative installed capacity (own elaboration based on IRENA (2019a) and CSP.guru (2020).

The diffusion speed of CSP and PV has exhibited very different dynamics (see Figure 11). While PV reached a cumulative global installed capacity of 580 GW in 2019, CSP remained almost 100 times smaller at just over 6 GW (IRENA 2020). Since the year 2000, when global installed capacity stood at less than 1 GW, the cumulative global PV fleet has grown by up to 80% per year, and still today, although the fleet is very large, it grows by more than 20% per year. The geographical diversity of the market has also increased, with ten countries adding more than 1 GW of PV in 2018 alone (IEA 2019). For CSP, capacity additions were only partly comparable to the success of PV in the five years between 2009 and 2014, when market growth, measured by the increase of yearly capacity additions, stood at, on average, about 30%, driven by expansion programs in Spain and the US (CSP.guru 2020). This boom led to the creation of a CSP industry that is still active globally today (Lilliestam et al. 2020). Market growth of CSP has, however, slowed down considerably and has only increased temporarily with the emergence of a support program in China. In relative terms, CSP has been losing ground on PV since 2014, and the future market outlook is mixed with few current policy support schemes open for new projects (Lilliestam et al. 2020).

The strong deployment and related technological development of PV have led to a technological shift from CSP to PV. This is also reflected on the project level for utility-scale solar projects in the US, where several planned CSP projects were transformed into PV stations (Bolinger and Seel 2018; Mehos et al. 2016). In both the US and Europe, driven to a large extent by the tremendous cost reduction of PV, CSP support and construction have stopped completely. The progress in PV and battery technologies opens the question if the solar field component of CSP will still be needed in the future and to which extent the storage niche for times without sunshine will be dominated by PVS or whether TES will play a role in combination with a CSP solar field or a PV array.

## 4.3 Method and data

### 4.3.1 Conceptualizing dispatchable solar power

The operational and economic characteristics of power plants are different according to whether they address peak or baseload demand. Peaker plants will only run for a short time at a relatively high price level, whereas baseload is required for more than 12 hours when electricity prices are usually lower. In theory, PV+BESS, PV+TES, as well as CSP+TES can cover peak or baseload demand based on their configuration. We investigate the specific cost of these technology combinations for different required storage hours to enable a comparison of a broad range of use cases. To understand the competitiveness of CSP+TES and PVS, we compare them for different hours of load delivered after sunset and see how relative specific cost change with the expected technological developments.

**Characteristics of CSP with TES and PVS**

CSP plants consist of three independent but closely interrelated components with different characteristics: the solar field, the TES, and the electricity-producing unit, i.e., the power block. A CSP system has two energy conversion steps. In the collection step, sunlight is concentrated by means of mirrors in the form of thermal energy in a heat transfer fluid (HTF). CSP plants utilize direct normal radiation (DNI) as one specific component of solar radiation. Second, the thermal energy is transformed into alternating current (AC) electricity using a conventional steam power block. Storage is possible between thermal and power generation in the form of thermal energy. All of these components can be sized differently and require different assumptions regarding their techno-economic parameters. Depending on the technology concept, the amount of thermal energy output is determined by the size of the solar field and the amount of solar irradiance. Varying the size of the solar field has an impact on the capacity factor of the electricity generating unit. This is, however, a complex interplay of solar field size, storage capacity, and electricity generation capacity. The size of the solar field can either be expressed in terms of actually covered land or by using the concept of a solar multiple. The solar multiple is a key metric in designing a CSP plant. It is the ratio of the thermal energy collected by the receiver at the reference point to the amount of thermal energy required to generate the rated turbine gross power (Kariuki, Machinda, and Chowdhury 2012). Increasing the solar multiple and storage allows for increased capacity factors but also increases investment costs. The concept of the three modeled technology combinations and their interactions is shown in Figure 12.

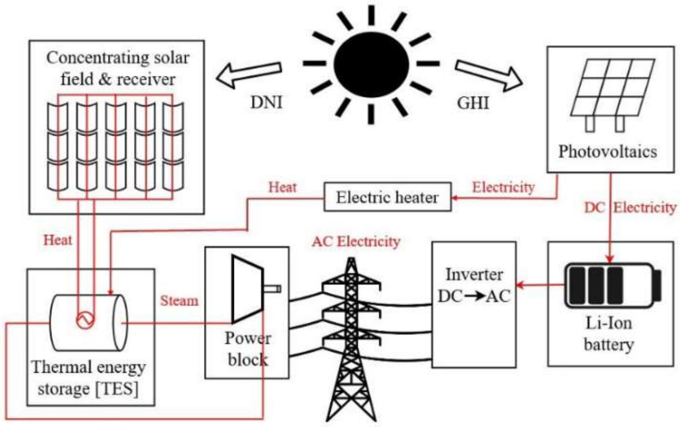



Figure 12: Conceptualization of PV combined with battery storage and CSP (solar field, receiver, thermal energy storage, and power block). Power flow in direct current (DC) and alternating current (AC). Solar radiation components are global horizontal irradiation (GHI) and direct normal irradiation (DNI). Own illustration using graphical content from Shlain (2019).

PV, on the other hand, uses the photoelectric effect to generate direct current (DC) electricity utilizing solar global horizontal irradiation (GHI). DC power then needs to be converted through an inverter to AC electricity in a second conversion step. Battery storage can be integrated before or after the solar inverter and stores the energy in the form of chemical energy. Consequently, Feldman et al. (2016) point out that the inverter functions much like the turbine in the case of a CSP plant. The Inverter Loading Ratio (ILR) fulfills the same function as changing the solar multiple in the case of a CSP turbine. Alternatively, the electricity generated by PV can be stored in the form of thermal energy in a TES utilizing an electric heater and a power block for the conversion from electricity to heat and back. Usage of TES as a long-term standalone power storage option detached from CSP plants is, in principle, possible and has been suggested in practice (1414 degrees, 2019; IEA-ETSAP & IRENA, 2013; SolarPACES, 2020). This option is characterized by a significantly lower round trip efficiency than PV+BESS (see Section 4.3.4). However, if PV+TES can be combined at a lower cost than CSP+TES, that would eliminate the need for the solar component of CSP plants while offering the same dispatchability from the TES to the grid.

In general, there are several conversion steps necessary, beginning from the collection of the solar radiation in the form of the solar field and receiver system or the PV panels over the conversion to storable energy in the battery system or the TES to the final conversion to provide grid-connected AC electricity (see Figure 13).

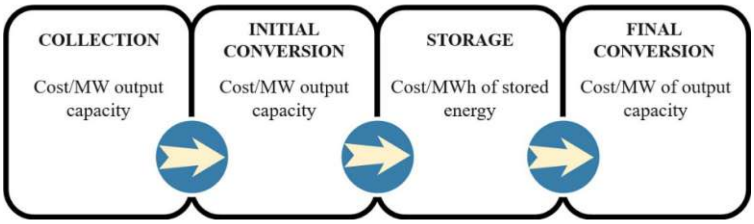



Figure 13: Conversion process from the collection of solar radiation to the final conversion to AC electricity and relevant cost parameters. Own illustration based on Lovegrove (2018).

**Solar radiation**

The following model-based analysis is conducted for a representative location in Spain, using solar data for the location of the CSP plant Andasol 1 in the Sierra Nevada in Spain[17] (EU Science Hub 2019). The solar radiation data represents a typical meteorological year (TMY) based on actual data for the years 2007-2016 and is split up into its radiation components. For the analysis, the solar radiation profile of a typical summer day was chosen (day 1 in week 29) to visualize the power plant and storage operations (see Figure 14).

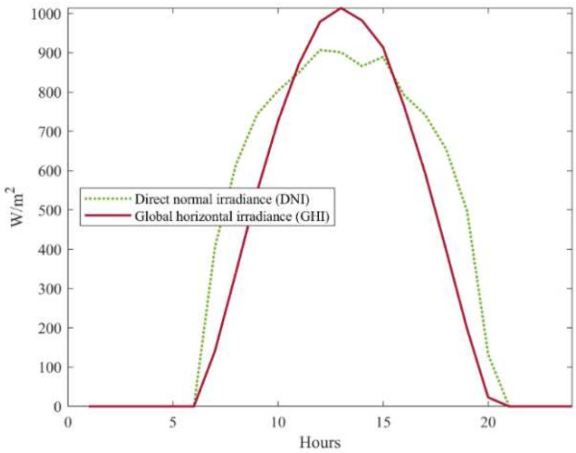



Figure 14: Solar profiles (GHI and DNI) for the modeled day and location in the Sierra Nevada in Spain. Day 1 in week 29 of a typical meteorological year based on the years 2007 – 2016.

Since we model a full year, the FLH for the CSP solar field as well as for the PV panels are calculated using the TMY data for the whole year (see Equations (6) and (7)), not only this one specific day. This means the calculated yearly electricity generation and resulting specific cost represent a typical, average meteorological year at this specific location. In this way, also cloudy days and seasonal differences are represented in the resulting annual electricity generation and, therefore, also in the annualized costs we evaluate. For CSP, the DNI, and for PV, the GHI is used for the calculation of FLH.

[17] Coordinates: *37.23078611, -3.070577778*

$$FLH_{CSP\ solar\ field} = \frac{Total\ annual\ DNI}{1000\ W/m^2\ DNI} = 2118\ h \tag{6}$$

$$FLH_{PV} = \frac{Total\ annual\ GHI}{1000\ W/m^2\ GHI} = 1843\ h \tag{7}$$

**Net solar-to-electricity efficiency of CSP**

In general, the thermal input for either the TES or the CSP power block and the overall CSP system depends on the net efficiency of a solar field and receiver system (IRENA, 2012; Jamil & Ali, 2016). Typical annual net solar-to-electricity efficiencies[18] are reported in the ranges of 8-25% (Müller-Steinhagen and Trieb 2004), 15-20% (Heath and Burkhardt III 2011), and 7-20% for solar towers and 11-16% for parabolic trough systems (IRENA 2012). We assume $\eta_{CSP} = 0.2$ in our model. For the power block efficiency, $\eta_{power\ block} = 0.42$ (COBRA 2019) is assumed.

### 4.3.2 Modeling specific costs with Balmorel

For the modeling task of this chapter, we use the energy system model Balmorel (Balmorel Community 2022). Balmorel (the BALtic Model for Regional Electricity Liberalisation) is an open-source, partial equilibrium energy system model (Wiese et al. 2018) following a bottom-up approach to model the electricity and district heat system. The model is built modularly, continuously being further developed by a community (Balmorel Community 2022).

Balmorel was one of the first open-source energy system models developed; the theoretical background was first described by the developers Ravn et al. (2001) and Ravn (2001). Following a deterministic bottom-up partial equilibrium approach, Balmorel can model several sectors, including electricity, district heating, individual heating, and transport. It can co-optimize energy dispatch and investment in the considered sectors using linear programming in GAMS. On the supply side, various technology types can be implemented, characterized by primary fuel type, input/output efficiency, operation and maintenance costs, and investment costs for new capacity. Using a perfect foresight approach, the model's objective function (Eq. (8)) minimizes the system cost[19] associated with the modeled technologies $g$: annualized investment costs of new investments $c^{Inv}$ [€/MW], fixed operation and maintenance (O&M) costs $c^{Fix}$ [€/MW] of existing units $C^{Ex}$ [MW] and new investments $C$ [MW], and variable operation and maintenance costs (including fuel and emission costs) $c^{Var}$ [€*h/MWh] of existing units and new investments (for further details on the selected equations, see Münster and Meibom (2011) and Bramstoft et al. (2020)). $Q$ [MW] represents the level of the commodity produced or consumed; $Q^{el}$ denotes the commodity of electricity, $Q^{dh}$ denotes the commodity of district heat.

[18] For the theoretical background on the solar-to-electricity efficiency, see Appendix A2.
[19] i.e., maximizing social welfare when assuming inelastic demands.

. This is done for the different regions ($r \in R$), areas ($a \in A$), technologies ($g \in G$), and time steps ($t \in T$). Areas $a$ are aggregated into transmission regions $r$. We model the energy system in hourly resolution.

$$\min\Big(\sum_{a\in A}\sum_{g\in G} c_g^{Inv} C_{a,g} + \sum_{a\in A}\sum_{g\in G} c_g^{Fix}\big(C_{a,g}^{Ex} + C_{a,g}\big) + \sum_{a\in A}\sum_{t\in T}\sum_{g\in G} c_g^{Var} Q_{a,t,g}\Big) \tag{8}$$

The optimization constraints are imposed by a set of linear relations reflecting the characteristics of the technologies, such as capacity, energy, and operational constraints of generation units and storage. Some of them are displayed below (Eq. (9)- Eq. (12)).

It is ensured for every time step $t$ that electricity demand $d^{el}$ [MWel] is covered in every region $r$ considering export and import $Q^{trans}$ [MWel] (including a share of losses $e^{loss}$ [-]) of electricity between regions and loading and unloading of storage technologies $G^{St}$ (Eq. (9)). $Q^{trans}_{r\prime,r,t}$ and $Q^{trans}_{r,r\prime,t}$ [MWel] denote the electricity imported to and exported from region $r$ and from a neighbouring region $r' \in R^{imp}$ or to a neighbouring region $r' \in R^{exp}$. Similarly, Eq. (10) ensures that the district heat demand $d^{dh}$ [MWth] is covered in each area $a$, but without the possibility of heat transmission between areas.

$s.t.$

$$\begin{aligned}\sum_{a\in A_r^R}\sum_{g\in G^{el}} Q^{el}_{a,t,g} + \sum_{r\prime\in R^{imp}_{r',r}} \big((1-e^{loss})\cdot Q^{trans}_{r\prime,r,t} + \sum_{a\in A_r^R}\sum_{g\in G^{St}} Q^{el,exSt}_{a,t,g} \\ = d^{el}_{r,t} + \sum_{r\prime\in R^{exp}_{r,r\prime}} Q^{trans}_{r,r\prime,t} + \sum_{a\in A_r^R}\sum_{g\in G^{St}} Q^{el,inSt}_{a,t,g} \quad \forall\, r\in R, t\in T\end{aligned} \tag{9}$$

$$\sum_{g\in G^{dh}} Q^{dh}_{a,t,g} + \sum_{g\in G^{St}} Q^{dh,exSt}_{a,t,g} = d^{dh}_{a,t} + \sum_{g\in G^{St}} Q^{dh,inSt}_{a,t,g} \quad \forall\, a\in A, t\in T \tag{10}$$

$$Q_{a,t,g} \leq av_{a,t,g}\big(C^{Ex}_{a,g} + C_{a,g}\big) \quad \forall\, a\in A, t\in T, g\in G^{dis} \tag{11}$$

$$Q_{a,t,g} + Q^{curt}_{a,t,g} = av_{a,t,g}\big(C^{Ex}_{a,g} + C_{a,g}\big) \quad \forall\, a\in A, t\in T, g\in G^{ndis} \tag{12}$$

The level $Q_{a,t,g}$ [MW] of electricity or district heat is constrained by the installed capacities $C^{Ex} + C$ [MW] and the availability $av$ [-] of the technology plant at that specific time step $t$ for dispatchable technologies $G^{dis}$ (Eq. (11)). For non-dispatchable technologies $G^{ndis}$, i.e. wind, hydro run-off-river, and solar, the production is determined by the availability of resources/generation profiles, but with the possibility of curtailing generation $Q^{curt}$ (Eq. (12)).

Endogenous optimization results in the hourly electricity and heat generation of all technology components, including storage and flexibility options, the installed generation capacities, and the overall system cost per year (considering the discount rate and economic lifetime) under the premise of minimizing the annualized cost of the energy system. Besides the total costs of the system, all variables are non-negative.

Wiese et al. (2018) describe the model structure, including the wide range of developed model extensions and how the open code enables usage in a broad geographic range. Balmorel has been used and adapted for energy system analyses on various scopes from regional case studies only in the electricity sector (e.g., Barragán-Beaud, Pizarro-Alonso, Xylia, Syri, & Silveira, 2018; Fedato et al., 2019) to integrated studies comprising electricity, heat, and transport sector for several countries (e.g., Hedegaard & Balyk, 2013; Jensen, Wiese, Bramstoft, & Münster, 2020).

In this chapter, we use the modeling framework for evaluating annualized investment and dispatch cost as well as storage operations in a closed model setup designed for the designated research question of competitiveness of different dispatchable solar power technologies. The modeled technologies are specified in terms of primary fuel type, input/output efficiency, operation and maintenance costs, and investment costs for new capacity. The data inputs most relevant for this analysis are techno-economic parameters of the solar power and storage technologies (see Sections 4.3.3 and 4.3.4) and the resource potentials in the form of solar hourly variations (see Section 4.3.1). Since the case study in this chapter analyzes a down-scaled, single-unit-operated, closed system, we do not model any grid conditions or further aspects of the electricity system in this stylized model setup. On the one hand, this allows for a direct comparison of the generation and storage capacities without distortion from solar radiation levels, network constraints or losses, or other external influences in the electricity system. On the other side, this also means that the calculated specific cost cannot be seen as LCOE in a real system. They are rather an indicator visualizing in a very comprehensive way the impact of technology cost developments and storage hours on the competitiveness of the technology options CSP and PVS.

**Cost calculation**

The cost calculated in this case study is the investment costs and variable and fixed O&M costs necessary to cover the continuous electricity load of 100 MW for the modeled range of hours between 1 and 24 hours. The period of delivery starts after sunset and has to be covered by the storage system without any additional solar radiation coming in. In the model-based investment and dispatch optimization, the necessary electricity generation (solar field and power block for CSP and PV panels) and storage capacities (Li-Ion battery and TES) are calculated. As a result, we get the specific cost for demand coverage under the specific assumptions. In the case of one storage hour, this means that only one hour of load after sunset (=100 $MW_{el}$) has to be covered every day, but all costs are also allocated to only 100 MWh. Accordingly, the increased overall system cost in the case when 24 hours of electricity have to be delivered are apportioned among 2400 MWh/day.

To illustrate the modeled process, Figure 15 shows the electricity generation in the case of four hours of continuous load (100 $MW_{el}$) covered by PV+BESS after sunset. During the day, the PV modules generate electricity which is stored in the Li-Ion battery system. The energy content of the battery is at the same time continuously increasing. After sunset, the required electricity delivery period starts, and the battery provides electricity to the grid and depletes at the same time. The process looks identical for CSP+TES, with the solar field heat generation corresponding to the PV generation, the power block electricity generation corresponding to the battery output, and the TES content corresponding to the battery content. In the case of PV+TES, the PV modules linked to an electric heater correspond to the solar field heat generation of CSP.

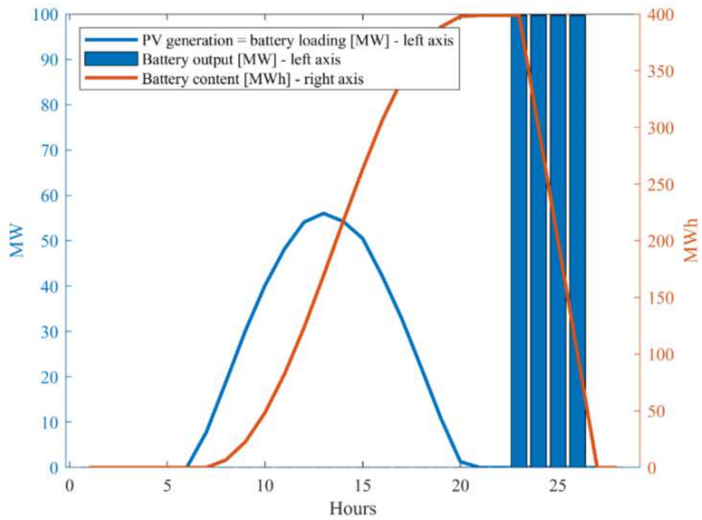



Figure 15: Electricity generation [$MW_{el}$] by PV and the battery system and storage content [$MWh_{el}$].

### 4.3.3 Assumptions on technology cost development

One of the most crucial parts of modeling technology developments is the underlying cost assumptions. However, many factors, like innovative disruptions or raw material availability, are very hard to predict for the future. In this chapter, we, therefore, build on a sound literature analysis of current cost as well as expected cost developments for all technology components until 2050. We then categorize them and build three datasets for three cost scenarios: One scenario using current technology cost and two scenarios representing different possible cost developments in the future (medium and low cost scenario). This covers several possible future pathways that enable us to evaluate to what extent different cost reductions impact the competitiveness of PVS and CSP+TES. For CSP, there are different technology concepts available that show different characteristics. To be able to collect specific technology data, we limit the analysis to the two most common technology types: parabolic trough and solar tower technology. The estimated cost developments could, therefore, be achieved by either technology type. The most common form of TES combined with CSP is molten salt storage (Turchi et al., 2019) which we also presume for the modeling task of this chapter.

Table 8 and Table 9 give an overview of cost assumptions used as model inputs. We use three cost scenarios to cover uncertainty in future costs. The quoted data under the medium and low cost scenarios refer in general to different points in time for PV and CSP (e.g., the medium scenario reflects 2040 for PV modules, but 2025 for several CSP components). This is because available literature deals with different time horizons, and CSP cost assumptions are rather scarce in general.

Table 8: Investment cost assumptions by component. Medium and low cost are cost development expectations up to 2050. All costs retrieved from the literature were converted to €2018. If there was no designated year mentioned for the cost assumptions, the year of publication was taken into account. Inflation rates are derived from Eurostat (2019). Exchange rates refer to the last day of the respective year from ÖNB (2021).

| **Investment costs** | Unit | | Cost in literature ($€_{2018}$ per unit) | Literature source | **Model input ($€_{2018}$ per unit)** |
|---|---|---|---|---|---|
| **Utility-scale PV** | $kW_{el}$ | ***Current Cost*** | *729* | (European Commission et al. 2020) *(Solar PV high potential)* | **900** |
| | | | *1239* | (Lovegrove et al. 2018) *(cost for 2017)* | |
| | | | *987* | (Fu, Feldman, and Margolis 2018) | |
| | | | *848* | (NREL 2019) | |
| | | ***Medium Cost*** | *541* | (European Commission et al. 2020) *(assumption for2040 – medium potential)* | **650** |
| | | | *594* | *NREL, 2019* | |
| | | ***Low Cost*** | *424* | *De Vita et al., 2018 (assumption for 2050 – very high potential)* | **400** |
| | | | *297* | (NREL 2019) | |
| **Li-Ion Battery** | $kWh_{el}$ | ***Current Cost*** | *625* | (European Commission et al. 2020) *(cost in 2015)* | **500** |
| | | | *510* | (Fleer et al. 2016) *(capacity-specific price for 2025)* | |
| | | | *332* | (Cole and Frazier 2019) *(complete 4-hour battery system)* | |

| | | | | | |
|---|---|---|---|---|---|
| | | | *506* | (Lovegrove et al. 2018) *(2017 cost)* | |
| | | | *570* | (Tsiropoulos, Tarvydas, and Lebedeva 2018) | |
| | | ***Medium Cost*** | *357* | (Fleer et al. 2016) | **300** |
| | | | *138* | (Cole and Frazier 2019) *(complete 4-hour battery system, mid-cost scenario for 2049)* | |
| | | | *264* | (European Commission et al. 2020) *(2030 cost)* | |
| | | | *425* | (Tsiropoulos, Tarvydas, and Lebedeva 2018) | |
| | | ***Low Cost*** | *68* | (Cole and Frazier 2019) *(complete 4-hour battery system, low cost scenario for 2049)* | **100** |
| | | | *234* | (European Commission et al. 2020) *(ultimate cost)* | |
| | | | *250* | (Tsiropoulos, Tarvydas, and Lebedeva 2018) | |
| **Solar field & receiver system** | *$m^2$* | ***Current Cost*** | *183* | (Turchi et al. 2019) | **300** |
| | | | *196* | (Dieckmann et al. 2017) *(2015 cost - parabolic trough incl. receiver)* | |
| | | | *324* | (Mehos et al. 2016) *(2015 cost)* | |
| | | | *209* | (ESTELA, DCSP, and Protermosolar 2015) *(2015 cost)* | |
| | | ***Medium Cost*** | *150* | (Dieckmann et al. 2017) *(2025 cost - parabolic trough incl. receiver)* | **225** |
| | | | *133* | (ESTELA, DCSP, and Protermosolar 2015) *(2025 cost)* | |
| | | ***Low Cost*** | *149* | (Turchi et al. 2019) *(solar field for tower plant 75 $/m^2 + 150 $/kW_th receiver)* | **150** |
| **Thermal energy storage** | *$kWh_{th}$* | ***Current Cost*** | *54* | (Turchi et al. 2019) *(parabolic trough)* | **40** |
| | | | *19* | (Turchi et al. 2019) *(power tower)* | |
| | | | *53* | (Mehos et al. 2016) | |
| | | | *44* | (Wang 2019b) | |

| | | | | | |
|---|---|---|---|---|---|
| | | | *36* | (Dieckmann et al. 2017) *(2015 cost - trough)* | |
| | | | *22* | (Dieckmann et al. 2017) *(2015 cost - tower)* | |
| | | | *29* | (ESTELA, DCSP, and Protermosolar 2015) *(cost for 2015)* | |
| | | ***Medium Cost*** | *22* | (Wang 2019b) | **25** |
| | | | *22* | (Dieckmann et al. 2017) *(2025 cost - trough)* | |
| | | | *19* | (Dieckmann et al. 2017) *(2025 cost - tower)* | |
| | | | *20* | (ESTELA, DCSP, and Protermosolar 2015) *(2025 cost)* | |
| | | ***Low Cost*** | *15* | (Mehos et al. 2016) | **10** |
| | | | *11* | (Wang 2019b) | |
| **Power block** | $kW_{el}$ | ***Current Cost*** | *1115* | (Kurup and Turchi 2015) | **1000** |
| | | | *882* | (Turchi et al. 2019) *(Power tower)* | |
| | | | *772* | (Turchi et al. 2019) *(Parabolic trough)* | |
| | | ***Medium Cost*** | *933* | (Dieckmann et al. 2017) *(2025 cost)* | **900** |
| | | **Low Cost** | 760 | (ESTELA, DCSP, and Protermosolar 2015) (2025 cost) | **800** |
| **Electric heater** | $kW_{th}$ | ***Current, Medium, and Low Cost*** | *347* | (European Commission et al. 2020) | **347** |

**CSP cost**

Concerning CSP, we assume a slight cost reduction for the power block from 1000 (current cost) to 800 $€_{2018}/kW_{el}$ (low cost). From historical development, we cannot see a significant cost reduction in CSP turbines using steam. However, Turchi et al. (2019) state that the increasing global installed capacity is expected to help decrease turbine costs as, e.g., new Chinese turbine manufacturers come into the market.

**Storage cost**

Storage cost is based on extensive storage needs that are projected for the future, which are themselves driven by increasing flexibility needs in the electricity system and additional demand from, e.g., electric mobility. A source of high uncertainty here is how resource prices may develop, and this is especially central to the technologies which are dependent on critical raw materials coming from globally concentrated production sites.

Since the cost for the solar field is usually given in €/m$^2$, an additional calculation is necessary to obtain the model input in €/kW$_{th}$. Using the data for the location of Andasol 1, we calculate the annual DNI per m$^2$. To get the thermal output of the solar field, the solar-to-steam efficiency has to be obtained. Based on the assumed $\eta_{CSP}$ and $\eta_{power\ block}$, we obtain a solar-to-steam efficiency of 0.48. By applying the specific FLH for this location, we obtain solar field and receiver costs of 630, 473, and 315 €$_{2018}$/kW$_{th}$, corresponding to the €$_{2018}$/m$^2$ literature values presented above.

The costs for the battery system comprise a capacity-specific (e.g., battery cells, cell housing, cell connectors, and battery management system, cooling) and a power-specific part (e.g., power electronics, inverter, transformers, contactors, fuses, and control systems). For the modeling, the investment costs for the utility-scale batteries are given capacity specifically [€/MWh] as input data, meaning that the power-specific costs have to be converted into capacity-specific costs as well. The power-specific costs are relatively smaller for larger storage hours and relatively higher for lower storage hours since, e.g., the inverter has the same size (100 MW output) for all storage hours. Since most of the sources we used for the collection of cost data define "utility-scale" in the case of batteries as 4 hours of storage, we take these storage hours as default and adapt the capacity-specific costs for the other hours. This results in relatively higher capacity-specific battery costs for storage hours shorter than 4 hours and lower capacity-specific costs for storage durations longer than 4 hours. The exact values were calculated using the ratio of capacity and power-specific cost data from Fu, Remo, et al. (2018) and Fleer et al. (2016) for the modeled storage hours. The share of the power-specific cost components increases more with lower storage hours than it decreases with higher storage hours since the overarching part of the investment costs is related to the capacity of the battery for long storage durations.[20]

**Electric heater cost**

In addition to the analyzed technology combinations PV+BESS and CSP+TES, another recently proposed option is the combination of PV with TES. In this case, electricity is transformed into heat via an electric heater almost without loss. However, to make thermal storage for electricity storage

[20] The 500, 300, and 100 €/kWh$_{el}$ (see Table 1) were used as input data for the 4 hours storage case and different shares of these values were calculated for the other storage hours: 1 hour (123 %), 2 hours (108 %), 8 hours (96 %), 12 hours (95 %), 16, 20 and 24 hours (94%).

competitive, the efficiency loss of energy transformation from electricity to heat and back has to be compensated by the cost advantages of the TES and the PV modules. To model the technology combination PV+TES, the additional technology component is an electric boiler for transforming the electricity generated by the PV modules into thermal energy stored in the TES. The costs are assumed to stay constant in all scenarios; variable O&M costs are 0.5 $€_{2013}/MWh_{th}$ and the efficiency for the electricity-to-heat conversion 1 (European Commission et al. 2020).

Table 9: Fixed operation and maintenance costs, annually by component. Medium and low cost are cost development expectations up to 2050.

| **Fixed Operation and Maintenance Costs, annually** | | Value | Unit | Source | €2018 /kW$_{el}$ | **Model input** |
|---|---|---|---|---|---|---|
| ***Utility-scale PV*** | ***Current Cost*** | *13* | *$€_{2013}/kW_{el}$* | (European Commission et al. 2020) *(Solar PV high potential)* | *14* | ***19*** |
| | | *20* | *$USD_{2017}/kW_{el}$* | (NREL 2019) | *17* | |
| | | *31* | *$USD_{2018}/kW_{el}$* | (Bolinger and Seel 2018) | *27* | |
| | ***Medium Cost*** | *11.5* | *$€_{2013}/kW_{el}$* | (European Commission et al. 2020) *(Solar PV high potential)* | *12* | ***13*** |
| | | *8* | *$USD_{2017}/kW_{el}$* | (NREL 2019) | *7* | |
| | ***Low Cost*** | *10.8* | *$€_{2013}/kW_{el}$* | (European Commission et al. 2020) *(Solar PV high potential)* | *11* | ***7*** |
| | | *4* | *$USD_{2017}/kW_{el}$* | (NREL 2019) | *3* | |
| ***Li-Ion Battery*** | ***Current Cost*** | *40.5* | *$€_{2013}/kW_{el}$* | (European Commission et al. 2020) *(2015 costs)* | *42* | ***50*** |
| | | *94.26* | *$AUD_{2017}/kW_{el}$* | (Lovegrove et al. 2018) *(2017 costs)* | *62* | |

| | | | | | | |
|---|---|---|---|---|---|---|
| | ***Medium Cost*** | *15* | *€2013/kWel* | (European Commission et al. 2020) *(2030 costs)* | *16* | ***32.5*** |
| | ***Low Cost*** | *13.1* | *€2013/kWel* | (European Commission et al. 2020) *(ultimate costs)* | *14* | ***15*** |
| ***CSP*** | ***Current Cost*** | *60* | *USD2018/kWel* | (Bolinger and Seel 2018) *(just solar collector field, thus maybe not fully representative)* | *52* | ***75*** |
| | | *66* | *USD2018/kWel* | (Turchi et al. 2019) | *58* | |
| | | *121* | *€2013/kWel* | (European Commission et al. 2020) | *126* | |
| | | *49* | *€2013/kWel* | (ESTELA, DCSP, and Protermosolar 2015) | *51* | |
| | ***Medium Cost*** | *99* | *€2013/kWel* | (European Commission et al. 2020) | *103* | ***60*** |
| | | *46* | *€2013/kWel* | (ESTELA, DCSP, and Protermosolar 2015) | *48* | |
| | ***Low Cost*** | *77* | *€2013/kWel* | (European Commission et al. 2020) | *80* | ***45*** |
| | | 44 | €2013/kWel | (ESTELA, DCSP, and Protermosolar 2015) | 46 | |
| ***Electric heater*** | ***Current, Medium, and Low Cost*** | *5* | *€2013/kWth* | (European Commission et al. 2020) | *5.2* | ***5.2*** |

Since the fixed O&M costs for CSP are commonly provided in literature for all components together, this has to be split up. For the power block, the annual O&M costs are assumed to be 25.6 €2013/kWel and to stay constant (European Commission et al. 2020). The remaining fixed O&M costs are attributed to the solar field and receiver. That means that the cost reductions in fixed O&M costs are also entirely attributed to the solar field plus receiver.

### 4.3.4 Further techno-economic assumptions

For all components except for the Li-Ion battery, an economic lifetime of 25 years is assumed (for batteries, 15 years, according to Cole and Frazier (2019)). It is possible that in parallel to the development cost reductions, also lifetime extensions are realized. However, for this analysis, we chose to keep the lifetime assumptions constant in all cost scenarios to not distort the effect of the price reductions. The round-trip efficiency for the battery is assumed to be 85% (Cole and Frazier 2019), for the TES 99% (COBRA 2019), and the net power block efficiency 42%. The round-trip efficiency for the storage stays the same for all storage hours. Dynamic losses are not considered. As a limitation of our analysis, this means that we do not consider the effect of the frequency of loading and unloading cycles on the efficiency of different storage sizes. The discount rate is assumed to be 5%. For all technology components besides the electric heater, no variable O&M costs are assumed (European Commission et al. 2020).

## 4.4 Results

Our results show that PV+BESS is cheaper than CSP+TES for short storage durations of up to 2-3 hours, regardless of the cost development. CSP+TES is and remains cheapest for more than 4 hours of storage except in the low cost PV+BESS case where very strong PV+BESS learning is assumed, and the tipping point moves to 10 storage hours. Hence, under most conditions, an economically beneficial night-time solar power market will be split between PV+BESS for short durations and CSP+TES for longer ones. When PV is combined with a TES and a power block instead of the battery, the system can take advantage of the decreasing specific cost with increasing storage hours and the lower specific storage cost for TES. However, PV+TES is more expensive than CSP+TES in all cost scenarios (see Figure 16). The results depend mainly on the learning of PV and especially BESS, whereas they are robust for CSP+TES learning. If PV+BESS costs decrease strongly, they capture most of the CSP niche even if CSP also progresses fast. For all segments, either PV+BESS or CSP+TES provide electricity at the lowest cost in all three cost scenarios.

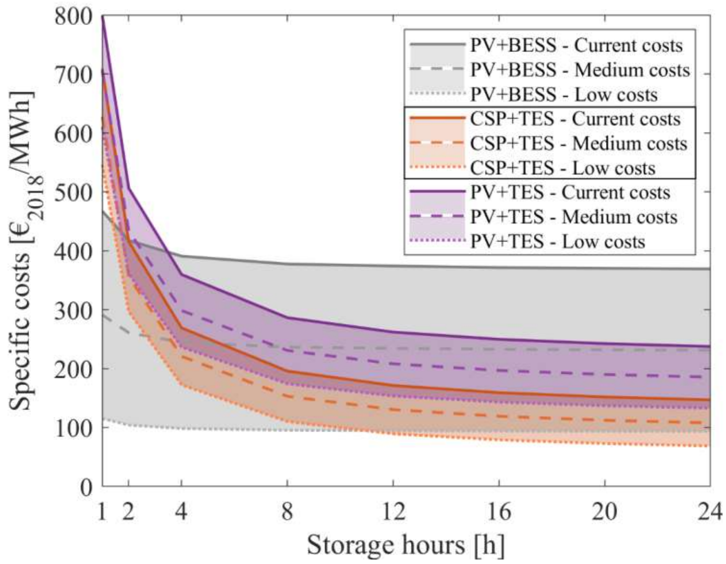



Figure 16: Specific cost for increasing storage hours for PV+BESS, CSP+TES, and PV+TES for three cost scenarios. PV+BESS is always the most economical solution for short storage times. CSP+TES becomes competitive after 2-3 h (current cost) and 4-10 h (future cost projections).

**Costs as a function of learning and storage size**

While the cost for PV+BESS scales almost linearly, the specific costs for CSP/PV+TES decrease with increasing storage hours. Depending on the cost scenario, there is an intersection of the price curves of CSP+TES and PV+BESS. For the current cost assumptions, this is between 2-3 storage hours, for the medium cost assumptions at around 4 hours, and for the low cost assumptions at around 10 storage hours. PV+TES is cheaper than PV+BESS for more than 4 storage hours (current cost), 8 hours (medium cost), or never (low cost) but always more expensive than CSP+TES. These findings are highly dependent on the relative cost development of all technology components. For example, if very strong learning is assumed for PV (low cost scenario) and CSP costs stay at current levels, PV+TES covers the niche for longer storage durations. For PV+TES, learning is the key parameter, stronger than storage duration. However, learning rates for PV are rather expected to flatten, and TES cost reductions apply to CSP+TES and PV+TES equally. In general, we encourage the reader to look at the price ranges instead of single points since we are dealing with cost projections.

**Technical details on the different configurations**

All technology components except for the power block are increasing linearly with increasing storage hours (see Table 10). The CSP+TES unit and the power block are uncoupled - i.e., the power block is in terms of size (the required 100 $MW_{el}$) and costs identical for all assessed storage hours while the cost of the CSP field and the corresponding TES increases linearly with rising storage period. Installed capacities are the same for all cost assumptions for PV+BESS and CSP+TES. In the case of PV+TES (results for the medium cost scenario are shown here), capacities for PV and the electric heater vary slightly between the scenarios because with decreasing PV costs, slightly more PV and less electric boiler capacity are deployed.

Table 10: Installed capacities for all technology components depending on the storage hours.

| | Storage hours [h] | 1 | 2 | 4 | 8 | 12 | 16 | 20 | 24 |
|---|---|---|---|---|---|---|---|---|---|
| **PV+BESS (all scenarios)** | PV [$MW_{el}$] | 12 | 23 | 46 | 93 | 139 | 186 | 232 | 279 |
| | Battery [$MWh_{el}$] | 100 | 199 | 399 | 798 | 1197 | 1596 | 1995 | 2393 |
| **CSP+TES (all scenarios)** | Solar receiver [$MW_{th}$] | 21 | 41 | 82 | 165 | 247 | 330 | 412 | 495 |
| | Thermal storage [$MWh_{th}$] | 239 | 478 | 957 | 1914 | 2871 | 3828 | 4785 | 5742 |
| | Power block [$MW_{el}$] | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |

The larger the ratio of the required amount of energy to the power output capacity, the cheaper the power block specifically gets because FLH are increased. This means that the share of the power block cost on the cost of the overall system decreases with increasing storage hours. Under current cost assumptions, it declines from 82% in the case of one storage hour to 16% in the case of 24 hours of stored energy (see Figure 17). In the case of CSP, the power block cost share is getting larger with decreasing overall investment cost as expected for future years since innovations are rather expected for the solar field, receiver, and thermal storage components.

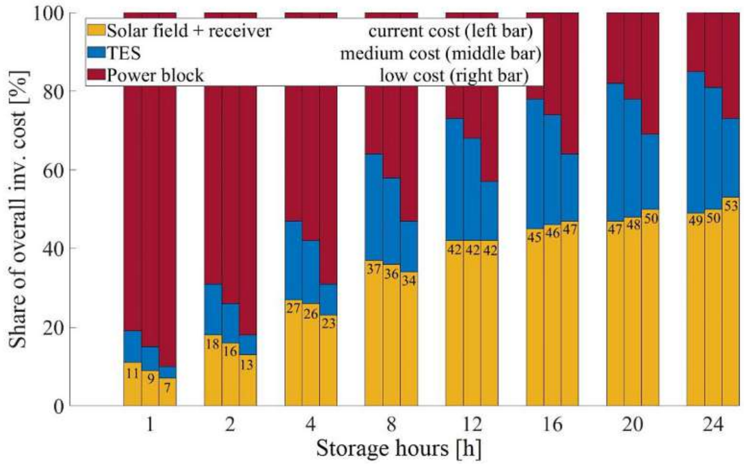



Figure 17: Shares of overall CSP investment cost for the components solar field + receiver, TES, and power block depending on the storage hours. Current cost (left bar), medium cost (middle bar), and low cost (right bar) scenario. The share of the power block decreases significantly with increasing storage hours.

In contrast, the cost split between PV and the Li-Ion battery storage remains almost constant for all storage durations (see Figure 18) because the share of power-related costs in the investment costs is much smaller than the share of power block costs for CSP. We observe the same downward trend for increasing storage hours for PV+BESS as for CSP; however, it is much less distinct. Since there is a stronger relative cost reduction expected for the Li-Ion battery than for the PV modules, the share of the PV module cost in overall investment cost becomes larger in the medium and low cost scenarios.

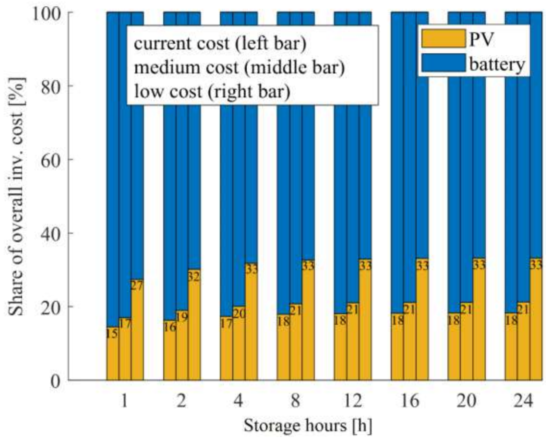



Figure 18: Shares of overall investment costs for the components PV and BESS depending on the storage hours. Current cost (left bar), medium cost (middle bar), and low cost (right bar) scenario. In contrast to CSP+TES, the ratio between the two components PV and BESS stays almost the same for all storage hours.

## 4.5 Discussion and limitations

The results of our analysis show that the competitiveness of CSP combined with TES in comparison to PVS in future fully decarbonized electricity systems is highly dependent on the required storage size. We find that PV+BESS is most competitive for short storage durations, even without learning, and CSP+TES is more economical for longer storage periods unless there is much stronger learning for PV+BESS than for CSP+TES. The tipping point of storage hours when PV+TES becomes more competitive than PV+BESS strongly depends on the price development of the technology components. The corresponding tipping points lie between 2-3 hours (current cost) today and in the future at around 4 hours, assuming the medium cost reduction scenarios. If both sets of technologies reduce cost strongly, the tipping point will move to about 10 hours; if CSP+TES costs do not decrease as envisioned, but PV+BESS costs decrease strongly, then it is conceivable that PV+BESS is cheaper than CSP+TES for the entire night-time storage niche up to 24 hours storage time. At the same time, if PV costs decrease very strongly compared to CSP costs, PV+TES might be able to cover longer storage durations at a lower cost than CSP+TES. The competitive advantage of CSP/PV+TES for longer storage periods is driven by the fact that the CSP power block is decoupled from the other technology components and that its size does not increase linearly with the storage hours in contrast to PV+BESS. Also, there is very much learning potential in BESS compared to the other technology components, and this greatly impacts the competitiveness of PV+BESS. The competitiveness of

PV+TES, however, strongly depends on the learning rates of PV since the cost reductions of TES apply to CSP+TES as well. For the competitiveness of CSP+TES compared to PV+BESS, the impact of storage duration is stronger than the impact of learning in CSP or TES.
These results are in line with Feldman et al. (2016), who find that for three hours of storage, PV+BESS tends to produce a lower projected LCOE than CSP+TES, whereas, for nine storage hours, it is the opposite. Lovegrove et al. (2018) find CSP+TES to be competitive for six storage hours and more, whereas PV+BESS is only considered competitive for shorter storage durations. Payaro et al. (2018) also find that for a capacity factor of 85%, CSP+TES is more competitive than PV+BESS in any cost scenario, whereas it depends on the learning for a 50% capacity factor. We add to these findings by providing updated technology costs and showing what these tipping points depend on, i.e., the learning rates in CSP and BESS technologies.

There are some limitations to our study. In our analysis, we looked at an isolated system providing electricity at full capacity for various durations after sunset. A real-world power system would likely not demand exclusively such a generation pattern but rather allow for generation also during sun hours, and it may not require baseload generation but rather (residual) load-following operation of the flexible power fleet. Operational behavior and economics (e.g., part-load operation, additional revenues in balancing markets, economies of scale) will look differently in a real electricity system where additional electricity to the analyzed storage hours could be sold on the market. Then, other factors like the availability of alternative generation assets might come into play that influence the competitiveness of all technology options. Contrary to what is reflected in our model setup, the storage options could provide different ancillary services, and BESS or TES, in combination with an electric heater, could make use of additional arbitrage opportunities by charging additional electricity from the grid. On the other hand, grid constraints and integration costs play a role in the expansion of renewable energy sources. For further considerations, when comparing different renewable energy options and their ability to dispatch their electricity generation, they should be taken into account (Mehos et al. 2016). Also, CSP and PV use different components of solar radiation to produce energy. The required continuous electricity generation from storage up to 24 hours in this study is more probable for CSP than PV because cloudy days without any DNI are possible, whereas 24 hours without any GHI are a rather theoretic setting.

There are some real-world examples showing the complementarity of the analyzed technology options. In Morocco, the Noor Midelt hybrid solar plant (800 MW) will be the first solar project in the world to combine PV as well as CSP with TES instead of the initial project plan to include PV+BESS. With PV prices decreasing faster than expected, this combination was found to be the optimal mix to deliver electricity for the day *and* five hours after sunset at 0.07 USD/kWh (SolarPACES, 2020). To gain ground sustainably in the electricity sector, CSP needs to keep up with the expected steep cost reductions expected for PV (Jorgenson, Mehos, and Denholm 2016). In terms of cost reductions, the advantage of CSP is that the globally installed capacity is much smaller than the PV capacity, meaning that, following the concept of technological learning, cost reductions can be achieved with relatively low capacity additions in absolute terms. Although CSP learning rates have not been as high as for PV, observed learning has been in some periods up to 18 % (Lilliestam et al. 2017), and CSP has shown the largest year-on-year electricity cost decrease of all renewable electricity technologies (26% for 2017-2018) (IRENA, 2019b). To achieve the medium cost reductions assumed in this analysis, the investment cost for the solar field and receiver system of CSP must decrease by 25% in total. With 5.8 GW of CSP projects being operational worldwide (SolarPACES 2019) and a learning rate of 20%, CSP has to add around 7 GW of global capacity to achieve this medium cost scenario. This seems feasible for a large country or world region, like the EU (and Spain), China, the US, or a group of MENA countries that have already collected experience with CSP. If one of these regions chooses to establish support policies explicitly for CSP, then they will have several competitive technology options – including TES, which can be combined with PV as well – available to provide dispatchable solar power. PV+BESS is suited for short evening or morning peaks, whereas CSP+TES can deliver baseload if need be for the whole night. Thus, the two options can complement each other to fulfill the specific demand profiles in different locations. To enable future electricity systems to cover short-term as well as long-term flexibility needs, it is advisable to further develop PVS as well as CSP+TES and support deployment of both options in the electricity market: both configurations have a role to play in the future fully decarbonized, renewable power system. This way, the optimal technology combinations will be available for the different applications and time scales and help to provide dispatchable renewable electricity for deeply decarbonized power systems.

## 4.6 Nomenclature

**Sets**

| | |
|---|---|
| $a, A$ | Area, set of areas |
| $A^R$ | Subset of areas in region |
| $g, G$ | Technologies, set of technologies |
| $G^{dis}, G^{ndis}$ | Subset of technologies that are dispatchable/non-dispatchable |
| $G^{St}$ | Subset of storage technologies |
| $r, R$ | Region, set of regions |
| $t, T$ | Time step, set of time steps |
| $R^{exp}, R^{imp}$ | Subset of regions that can be exported to/imported from |

**Parameters**

| | |
|---|---|
| $av$ | Availability of the technology (-) |
| $C_g^{Ex}$ | Existing technology capacity (MW) |
| $c^{Fix}$ | Fixed operation and maintenance costs (€/MW) |
| $c^{Inv}$ | Annualized investment costs (€/MW) |
| $c^{Var}$ | Variable operation and maintenance costs (€/(MWh/h)) |
| $d^{dh}$ | District heat demand ($MW_{th}$) |
| $d^{el}$ | Electricity demand ($MW_{el}$) |
| $e^{loss}$ | Transmission loss (-) |

**Variables**

| | |
|---|---|
| $C$ | Newly invested capacity (MW) |
| $Q$ | Commodity level (generation or consumption) (MW) |
| $Q^{curt}$ | Curtailed electricity ($MW_{el}$) |
| $Q^{dh}$ | District heat level ($MW_{th}$) |
| $Q^{dh,inSt}, Q^{dh,exSt}$ | Heat sent to/taken from storage ($MW_{th}$) |
| $Q^{el}$ | Electricity level ($MW_{el}$) |
| $Q^{el,inSt}, Q^{el,exSt}$ | Electricity sent to/taken from storage ($MW_{el}$) |
| $Q^{trans}$ | Transmitted electricity ($MW_{el}$) |

# 5 Flexible demand: Case study 2 - demand response by heat pumps

Following the analysis of the case study on a supply-side flexibility option in the previous chapter, this chapter now presents a demand-side flexibility option: demand response by decentral heat pumps. It answers the research question "*What is the potential of decentral heat pumps for providing flexibility to the future electricity system?*" and is based on Schöniger, Mascherbauer, et al. (2023). After choosing a country with the highest solar resource in the EU in the previous chapter, Austria here serves as a showcase for a central European country with significant heating demand, which will be increasingly electrified alongside decarbonizing the energy system. The topical focus on electric heating, therefore, sheds light on one sector coupling application that will gain importance in many countries in the coming years. This chapter puts focus on one specific demand category, namely decentral heat pumps and their load shifting potential in Austria in 2030. It also highlights the impact of chosen simplifications for modeling flexibility options in complex energy system models with a wide range of flexibility options, as then done in Chapter 6.

## 5.1 Background

While flexibility options historically have focused on the supply side, demand response is a balancing option to adapt electricity demand to variable generation patterns. The electricity consumers' demand is, to a certain extent, elastic, dependent on the framework conditions and market design. Demand response leads to a particular potential of provided physical storage, indirect storage like thermal inertia of buildings, or the willingness to adapt demand behavior (Gils 2016).

Increased sector coupling caused by the decarbonization of other sectors, like (renewable) P2H, is another promising option for flexibility provided to the electricity system, specifically in countries where e-mobility or e-heating is rapidly growing. For achieving fully decarbonized energy systems, smartly integrated system design is vital to benefit from the flexibility provided by sector coupling (Mathiesen et al. 2015; Kiviluoma, Rinne, and Helistö 2018). Decarbonizing the heating sector requires increasing capacities of heat pumps (HPs) that enable efficient conversion of electricity into thermal energy, which is usually cheaper and storable for extended periods. These technologies can provide flexibility to the electricity system in future energy systems by exploiting the building mass's thermal inertia or linked buffer tanks to shift electricity demand to hours of higher renewable energy production in the electricity grid.

There are different ways to implement HP flexibility in models, as described in detail in the subsequent chapter (see Chapter 2): On the one hand, in many studies, bottom-up building sector models are used to represent heating technologies in a high level of detail. These models simulate

HPs and storage systems with their techno-economic parameters like the coefficient of performance (COP), storage loss, building type, and temperature dependency in high granularity. Still, they often do not explicitly consider the overall electricity system but feed in electricity price signals as exogenous inputs. On the other hand, many analyses use energy system models that cover several sectors, like electricity, heating and cooling, transport, fuel markets, and industrial processes. Whereas detailed building sector models simulate the flexibility potential in a high degree of detail, energy system models have to break down the information from building sector models to the minimum necessary data. That means modelers have to simplify the electricity demand profile of HPs and the assumed characteristics of the "storage" option HP.

This chapter addresses two main research questions related to this topic: What is the flexibility potential of heat pumps in decarbonized electricity systems? How can we adequately model the flexibility potential in energy system models without losing relevant information on HP technology characteristics? We identify the potential flexibility that residential HPs for space heating can offer to a decarbonized electricity system by combining a detailed bottom-up building sector model and an energy system model instead of focusing on one side of the analysis. We analyze system-wide effects in high temporal resolution for an entire year. We further investigate the impact of the choice of techno-economic attributes in more detail and conduct a deterministic sensitivity analysis to derive the factors that impact the potential in modeling the most. This enables us to draw conclusions on the choice of the modeling approach and provide general advice for the model-based assessment of flexibility provision by HPs in energy system models. Austria's electricity system in 2030 serves as a case study to provide answers to the research questions stated above. In Austria, the Renewable Expansion Act adopted in July 2021 created the legal and organizational framework for implementing Austria's energy and climate policy goals: 100% electricity from renewable sources by 2030 (nationwide, at a yearly balance) and climate neutrality by 2040. This implies 27 TWh of additional annual electricity generation from renewable sources by 2030, adding significant amounts of fluctuating solar and wind generation to the system. Because of this 100% renewable target in the electricity sector by 2030 and the topography of a rather cold country with high penetration rates of (recently) installed HPs, the lessons learned from Austria can provide interesting insights for other countries with similar characteristics or policy intentions. They may also offer useful insights for the path towards full decarbonization of other sectors within Austria or elsewhere since the value of flexibility measures increases with more ambitious climate targets (Nagel, Kirkerud, and Bolkesjø 2022).

## 5.2 Literature review on heat pump flexibility

A broad range of literature describes the flexibility potential of demand response applications and HPs as one option. The literature dealing with HP flexibility in general and, more specifically, with a

focus on Austria, can be divided into two fields: On the one side, bottom-up, very detailed technology-focused studies on HPs at the building and applications level. On the other side, studies that use integrated energy system modeling to cover several sectors like electricity, heat, and transport and their interactions through sector coupling. Our study combines both approaches – a detailed building sector model and integrated energy system modeling – for the specific case of Austria.
Several preconditions must be met for HPs to provide flexibility to the overall electricity system. First, flexibility options used for load shifting rely on the availability of a buffer system and a utilization rate of less than 100%, enabling both a downward and upwards regulation of the demand profile (Lund et al. 2015). A further precondition for the efficient use of this flexibility option is the automation of the control system, and communication interfaces with the overall electricity system requiring as little interaction as possible with the end user. Increasing shares of installed HPs have control systems that can also be accessed externally, e.g., by using a cloud system provided by the component manufacturer and used by aggregators or grid operators. Another precondition is that end users see time variable tariffs as an incentive to provide flexibility to the system (Patteeuw, Henze, and Helsen 2016).

Several studies have focused on the potential role of HPs and electric heating as flexibility options in the electricity system using energy system models. The literature shows a consensus that power-to-heat can contribute to decarbonization and integrate variable renewable electricity generation. Kirkerud, Bolkesjø, and Trømborg (2017) analyzed the Northern European power system, characterized by a high share of power-to-heat sector coupling in 2030. They find that power-to-heat in district heating can increase system flexibility in the short and long-term perspectives. Since district heating (with large storage tanks) is the prevailing space heating technology in urban parts of the Nordics, district heating HPs can also cover seasonal variability in electricity generation. Kirkerud, Nagel, and Bolkesjø (2021) analyze the economic potential of various demand response technologies for the Nordic power market, finding that demand response may contribute to 18.6% of the total peak load in 2050 in this area. Most of this potential is provided by the household and tertiary sector, while electricity-to-heat is the flexibility option that contributes the most. On the contrary, Schill and Zerrahn (2020), analyzing the German 2030 energy system, state that short-term electric storage heaters are unsuitable for balancing inter-annual supply because of the seasonal mismatch of heat demand and renewable generation. Only minor benefits for the short-term operation can be seen in their study. So, the size of the storage tanks and the application in decentral buildings versus central seasonal storage facilities is essential when analyzing HP flexibility potential. We focus on decentral HPs in Austria in this study.
Often in energy system modeling, the (relatively new) aspect of HP flexibility is modeled as a type of electricity storage that is well-known and has been implemented in energy system models for a long time. This type of functional storage is characterized by a storage capacity [MWh] and a charging/discharging power [MW], which is, in the case of HPs, equal to the installed HP capacity and

able to provide flexibility to the system. The representation of HPs as functional storage in the energy system can be refined by adding certain techno-economic constraints for shifting time and availability, e.g., the frequency of the application (cycling) and the shifting time. In reality, these parameters are not static but change over time because they depend, e.g., on outside temperatures. For example, in winter, more negative flexibility can be provided by HPs because a higher load can be shifted. Still, when it is freezing, the possible shifting time differs from summer situations (Sperber, Frey, and Bertsch 2020). The implementation of time-dependent parameters and temporal sums leads to increased complexity and runtime of energy system models, with demand response often being only one of the multiple aspects to be analyzed in the system. When modeling flexibility options, the most important properties are i) the shifting time, ii) the amount of shiftable energy or power, and iii) the associated cost or efficiency loss (Marszal et al. 2019). The provided flexibility to the system thereby depends on the heating demand (depending on outside temperature, comfort level, and building standards), the losses (depending on outside temperature and insulation), the comfort level (acceptable deviation from standard indoor temperature), and thermal mass of the building. In reality, the forecast accuracy of renewable electricity generation and electricity prices will also be decisive for the used shifting potential. The motivation for demand shifting can be manifold: Minimization of $CO_2$ emissions, maximization of the integration of VRE into the system, maximization of self-consumption of decentral generation, peak shaving, or overall system cost reduction (Khorsandnejad and Malzahn 2021). We minimize overall system cost and derive results for the potential of HPs to shift peak load periods, reduce system cost, price variability, and curtailment of wind and solar generation.

Olkkonen et al. (2018) also stress the importance of considering the varying availability of flexibility options over seasons and daytime since they find for Finland that demand-side flexibility resource capacity varies significantly, resulting in available capacity between 80 and 5600 MW. They state that the results are very sensitive to constraints of shifting time intervals of the considered demand-side flexibility options. We analyze the limitation of shifting time in a sensitivity scenario and model the flexibility in hourly resolution over the whole year, capturing short- and long-term dynamics. Studies have found that the resulting flexibility needs in energy system modeling are very sensitive to the choice of method for time aggregation (Koduvere, Buchholz, and Ravn 2018). Gils (2016) developed a novel demand response application providing a transferable approach for any linear optimization model and applied it to the case study of Germany. He stresses that demand response is most suited for the provision of power, not energy, which makes the appropriate representation of temporal resolution even more critical.

Patteeuw, Henze, and Helsen (2016) model the electricity generation system and residences with HPs in an integrated modeling approach. They compare a direct-load control scenario and several dynamic time-of-use pricing scenarios and identify better performance for the former, especially at high levels of residential HP penetration. This finding implies the importance of appropriate tariff structures, price signals to the customers, control automation, aggregation entities, and high-quality forecasts for efficient use of demand-side flexibility provided by HPs.

Østergaard and Andersen (2021) evaluated the impact of electricity taxes on i) the incentive to increase HP and thermal energy storage capacities and ii) the alignment of HP operation with the dynamic electricity system needs. They do not find incentives for more HP capacity but for tentatively 20% more thermal storage and, therefore, more flexible operation according to the electricity prices. Higher thermal energy storage utilization leads to higher losses and energy consumption. Fitzpatrick et al. (2020) find an increase in overall primary energy consumption of up to 9.1% when HPs are operated flexibly. They state that real-time pricing is the most suited tariff structure for offering energy flexibility with the lowest associated electricity costs. For their case study of a residential building in Germany, they state a building's potential energy flexibility of up to 1370 $kWh_{el}$ over the heating season with average specific (marginal) costs of between €0.024–0.035 per $kWh_{el}$ of flexibility provided.

The effects of sector coupling on electricity price formation have been studied. It could be shown that sector coupling can reduce low or even negative prices in future electricity markets. That cross-sectoral demand bidding will be crucial for the price formation in future electricity markets (Härtel and Korpås 2021), increasing the market value and competitiveness of VRE producers (Kirkerud, Bolkesjø, and Trømborg 2017).

Literature focusing on HP flexibility potential in Austria presents rather heterogeneous findings mainly due to the assumptions taken to assess the flexibility potential. These assumptions are related to the assumed market penetration of HPs in the future electricity system, shifting potential depending on the building stock, and renovation rates in the country.

Haas, Auer, and Resch (2022) identify in their analysis of how to integrate high amounts of variable renewable energy sources in Austria the critical relevance of flexibility options. Besides the need for business models fostering their investment, they see the need for i) the establishment of smart infrastructure to control flexibility options like HPs, and ii) coordinating entities for aggregating various flexibility options in Austria.

Most of the studies done so far for Austria focus on case studies and the building perspective of HP flexibility. This chapter condenses these findings and evaluates their impact on the overall electricity system in Austria in 2030.

Moser et al. (2015) analyzed the flexibility potential of various applications in the residential sector. They find a maximum load shifting potential of 1.3 kW per household HP for the residential sector in Austria. This value is the average of a broad range of different households. They also stress the negative impact of increased COPs on flexibility potential and the positive effect of increased market penetration of HPs in the heating sector. They state a maximum shifting time of 1 hour, for which 85% of this potential is available. Weiß (2019) conducted a very detailed analysis of the impact of building design parameters on energy flexibility with a focus on high-performance buildings in

Austria. By developing a simulation-based methodology to quantify energy flexibility, he includes the perspective of building designers, owners, and grid operators. His case studies show the impact of building design on energy flexibility. He states possible load shifting times of HPs for more than 24 hours due to his focus on zero and plus energy buildings. Spreitzhofer (Spreitzhofer 2018) focused more specifically on HP owners' perspectives. She analyzed the economic potential of the flexible use of HPs in single-family houses for the Austrian balancing market for manual frequency restoration reserve. She simulated a pool of 400 single-family houses with varying thermal characteristics to derive a technically feasible flexibility range and achievable economic revenues. As the most critical factors for the flexibility potential, she identified building insulation, electric power of the installed HPs, and inhabitants' convenience. Interestingly, she also finds that the impact of an additional storage tank on the flexibility potential is low compared to those factors. The highest potential lies in existing buildings because of their high heat load, followed by low-energy houses with air heat pumps. She shows that the highest potential for all building types lies in winter, followed by autumn and spring. The flexibility potential in summer is for most building types negligible. For the heat shifting time, she finds a high dependency on the building type and values between 4-8 hours and 12 hours (for a passive house). To make this potential accessible, she emphasizes the importance of affordable and standardized automation of the control system and communication infrastructure. Mascherbauer, Schöniger, et al. (2022) analyzed the response of individual households' energy consumption to variable real-time electricity prices with an hourly technology operation model. They find that the economic incentive to shift load is higher for older buildings with higher energy demand. For different price profiles for 2030, they find an annual amount of shifted electricity between 11 and 26 $GWh_{el}$ by the thermal mass alone in Austria's single-family houses.

Suna et al. (2022) analyzed Austria's electricity and district heating system in 2030, evaluating a wide range of flexibility needs and options, including HPs, for different timescales (daily, weekly, monthly, and annually). They assumed an installed HP capacity of 2909 $MW_{el}$ for space heating in the residential and commercial sectors, with 30% of the HPs being controllable for demand response. The power system's associated storage size (representing buffer tanks and building mass considering new buildings and refurbished existing buildings) is 2494 $MWh_{el}$, corresponding to a shifting time of 2.9 hours. After considering simultaneity effects, they state a maximal potential of 526 $MW_{el}$ of flexible HPs in Austria in 2030. They found that the vast majority of the flexibility contribution of HPs takes place on the daily time scale. In contrast, HPs do not contribute to balancing weekly or seasonal mismatches of supply and demand. On the daily time scale, residential and commercial HPs provide around 10% of the flexibility needed to balance hourly fluctuations per day according to their integrated power and district heating modeling. This corresponds to approximately 480 $GWh_{el}$/a shifted by HPs in Austria in 2030.

## 5.3 Method, models, and data

There are two main methodological steps in this work, one preparatory step and the energy system modeling, which is the focus of this chapter. First, the flexibility potential of the building stock heated by HPs is modeled in a detailed building sector model to identify the central characteristics of the flexibility provided (based on the method developed by Mascherbauer, Kranzl, et al. (2022) and Mascherbauer, Schöniger, et al. (2022)). The information derived from the first step feeds into the bottom-up energy system modeling as described below. We model the electricity and district heat sector and decentral HPs in Austria's residential and commercial sectors. The investment and dispatch optimization of the electricity system is conducted in the open-source energy system modeling framework Balmorel (The Balmorel Open Source Project 2019; Wiese et al. 2018), minimizing overall system cost in hourly resolution for the year 2030 in Austria. We derive generation mix, overall system cost, electricity spot prices, and emission levels as output. We apply a deterministic sensitivity analysis and evaluate relevant energy system output variables, with pessimistic and optimistic techno-economic HP values of each uncertain variable (Chelst and Bodily 2000).

### 5.3.1 The energy system model

For this chapter, the energy system model Balmorel is used, which is described in Chapter 4.3.2. For our analysis, we focus on the electricity and district heat sector and include individual heating by HPs in the residential and commercial sectors. We model the Austrian electricity and district heat system and the neighboring countries in hourly resolution, considering every country as one region (one node), disregarding inner-national transmission and distribution bottlenecks. The electricity and district heat sectors of the neighboring countries Czech Republic, Germany, Hungary, Italy, and Slovenia are modeled to capture export and import dynamics. HP flexibility is only assumed for Austria since this is the focus of our study. To evaluate the flexibility potential of HPs, the scenario with flexible HP operation is compared to a reference case where inflexible electricity demand of the HPs is assumed.

### 5.3.2 Implementation of heat pump flexibility in Balmorel

Demand-side flexibility is implemented in Balmorel via the add-on "demandresponse" (Balmorel Community 2022), which was developed by Kirkerud, Nagel, and Bolkesjø (2021) for Balmorel following a theoretical concept close to Gils (2016). The add-on enables the model to endogenously optimize the demand profile of flexible consumers under given restrictions. In times of high marginal costs of the supply side of the electricity system, i.e., high electricity spot prices, the demand will be reduced. In contrast, electricity demand will be increased in times of low electricity prices. The add-on is used and further developed for this study. The heat demand profile is provided in one profile for the whole year in this study compared to a combination of seasonal and weekly patterns in the original add-on. Further, thermal losses are only applied for preheating, not for precooling.

The scheduled electricity demand by HPs is defined by the installed capacity of HPs, which are able to shift their demand, their full-load hours, and the hourly demand profile.

The modeling of load shifts is done by utilizing a "virtual storage" concept. The following parameters and variables describe this storage and were developed by Kirkerud, Nagel, and Bolkesjø (2021) and adapted for the purpose of this study:

The load shifting $P_c(t)$ [$MWh_{el}$] describes the difference between the scheduled electricity demand $L_c(t)$ [$MWh_{el}$] and the realized electricity demand $R_c(t)$ [$MWh_{el}$] (Eq. (13)) at time step $t$. If the realised demand is lower than the scheduled demand, i.e., the load was reduced and negative flexibility was provided to the system, $P_c(t)$ [$MWh_{el}$] is positive.

$$P_c(t) = L_c(t) - R_c(t) \tag{13}$$

The upwards or downward demand shifting $P_c(t)$ [$MWh_{el}$] of technology $c$ determines the energy content $E_c(t+1)$ [$MWh_{el}$] of the virtual storage, which can take negative and positive values, meaning the load can be shifted to a previous or a later point in time (Eq. (14)).

$$E_c(t+1) - E_c(t) = P_c(t) \tag{14}$$

There are two options to define the limitations of the virtual storage within those the model can optimize the shifting of flexible loads: Either by defining a) a rigid shifting time $\Delta t_c$ [h] or b) a fixed limit of $E_c^{max}(t)$ [$MWh_{el}$].

In the case of a), the upper limitation of the virtual storage is the sum of all loads within $\Delta t_c$ [h] and is, thus, time-dependent since it depends on the scheduled loads of the considered time frame, which is set by $\Delta t_c$ [h] (Eq. (15)).

$$E_c^{max}(t) = \sum_{tt} L_c(tt) \quad \forall t \leq tt \leq t + \Delta t_c \tag{15}$$

The maximal possible demand reduction (downward shift) $P_c^{max}(t)$ [$MWh_{el}$] is the load to the extent scheduled at time step $t$ (Eq. (16)).

$$P_c^{max}(t) := L_c(t) \tag{16}$$

The maximal possible demand increase $P_c^{min}(t)$ [$MWh_{el}$] (upwards shift) is the difference between the scheduled load and the maximal demand (defined by the installed capacity) of the technology $\Lambda_c$ (Eq. (17)).

$$P_c^{min}(t) := L_c(t) - \Lambda_c \tag{17}$$

Eq. (16) and Eq. (17) are ensured by

$$P_c^{min}(t) \leq P_c(t) \leq P_c^{max}(t) \ \ \forall\, t, c. \tag{18}$$

In the baseline scenario, the electricity demand of the HPs is part of the overall electricity demand in Austria and is assumed to be inflexible as the general electricity demand. Given the techno-economic constraints, the electricity is handled separately and can be shifted in time in the flexibility scenarios.

Figure 19 shows the main variables and parameters describing the load-shifting potential of HPs in the case of a) limitation by shifting time. It describes the theoretical concept developed by Gils (2016) and implemented in Balmorel by Kirkerud, Nagel, and Bolkesjø (2021).

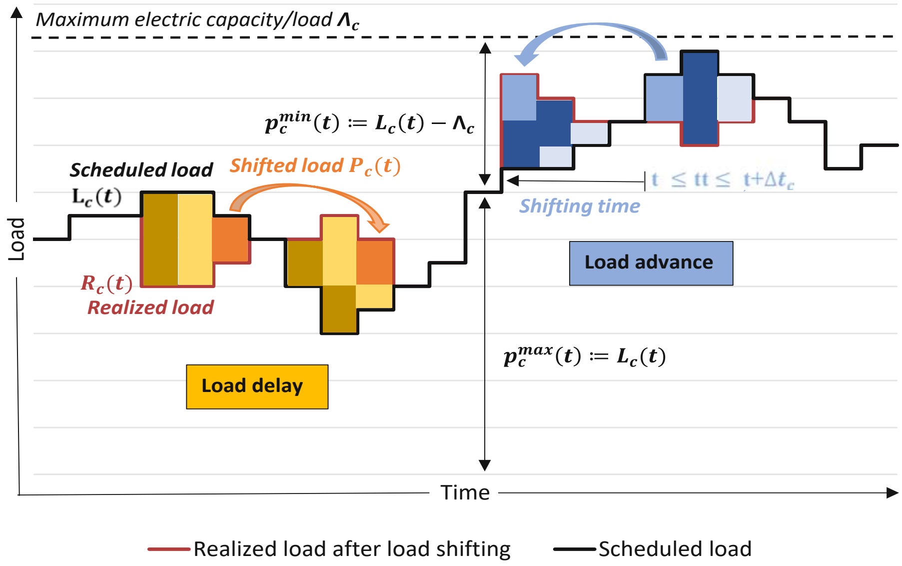



Figure 19: Parameters and variables describing the flexibility potential of load shifting of HPs in Balmorel by using shifting time $\Delta t_c$ as a limitation.

### 5.3.3 Heating profiles

A crucial element when assessing the flexibility of HPs is the nature of the heating profile, which determines the profile of the electricity demand for HPs. Following the seasonal patterns of heating degree days, heat demand is highest in winter and lowest in summer in Austria, which has an effect on the flexibility potential provided by power-to-heat technologies.

For the purpose of this study, we use the hourly heat demand profile for space heating in the residential sector for the year 2010, provided by Pezzutto et al. (2018). The profiles are based on hourly profiles for typical day types depending on the country-specifics and depend on the temperature, resulting in a yearlong assembled demand profile (unitless and normalized). The original data is on NUTS2 level and was aggregated for Austria[21]. The heating profile follows a seasonal pattern as well as daily patterns. The hourly profile during one week follows the typical day structure with higher demand during the night than during the day (see Figure 20). This pattern is more distinct during the winter than during the summer: The profile is rather flat during the summer and shows more fluctuations during the winter. Figure 20 shows the heat demand profiles of different selected weeks in 2010.

[21] Even weight for all NUTS2 regions

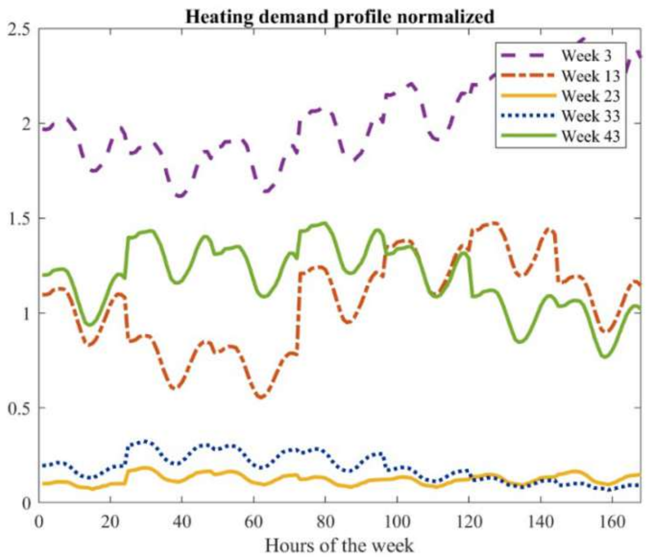



Figure 20: Heat demand profiles for the residential sector for weeks 3, 13, 23, 33, and 43 (normalized) in Austria for the year 2010. (Source: Own illustration based on Pezzutto et al. (2018))

### 5.3.4 Flexibility parameters

In the heating sector, opposing trends of decarbonization leading to a strong increase in installed HP capacities, higher standards in temperature comfort and housing space on the one side, and improved energy efficiency and better building standards on the other side are expected (Kirkerud, Bolkesjø, and Trømborg 2017). These trends are the basis for any assumed HP capacities and respective electricity demand for heating in modeling, which lay the basis for their flexibility potential. The technical flexibility or load shifting potential of HPs is dependent on various factors like outdoor temperature, COP, or building type. This chapter shows the impact of these different factors on the load shifting potential of HPs.

A detailed hourly technology operation model is used to model individual households' load shifting dynamics using a simplified five resistance one capacity (5R1C) approach following the DIN ISO 13790 (for further details, see Mascherbauer, Schöniger, et al. (2022) and Mascherbauer, Kranzl, et al. (2022)). Newer or better-insulated buildings can shift the demand for a longer time but have a lower heat demand. To visualize the impact of the building type, we compare two single-family building types: House 1 (see Figure 21, Panel (a) and (b)) has a low insulation status but a high thermal mass. House 3 (see Figure 21, Panel (c) and (d)) is well insulated but has only a medium thermal mass. The analysis shown in Figure 21 is done for a winter day at -5°C; constant room temperature without interference should be 20°C. The continuous heating power to achieve this indoor temperature under given conditions is around 10 $kW_{el}$ for house Nr 1 and about 6 $kW_{el}$ for House 3, which are representative values for single-family houses in Austria.

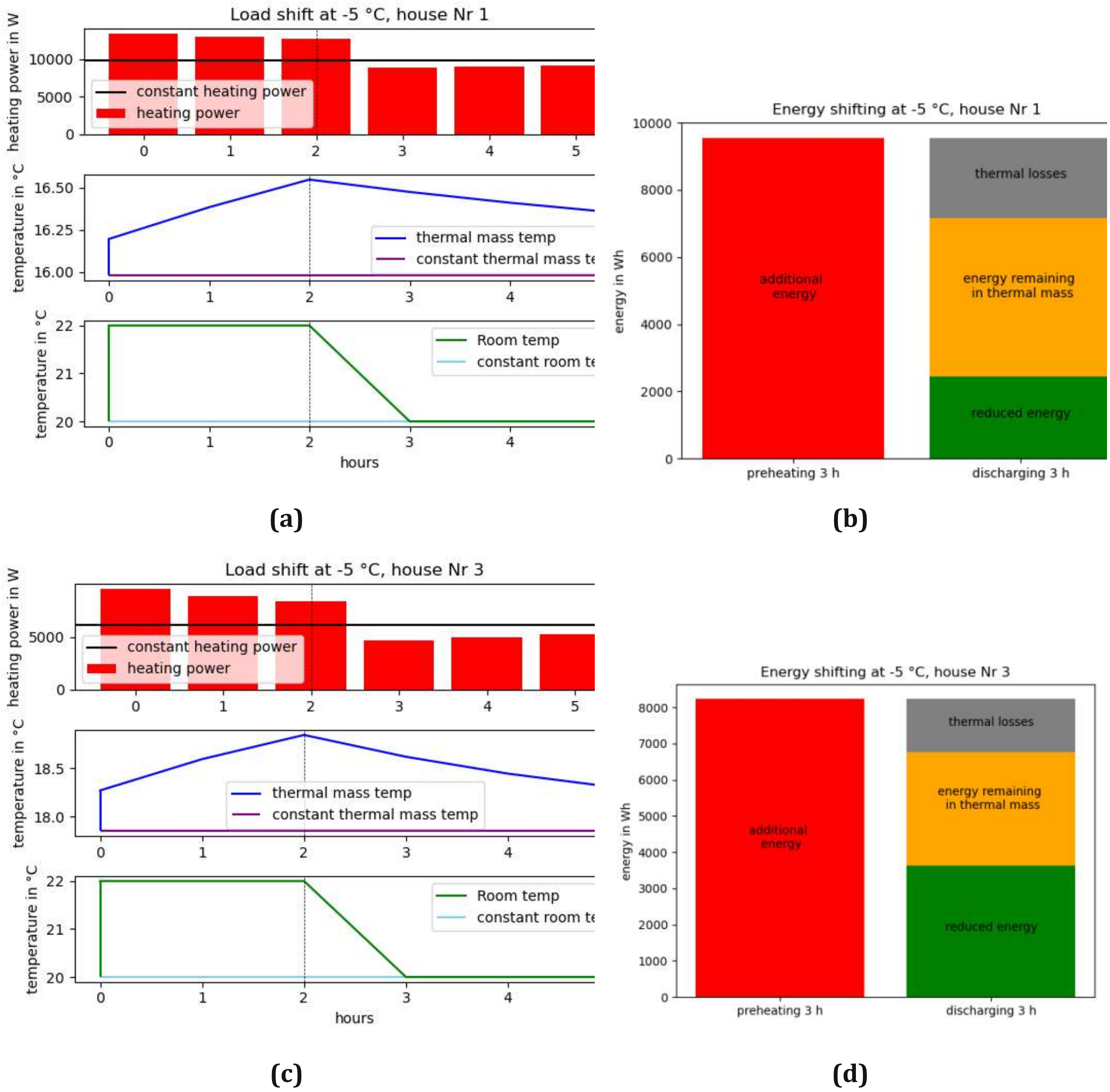



Figure 21: Heating power, thermal mass temperature, room temperature, shifted energy when preheating for three hours to 22°C instead of 20°C at -5°C outside temperature for two different building types.

Figure 21 (Panel (a) and (c)) shows the heating power, the thermal mass, and the room temperature for the case with and without load shifting ("constant"). In the example, the building is preheated for three hours which results in a room temperature of 22°C instead of 20°C. The thermal mass temperature is continuously increasing during the first three hours and decreasing in the following hours since the energy is stored in the thermal mass and discharged during the following hours. Consequently, the electricity demand can be reduced in the following three hours compared to the constant heating profile. The additional thermal energy is consumed in three ways (Figure 21 Panel (b) and (d)): i) the thermal energy that is used for heating in the following three hours, ii) the energy remaining in the thermal mass, and ii) the thermal losses. The longer the shifting process takes, the higher the share of the thermal losses. Because of these thermal losses, using the storage capacity for longer storage durations is not economical.

The calculations are similar to the finding of Wolisz et al. (2013), who identified a heating demand reduction of 20% for the four hours following a two-hour preheating phase.

The stored energy which can be used to shift the electricity demand of HPs depends on the outside temperature. The colder, the more energy is needed for heating, and the more energy can be shifted (see Figure 22). This relationship is the same for all building types assessed. Additionally, the interference time accepted to deviate from the desired room temperature of 20°C is an essential factor. This depends on the users' willingness to reduce comfort for a specific period. The longer they are willing to deviate from their desired room temperature (22°C instead of 20°C), the higher the amount of energy that can be shifted (see Figure 22). The same analysis can be done for reduced room temperature (load delay = precooling).

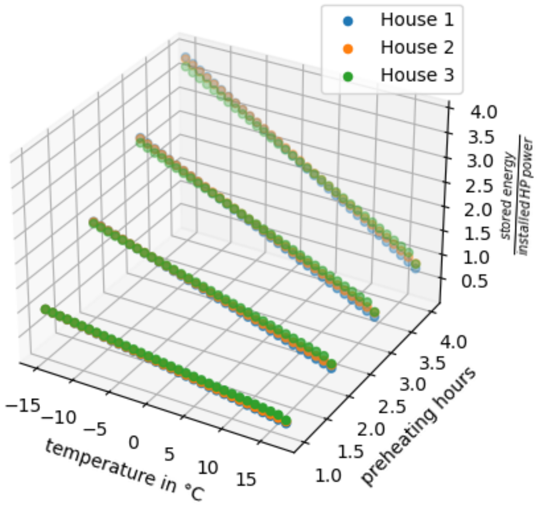



Figure 22: Stored energy [kWh] divided by installed heat pump power [kW] in dependence of outdoor temperature [°C] and preheating hours [h] (accepted time of interference to increase the room temperature from 20°C to 22°C). Houses 1-3 are single-family houses differing in thermal insulation status (in increasing order from 1 – low to 3 – high).

The associated storage capacity in the assessed cases lies between 0.5 and 4 kWh stored energy per kW installed HP capacity considering only the thermal mass of the buildings. Suna et al. (2022) find a capacity of 2.9 kWh/kW, including a buffer tank of 250 liters. For our standard flexibility scenario, we assume a capacity of 3 kWh/kW representing the thermal mass of the building as well as a buffer tank.

The temperature dependence is partly implemented in the modeling by the heating profile, but dynamic thermal losses are not modeled. In reality, those losses vary depending on the building type, insulation, and outside temperature. However, a constant efficiency loss per hour of 5% is assumed because of the thermal storage effect (Kirkerud, Nagel, and Bolkesjø estimate 3%).

In our standard flexibility scenario, the indoor temperature cannot fall below 20°C. This implies that only preheating is possible since regulating the demand downwards first and making up for the demand difference afterward would imply a temperature drop below the intended level. No variable or fixed costs are assumed in the standard flexibility scenario because load shifting does not cause a utility loss for the consumer when operated within the given constraints. However, a sensitivity analysis with variable shifting costs is conducted.

### 5.3.5 Energy system data

This section describes the overall energy system assumptions. The electricity system is modeled in hourly resolution for the year 2030. The generation profiles for PV, wind, and hydro represent the weather year 2008. The $CO_2$ price is 52.8 €$_{2015}$/t $CO_2$ (Distributed energy scenario from ENTSO-E, 2021). The assumed electricity and district heating demand and installed conventional capacities stem from the AURES II project (AURESII 2022). Assumptions on the renewable deployment of PV, wind, and hydro RoR were aligned with the Ten-Year Network Development Plan (TYNDP) 2020 National Trends Scenario (ENTSO-E 2021b). The assumptions for Austria are taken from the national energy and climate plan (WAM scenario) (Environment Agency Austria 2020), and renewable capacities are refined according to the 100% renewable target until 2030 (Republic of Austria 2021). We model the public grid in Austria. Austria's overall electricity demand (without storage losses, transmission and distribution losses, and self-consumption) is 74.6 TWh, whereas 2.6 TWh is consumed by electric cars. The electricity is generated by the power plants shown in Table 11.

Table 11: Installed electricity generation capacities in $MW_{el}$ for the modeled countries

| MW | Austria | Czech Republic | Germany | Hungary | Italy | Slovenia |
|---|---|---|---|---|---|---|
| Coal | | 5 768 | 19 563 | 884 | 5 084 | |
| Geothermal | 8 | | 37 | 56 | 967 | 7 |
| Lignite | | 763 | 16 370 | 220 | | |
| Natural gas | 3349 | 1262 | 58980 | 3318 | 27856 | 877 |
| Oil | 15 | | 558 | 170 | 1 240 | |
| Waste | 150 | 100 | 1 661 | 59 | 580 | 38 |
| Nuclear | | 2 660 | | 1 887 | | 727 |
| PV central | 776 | 1 165 | 35 093 | 2 902 | 17 452 | 400 |
| PV decentral | 10751 | 3 735 | 94 299 | 3 743 | 30 796 | 1 690 |
| Hydro reservoirs | 3531 | 758 | 1 065 | 32 | 4 550 | |
| Hydro pump storage | 4800 | 1 172 | 9 422 | - | 7 276 | 180 |
| Hydro RoR | 6 807 | 395 | 4036 | 57 | 10 653 | 1 206 |
| Biogas | 73 | 275 | 4 682 | 121 | 1 417 | 45 |
| Biomass | 349 | 604 | 4 312 | 628 | 1 550 | 53 |
| Wind offshore | | | 16 717 | | 1 236 | |
| Wind onshore | 6 870 | 960 | 81 501 | 376 | 20 962 | 150 |
| Sum | 37 479 | 19 617 | 348 296 | 14 453 | 131 619 | 5 373 |

The assumption on net-transfer capacities (NTC) for transmission is displayed in Table 12, assuming a possible utilization of 80%.

Table 12: NTC capacities [MW] between countries in 2030. Values are taken from the National Trends Scenario of the TYNDP (ENTSO-E 2021b), assuming a possible utilization of 80%.

| MW | CZ | DE | HU | IT | SI |
|---|---|---|---|---|---|
| AT | 720 | 4320 | 640 | 544 (export)/ 400 (import) | 760 |

### 5.3.6 Scenarios

We assess 11 scenarios (see Table 13): First, we model the reference scenario where the residential HPs are assumed to be inflexible, following the given heat demand profile ("Reference"). This scenario serves as a reference to evaluate the flexibility potential of the residential HPs in all other scenarios.

The installed HP capacity for heating is assumed to be 2900 $MW_{el}$ in Austria in 2030, and the flexible, controllable share 30% (Suna et al. 2022). This results in an installed flexible HP capacity in the standard case of 870 $MW_{el}$, leading to an annual flexible electricity demand of 957 GWh (1100 full-load hours, according to Suna et al. (2022)). In the standard flexibility case, an associated storage capacity of 3 $kWh_{el}$ is assumed per $kW_{el}$ installed heat pump capacity ("Standard flexibility"). As deterministic sensitivity analyses, this is varied by 50% (4.5 and 1.5 kWh/kW – "Thermal storage +/- ") as this value can change and depends on assumed building stock, etc. (see again Section 5.3.4). Another critical but uncertain parameter is the installed heat pump capacity in the future since this depends on the penetration rate, technology development, price paths, national strategies, etc. We assess this in the sensitivity analyses where the installed capacity is varied by 50% (4350 and 1450 $MW_{el}$ – "HP capacity +/-"). Besides the installed capacities, the share communicating with the grid and thus can provide flexibility to the overall system is decisive for the flexibility potential. This aspect is evaluated in the sensitivity analyses "Control+/-" (15 and 45% controllable share). As described in Section 5.3.2, shifting limitations in modeling can be implemented via a storage capacity as done in our analysis (3 kWh/kW) or by a hard shifting time restriction. In the scenario "3 h shifting time restriction", a hard time restriction is implemented to analyze the impact of the two different model approaches. It is assumed that only preheating is possible because the indoor temperature level has to be kept above 20°C, i.e., precooling and reheating at a late point in time is not possible due to the comfort losses that reduce the acceptance of the demand shifting by users. However, in one scenario ("Cooling allowed"), we assess the impact of the acceptance of such a measure. In the standard case, no costs are assumed for the shifting behavior because HP owners have an economic incentive to shift demand to times of lower electricity prices and reduce their expenses. However, there can be costs and utility losses due to deviations from the desired heating profile for controlling, aggregation, and equipment. Also, Mascherbauer, Schöniger, et al. (2022) show that the economic incentive for single-family house owners is very low. Therefore, we conduct a sensitivity analysis where variable shifting costs of 29,5 $€_{2015}$/MWh (Fitzpatrick et al. 2020) are assumed ("Shifting costs").

Table 13: Scenario assumptions.

| | Inflexible scenario | Flexible scenarios | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Reference** | **Standard flexibility** | Thermal storage + | Thermal storage - | HP capacity + | HP capacity - | Control + | Control - | 3 h shifting time restriction | Cooling allowed | Shifting costs |
| Installed HP capacity [$MW_{el}$] | 2900 | 2900 | 2900 | 2900 | **4350** | **1450** | 2909 | 2909 | 2909 | 2909 | 2909 |
| Controllable share [%] | - | 30% | 30% | 30% | 30% | 30% | **45%** | **15%** | 30% | 30% | 30% |
| Flexible HP capacity [$MW_{el}$] | - | 870 | 870 | 870 | 1305 | 435 | 1309 | 436 | 870 | 870 | 870 |
| Storage capacity [MWh/MW installed HP capacity] | - | 3.0 | **4.5** | **1.5** | 3.0 | 3.0 | 3.0 | 3.0 | **time-dependent** | 3.0 | 3.0 |
| Precooling allowed | - | x | x | x | x | x | x | x | x | ✓ | x |
| Var. shifting costs [$€_{2015}$/MWh] | - | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | **29.5** |

## 5.4 Results

This section presents and compares the results for the different scenarios. First, the results of the inflexible scenario are presented, serving as the reference scenario to which the various flexible scenarios are compared.

### 5.4.1 Reference scenario: the inflexible case

In the reference scenario, the HPs operate in an inflexible mode. That means the HP electricity demand is coupled inflexibly to the heating demand it covers. These scenarios serve as a reference to analyze the impacts of HP flexibility in the different flexible scenarios done. Table 14 shows the electricity generation mix in the reference scenario. In Austria, 11.49 TWh of electricity are generated from natural gas. Considering the national target of 100% renewable generation (annual, national balance), this is only possible by Austria becoming a net exporter of electricity.

Table 14: Electricity generation per modeled country and fuel.

| Electricity generation [TWh] | Wind | PV | Hydro | Natural gas | Coal | Lignite | Nuclear | Bioenergy + waste | Geo-thermal |
|---|---|---|---|---|---|---|---|---|---|
| AT | 16.29 | 10.93 | 48.51 | 11.49 | - | - | - | 3.22 | 0.06 |
| CZ | 2.51 | 4.29 | 3.48 | 3.58 | 13.20 | 0.65 | 22.43 | 3.64 | - |
| DE | 185.26 | 113.57 | 35.46 | 18.29 | 94.47 | 53.97 | - | 22.85 | 0.30 |
| HU | 0.87 | 6.81 | 0.37 | 10.08 | 6.57 | 0.36 | 16.10 | 2.10 | 0.49 |
| IT | 56.26 | 62.17 | 46.64 | 107.76 | 38.92 | - | - | 3.93 | 8.28 |
| SI | 0.30 | 2.13 | 4.76 | 2.98 | - | - | 6.27 | 0.30 | 0.05 |

Based on the generation mix and transmission between the countries, average hourly electricity prices of 56.68 (Germany) and 70.23 €/MWh (Hungary) can be observed (see Table 15).

Table 15:Average hourly electricity price in the reference scenario per country.

| | AT | CZ | DE | HU | IT | SI |
|---|---|---|---|---|---|---|
| Electricity price [$€_{2015}$/MWh] | 62.44 | 60.70 | 56.68 | 70.23 | 69.68 | 68.69 |

### 5.4.2 Flexible scenarios

In the flexible scenarios, HPs can shift their electricity demand according to the method presented in Section 5.3.2 and to the scenario-specific limitations. Introducing flexible electricity demand by residential HPs in the model, this part of the demand can react to Austria's endogenously generated market price signals. In hours of lower electricity prices, the HPs reduce their electricity demand considering the given boundaries, and in times of higher electricity prices, they increase electricity demand.

As the standard flexibility scenario, the scenario with assumed heat storage of 3 kWh/kW is chosen (see again Table 13). Figure 23 shows the load shifting behavior of the residential HPs in a randomly chosen week (week 2) of 2030 in the standard flexibility scenario.

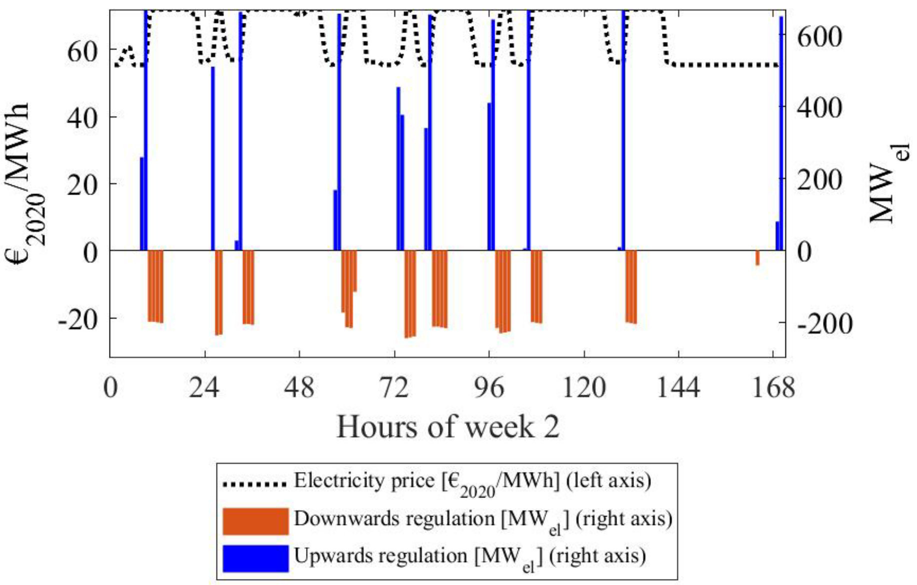



Figure 23: Load shifting behavior of the installed residential heat pumps (right axis) and electricity price (left axis) in 80 randomly chosen consecutive hours of the modeled year. Standard flexibility scenario (3 kWh/kW heat storage).

In times of (relatively) lower electricity prices, the HPs increase their electricity demand compared to the scheduled demand; in times of (relatively) higher prices, thy reduce their demand. Since only preheating is possible due to the minimal temperature requirement, the load peaks take place first (and are more distinct) than the load reductions, which are distributed over more hours. The shifting behavior is not dependent on an absolute threshold but can be observed relative to the electricity price in the previous and following hours.

The following sections give an overview of the various effects of the load shifting of heat pumps on the electricity system in the assessed Austrian case. The results are presented as an explorative, deterministic sensitivity analysis, evaluating the impact of input choice on the analyzed output variable. In the presented tornado charts (Figure 24 - Figure 30), the axis shows the value in the standard flexibility case (3 kWh storage capacity/kW installed HP capacity). The bars show the sensitivities for the i) +/-50% thermal storage, ii) +/-50% installed HP capacity, iii) +/-50% share of controllable HPs, iv) the introduction of a hard shifting time restriction, v) the possibility of precooling (additionally to preheating), and vi) the consideration of variable shifting costs (for the scenario assumptions, see again Table 13).

**Shifted electricity demand**

First, the amount of shifted electricity demand is a measure of flexibility provided to the system. The values presented in Figure 24 show the sum of the downwards regulated electricity demand, i.e., the reduction of peak load. The upwards-shifted electricity amounts to the same number plus efficiency losses caused by the shifting process.

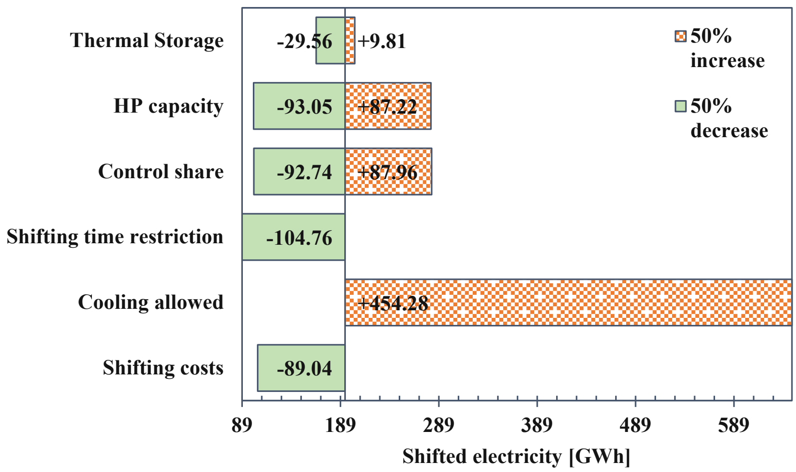



Figure 24: Shifted electricity downwards [GWh] for the flexibility scenarios compared to the standard flexibility scenario. In the standard flexibility scenario, the shifted electricity amounts to 194.01 GWh.

In the standard flexibility scenario, 194.01 $GWh_{el}$ are shifted, i.e., 19.7% of the previously identified flexible HP electricity demand. In general, pessimistic sensitivity analyses have a more significant impact than positive ones. A hard shifting time restriction reduces the amount of shifted energy compared to the modeling approach of associated storage capacities (3 kWh/kW). This is also in line with the literature (Olkkonen et al. 2018) that finds flexibility potential quite sensitive regarding assumed shifting time limitations. Considerably, assuming variable shifting costs of 29.5 €$_{2015}$/MWh reduces the flexibility provided to the same extent as halving the available heat pump capacity.

The amount of shifted electricity is highest in the scenario, where (in addition to preheating) also precooling is allowed. The reason for this is that, in contrast to preheating, precooling has no losses. For preheating, an hourly loss of 5% is assumed (see Section 5.3.4). This means an efficiency loss caused by the shifting process. This is not the case for precooling and leads to higher utilization of flexibility when precooling is possible.

### Curtailment

The results show that HP flexibility reduces curtailment of wind, PV, and hydro RoR generation (see Figure 25 for wind and PV). The avoided curtailment in the standard flexibility case amounts to 19.16 GWh (wind) and 20.79 GWh (PV) in Austria. Numbers for hydro RoR amount to 17.40 GWh compared to the standard flexibility scenario. This corresponds to 0.12% wind generation and 0.19% PV generation.

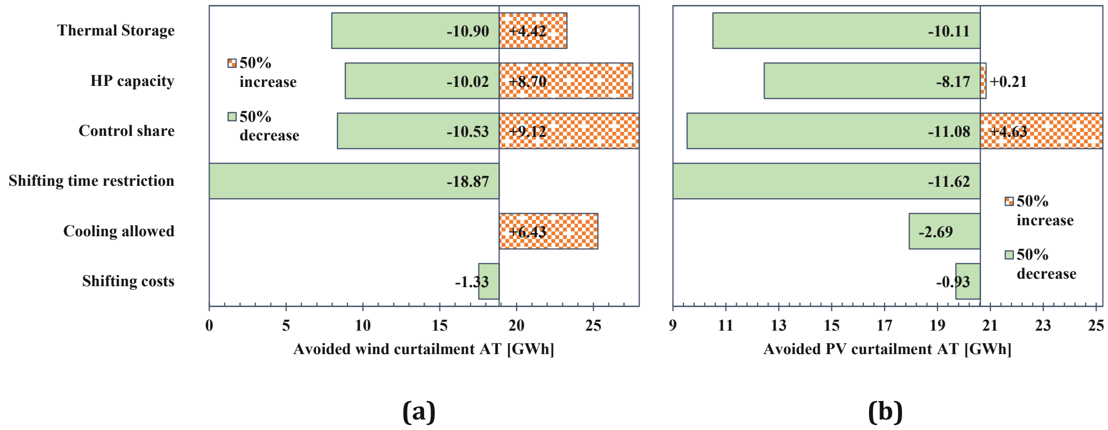



Figure 25: Avoided wind curtailment [GWh] (Panel (a)) and avoided PV curtailment [GWh] (Panel (b)) for the flexibility scenarios compared to the standard flexibility scenario. In the standard flexibility scenario, the avoided wind curtailment is 19.16 GWh, and the avoided PV curtailment is 20.79 GWh.

The hard shifting time restriction is a more relevant limitation for wind than for PV: -18.87 GWh compared to -11.62 GWh in the case of PV. This shows that wind generation could more often make use of more extensive storage than this limitation of the HP flexibility compared to PV.

Figure 25 shows that wind power can benefit more from increased HP flexibility than PV generation, i.e., additional flexibility provided by heat pumps can mainly be used by wind generation. This is due to the higher temporal correlation between wind generation and HP utilization (see Table 16), because wind generation and HP demand are both higher during winter and during the night than during summer and during the day. Increasing the storage capacity in the "Thermal storage +" scenario does not benefit PV curtailment because the heating demand in times of high solar generation is low, and additional storage cannot be used. Whereas wind shows a positive correlation with heating demand in Austria (0.280), PV (-0.299) and hydro RoR (-0.057) generation show a negative correlation.

Table 16: Correlation between heating demand and solar, hydro RoR, and wind electricity generation in Austria

| Correlation coefficient | Solar | Run-of-river | Wind |
|---|---|---|---|
| Heating demand | - 0.299 | - 0.057 | 0.280 |

Especially for PV generation, a distinct, inverse seasonal pattern is observable compared to the heating demand (see Figure 26), indicating a negative correlation.

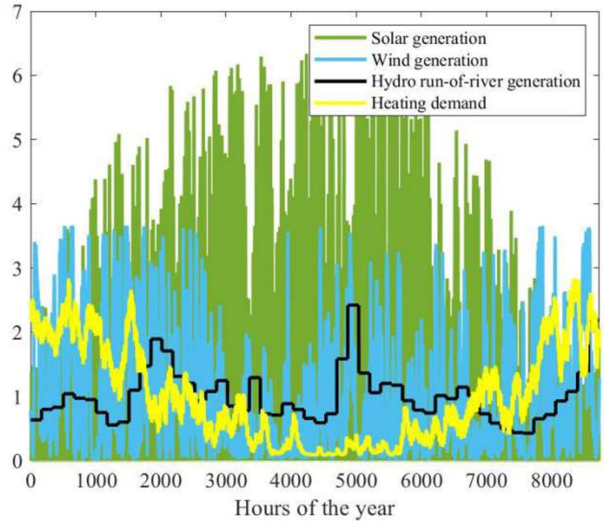



Figure 26: Austria's solar generation, wind generation, hydro RoR generation, and heating demand profiles (normalized).

These patterns show that HPs contribute to short-term flexibility, whereas the seasonal mismatch has to be covered by other flexibility options like export and import. However, on the daily time scale (hourly fluctuations within a day), the contribution can be considerable in terms of power. Suna et al. (2022) show in their analysis that heat pumps provide up to 10% of the flexibility needed within a day (hourly fluctuations within a day, aggregated over the whole year).

**System impacts**

In general, the overall system cost is reduced by HP flexibility since the model only chooses this option when the objective function of minimizing overall system cost is reduced. The highest reduction can be seen in the scenario when precooling is allowed (-0.014%) (see Figure 27). The reason for that is again that there are no thermal losses in the case of precooling.

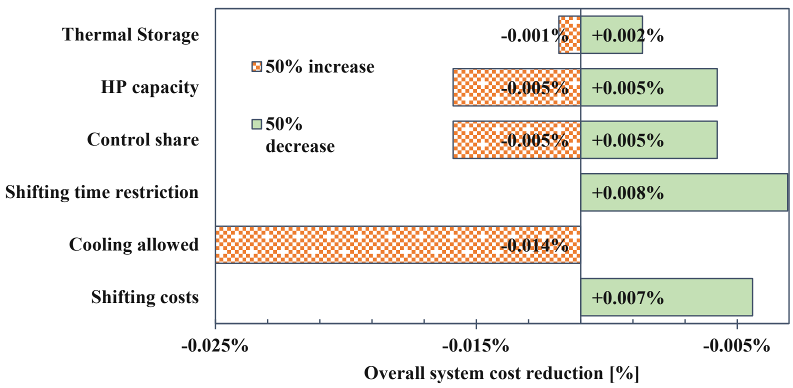



Figure 27: Overall system cost reduction [%] for the flexibility scenarios compared to the standard flexibility scenario. In the standard flexibility scenario, a -0.011% reduction is achieved.

Overall, system cost reductions are relatively low. However, it has to be kept in mind that six countries and their aggregated system cost are modeled, and Austria is a relatively small part of it. In all flexible scenarios, the average electricity price of the reference scenario (62.44 $€_{2015}$/MWh) is increased to between 62.49 $€_{2015}$/MWh ("3 h shifting time restriction") and 62.70 $€_{2015}$/MWh ("HP capacity +" and "Control+"). This means that hours of low prices are reduced, improving market values for renewable and helping their integration. Also, the standard deviation of the electricity price is reduced, creating a more stable market environment (see Table 17).

Table 17: Standard deviation of the electricity price in selected modeled scenarios.

| | Reference | 3 h shifting time restriction | HP capacity + | Standard flexibility |
|---|---|---|---|---|
| Standard deviation electricity price [$€_{2015}$/MWh] | 17.95 | 17.83 | 17.18 | 17.40 |

This result shows that HP flexibility can decrease price variance, which is expected to increase with a high share of fluctuating renewable electricity generation, especially in systems lacking sufficient transmission or large storage capacities (Schöniger and Morawetz 2022). This balancing effect of HP flexibility is also visible when analyzing the residual load (defined as exogenous load – wind generation – PV generation – hydro RoR generation) in Austria in different scenarios. Figure 28 shows the residual load for the reference scenario and the standard flexibility scenario, which ranges between about 10 and -10 GW over the year with the given energy mix and export/import dynamics of the year 2030. It shows very similar characteristics for both scenarios, i.e., the maximal values and distribution of hourly residual load are barely impacted by the modeled HP flexibility.

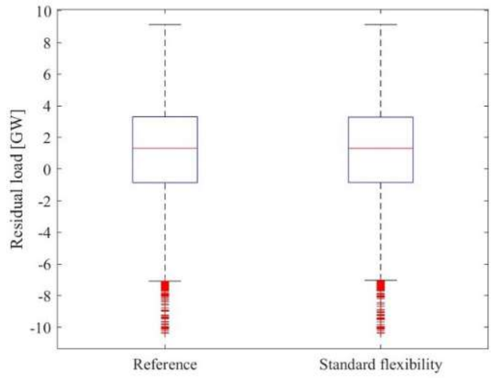
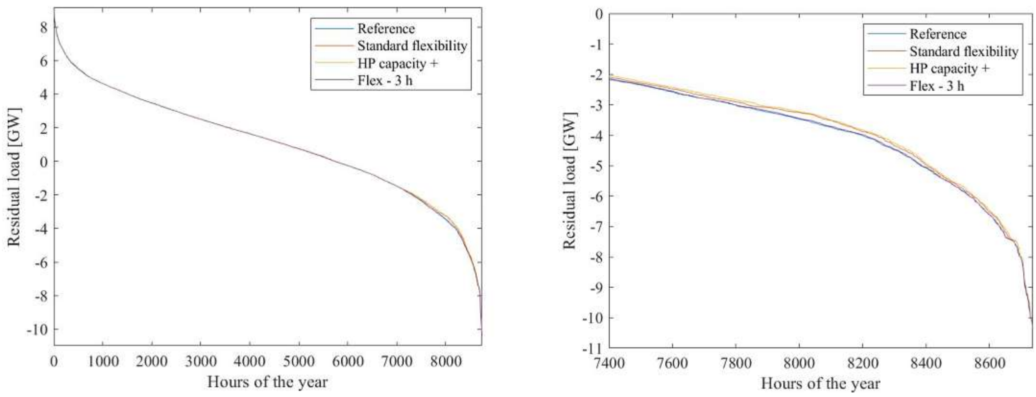



Figure 28: Residual load boxplot and duration curve for the reference scenario and the standard flexibility scenario.

However, evaluating the single hours in greater detail reveals some differences: Figure 29 shows the residual load duration curve for the standard flexibility scenario and three flexible scenarios. While changes in the overall load duration curve are barely visible (Panel (a)), scenarios differ on the part of the curve with negative residual load (Panel (b)). This means that the system especially profits from heat pump flexibility during high renewable generation. Flexibility provision takes place mainly in the form of uptake of surplus renewable generation, not in the form of reduction of load during peak demand times. This flexibility provision by HPs mainly affects wind generation during winter since the highest PV generation occurs in summer.




**(a)** **(b)**

Figure 29: Duration curve for four scenarios for all hours (Panel (a)) for all hours with a negative residual load (Panel (b)).

In hours when a positive residual load is decreased, the average reduction is -2.6%[22] in the standard flexibility scenario and -3.8% in the "HP Capacity +" scenario (upper bound scenario). The down-regulation shapes up to 4.6% of the Austrian exogenous load in the standard flexibility case.
In the hours when a negative residual load is increased, the average increase is 15.8% in the standard flexibility scenario and 21.6% in the "HP Capacity +" scenario. The shifting takes place mainly in the form of additional high peaks in times of low prices (shortly before they increase again, see again Figure 23) and then continuous reduction over several hours.
This shows that the heat transfer coefficients are of central relevance regarding possible maximal heat transfer into and out of the thermal mass.
The assumed fossil fuel prices and $CO_2$ price lead to the result that overall $CO_2$ emissions are reduced in all flexibility scenarios compared to the reference scenario without flexibility (see Figure 30).

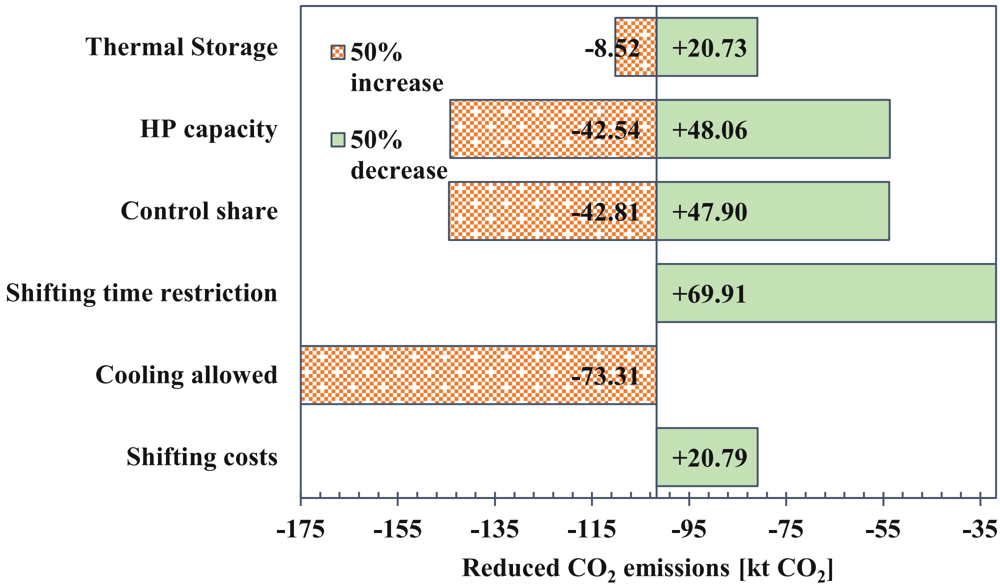



Figure 30: $CO_2$ emissions in the power and district heating sector in the modeled flexible scenarios compared to the inflexible scenario.

However, this depends on the technology mix and the assumed carbon and fossil fuel prices because the objective function minimizes costs, not emissions. Also, spill-over effects are observable, and $CO_2$ emissions in some countries are increased. This shows that flexibility always has to be analyzed in the context of neighboring energy systems and their interrelations.
Another result is that the necessary peak power capacity is not reduced in Austria, but this depends mainly on the district heat demand during winter provided by combined heat and power units.

[22] The stated average reduction and increase values are 5% trimmed mean values since in single hours, the values can be very high (in hours of a residual load close to 0).

## 5.5 Discussion and limitations

We conduct an energy system analysis evaluating the flexibility potential that decentral heat pumps for space heating can provide to a decarbonized electricity system. The Austrian electricity system serves as a showcase for a high-share renewable electricity system because of its national target to increase renewable electricity supply so that renewable-based supply equals overall electricity demand at an annual balance by 2030. The country is modeled in the context of its neighboring countries, considering import and export dynamics.

Former studies about heat pump flexibility can be divided into two fields: i) Detailed building sector model analyses with a high-detail representation of techno-economic parameters like insulation status, technology, comfort level, thermal losses, etc., and ii) energy system analyses in a broader context and consideration of various flexibility options and their interactions with the overall energy system. This chapter focuses on the latter. Besides analyzing the heat pump flexibility potential in Austria in 2030, we analyze the impact of the choice of input parameters by a deterministic sensitivity analysis. This chapter thus provides information to energy system modelers about which input parameters are most important when condensing detailed building sector model information and feeding it into energy system models as it is done in the holistic approach in Chapter 6. We run 11 scenarios using the open-source energy system model Balmorel, implementing heat pump flexibility in 10 scenarios with outputs being compared to one reference scenario.

Overall, positive system-wide effects of heat pump flexibility in Austria can be shown: reduction of system cost, renewable curtailment, and $CO_2$ emissions, as well as mitigating effects of the merit-order effect, smoothing of the residual load, and consequently, increased market integration of renewables. However, the respective amounts are relatively small. Avoided curtailment is about 0.2% of annual wind or PV generation (see Figure 25), and reduced $CO_2$ emissions amount to about 0.04% of the overall system[23] (see Figure 30). The reduction of emissions also depends on fossil fuel and carbon prices since the model minimizes overall system cost, not emissions. This means that emissions do not necessarily decrease with heat pump flexibility in a different system (e.g., higher coal share and lower carbon prices).

However, in the short term, the impact in terms of power can be considerable. Installed overall peak load capacity is not reduced, and this result confirms the findings of Kirkerud et al. (2021). Heat pump flexibility shows its effect mainly in times of negative residual load when it increases electricity demand. During these hours, the increased electricity demand by upwards regulation of heat pumps amounts to, on average, 15.8% of the residual load (see Figure 29), increasing the market values for renewables. System-wide effects are rather observable in terms of an increased residual load than in

[23] The overall system consists of the electricity and district heat sectors of six countries, with Austria contributing only a very small share to the overall costs and emissions. This is one reason why heat pump flexibility in Austria has a small effect on these two overall variables.

terms of reduction of peak load. In hours when the Austrian load is decreased by heat pump downshifting, up to 4.6% of the load is reduced. The average electricity price is increased in all flexibility scenarios, mainly due to the increase of residual load in times of high renewable generation. Since the flexibility potential of HPs is higher in winter and during the night than in summer and during the day in Austria, wind power integration benefits more from it than solar power. Kirkerud, Bolkesjø, and Trømborg (2017) also found that the flexible use of heat boilers is correlated positively with wind speed levels.

This economically fosters the integration of VRE since it reduces the merit order effect. Electricity price volatility is decreased by heat pump flexibility in all flexible scenarios compared to the inflexible case, leading to a more stable market environment.

The amount of electricity shifted in the standard flexibility case is 194 $GWh_{el}$, amounting to 19.7% of the identified available flexible heat pump electricity demand (see Section 5.4.2). That amount varies between 89 $GWh_{el}$ and 648 $GWh_{el}$ in the sensitivity analyses. An increase in consumers' acceptance of deviations below the intended indoor temperature (below 20°C as assumed in the "cooling allowed" scenario) increases the used flexibility potential significantly. Comparing our results to the literature, we find that the amount of shifted electricity in the standard flexibility scenario is in the medium range. Mascherbauer, Schöniger, et al. (2022), who consider only the thermal capacity of single-family houses without buffer tanks, find an amount of shifted electricity between 11 and 26 $GWh_{el}$ for Austria when only the house-owners perspective is considered. Suna et al. (2022), who modeled more countries and all relevant flexibility options in Austria in a system optimization approach, found 480 $GWh_{el}$/a to be shifted by HPs in Austria in 2030, considering thermal mass as well as typical buffer tank sizes of all buildings heated by heat pumps.

The conducted sensitivity analysis shows that the installed capacity of flexible heat pumps is the most critical assumption for the flexibility potential estimation. Installed heat pump capacities and share of controllable capacities show similar impacts since either one or the other parameter determines the installed, controllable capacity that can provide flexibility to the system. This stresses the importance of considering feedback mechanisms between energy efficiency and flexibility which is also found by Rinaldi et al. (2022). The limitation of shifting time (in hours) is a parameter that reduces the potential compared to the modeling approach, where flexibility is provided via a storage capacity (kWh/kW) and thermal losses. Also, the assumption of variable shifting costs is a game changer: Assuming these costs reduces the (already small) economic business case considerably.

When analyzing the flexibility that heat pumps can provide to the electricity system, the chosen model conditions are highly relevant: Generally, the more integrated and interconnected the modeled system, the lower the need for flexibility. This means the selected geographical scope of the analysis and the availability of other flexibility options, e.g., transmission capacities, demand side response, or investment options for large storage facilities in the electricity and district heat sector, impact the evaluated potential. We model Austria and its neighboring countries somewhat underestimating the flexibility potential of exports and imports beyond those countries' borders.

Also, we do not explicitly model other demand side flexibilities, e.g., smart charging for e-vehicles. The availability of such options is expected to decrease the HP potential. However, the techno-economic assumptions for the heat pump flexibility were taken rather conservatively, considering the mentioned limitations of the modeling approach. As done in our analysis, a joint optimization approach serves as an upper bound for achievable operational cost savings (Patteeuw, Henze, and Helsen 2016). In reality, real-time implementation will rely on price signals that can be either expectations or real-time pricing with suboptimal results compared to the overall system optimization approach. Further, heat pumps in district heating with large seasonal storage could help to mitigate the seasonal mismatch of electricity demand and supply (Kirkerud, Nagel, and Bolkesjø 2021) but are not the focus of this chapter.

## 5.6 Nomenclature

**Sets**

| | |
|---|---|
| $c$ | Load shifting technologies |
| $tt$ | Timestep within the timeframe of load shifting |

**Parameters**

| | |
|---|---|
| $L$ | Scheduled demand ($MWh_{el}$) |
| $\Delta t$ | Maximal shifting time (h) |
| $\Lambda$ | Maximum electric capacity/load ($MWh_{el}$) |

**Variables**

| | |
|---|---|
| $E$ | Energy content of “virtual storage” ($MWh_{el}$) |
| $P$ | Shifted demand ($MWh_{el}$) |
| $P^{max}$ | Maximal possible demand reduction (downward shift) ($MWh_{el}$) |
| $P^{min}$ | Maximal possible demand increase (upwards shift) ($MWh_{el}$) |
| R | Realized demand after load shifting ($MWh_{el}$) |

# 6 Matching flexibility needs and solutions: Case study of Austria

This chapter combines all aspects of the analyses in the former chapters in a wholistic approach and answers the last research question *"How high are the expected flexibility needs of the Austrian electricity system in 2030, acting as a role model for a (strongly) VRE-based power system, and which flexibility options are pertinent to meet the flexibility needs?"*. This chapter is mainly based on Suna et al. (2022)[24].

## 6.1 Background

As a contribution to the global combat against climate change and in accordance with the EU's energy and climate plans, the Climate and Energy Strategy of the Austrian Federal Government, as published in June 2018 (BMNT & BMVIT 2018), set an ambitious target for the expansion of domestic electricity generation from renewable energy sources. The strategy's goal is to increase the uptake of renewable energy sources to a level where, at a yearly balance, domestic electricity consumption shall be fully covered by renewable energy sources by 2030. Despite the fact that Austria has already achieved a high share of renewable energy sources, i.e., 78% by 2020 (Eurostat 2022) with this goal, the country's energy system, and specifically the power system, faces a significant transformation. However, both the national strategy (BMNT & BMVIT 2018), and the corresponding law (Republik Österreich 2021), does not prohibit the use of natural gas (or other fossil fuels). These fuels are used mainly in combined heat and power (CHP) plants, supplement the electricity supply, and also provide heat for district heating systems and steam supply in the industry. Since domestic electricity demand shall be covered by renewables, the net balance of electricity exports to neighboring countries has to be equal to fossil-based electricity supply at a yearly balance. This would make Austria return to its former position of exporting country in the European electricity market. Taking a closer look at the Austrian energy system of tomorrow, and specifically at system flexibility needs and options for safeguarding the security of supply, may serve as a blueprint for many countries around the globe.

This chapter aims to assess the short- to long-term flexibility needs of the Austrian electricity system by 2030, which is intended to rely almost exclusively on renewables and the use of flexibility options

[24] The author of this thesis contributed to the conceptualization, the data analysis and the input data gathering and processing. Assistance was also provided to the result interpretation and the writing of the paper. CRediT author statement Franziska Schöniger: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – Original Draft, and Visualization.

for meeting those needs. For the assessment, the authors apply and extend novel methods, providing insights not only into the overall demand for flexibility but also into the underlying dynamics. In the modeling task of this chapter, flexibility is defined as the capability to promptly (within one hour) change the generated or consumed electricity at a defined network node of the electricity system stimulated by an external incentive so that generation or consumption units can be used in a way that serves the system. Related research questions include:

- How high are the expected flexibility needs of the Austrian electricity system in the future due to the implementation of a 100% renewable electricity supply by 2030 (balance sheet)?
- How robust do the results appear considering weather extremes, such as so-called "dark doldrums", referring to a period of low or zero power production from VRE?
- Which flexibility options are pertinent to meet flexibility needs?

For this purpose, a high-resolution model for power and district heating is used to calculate two distinct scenarios. The basis for the model-based assessment is a bottom-up analysis of key input parameters, such as developments in future electricity demand or options to meet future flexibility needs. The latter includes storage systems, i.e. (pumped) storage hydropower plants, battery systems, power-to-gas (P2G); demand-side flexibility, including electric boilers, HPs, e-mobility, and DSM; flexible power plants, i.e., CHP and thermal power plants, curtailment of VRE and the contribution of cross-border electricity exchange using transmission networks to increase the flexibility and stability of the energy system. Based on the model, flexibility needs and options are then assessed for the two scenarios and for different timescales (i.e., daily, weekly, monthly, and annually).

## 6.2 Methodology

Below, key assumptions and applied methodology for conducting a model-based power system flexibility assessment are summarized.

### 6.2.1 Key assumptions

Except for Austria, all assumptions for other European countries are made in accordance with the National Trends scenario of the European TYNDP 2020, published by the European Association for the Cooperation of Transmission System Operators for Electricity ENTSO-E (2021b). Assumptions on underlying demand trends or the renewable expansion until 2030 in the European context are described in Appendix A3. Further details on the assumptions for Austria are provided below.

#### 6.2.1.1 Estimation of electricity demand in Austria and required renewable uptake by 2030

The level of renewable expansion and the necessity and importance of the flexibility options in line with the targeted renewable share depend on the future development of the electricity demand in the country. This analysis builds on the WAM (With Additional Measures)-NECP scenario (UBA 2019), which serves as the basis for the National Energy and Climate Plan (NECP) (Federal Ministry for Sustainability and Tourism Republic of Austria 2019), and thus respects the proposed renewable target for 2030. According to this scenario, electricity demand is expected to grow from 71 TWh in 2020 (Eurostat 2022) to 85.2 TWh by 2030. This increase is mainly driven by enhancements in sector coupling between electricity and transport (e-mobility) as well as heating and cooling (HPs), accompanied by ongoing electrification in the industry in line with decarbonization needs.

#### 6.2.1.2 Required renewable uptake until 2030

Certain restrictions were formulated for the renewable target on electricity supply, as defined in the NECP (Federal Ministry for Sustainability and Tourism Republic of Austria 2019). These limit the demand, which can be taken as the basis for the targeted renewable share (i.e., 100% at yearly balance). Electricity consumption related to control and the stabilization of grid operations were not included in the calculation of the renewable share target, and the same goes for highly efficient fossil-based industrial auto-producers for reasons of resource efficiency. According to UBA (2019), these restrictions will lead to a reduction of the accounting basis for electricity consumption by about 8.1 TWh in 2030. This corresponds to a targeted renewable share of approximately 97% by 2030 in the public grid.

Table 18 summarizes the assumptions on projected gross electricity demand and renewable-based supply in Austria by 2030. For comparison, it also includes 2020 data using the same data source (UBA 2019).

Table 18: Key assumptions on projected electricity demand and corresponding renewable-based supply in Austria by 2030 (in comparison to 2020 (UBA 2019))

| **Electricity demand and renewable-based supply (at yearly basis) in TWh** | **2020** | **2030** |
|---|---|---|
| Gross electricity demand (total) | 76.0 | 85.2 |
| Of which: the company's own consumption covered by its own production (not in the public grid) | 7.4 | 8.1 |
| **Gross electricity demand (public grid)** | 68.6 | 77.1 |
| **Renewable generation (public grid)** | 53.7 | 75.0 |
| Renewable share (of demand in %) | 78% | 97% |
| Hydro | 41.2 | 43.9 |
| Photovoltaics | 1.8 | 11.6 |
| Wind | 7.9 | 16.7 |
| Biomass, biogas, and geothermal electricity | 2.8 | 2.8 |

### 6.2.1.3 Flexibility options and modeling approach

The following flexibility options are considered in the model-based assessment, whereby modeling informs on their cost-effective use according to underlying characteristics and availability:

- Flexible generation technologies: CHP and thermal power plants (natural gas, biomass, and other power plants including biogas engine and waste incineration) and curtailment to manage oversupply (PV, wind, RoR hydropower plants).
- Transmission network (cross-border exchange),
- Load management via P2H (electric boilers and heat pumps in district heating and in decentralized buildings),
- E-mobility,
- Industrial load management,
- Power-to-Gas (Hydrogen)
- (Pumped) hydropower storage plants
- Lithium-ion batteries and prosumers.

The model-based analysis builds on a detailed assessment of the potential of flexibility options in Austria by 2030, as conducted in this study. Details on their model representation are provided in Appendix A3.

In this analysis, the power and district heating system model HiREPS (High Resolution Power System Model) was applied to investigate Austria's flexibility needs in 2030 in accordance with the previously made assumptions and corresponding scenarios. HiREPS is a large-scale optimization model with an hourly temporal resolution for the whole assessment year. The load flow calculation in the European electricity market is carried out with one node per country, whereby the electricity systems of Austria and Germany are simulated in a higher level of detail. The model is described in detail in Appendix A3 (see Figure A 2).

### 6.2.2 Scenario Definition

In accordance with previous analyses (e.g., European Commission (2019) or Brunner et al. (2020)), two issues are of central relevance for scenario definitions:

- Meteorological conditions (i.e., weather pattern) that influence the electricity infeed of VRE like wind, solar, and hydro; and
- Limitations in the availability of certain flexibility options to cope with identified needs.

The applied scenario definition, as described below, aims to acknowledge both issues. Thus, regarding the availability of technological (but also regulatory) flexibility options, two scenarios are assessed for 2030, namely **"Typical Year 2030"** and **"Extreme Year 2030"**.

For the **"Typical Year 2030"** scenario, electricity generation from VRE uses weather data from 2008. Meteorological conditions of this year can be classified as typical for Austria, and underlying patterns of VRE-based electricity infeed reflect an average year (i.e., the yearly sum of the hourly generation profiles corresponds to the long-term average).

In contrast, the scenario **"Extreme Year 2030"** marks an extreme case from a meteorological perspective, with dark doldrums causing extremely low infeed of hydro, wind, and solar, combined with further restrictions on hydropower storage units. Since hydropower, and specifically (pumped) hydropower storage plants, play a key role in balancing electricity demand and supply in Austria, a further restriction is considered for this type of unit. Therefore, we assume low water levels in reservoirs before the dark doldrums: The simulation of the weather years 2006 to 2009 reveals that the lowest water levels in the reservoirs were observed in January 2007. The weather analysis also shows that comparatively long dark doldrums, i.e., weak/no sunlight during daytime combined with almost no wind and rain, were observed in 2006. For modeling purposes, an extreme situation is constructed building on these assumptions. This scenario can be considered as a worst-case combination, in which low water levels of the storage lakes (according to January 2007) are combined with dark doldrum periods according to the weather year 2006.

The best-known cold dark doldrums in recent years occurred in Austria and Germany in January 2017 (Next Kraftwerke 2018; E-Control 2018) (for details, see Appendix A3, Figure A 3). The analysis of an extreme (weather) case, as undertaken in this study, is based on a two-week dark doldrums period, equivalent to the dark doldrums period of 2017.

Both scenarios consider all flexibility options described in Section 6.2.1.3 under the assumption of making the best use of available flexibility options from an economic perspective.

### 6.2.3 Flexibility assessment: Definition of key parameters

As a standard, the starting point for determining the need for flexibility is the analysis of the residual load (RL), whereby both variables are closely related. In this chapter, $RL$ – expressed as an hourly power value in GW – represents the difference between the total power demand of the public grid (PG) and the electricity infeed from VRE. Eq. (19) below shows further details on the underlying calculation approach.

$$RL(t) := Load \quad public\ grid\ AT(t) - Run\ of\ river\ hydro(t) - Wind(t) - PV(t) \tag{19}$$

$RL$ can be positive (temporary generation deficit), negative (temporary generation surplus), or, in individual cases, zero (generation and consumption balanced). Within an analysis of $RL$, typically for a given year (e.g., 2030), the main parameters of the $RL$ for both energy directions are the respective extreme values of the output (in GW) and the hourly gradient/ramp (in GW/h).

The $RL$ includes the electricity purchase for charging e-vehicles, assuming uncontrolled charging is the default. For electric heating and electric hot water supply, no load shifting is set as default. The use of electricity for the provision of district heating (e.g., large-scale heat pumps) and the use of electricity in storage technologies (pumped hydropower storage, batteries) are not included in the $RL$, as these forms of use are classified as flexibility options. To ensure system stability and security of supply, the $RL$ should be covered at all times within both energy directions.

**Quantifying the need for flexibility for different time periods**

Based on the determination of $RL$, the calculation of the flexibility needs is then performed according to the method proposed by the European Commission et al. (2019), which defines flexibility needs by analyzing the dynamics of $RL$ on a daily, weekly, and annual level. In this chapter, monthly flexibility needs are additionally included. In addition, a different approach is followed to determine annual flexibility needs to include medium-term fluctuations. Below, we elaborate on the underlying definitions at distinct time scales in further detail. It should also be emphasized that in addition to compensating for the short- to long-term fluctuations in the $RL$, **the cumulative annual balance of *RL*** should also be provided.


**(a)** **(b)**

Figure 31: Definition of flexibility needs to balance the hourly variation within a day (Panel (a)) and the monthly fluctuations within a year (Panel (b)), exemplified based on historical generation and consumption data for Austria in 2020 (ENTSO-E 2021a)

- ***Daily flexibility needs:***

Daily flexibility needs measure the hourly fluctuations within a day. They are calculated from the sum of the positive hourly deviations of *RL* from the respective daily mean value of *RL*. The daily flexibility needs over one year are determined as the annual sum of the hourly values. The shaded areas in Figure 31 (Panel (a)) show the daily flexibility requirements for one representative winter day. The result is quantified as energy quantity per day (e.g., MWh/day). The sum of these positive daily differences for 365 days of a given year shows the total daily flexibility needs to be covered for short-term (hourly) fluctuations within a year (expressed in GWh or TWh per year).

- ***Weekly flexibility needs:***

In accordance with our approach to determine daily flexibility needs, weekly flexibility needs can be calculated similarly by measuring the daily fluctuations within a week. Thus, the weekly flexibility requirement for a given year is then calculated by summing up the positive deviations of the daily mean value of *RL* from the corresponding weekly mean value of *RL* over the whole year.

- ***Monthly flexibility needs:***

Monthly flexibility needs express weekly fluctuations within a month. They are calculated by summing up weekly mean values of *RL* from the corresponding monthly mean value by totaling each hour over the whole year.

- ***Annual flexibility needs:***

In addition to the fluctuations in the *RL* on different time scales, the provision of the annual sum of *RL* is of fundamental importance. The annual flexibility needs (the green area in TWh as represented in Figure 31 (Panel (b)) are calculated by summing up the positive deviations of the monthly mean value of *RL* from the corresponding annual mean value of *RL* over the whole year.

However, flexibility needs identified within the respective timescales (day, week, month, and year) cannot be added but rather measure the variability of *RL* for the corresponding timescales. It should also be noted that merely meeting the need for flexibility, i.e., balancing variability, is not sufficient to ensure supply security. Here, it is important to maintain a holistic perspective whilst balancing the overall *RL*, both in the positive and negative direction. Thus, further measures must be provided accordingly.

## 6.3 Results

This chapter is dedicated to the results obtained from the analysis of power system flexibility needs and the contribution of flexibility options in covering those needs within Austria by 2030.

### 6.3.1 Key results on the power system in 2030 (public grid), supply and demand

Table 19 shows the annual balance of electricity supply and demand in 2030, broken down by components. Here, electricity demand includes grid losses and electricity for filling pumped hydropower storage (PHS) units but excludes the self-consumption of power plants.

In electricity supply, differences in the annual electricity generation from VRE can be seen between the scenarios **"Typical year 2030"** and **"Extreme year 2030"**, reflecting differences in underlying weather years. These differences are comparatively small for RoR and PV. In the case of wind energy, the weather year 2006, on which the scenario "Extreme year 2030" scenario is based, is windier over the whole year (but not during the critical weeks) than 2008, serving as the basis for the scenario "Typical year 2030". Accordingly, wind power generation increases from the default value of 16.8 TWh ("Typical year 2030") to 18.8 TWh ("Extreme year 2030"), despite the fact that the underlying capacity expansion is identical, in accordance with WAM-NECP scenarios (UBA 2019). The total generation of (pumped) hydropower storage plants, including pumped electricity, is 18.8 TWh in the scenario "Extreme year 2030", compared to 17.7 TWh according to the scenario "Typical year 2030". This implies a generation surplus of 1.1 TWh in the scenario "Extreme Year 2030" compared to the default, despite lower natural inflow (0.8 TWh) according to the weather data. This indicates increased requirements for balancing fluctuations in load and generation. Also, increased foreign demand for controllable power during some hours and days is regarded as a causal factor. There are striking differences in the use of fossil power plants: the utilization of natural gas-fired CHP plants in the scenario "Extreme year 2030" scenario (6.4 TWh) is significantly lower than in the "Typical year 2030" (9.3 TWh) at the annual balance. This indicates the high dependency on foreign demand for this generation asset, which reduces its contribution to cover domestic flexibility needs. During critical weeks in the “Extreme year 2030” scenario, the flexibility provision of gas-CHP plants is, however, strongly valuable.

In the case of large batteries and P2G systems, there is no additional expansion beyond the pre-set levels used as input to the modeling.[25] As a general trend, it should be noted that in the scenario “Typical Year 2030”, almost exclusively pre-set power plants (i.e., according to ENTSO-E’s National Trends Scenario of TYNDP 2020) are used across Europe to balance the power system. Therefore, no additional thermal power plants are suggested by the model.

Table 19: Breakdown of supply and demand in the public grid by technology in Austria by 2030 according to analyzed scenarios

| Supply Technologies | “Typical year 2030” Installed capacity [MW] | “Extreme year 2030” Installed capacity [MW] | “Typical year 2030” Generation [TWh] | “Extreme year 2030” Generation [TWh] | Demand technologies | “Typical year 2030” Demand [TWh] | “Extreme year 2030” Demand [TWh] |
|---|---|---|---|---|---|---|---|
| **RoR Hydropower** | 6 282 | 6 282 | 31.52 | 31.47 | **Load including grid losses** | 70.79 | 70.79 |
| **(Pumped) Hydropower Storage (PHS)** | 11 236 | 12 311 | 17.69 | 18.80 | **Electricity for pumping of PHS** | 6.20 | 8.67 |
| **Battery (discharge)** | | | 0.00 | 0.00 | **Battery (charge)** | 0.00 | 0.00 |
| **Wind** | 6 521 | 6 521 | 16.78 | 18.80 | **E-vehicles** | 2.60 | 2.60 |
| **PV** | 11 663 | 11 663 | 11.60 | 11.43 | **District Heating-P2H** | 0.01 | 0.06 |
| **Other renewables*** | 430 | 430 | 2.81 | 2.80 | **P2G (Hydrogen)** | 1.18 | 1.18 |
| **Gas-CHP** | 2 769 | 2 769 | 9.33 | 6.44 | | | |
| **Gas Turbines and Oil** | 579 | 579 | 0.00 | 0.01 | | | |
| **Waste incineration** | 125 | 125 | 1.01 | 1.00 | | | |
| **Import** | 15 | 15 | 9.68 | 11.65 | **Export** | 19.61 | 19.11 |
| **Total** | | | 100.41 | 102.41 | **Total** | 100.41 | 102.41 |

*Other renewables comprise here biomass, biogas, and geothermal

[25] In a sensitivity analysis, the impact of large scale batteries was analyzed (Esterl et al. 2022). Their provision of short-term flexibility replaces the flexibility provided by gas CHP plants, pump storage (in the short term), and household and service sector DSM.

### 6.3.2 Residual load analysis

The need for flexibility is determined by the *RL* analysis since the *RL* discloses the part of the load that must be covered by flexibility options. The *RL* can be both positive, in case of a shortfall, or negative, when electricity generation from VRE is larger than domestic electricity demand. Figure 32 shows the temporal development of *RL* in Austria at present (2020), based on data from ENTSO-E (2021a), and compares scenarios for 2030.

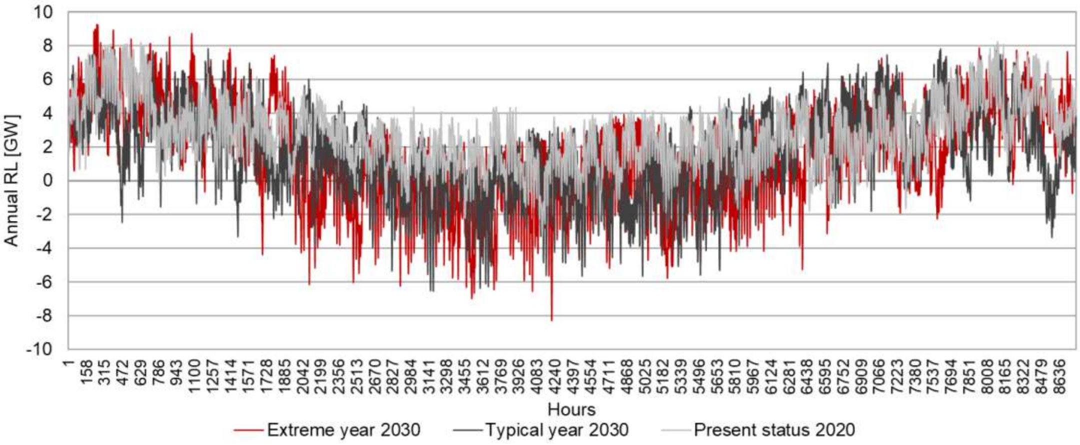


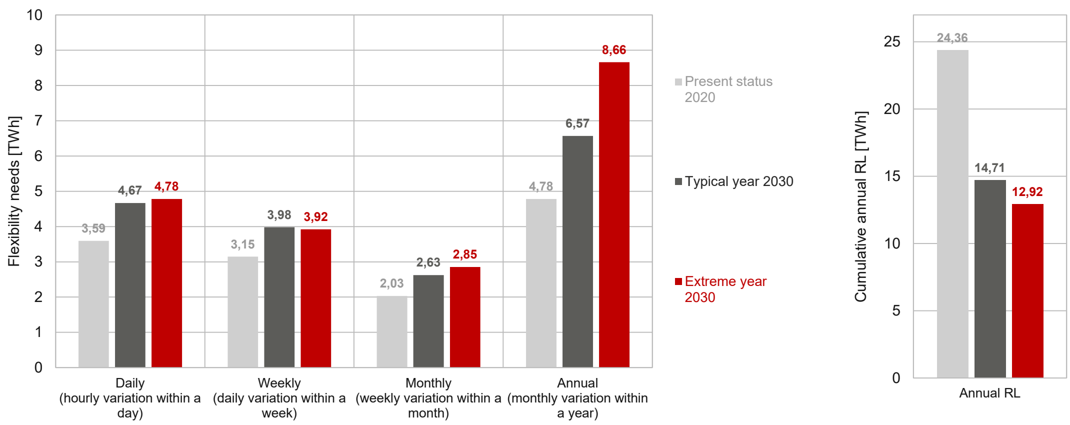

Figure 32: Status quo (2020) and comparison of scenarios (2030) for the temporal development of RL in Austria

In cumulative terms, i.e., the yearly balance of *RL*, a strong decrease in *RL* can be expected in the future. As listed in Table 20, cumulative *RL* is expected to decline from 24.4 TWh today (2020) to 12.9-14.8 TWh by 2030, depending on the scenario and weather. Concerning maximum positive *RL*, almost no change can be observed. However, for maximum negative *RL*, a strong increase can be observed, from -3.25 GW today to -6.55 to -8.3 GW by 2030. This is a consequence of the anticipated extensive expansion of VRE since Austria's electricity trade balance will also change by the same magnitude. Regarding the temporal fluctuations of *RL*, data for 2020 show considerable gradients, both positive (6.25 GW/h) and negative (-4.35 GW/h). Modeling indicates a significant decline in these fluctuations as a result of the expansion of VRE and the associated decrease in *RL*. If the *RL* falls in absolute terms, a decline in the gradient also seems plausible. It should also be mentioned at this point that, in general, there is a good correlation between the generation profile of PV (a central pillar of domestic electricity supply in the future, especially at a decentralized level) and the load profile, which may also have a balancing effect on the dynamics of *RL*.

Table 20: Key results for RL and flexibility needs in the Austrian electricity system today (2020) (ENTSO-E 2021a) and in the future (2030) according to analyzed scenarios

| **Residual Load (RL)** | **2020** | **"Typical year 2030"** | **"Extreme year 2030"** |
|---|---|---|---|
| Annual Average RL [GW] | 2.77 | 1.67 | 1.48 |
| Annual Balance of RL [TWh] | 24.36 | 14.71 | 12.92 |
| Maximum positive RL [GW] | 8.24 | 8.02 | 9.26 |
| Maximum negative RL [GW] | -3.25 | -6.55 | -8.30 |
| **Temporal Change of RL** | | | |
| Max gradient positive RL [GW/h] | 6.25 | 2.50 | 2.37 |
| Max gradient negative RL [GW/h] | -4.35 | -2.17 | -1.97 |
| **Flexibility needs [TWh]** | | | |
| **Daily** | 3.59 | 4.67 | 4.78 |
| **Weekly** | 3.15 | 3.98 | 3.92 |
| **Monthly** | 2.03 | 2.63 | 2.85 |
| **Annual** | 4.78 | 6.57 | 8.66 |

Figure 33 shows the flexibility needs broken down by time period in accordance with the methodology applied for that analysis (see Section 6.2.3). In the case of short-term flexibility (daily, i.e., hourly fluctuations within a day), an increase from today's 3.6 TWh to 4.7-4.8 TWh in 2030 can be observed. In the medium term (i.e., daily fluctuations within a week or weekly fluctuations within a month), a similar pattern emerges. Here, the need for flexibility increases by 26% to 40%, depending on the scenario and timescale. In the long term (i.e., the monthly fluctuations within a year), the strongest increase in flexibility demand can be observed. The flexibility needs increase from 4.8 TWh today to 6.6-8.7 TWh in the future, which corresponds to an increase ranging between 37% and 81%. Clear, weather-related differences between the scenarios occur. As expected, the long-term flexibility needs are highest in the scenario "Extreme year 2030" (8.7 TWh), reflecting weather conditions, including a dark doldrums period.




**(a)** **(b)**

Figure 33: Status quo (2020) (ENTSO-E 2021a) and comparison of scenarios (2030) of the temporally subdivided flexibility demand (Panel (a)) incl. indication of the annual balance of RL (Panel (b))

The results confirm findings from Heggarty et al. (2020), who analyze flexibility needs in the future French electricity system and find that annual flexible energy requirements are higher than weekly and daily ones. However, the order of magnitude is much higher for France, partly caused by high electric heating demand and a different VRE generation mix than in Austria.

### 6.3.3 Contribution of flexibility options in meeting flexibility needs

Figure 34 ("Typical year 2030") and Figure 35 ("Extreme year 2030"), respectively, show the future contribution of different flexibility options to meet the flexibility needs arising at different time periods. Panel (b) shows how flexibility options contribute to meeting the demand for *RL* at an annual balance. Appendix A3 provides a detailed list of the scenario-specific contributions of flexibility options by time period (Table A. 17) for 2030 and offers a comparison with the status quo (Table A. 16). Furthermore, a capacity and generation balance of the flexibility options is provided (Table A. 18), including the status quo (2020), based on ENTSO-E (2021a), and 2030, according to modeled scenarios – indicating the contribution of flexibility options in terms of peak capacity and yearly generation.

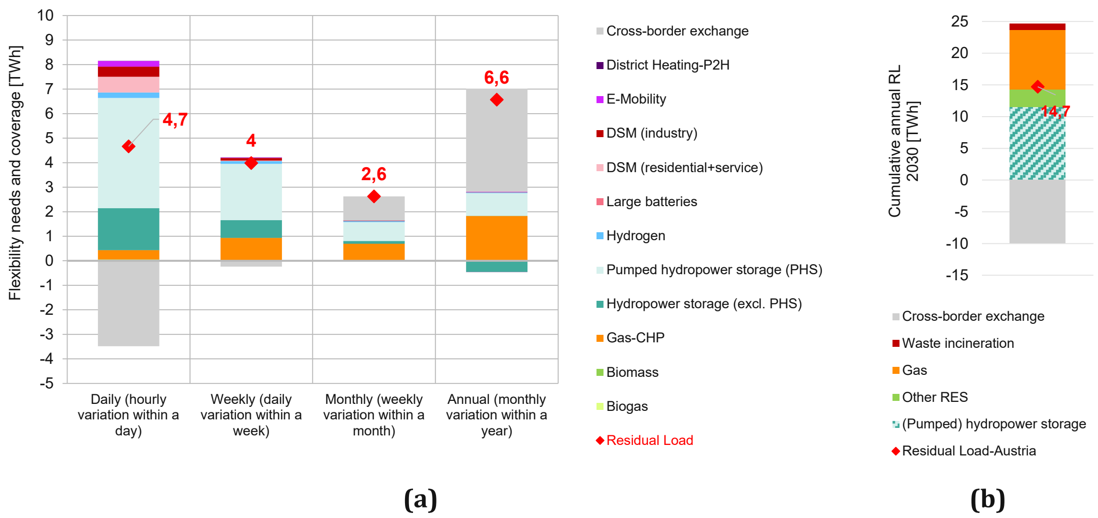
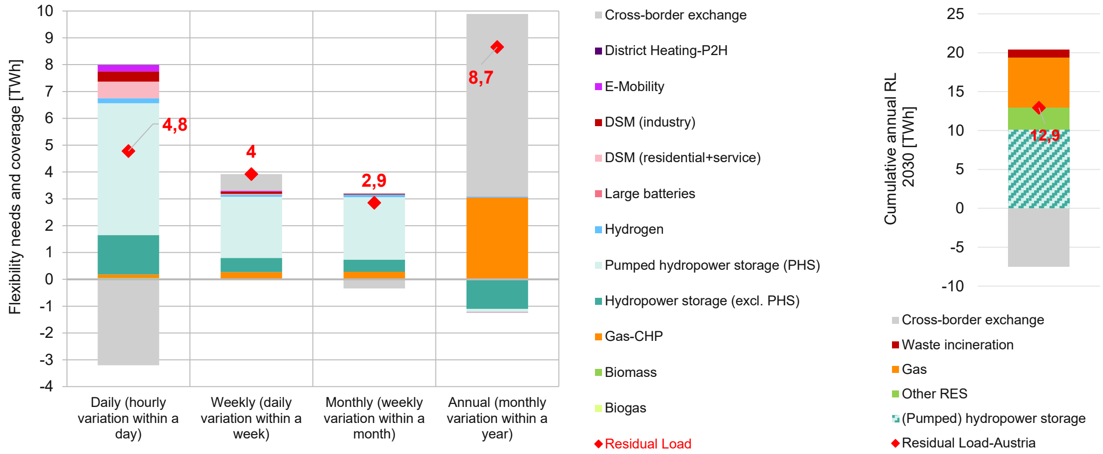



Figure 34: Contribution of flexibility options to cover flexibility needs at the different time periods (Panel (a)) and annual balance of RL (Panel (b)) in 2030 according to the scenario "Typical Year 2030"




**(a)** **(b)**

Figure 35: Contribution of flexibility options to cover flexibility needs at the different time periods (Panel (a)) and annual balance of RL (Panel (b)) in 2030 according to the scenario "Extreme Year 2030"

The analysis starts with a close look at how flexibility options contribute to meeting the demand for *RL* at an annual balance as illustrated in Panels (b) of Figure 34 ("Typical Year 2030") and Figure 35 ("Extreme Year 2030"). In both scenarios, (pumped) hydropower storages contribute most to meeting corresponding flexibility needs, followed by gas-fired CHP plants and other renewables (i.e., biomass and biogas). Waste incineration plants that are operated constantly throughout the year do not contribute to covering the variability of *RL*, but they contribute to covering the *RL* at the annual balance. The clearly positive export balance in cross-border electricity exchange is evident in both scenarios.

In both scenarios, **daily flexibility needs** show that the intra-day fluctuations are significantly higher than fluctuations within a week or month. (Pumped) hydropower storages are dominant in meeting these short-term flexibility needs. Apart from meeting domestic needs, these plants also provide flexibility to neighboring countries, as more short-term flexibility is provided in Austria than is required domestically. Flexibility options on the consumer side (e.g., e-mobility, DSM in industry, households, and services, or hydrogen) also contribute to covering short-term flexibility needs. However, by 2030 their contribution still remains comparatively small. The negative contribution of cross-border electricity exchange indicates that Austria offers short-term flexibility to its neighbors.

Concerning **weekly and monthly flexibility needs**, a similar pattern can be observed: (Pumped) hydropower storage covers the majority of corresponding needs, and, complementary to consumer-side flexibility options, also gas-fired CHP plants offer flexibility, specifically in the scenario "Typical Year 2030". The cross-border exchange has an ambiguous role, depending on whether it causes an increase in related flexibility needs or contributes to meeting them.

**Annual flexibility needs** show that Austria's cross-border exchange with neighboring countries (i.e., imports in case of a supply shortage and exports in times of oversupply) contributes the most to balancing monthly fluctuations in *RL*. Additionally, thermal power plants mainly fueled by natural gas and biomass make a significant contribution to balancing long-term fluctuations. Since they can be operated flexibly or, in the case of CHP, generate more electricity during winter months driven by seasonal heat demand, they are an important asset for Austria in meeting its long-term flexibility needs. In terms of security of supply, this is of particular importance in times of dark doldrums, as shown in the results of the scenario "Extreme Year 2030". Hydropower storage without pump operation contributes to covering *RL* both in the summer and in the winter months. However, as these power plants produce more electricity during summer months due to the increased natural inflow, their contribution to meet annual flexibility needs, i.e., the monthly fluctuations measured against the annual average, is negative. More precisely, these assets generate more electricity in summer than in winter in both scenarios and therefore do not mathematically contribute to reducing the seasonal imbalance between supply and demand in Austria. In accordance with the above, the identified seasonal imbalance is mainly covered by cross-border exchange, gas-fired CHP, and PHS plants.

## 6.4 Discussion and limitations

In this chapter, a model-based analysis of the system effects of the planned renewable expansion in Austria, aiming for an (almost) fully renewable-based electricity supply (at a yearly balance) by 2030, is undertaken.

The analytical focus is to identify corresponding needs in power system flexibility in a structured manner by assessing flexibility needs at different time periods. Additionally, the analysis shows how available flexibility options may contribute cost-effectively to meeting those needs. The importance of assessing flexibility needs and corresponding options as one of the main criteria for supply security, specifically with the growing share of VRE in the power system, is demonstrated.

The joint analysis of the load and the VRE appears useful for investigating the need for flexibility on the electricity side. Fluctuations in *RL* describe this connection in a suitable way (see Section 2.2). The *RL* and the resulting need for flexibility in Austria's wholesale electricity market in 2030 is the focus of a scenario comparison, in which a "Typical year 2030" and an "Extreme year 2030" scenario are considered with regard to weather influence.

The results for the year 2030 show an increase in the need for flexibility compared to today. This is specifically true for the temporal fluctuations in *RL*, while the absolute need to cover the *RL* decreases significantly from 24.4 TWh in 2020 to 12.9-14.8 TWh by 2030. Regarding the temporal dynamics of the *RL*, 2020 data shows considerable gradients, both positive and negative. Modeling of the year 2030 provides, in both scenarios, a restrained picture in this respect.

The strong increase of negative *RL* and (relatively) negative gradients of *RL* (GW/h) due to growing temporary power surpluses is remarkable. The main reason for this is the high share of electricity generation from VRE in combination with a growing demand for electricity in new areas of electricity consumption (e-mobility, P2H, and industry) in the future, leading to stronger dynamics also on the demand side.

In this chapter, flexibility needs are analyzed from short- to long-term periods (i.e., daily, weekly, monthly, and annual). In addition, the cumulative annual balance of *RL* is provided. The results show that in terms of magnitude, long-term flexibility needs are most significant in Austria (see Figure 33). This is the result of an assumed extensive uptake of VRE, especially of PV, which may create a surplus in power supply, and, consequently, a negative *RL* during the summer period, whereas they may cause a shortfall in *RL* during the winter months. Depending on the scenario, daily flexibility needs (summarized over a whole year) total 4.7 to 4.8 TWh. The highest difference between scenarios can be seen in the case of annual flexibility needs. Here, the scenario "Extreme year 2030" (8.7 TWh) is about 2.1 TWh higher than in the scenario "Typical year 2030" (6.6 TWh) as a result of the low availability of hydropower, wind, and solar during critical time periods (dark doldrums).

In principle, different flexibility options are available to cover the need for flexibility. According to the modeling, the following pattern is identified:

Options on the consumer side (load-shifting in households, service, and industry; e-cars; hydrogen production, etc.) contribute to balancing short-term fluctuations in the *RL* but make (almost) no contribution to seasonal balancing in the long term.

Large batteries, if available by 2030, have the potential to contribute to covering demand in the short term, similar to DSM. Their availability and use would slightly reduce the use of thermal power plants, especially gas-fired CHP plants, hydro pump storage, and DSM in the household and service sectors.

(Pumped) hydropower storage plants in Austria allow flexible use on all timescales. However, actual usage patterns show that their contribution is typically higher in the short and medium term, as well as in covering *RL* at the annual balance. In general, (pumped) hydropower storage units are of key importance to meet the demand for flexibility in the domestic electricity market today, and this can also be expected in the future (2030). Modeling shows a significant additional expansion of the pump and turbine capacity, in addition to the planned expansion according to specifications in the WAM-NECP scenario (UBA 2019). This flexibility option would also be available to its full extent in extreme events.

Thermal power plants, specifically gas-fired CHP plants, usually show an opposite pattern: their contribution tends to be highest in the long term, i.e., when balancing seasonal mismatch and for providing *RL* at the annual balance. In the short term, the need for flexibility is only slightly covered by this option.

Today and in the future, the cross-border exchange of electricity remains a central pillar of flexibility in the domestic electricity market, both to utilize surpluses and to compensate for deficits. Its contribution to seasonal compensation (i.e., covering the higher *RL* in winter months) is by far the highest among all flexibility options. In the short term (i.e., to compensate for hourly fluctuations during the day), this effect is inverted. According to modeling, Austria may export short-term flexibility to neighboring countries in future years.

The envisaged strong uptake of renewables in Austria represents an important contribution towards the decarbonization of the electricity system, and the reliance on fossil fuels will consequently be reduced. Since the Austrian strategy and also the corresponding law do not prohibit the use of fossil fuel, gas-fired CHP plants may still play a vital role in the electricity supply and, as shown in this analysis, also for the provision of flexibility by 2030. Additionally, the flexibility provided via cross-border electricity exchange needs to be classified as "grey" since the exact decomposition can hardly be tracked back to one source of origin as long as the neighboring countries have not followed a similar strategy. The model-based analysis performed reflects, however, the tendency towards decarbonization that relies to a large extent on renewables across the whole of Europe. However, additional flexibility options like hydrogen or green gas may be required then to solve the seasonal imbalance in flexibility in a country like Austria for a fully decarbonized future electricity system.

There are some limitations to the method applied in this section with regard to the quantification of flexibility needs and coverage. The energy system model applied assumes a perfectly efficient market under perfect foresight and perfect competition. Also, in the energy system modeling, potential dynamics on the distribution grid level are not covered, rather underestimating the flexibility needs or overestimating the flexibility potential by decentral options. Further, other markets than the energy-only market are not considered. This means that, e.g., backup capacities might be lower than in models with balancing markets, and modeled electricity spot prices reflect marginal pricing rules without considering the eventual capacity remuneration of the generators (Härtel and Korpås 2021). The use of flexibility options is also highly dependent on the availability of export and import capacities (see Chapter 3). In the analysis of this thesis, an 80% availability of the planned NTC capacities (ENTSO-E 2021d) is assumed, also taking into account system requirements, technical availability, and market limitations (see Appendix A3). However, further sensitivity analyses regarding changes in this transmission availability would be needed to show possible changes in flexibility needs and the use of flexibility options (Jorgensen, Mai, and Brinkman 2017).

# 7 Synthesis of results

This chapter synthesizes the results of this thesis, including an elaboration on the limitations of the underlying analyses. First, it summarizes the findings answering the four research questions stated in Chapter 1.2. Further, the findings are discussed in a broader context. Finally, the policy implications of the findings are presented.

## 7.1 Findings referring to the research questions

This thesis evaluates the role of flexibility in electricity systems with high shares of VRE by analyzing four specific research questions (see Section 1.2). In this section, the most important findings referring to these research questions are summarized. This thesis focuses on flexibility for energy, transmission, and partly power, covering hourly to annual timescales. Fluctuations below the hourly resolution and flexibility for voltage are not covered in the presented analyses.

**Research Question 1:** *"How has the need for flexibility evolved in recent years, and what development is expected for decarbonized electricity systems?"* is targeted at getting a deeper understanding of flexibility needs and deals with the different phases of VRE integration that electricity systems go through. It analyzes the spot price variance as an indicator of short-term flexibility needs in electricity systems. It is shown that short-term flexibility needs increase with high shares of VRE in a wide range of European countries. However, short-term flexibility needs can even decrease with moderate amounts of VRE: Minimum price variance for most countries is found to be between a 10% and 40% VRE production share. How the flexibility needs for decarbonized electricity systems will evolve is highly dependent on the current share of VRE in an electricity system and on the system design, i.e., generation mix and available flexibility options. These flexibility options reduce the price variance by either changing the variance of VRE generation or the shape of the merit order. An important finding here is that the availability of the flexibility options export and import capacities, flexible power plants, and hydro (pump) storage is more important for a country's ability to balance short-term fluctuations than the level and variance of the renewable infeed itself. Several countries show how these factors can foster successful integration of high shares of VRE and keep price variance low even with high shares of VRE. The finding that short-term flexibility needs further rise with high shares of VRE is supported by the results from empirical analysis (Chapter 3) as well as by energy system modeling results (Chapter 6). Additionally, modeling results show that flexibility needs increase on all timescales compared to today in the Austrian electricity system until 2030. Austria serves here as an example of a high-share renewable electricity system because its goal is to cover the total national electricity consumption, measured by yearly balance, with renewables until 2030. Additionally to supporting the hypothesis that increasing VRE lead to higher flexibility needs, the applied methods are able to differentiate the effect between short-, medium-, and long-term flexibility needs and depending on the current VRE share in a country.

**Research Question 2** and **Research Question 3** deal with the different flexibility options that can cover these flexibility needs in future electricity systems – exemplified by one option on the generation and one option on the demand side. Research Question 2: *"What are the economics of different dispatchable solar power technologies, and how do storage time requirements impact technology choices for flexibility options?"* is answered by a case study on dispatchable solar power in Spain. Power systems rich in solar resources face the great challenge of covering demand during the night, which can be covered by different combinations of solar and storage technologies. It is shown that there are distinct niches in the power system for PV with battery storage (BESS) for short storage durations and concentrating solar thermal power (CSP) with thermal energy storage (TES) for longer ones. The corresponding tipping points lie at 2–3 hours (current cost), and 4–10 hours if expectations on future cost developments are taken into consideration. This shows that the requirements on storage time are a key factor for the choice of technology options in future power systems. However, which technology mix is economically optimal from a system perspective also depends on technological learning, which is strongly impacted by policies. If CSP+TES costs do not decrease as envisioned, but PV+BESS costs decrease strongly, then it is conceivable that PV+BESS is cheaper than CSP+TES for the entire night-time storage niche up to 24 hours storage time. For the competitiveness of CSP+TES compared to PV+BESS, the impact of storage duration is stronger than the impact of technological learning in CSP or TES components.

**Research Question 3:** *"What is the potential of decentral heat pumps for providing flexibility to the future electricity system?"* evaluates the role of the demand side in providing flexibility in future electricity systems, exemplified by a case study of decentral heat pumps in Austria in 2030. The results show positive system-wide effects of heat pump flexibility in Austria, but the respective quantifications are relatively small: reduction of system cost, renewable curtailment, and $CO_2$ emissions, as well as mitigation of the merit-order effect, smoothing of the residual load, and consequently, increased market integration of renewables. While installed overall peak load capacity in the system is not reduced by heat pump flexibility, their provision of short-term flexibility is considerable. Around one fifth of the flexible demand of heat pumps is shifted in the modeled scenarios. The flexibility potential is mainly concentrated in the heating season since the potential in summer is low, and there is negligible potential for balancing the seasonal mismatch of electricity demand and renewable generation. The effect of heat pump flexibility is concentrated on the short-term balancing of the system (hourly). It is shown that the flexibility of heat pumps is mainly provided in the form of increased electricity demand during times of surplus renewable generation instead of demand reduction during residual peak load times. Our results show that heat pumps can support wind integration better than solar integration due to the temporal correlation of heat demand (and associated flexibility potential) and wind power generation. Both have their peak during the winter and during the night in Austria. The results show that heat pump demand response is not expected to be a main contributor to flexibility provision in the Austrian electricity system in 2030 in terms of shifted energy (100-650 $GWh_{el}$ depending on the scenario) under the chosen techno-economic assumptions but can provide valuable power flexibility in the short-term. This is especially helpful for increasing market values for VRE during the winter and fostering their market integration. The considered sensitivity analyses show that the economic potential for heat pump flexibility is rather low, especially when considering variable costs for aggregation and communication infrastructure.

**Research Question 4:** *"How high are the expected flexibility needs of the Austrian electricity system in 2030, acting as a role model for a (strongly) VRE-based power system, and which flexibility options are pertinent to meet the flexibility needs?"* combines all aspects of the former research questions in an integrated manner and comprehensively analyzes the spectrum of flexibility options and their different roles in an electricity system with high shares of VRE. The findings of RQ 2 show that the requirement of storage time is a key factor for the choice of flexibility options. In the analysis answering RQ 4, flexibility needs and their coverage are quantified on daily, weekly, monthly, and annual timescales using residual load fluctuations as an indicator. In the modeled "Typical Year" scenario, daily, weekly, monthly, and annual flexibility needs (summarized over a whole year[26]) total 2.6 to 6.6 TWh. The results show that in terms of magnitude, long-term flexibility needs are most significant in Austria in 2030 as a result of an assumed extensive uptake of VRE which creates a surplus in power supply during summer and a shortfall during winter months. The lowest flexibility need is modeled for the monthly timescale (weekly variation within one month). The highest difference between scenarios and weather years is seen on the scale of annual flexibility needs. (Pumped) hydro storage, DSM, utility-scale batteries, and flexible sector coupling contribute to balancing short-term fluctuations. The results show competing effects between batteries and thermal power plants, DSM in the household and service sector, and pumped hydropower (in the short term). Austrian pumped hydropower plants are seen as important flexibility options now and in the future electricity system. While they are able to provide flexibility on all time scales, their contribution is found to be highest in the short and medium term in Austria. According to modeling, Austria may export short-term flexibility to neighboring countries in future years. Cross-border exchange of electricity and thermal power plants are the main providers of flexibility to balance the seasonal mismatch of demand and supply in Austria in 2030, according to the scenarios. While utility-scale batteries or hydrogen storage is not endogenously invested in the modeled scenarios, these options

[26] Daily = hourly fluctuations within one day; weekly = daily fluctuations within one week; monthly = weekly fluctuations within one month; annual = monthly fluctuations within one year

might become more important with the full decarbonization of all sectors in Austria and increasing VRE deployment also in the neighboring countries after 2030.

## 7.2 Discussion and synthesis of the results

The role of flexibility in electricity systems is strongly linked to the decarbonization of energy systems and the corresponding rapid uptake of VRE. There are different phases of VRE system integration (IEA 2020a) and associated needs for flexibility which are covered by the different research questions in this thesis:

1. VRE has no noticeable impact on the system
2. VRE has a minor to moderate impact on system operation
3. VRE generation determines the operation pattern of the system
4. The system experiences periods where VRE makes up almost all generation
5. Growing amounts of VRE surplus (days to weeks)
6. Seasonal or inter-annual surplus or deficit of VRE supply

Each of the phases is characterized by different challenges for the electricity system in terms of flexibility needs and hence, different applicable solutions to enhance VRE integration and secure system stability and adequacy. In phase 2, minor operational modifications are sufficient as flexibility measures like adapted operational patterns of already existing flexibility options. In the following phases, fundamental changes in the electricity system are required: This concerns investment in new flexibility options (e.g., pumped hydropower in Chapter 6) and measures to balance the mismatch between supply and demand on various timescales (IEA 2020a).
The findings of Chapter 3 can be linked to the different phases of VRE integration. They show that VRE can decrease short-term variations in the electricity system in a short to medium time horizon but then increase it the further an electricity system proceeds towards full decarbonization. The minimum short-term flexibility need for the analyzed European countries is found to be at 10-40% VRE share in an electricity system. Systems with more than 10% VRE in annual electricity generation are defined to be in phase 3, and systems with more than 30% in phase 4 (IEA 2020a). In 2021, 14.0% of the EU's gross electricity consumption was covered by wind energy, 5.7% by solar energy, and 12.0% by hydropower (Eurostat 2023). This means that many countries are expected to enter phase 4 in the coming years. However, there are significant differences between the single Member States. The findings of this thesis show that the experienced short-term fluctuations are highly dependent on the electricity system design and the availability of flexibility options in the system. Most countries analyzed in Chapter 3 are in phase 3 or phase 4 now and, therefore, are expected to see increasing flexibility needs on all time scales with increasing shares of VRE from now on. The

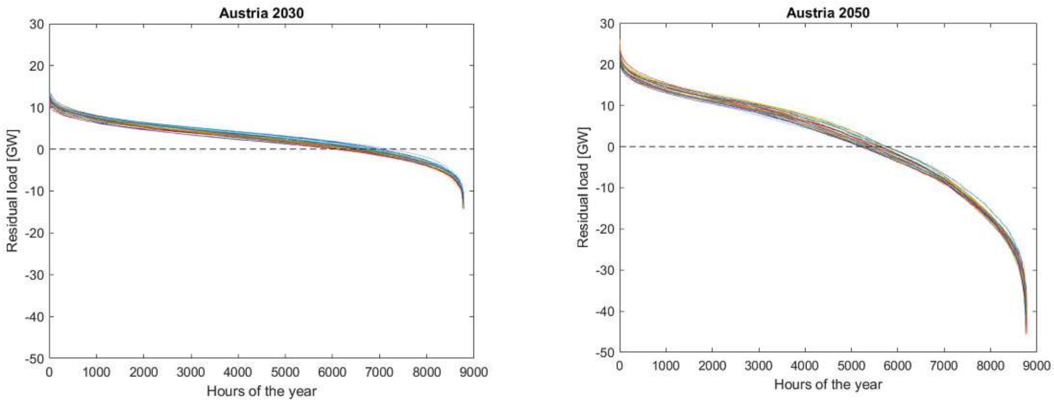
expected increasing short-term price fluctuations can act as an incentive for additional investment in short-term flexibility options.

The findings of this thesis stress the importance of the shapes of demand and supply curves for understanding flexibility needs and options in electricity systems. By changing the shape of the residual load curve, VRE can also decrease flexibility needs (see Chapter 3). Low amounts of PV, for example, flatten the demand curve by reducing peak demand during noon and reduce short-term flexibility needs. After a certain point, however, short-term storage potential is found to be increased by increasing PV penetration (e.g., beyond 11% of annual demand generated by PV in California, see Denholm and Margolis (2018)). In the current phase, short-term and medium flexibility needs due to higher electricity demand are the main concern for most countries driven by the electrification of other sectors and increased installed VRE capacities. The analysis shows that there are different options available on the demand and supply side to provide that flexibility. In the analysis for Austria for 2030, thermal power plants, batteries, DSM, and pumped hydropower are the main contributors to flexibility provision in Austria in the short term. (Pumped) hydropower plants are seen as important flexibility options now and in the future electricity system being able to provide flexibility on all timescales. However, their contribution is found to be highest in the short and medium term in Austria. According to modeling, Austria is found to be an exporter of short-term flexibility (mainly due to pumped hydropower) and an importer of long-term flexibility. The latter is due to the strong seasonal mismatch of electricity generation and demand due to the high seasonality of hydropower, PV generation, and heating demand. Besides the cross-border exchange of electricity, thermal power plants are seen as the main providers of flexibility in Austria in 2030.

In the later phases of decarbonization, times with VRE surplus generation increase. This is due to increased installed VRE capacities to cover rising electricity demand caused by the decarbonization of other sectors. Chapter 6 exemplifies for Austria the strong increase of the minimum negative residual load until 2030. In Figure 36, the residual load duration curve for the Austrian electricity system in 2030 (Panel (a)) – reaching 100% renewable generation (annual, national balance)– and in 2050 (Panel (b)) – after having achieved full decarbonization of the whole energy system – are displayed[27]. A further substantial increase of negative residual load after 2030 is expected – in terms of the number of hours as well as in terms of the extent of the negative residual load peaks. It should be noted that the variation between weather years on the residual load is relatively small compared to the effect of the transformation of the energy system. This shows, like the analysis of historic

[27] 30 climate years considering climate change are presented for 2030 and 2050, i.e., the years 2015-2044 and 2035-2064. Climate change signal according to the EURO-CORDEX climate scenario ICHEC-EC-EARTH - KNMI-RACCMO22E RCP4.5.

flexibility demand in Chapter 3, that the system design in terms of generation mix and demand components is of key relevance for the future balance of demand and supply – and associated flexibility needs.




**(a)** **(b)**

Figure 36: Residual load duration curve for Austria in 2030 (Panel (a)) and in 2050 (Panel (b)); each panel comprises 30 climate years (Source: Schöniger, Resch, et al. (2023))

In the analysis of decentral heat pump flexibility in this thesis (see Chapter 5), it is shown that flexible sector coupling rather takes up surplus renewable generation than covering peak demand which would require much higher storage energy capacity (Rinaldi et al. 2022). The finding that flexibility is mainly provided by consuming surplus VRE generation is also supported for other types of sector coupling in the literature (Schill 2020) and makes sector coupling flexibility attractive for decarbonized energy systems with increasing times of negative residual load (see Figure 36). As seen in the case study of decentral heat pumps (see Chapter 5), the flexibility provided in this way improves the market value of VRE generation and, therefore, can foster successful market integration of VRE and efficient use of installed VRE capacities. Further, it is also known from the literature that, especially towards fully decarbonized systems, the need for storage for peak load coverage and long-term storage increases. That means that the necessary E/P ratio of provided flexibility increases (Schill 2020) which requires different flexibility options than in the phases before. In the modeling task analyzing all flexibility options in Austria in 2030 (see Chapter 6), there is no endogenous investment in long-term hydrogen storage. On the one hand, the model invests in additional (pumped) hydro storage, which offers great potential for flexibility on all timescales in Austria. On the other hand, the picture might change when modeling years beyond 2030 when full decarbonization of the whole energy system is achieved and a substantial further increase of negative load is expected (see Figure 36).

Proceeding on the different phases of VRE system integration, first, already installed flexibility options are used, then short- to medium-duration storage is increasingly deployed (e.g., DSM, batteries), and relatively late, large storage capacities are needed. There is a range of studies showing that storage needs stay moderate for a long time before they sharply increase at around 70-80% of VRE generation in the system (Schill and Zerrahn 2018; Schill 2020; Child et al. 2019) and that during this last phase system costs are highly sensitive to long-term storage costs (Dowling et al. 2020). The analysis of different dispatchable solar power technologies in Chapter 4 shows the importance of technological learning in this regard. Technology options that can cover longer storage durations more cost- and resource-efficiently should be supported during phases when the market alone does not provide enough incentive to deploy them. This enables the system to have a broad mix of flexibility options ready at the time when they are needed on the path towards 100% renewable electricity systems.

The findings of this thesis give some insights into the flexibility needs on different timescales for Austria in 2030. Flexibility need on the annual timescale is expected to increase the most compared to today's electricity system and compared to daily, weekly, and monthly needs. Also, when modeling different weather years, the highest difference in evaluated flexibility needs can be observed on the annual scale because of infrequent low-resource periods in single years. That means when taking into account the interannual variability of the future electricity system, the need for long-term storage compared to average weather years increases significantly. This implies that system planning should consider different weather years (also including climate change projections) to accurately capture (long-term) storage requirements. It is also found in the literature that the role of flexibility options transitions from smoothing short-term fluctuations and bridging extreme events to balancing interannual variability (Ruhnau and Qvist 2022).

Finally, the complex interactive effects between different components of the electricity system have to be considered when evaluating system-optimal solutions. There are synergistic as well as antagonistic combinations of generation technologies and flexibility options. The degree of diversity between the constituent resources is crucial for their nature of interactions (Schlag et al. 2020). As shown in Chapter 3, adding more of one generation technology leads ultimately to higher flexibility needs than adding a second technology type: High wind generation increases short-term fluctuations at high solar penetration levels but decreases them at low solar levels – and the other way around. Electricity systems in Europe can take advantage of the complementary resource patterns of wind speed (which is stronger during the night and in winter) and solar radiation (which is higher during the day and during summer) here. In terms of seasonal fluctuations, the high generation of (summer) hydropower in Austria and (winter) offshore wind in its Northern neighboring countries is also found to benefit the overall system (see Chapter 6). Another classic example of synergistic pairing is solar and storage which can improve each others' economics and decrease inner-daily flexibility needs. The case study on PV and CSP in Chapter 4 shows how even within one single technological field (dispatchable solar power), short- and long-term storage can bring resource benefits to the overall system. An example of antagonistic pairings would be demand response and large-scale batteries in the system, which generate self-cannibalism effects in the system and reduce each other's competitiveness (see Chapter 6). The role of transmission capacity as a flexibility option is found to be ambivalent. According to the modeling, it is one of the main provisioners of flexibility to Austria in 2030, especially for balancing the seasonal mismatch of demand and supply. The extent to which balancing VRE generation is possible via exchange with neighboring electricity systems is dependent on the generation mix and the correlation of VRE generation profiles within the two regions. Transmission capacity is also a competing technology for many flexibility options since exports or imports can substitute, e.g., storage within the narrower (country-specific) system boundaries. However, transmission can also improve arbitrage opportunities for storage since cheap imports from beyond the system's boundaries can be used for charging, and flexibility can be exported, as seen in the case of pump storage in Austria (see Chapter 6).

## 7.3 Policy implications

Policy implications in the field of power system flexibility are relevant for a wide range of decision makers (see Figure 37).

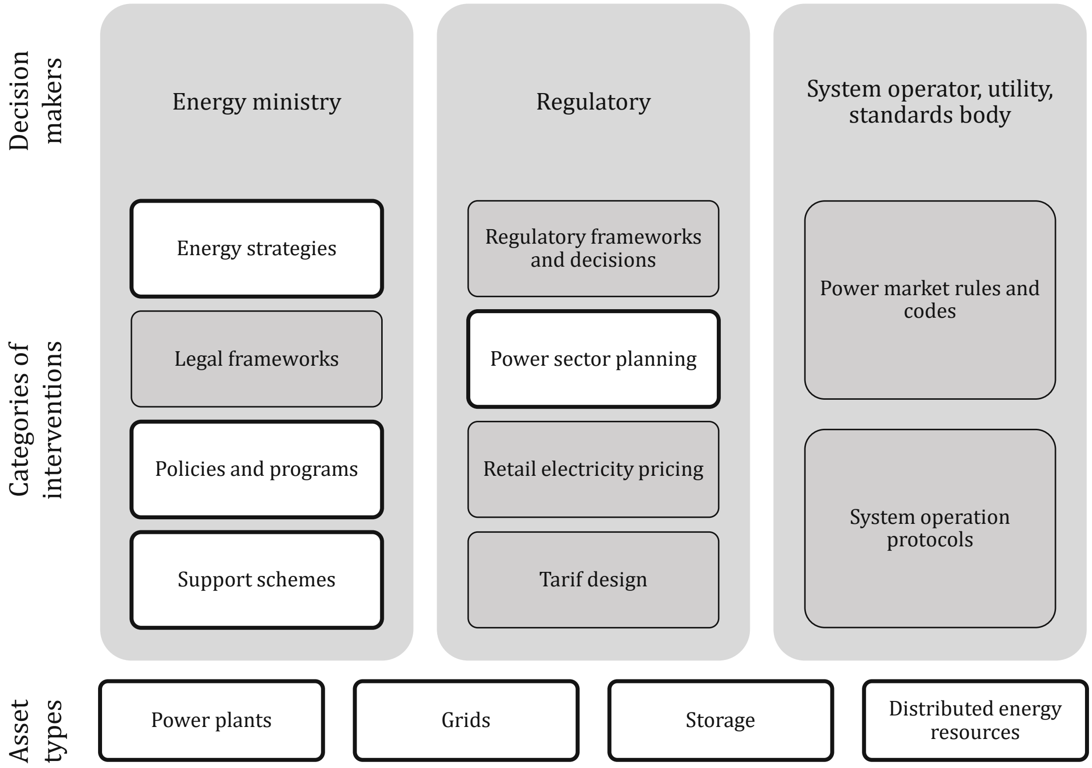



Figure 37: Policy implications for typical decision makers related to flexibility in the electricity system. The contributions of this thesis are mainly seen in the white boxes. (Source: Own illustration based on IEA (2020a))

Given the scope of the analysis undertaken in this thesis, the insights might be useful mainly on the ministry and regulatory level to feed into electricity strategies, policies, and related support schemes and to conduct power sector planning exercises.

The findings of this thesis show that a large volume of VRE ultimately increases price variance, i.e., short-term flexibility needs (see Chapter 3). The highest short-term fluctuations are seen for low and high shares of VRE, while for moderate VRE amounts, short-term flexibility needs are lower. This means that along the deployment path of rising VRE shares in a market, short-term fluctuations (hourly fluctuations within a day) may even be lowered by VRE. This indicates that during the current phase of moderate amounts of VRE in many countries (see Section 7.2), they are still expected to see lower price variance with increasing VRE share (see again Figure 8), and price variance alone cannot be the driver for these investments. The findings call for policies to secure investments in flexibility options, such as grid expansion, storage facilities, flexible power plants, and DSM, in periods of low price variance when market-based solutions might fail and eventually lead to situations where grid stability is at risk. Targeted policies for increased flexibility options are necessary to tackle this issue. Waterson (2017), e.g., argues that market reforms are necessary for storage concepts to function competitively. However, concrete policy plans and measures for this kind of support are difficult to find in the plans of European countries (Thonig et al. 2020). Therefore, it is important that further studies quantify how price variance changes investment decisions in generation capacities, as well as storage, transmission, and DSM, in the medium to long term. Policy action to support investments in supply and demand management must be taken while price variance is temporarily low.

Another major conclusion of the evaluation of historic flexibility needs in Europe is that the covariance and interplay of VRE and demand are important drivers in decreasing price variance. This implies that VRE technologies, whose production tends to coincide with times of peak load, as well as technologies that complement each other's generation patterns, decrease price variance. Continuous deployment and integration of different technologies, therefore, help to stabilize the electricity system because they show partly compensating effects. One policy implication of this is that targeted technology-specific support to reach a balanced technology mix has advantages over technology-neutral, least-cost policies, which might result in a strong concurrence of VRE infeed (del Río 2017). The variance of the VRE infeed is mainly determined by the availability of the natural resource (i.e., solar radiation or wind). However, policy design impacts the way VRE plants operate. For example, feed-in premiums or contracts-for-difference that force VRE producers to market their electricity themselves instead of fixed feed-in tariffs give incentives to consider market signals and shift generation to times of higher prices, hence usually times of higher demand or lower VRE infeed. Schmidt et al. (2013) show that under a feed-in premium, wind generators are incentivized to consider the covariance between renewable production and demand as well as between different wind power locations for their power plant design. However, this is, of course, only possible to a limited extent. A feed-in premium puts more risk on the VRE producer and should preferably be deployed at the later stage of the VRE deployment path of a country (maximization of the value of electricity) when the integration of high shares of VRE is a major concern; however, the feed-in premium is a well-proven means of achieving fast, high-volume deployment at an earlier stage (maximization of produced energy) (del Río and Kiefer 2021). Our finding that price variance even decreases for moderate levels of VRE infeed supports this strategy for VRE support.

By diving deeper into specific flexibility options, this thesis analyzes the effects of technological learning and storage time requirements on the competitiveness of different flexibility options. Chapter 4 shows that, following the concept of technological learning, cost reductions can be achieved with relatively low capacity additions in absolute terms for technologies with currently low installed capacities. This means that currently relatively expensive options but, in the future, still needed flexibility options might be worth to be subsidized from a system point of view. This is exemplified by two dispatchable solar power options in this thesis. Since CSP+TES and PV+BESS are competitive for certain storage requirements, it is important to continue the development of all technology combinations towards the 2050 horizon. As fossil generators are phased out over time, this need will arise, and dispatchable renewable options must be available when needed in the future. Having different technological options ready allows us to take advantage of optimal solutions for different demand profiles and can contribute to minimizing the overall system cost. In the end, policy decisions on electricity market design will decide which degree of solar dispatchability is required and rewarded. As the system value for short- and long-term storage is not the same, revenues from these segments might also be different, and yet, technologies to serve both segments will be needed.

Looking at the field of demand-side flexibility options, there are two main policy implications from the findings referring to heat pump flexibility in this thesis. Firstly, the findings of Chapter 5 show limited potential for decentral heat flexibility in Austria in 2030 but still significant contributions to short-term balancing when variable costs of flexibility provision are kept low. Heat pump technology is a central technology for achieving energy efficiency and decarbonization targets in the energy system. Therefore, it is expected that there will be significant capacities of decentral heat pumps installed in the system anyhow. Policies should, therefore, ensure a regulatory framework and market design which enables the system-wide flexible use of this potential at low costs and provide low-level access to the necessary metering and communication infrastructure. This includes tariff designs across sector boundaries to enable efficient use of this flexibility potential. Secondly, the potential of heat pump flexibility is higher in winter than in summer. However, the summer is characterized by high shares of fluctuating PV generation, which increases the demand, especially for negative flexibility, during summer noon. With the increasing impacts of climate change, demand for heating is expected to decrease, but demand for cooling is expected to increase (Viguié et al. 2021). This development could lead to a more evenly distributed electricity demand for heating and cooling over the year, enabling easier balancing between solar generation and cooling on the one side and wind generation and heating on the other. Therefore, future research should emphasize the flexibility potential of cooling because it is negatively correlated with heating and positively correlated with the generation patterns of PV.

Finally, the structured flexibility assessment undertaken in Chapter 6 provides insights into the electricity system of tomorrow and on identifying needs stemming from its transition. From a perspective of policy-making, an increase in the use of identified flexibility options with regard to operational security as well as adequacy seems vital, provided regulatory barriers are tackled and market signals are provided to all affected actors. Targeted regulation frameworks and proven practices coordinated by the system operator appear to be central for an efficient and effective provision of flexibility on all timescales by different players. This requires, on the one hand, regulatory and market conditions that are as open as possible to different kinds of flexibility options. On the other hand, targeted support for options that are not yet part of a level playing field but will be needed in the future might be beneficial from an overall system perspective. Mobilizing flexibility options well in time will contribute to safeguarding the electricity supply in times of rapid energy system transformation. Long-term storage, like hydrogen storage, is not deployed in the modeled scenarios until 2030 in Austria (see Chapter 6). However, the literature suggests that during the final phases of fully decarbonized energy systems (including all sectors), long-term flexibility options become increasingly important (see Section 7.2). This calls for incentives for the development and integration of long-duration storage technologies, even if they may not be deployed based on market mechanisms in the medium to long term.

# 8 Conclusions and outlook

In decarbonizing energy systems, the issue of flexibility has increasingly become the focus of research, system planning, and operation of generation and transmission. This thesis aims to understand better flexibility needs and options in electricity systems with high shares of variable renewable electricity (VRE).

It comprises four main contributions: The first analyzes the need for flexibility using an empirical approach, evaluating past developments and main drivers of short-term fluctuations in European countries, and assessing the flexibility options that helped to balance them. The second and the third contribution present two flexibility options in great techno-economic detail to evaluate the main drivers behind the competitiveness and operations of flexibility options and provide an insight into the peculiarities of different geographical conditions. While the first example – dispatchable solar power – is of main concern in electricity systems rich in solar resources and a supply-side example, the second option – decentral heat pumps on the demand side – is of high interest in markets where decarbonization of the heating sector will substantially increase this potential of flexible sector coupling in the coming years. Finally, the fourth contribution analyzes the flexibility needs and options in an integrated manner and shows their interactions and potentials on different timescales for Austria in 2030. Findings and conclusions from the Austrian analysis are of interest to the scientific community since Austria plans to be one of the first countries in Europe to reach a 100% renewable share (annual, national balance) in the electricity sector in 2030.

With rising shares of VRE and decreasing shares of thermal power plants towards fully decarbonized electricity systems, flexibility needs on all analyzed timescales – daily, weekly, monthly, and annual – are expected to increase compared to today, with annual needs increasing the most in Austria. However, this causality is not straightforward but has to be differentiated. First, different categories of flexibility needs are considered depending on the analyzed aspect of the energy system: While flexibility for power and voltage refer primarily to short-term fluctuations and security of supply, flexibility for transmission and energy are also linked to medium- and long-term flexibility needs and system adequacy. Further, regional differences in the electricity systems, like interconnection grades, generation mix, and demand components (e.g., the share of electric heating), are highly relevant for identifying flexibility needs. Such factors impact the optimal, regionally-tailored combination of generation technologies and flexibility options, which is by itself again strongly dependent on technological learning and cost competitiveness between different options. Therefore, targeted policies and resulting learning curves (especially of technologies with high learning potential) are essential factors in determining the future availability and deployment of different flexibility options with a wide range of techno-economic characteristics and technological readiness levels. The research questions underlying this thesis aim not to identify the best flexibility option but to provide an understanding of the interactions and relative advantages of the wide range of available or yet-to-be-developed flexibility options covering different flexibility needs.

One of the main conclusions of this thesis is that a balanced mix of generation technologies and flexibility options is a major source of flexibility and can foster the successful integration of VRE in electricity systems. The findings show that the electricity system design in terms of generation mix and available flexibility options has a higher impact on the electricity system's ability to balance supply and demand than VRE infeed and weather fluctuations. The interactions between different options and their spatial and temporal distribution are of central importance for a robust electricity system design. System planning and design should consider the complementarity of various VRE sources like PV, onshore wind, and offshore wind and their geographic spreading. Well-balanced portfolios regarding VRE generation, dispatchable capacities, storage, and high interconnection grades need holistic, long-term policy and regulatory conditions to ensure sustainability, market integration, and investment security for different flexibility options. Targeted technology-specific support can enhance flexibility options that might not be deployed by market mechanisms or technology-neutral support alone. This applies, e.g., to short-term storage in early phases of VRE integration when price fluctuations can even be lowered by additional VRE deployment. Similarly, long-term storage becomes only relevant when systems are nearly fully decarbonized – but is then of high importance to ensure security and adequacy in the system and, therefore, should be ready to be deployed.

There are several technological, economical, and societal challenges and opportunities related to the role of flexibility in electricity systems. Two of the main challenges of decarbonizing energy systems – increased electricity demand caused by sector coupling and increased VRE generation – provide a potential for flexibility through system-optimized sector coupling. Flexible sector coupling has its highest potential in taking up surplus renewable generation and increasing market values for VRE generation, fostering market integration. With the increasing decarbonization of other sectors, many decentral end-user demand capacities like heat pumps or e-vehicle charging are expected to be installed in the energy system. The cost-efficient aggregation, control, and communication infrastructure to make these this potential usable at low variable costs in a system-optimal way appears of key relevance to exploit this potential. In the longer term, the quality of forecasting VRE generation will also gain importance in dealing with the variability of VRE production since, despite the relative forecast error decreasing with increasing VRE shares, absolute errors still play an important role. A broad set of forecasting methods is currently being analyzed to tackle this challenge and needs to be further developed.

Further, the economic challenges of VRE integration require market mechanisms and remuneration schemes that provide incentives to increase flexibility on all needed timescales. Further research on fair and transparent methods is necessary to evaluate the contributions of different flexibility options in the system. Improved short-term trading opportunities are an observable trend in Europe and can foster short-term flexibility provision. Further research is needed on how long-term flexibility can be incentivized in the best way so that it is readily available and cost-effective in future energy systems. Regulations and tariff design should support the reliable and efficient planning and operation of a broad set of flexibility options and reduce barriers to market participation. Policies in the field should foster the development and integration of flexibility options and resource diversity to ensure that the needed infrastructure is there when full decarbonization needs to take place. Further research in local market design and aggregation methods can also help to unfold untapped potential for decentral flexibility options.

Finally, societal dimensions of flexibility regarding acceptance and affordability have to be considered. Some well-proven flexibility options like (pumped) hydro storage and transmission expansion have been used for a long time. However, they face societal challenges of further implementation due to a lack of acceptance or limited potential. Further applied research is needed to support the implementation of high-level decarbonization targets on a regional and local level. This requires developing and applying transparent cost-benefit assessments, including environmental and distributive effects, and improved educational and participation processes for stakeholders.

Besides the mentioned challenges, great uncertainty and risk come from possible climate change impacts on the future energy system. Dedicated further research is needed to account for the potential impacts of climate change on flexibility demand and supply in coming years.

This thesis shows how the deployment of flexibility options, such as transmission capabilities, flexible generation assets, storage, and DSM, and targeted policy design can reduce increasing flexibility needs in the long term and draws the hopeful conclusion that taking these measures can foster the successful integration of VRE in fully decarbonized electricity systems.

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# Appendices

## A1. Appendix to Chapter 3

**Formal description of the theoretical model**

Based on Wozabal, Graf, and Hirschmann (2016), the supply covering the residual load can be described by a differentiable function as

$$\boldsymbol{k(X) = a + bX + cX^2 + dX^3}\ , \tag{A.1}$$

where $k$ denotes the total costs per energy unit, $X$ is the residual supply, and $a$, $b$, c and $d$ are the respective coefficients. Given a certain level of residual load, the change in costs (or marginal costs) is

$$\boldsymbol{\frac{dk(X)}{dX} = b + 2cX\ + 3d\,X^2}\ . \tag{A.2}$$

Assuming an inelastic (i.e., vertical) residual load, the change in price is the derivative of the cost function

$$\boldsymbol{\frac{dk(X)}{dX} = \frac{dp(X)}{dX}}\,, \tag{A.3}$$

where $p$ is the spot price of electricity. This derivative, which differs depending on the level of $X$ (and the parameters), describes the part of the price variance influenced by the shape of the supply curve. Price variance is also caused by the variance in $X$, which can be the result of the variance of VRE production or of the variance of the load itself. For the special case in which the variance of $X$ is not "broader" after an increase in VRE than before the increase, Wozabal, Graf, and Hirschmann (2016) formally show that the variance of the price decreases. In the general case, the change in the variance of the price depends in a nontrivial way on the interaction between the shape of the supply function and the distribution of the residual load. There is no straightforward economic interpretation of this interaction, but a Taylor approximation can be used to describe the interaction of supply function shape and the variance of the residual load (Wozabal, Graf, and Hirschmann 2016).

Approximating the supply function from equation (A.1) by a first-order Taylor approximation around $E(X) = \mu$ yields

$$\boldsymbol{k(X) = \ a + \ b\mu + c\mu^2 + d\mu^3 + (b + 2c\mu + 3d\mu^2)(X - \mu)}. \tag{A.4}$$

By applying the variance operator on both sides and taking into account that $\mu$ is a constant, we obtain

$$\boldsymbol{Var\big(k(X)\big) = (b + 2c\mu + 3d\mu^2)^2 Var(X)} \tag{A.5}$$

and

$$\boldsymbol{Var\big(k(X)\big) = \left(\frac{d\,k(\mu)}{d\,X}\right)^2 Var(X)}. \tag{A.6}$$

The variance of the price is approximated by the square slope of the supply function (which equals the marginal cost function) evaluated at the mean of the residual load times the variance of the residual load. This confirms the intuition from the figures that the shape of the supply function and the variance of the residual load determine the variance of the electricity price.

### Detailed results of Chapter 3

Table A.1: Panel model results for the Basic Model.

| | Basic Model | | |
|---|---|---|---|
| | Pooled | Fixed effects | First difference |
| (Intercept) | 341.92 (.000) | | 0.01 (.991) |
| Residual Load | -5.41 (.000) | -5.19 (.000) | -3.92 (.000) |
| Residual Load² | 0.06 (.000) | 0.05 (.000) | 0.04 (.000) |
| Residual Load var | 0.13 (.000) | 0.19 (.000) | 0.22 (.000) |
| Gas Price | 15.44 (.001) | 15.82 (.000) | -14.17 (.146) |
| Lagged Gas Price | -7.54 (.095) | -8.02 (.017) | -0.34 (.848) |
| Share oil gas | -137.98 (.000) | | |
| Share hydro storage | -217.72 (.000) | | |
| Share export import | -81.85 (.000) | | |
| Observations | 14266 | 14266 | 14258 |
| $R^2$ | 0.106 | 0.088 | 0.047 |
| Joint significance of Residual Load and Residual Load² | 15.31 (.000) | 47.03 (.000) | 36.23 (.000) |

Note: p values in parenthesis based on HAC robust (Pooled), clustered (FE), and Newey West (FD) standard errors. Joint significances report the F-statistics with respective standard errors in parenthesis. Dummies for weekdays and months are included in all models but not shown.

Table A.2: Panel model results for the Extended Model.

| Extended Model | Pooled | Fixed effects | First difference |
|---|---|---|---|
| (Intercept) | 836.90 (.000) | | 0.01 (.991) |
| Load | -18.12 (.000) | -20.47 (.000) | -12.63 (.000) |
| Load² | 0.15 (.000) | 0.17 (.000) | 0.11 (.000) |
| VRE | 9.57 (.000) | 13.47 (.000) | 8.16 (.000) |
| VRE² | 0.06 (.000) | 0.02 (.000) | 0.02 (.000) |
| Load var | -0.17 (.053) | 0.08 (.235) | 0.14 (.005) |
| VRE var | 0.11 (.000) | 0.11 (.000) | 0.12 (.000) |
| VRE Load cov | -0.46 (.000) | -0.43 (.000) | -0.50 (.000) |
| Load*VRE | -0.17 (.000) | -0.18 (.000) | -0.12 (.000) |
| Gas Price | 16.17 (.001) | 14.63 (.000) | -14.66 (.135) |
| Lagged Gas Price | -7.41 (.087) | -6.96 (.034) | -0.28 (.877) |
| Share oil gas | -52.04 (.048) | | |
| Share hydro storage | -301.49 (.000) | | |
| Share export import | -70.62 (.000) | | |
| Observations | 14266 | 14266 | 14258 |
| $R^2$ | 0.123 | 0.102 | 0.052 |
| Joint Significances | | | |
| Load, Load² | 10.01 (.000) | 45.85 (.000) | 16.13 (.000) |
| VRE, VRE² | 42.41 (.000) | 12.71 (.000) | 13.76 (.000) |
| Load, Load², VRE, VRE² | 14.06 (.000) | 78.53 (.000) | 28.69 (.000) |
| Load var, VRE var, VRE Load cov, Load*VRE | 38.62 (.000) | 209.63 (.000) | 220.73 (.000) |

Note: p values in parenthesis based on HAC robust (Pooled), clustered (FE), and Newey West (FD) standard errors. Joint significances report the F-statistics with respective standard errors in parenthesis. Dummies for weekdays and months are included in all models but not shown.

Table A.3: Panel model results for the Wind & Solar Model.

**Wind & Solar Model**

| | Pooled | Fixed effects | First difference |
|---|---|---|---|
| (Intercept) | 702.45 (.000) | | 0.02 (.976) |
| Load | -15.37 (.000) | -18.06 (.000) | -7.40 (.015) |
| Load² | 0.14 (.000) | 0.16 (.000) | 0.08 (.001) |
| Load var | -0.12 (.166) | 0.12 (.050) | 0.14 (.004) |
| VRE var | 0.13 (.000) | 0.09 (.000) | 0.10 (.000) |
| VRE Load cov | -0.34 (.000) | -0.41 (.000) | -0.47 (.000) |
| Wind | 6.70 (.001) | 9.69 (.000) | 5.89 (.000) |
| Wind² | 0.06 (.000) | 0.03 (.000) | 0.02 (.000) |
| Solar | 27.54 (.005) | 32.55 (.000) | 39.56 (.000) |
| Solar² | 0.98 (.005) | 0.75 (.007) | 0.79 (.027) |
| Load*Wind | -0.15 (.000) | -0.15 (.000) | -0.10 (.000) |
| Load*Solar | -0.71 (.000) | -0.64 (.000) | -0.67 (.000) |
| Wind*Solar | 0.66 (.000) | 0.65 (.000) | 0.55 (.000) |
| Gas Price | 15.98 (.001) | 14.67 (.000) | -15.45 (.109) |
| Lagged Gas Price | -6.91 (.105) | -6.76 (.036) | -0.28 (.872) |
| Share oil gas | 17.21 (.614) | | |
| Share hydro storage | -319.56 (.000) | | |
| Share export import | -92.18 (.000) | | |
| Observations | 14266 | 14266 | 14258 |
| $R^2$ | 0.139 | 0.113 | 0.060 |
| Joint Significances | | | |
| Load, Load² | 10.94 (.000) | 37.36 (.000) | 23.79 (.000) |
| Wind, Wind², Load*Wind, Wind*Solar | 17.57 (.000) | 91.52 (.000) | 51.27 (.000) |
| Solar, Solar², Load*Solar, Wind*Solar | 21.43 (.000) | 65.09 (.000) | 67.92 (.000) |
| Load, Load², Wind, Wind², Solar, Solar², Load*Wind, Load*Solar, VRE Load cov | 26.23 (.000) | 292.42 (.000) | 273.95 (.000) |
| Load var, VRE var | 28.20 (.000) | 31.66 (.000) | 35.62 (.000) |

Note: p values in parenthesis based on HAC robust (Pooled), clustered (FE), and Newey West (FD) standard errors. Joint significances report the F-statistics with respective standard errors in parenthesis. Dummies for weekdays and months are included in all models but not shown.

Table A.4: Panel model results with all interaction terms for the Basic Model.

| | Basic Model | | |
|---|---|---|---|
| | Pooled | Fixed effects | First difference |
| (Intercept) | 1485.08 (.000) | | -0.01 (.994) |
| Residual Load | -52.35 (.000) | -52.77 (.000) | -49.88 (.000) |
| Residual Load² | 0.48 (.000) | 0.45 (.000) | 0.41 (.000) |
| Residual Load var | 1.22 (.000) | 1.60 (.000) | 1.81 (.000) |
| Gas Price | 15.70 (.000) | 16.42 (.000) | -15.48 (.104) |
| Lagged Gas Price | -7.06 (.098) | -7.81 (.012) | -1.12 (.521) |
| Share oil gas*Load | 101.50 (.002) | 98.51 (.001) | 101.49 (.000) |
| Share oil gas*Load² | -0.94 (.001) | -0.88 (.001) | -0.94 (.000) |
| Share oil gas*Load var | -0.76 (.131) | -1.18 (.004) | -1.40 (.002) |
| Share hydro storage*Load | 37.20 (.243) | 31.68 (.280) | 43.56 (.101) |
| Share hydro storage*Load² | -0.34 (.248) | -0.26 (.336) | -0.31 (.205) |
| Share hydro storage*Load var | -2.87 (.000) | -3.13 (.000) | -3.66 (.000) |
| Share export import*Load | 18.82 (.000) | 19.59 (.000) | 17.44 (.000) |
| Share export import*Load² | -0.16 (.000) | -0.15 (.000) | -0.12 (.003) |
| Share export import*Load var | -0.69 (.000) | -0.89 (.000) | -1.00 (.000) |
| Share oil gas | -2626.84 (.003) | | |
| Share hydro storage | -958.91 (.255) | | |
| Share export import | -542.67 (.000) | | |
| Observations | 14266 | 14266 | 14258 |
| $R^2$ | 0.150 | 0.151 | 0.103 |
| Joint Significances | | | |
| Residual Load, Residual Load² | 11.05 (.000) | 162.49 (.000) | 144.36 (.000) |
| Share oil gas interactions | 5.64 (.000) | 32.88 (.000) | 68.75 (.000) |
| Share hydro storage interactions | 24.67 (.000) | 83.61 (.000) | 87.30 (.000) |
| Share export import interactions | 38.83 (.000) | 147.56 (.000) | 152.86 (.000) |

Note: p values in parenthesis based on HAC robust (Pooled), clustered (FE), and Newey West (FD) standard errors. Joint significances report the F-statistics with respective standard errors in parenthesis. Dummies for weekdays and months are included in all models but not shown.

Table A.5: Panel model results with all interaction terms for the Extended Model.

| | Extended Model | | |
|---|---|---|---|
| | Pooled | Fixed effects | First difference |
| (Intercept) | -231.79 (.701) | | 0.00 (.996) |
| Load | 4.28 (.815) | -34.27 (.012) | -6.08 (.613) |
| Load² | 0.09 (.511) | 0.34 (.001) | 0.11 (.210) |
| VRE | 11.58 (.275) | 39.41 (.000) | 19.08 (.096) |
| VRE² | 0.73 (.000) | 0.55 (.000) | 0.70 (.000) |
| Load var | -0.41 (.268) | 1.26 (.000) | 1.61 (.000) |
| VRE var | 2.27 (.000) | 2.56 (.000) | 2.51 (.000) |
| VRE Load cov | -3.40 (.000) | -3.06 (.000) | -3.72 (.000) |
| Load*VRE | -0.62 (.000) | -0.82 (.000) | -0.62 (.000) |
| Gas Price | 15.64 (.000) | 14.78 (.000) | -15.63 (.096) |
| Lagged Gas Price | -7.12 (.088) | -7.03 (.021) | -1.06 (.543) |
| Share oil gas*Load | 16.98 (.679) | 78.86 (.016) | 35.99 (.226) |
| Share oil gas*Load² | -0.32 (.325) | -0.72 (.008) | -0.46 (.072) |
| Share oil gas*VRE | 2.48 (.942) | -39.38 (.185) | -22.28 (.400) |
| Share oil gas*VRE² | -1.28 (.007) | -1.11 (.012) | -1.68 (.000) |
| Share oil gas*Load var | 1.97 (.008) | -0.89 (.087) | -0.93 (.168) |
| Share oil gas*VRE var | -2.21 (.013) | -2.97 (.000) | -3.28 (.000) |
| Share oil gas*VRE Load cov | 2.12 (.102) | 1.70 (.118) | 2.96 (.027) |
| Share oil gas*(Load*VRE) | 0.80 (.185) | 1.26 (.021) | 1.26 (.006) |
| Share hydro storage*Load | -94.54 (.048) | -19.98 (.629) | -53.88 (.165) |
| Share hydro storage*Load² | 0.54 (.160) | 0.06 (.856) | 0.41 (.213) |
| Share hydro storage*VRE | 17.87 (.604) | -26.10 (.397) | 4.29 (.879) |
| Share hydro storage*VRE² | -0.96 (.008) | -0.61 (.048) | -0.78 (.007) |
| Share hydro storage*Load var | -1.04 (.158) | -2.63 (.000) | -4.46 (.000) |
| Share hydro storage*VRE var | -5.37 (.000) | -5.86 (.000) | -4.71 (.000) |
| Share hydro storage*VRE Load cov | 7.19 (.000) | 6.14 (.000) | 7.39 (.000) |
| Share hydro storage*(Load*VRE) | 0.44 (.450) | 0.72 (.172) | 0.41 (.358) |
| Share export import*Load | -12.08 (.280) | 8.45 (.359) | -3.48 (.670) |
| Share export import*Load² | 0.05 (.549) | -0.08 (.249) | 0.04 (.565) |
| Share export import*VRE | -7.53 (.179) | -20.78 (.000) | -9.35 (.073) |
| Share export import*VRE² | -0.28 (.000) | -0.18 (.001) | -0.20 (.000) |
| Share export import*Load var | -0.29 (.060) | -0.91 (.000) | -1.13 (.000) |
| Share export import*VRE var | -1.20 (.000) | -1.27 (.000) | -1.21 (.000) |
| Share export import*VRE Load cov | 1.97 (.000) | 1.79 (.000) | 1.99 (.000) |
| Share export import*(Load*VRE) | 0.26 (.004) | 0.34 (.000) | 0.20 (.014) |
| Share oil gas | -190.35 (.882) | | |
| Share hydro storage | 3256.18 (.026) | | |
| Share export import | 483.58 (.188) | | |
| Observations | 14266 | 14266 | 14258 |
| R² | 0.172 | 0.157 | 0.106 |
| Joint Significances | | | |
| Load, Load² | 6.90 (.000) | 82.11 (.000) | 34.85 (.000) |
| VRE, VRE² | 13.36 (.000) | 149.72 (.000) | 74.53 (.000) |
| Load, Load², VRE, VRE² | 7.81 (.000) | 172.57 (.000) | 94.61 (.000) |
| Load var, VRE var, VRE Load cov, Load*VRE | 14.09 (.000) | 411.61 (.000) | 411.91 (.000) |
| Share oil gas interactions | 4.42 (.000) | 54.20 (.000) | 67.98 (.000) |
| Share hydro storage interactions | 15.36 (.000) | 98.29 (.000) | 96.01 (.000) |
| Share export import interactions | 14.09 (.000) | 163.56 (.000) | 185.64 (.000) |

Note: p values in parenthesis based on HAC robust (Pooled), clustered (FE), and Newey West (FD) standard errors. Joint significances report the F-statistics with respective standard errors in parenthesis. Dummies for weekdays and months are included in all models but not shown.

Table A.6: Panel model results with all interaction terms for the Wind & Solar Model.

| | **Wind & Solar Model** | | |
|---|---|---|---|
| | Pooled | Fixed effects | First difference |
| (Intercept) | -575.07 (.330) | | 0.01 (.993) |
| Load | 15.99 (.351) | -12.84 (.340) | 10.98 (.404) |
| Load² | 0.00 (.993) | 0.22 (.024) | 0.02 (.870) |
| Load var | 0.06 (.872) | 1.24 (.000) | 1.66 (.000) |
| VRE var | 2.11 (.000) | 2.32 (.000) | 2.61 (.000) |
| VRE Load cov | -2.85 (.000) | -3.21 (.000) | -3.44 (.000) |
| Wind | 12.43 (.236) | 41.17 (.000) | 20.71 (.055) |
| Wind² | 0.67 (.000) | 0.63 (.000) | 0.73 (.000) |
| Solar | -7.62 (.782) | 113.18 (.000) | 95.89 (.001) |
| Solar² | 2.70 (.029) | -0.77 (.417) | -2.12 (.043) |
| Load*Wind | -0.62 (.000) | -0.86 (.000) | -0.66 (.000) |
| Load*Solar | -0.94 (.019) | -1.46 (.000) | -1.34 (.000) |
| Wind*Solar | 1.93 (.001) | 1.38 (.005) | 1.82 (.000) |
| Gas Price | 15.57 (.000) | 14.57 (.000) | -16.20 (.084) |
| Lagged Gas Price | -6.96 (.094) | -6.98 (.021) | -1.07 (.529) |
| Share oil gas*Load | -11.00 (.769) | 41.10 (.190) | -3.97 (.892) |
| Share oil gas*Load² | -0.12 (.710) | -0.51 (.050) | -0.23 (.341) |
| Share oil gas*Wind | -20.24 (.554) | -46.77 (.119) | -32.27 (.215) |
| Share oil gas*Wind² | -1.33 (.010) | -1.54 (.002) | -1.91 (.000) |
| Share oil gas*Solar | -135.74 (.255) | -212.19 (.051) | -332.25 (.001) |
| Share oil gas*Solar² | 7.20 (.272) | 6.78 (.220) | 4.51 (.360) |
| Share oil gas*Load var | 1.30 (.074) | -0.91 (.079) | -1.14 (.096) |
| Share oil gas*VRE var | -1.51 (.269) | -3.08 (.019) | -4.07 (.000) |
| Share oil gas*VRE Load cov | 1.48 (.305) | 1.79 (.148) | 1.60 (.298) |
| Share oil gas*(Load*Wind) | 1.08 (.086) | 1.45 (.011) | 1.45 (.002) |
| Share oil gas*(Load*Solar) | 2.29 (.219) | 2.80 (.078) | 5.41 (.000) |
| Share oil gas*(Wind*Solar) | -1.22 (.698) | -5.89 (.028) | -6.77 (.003) |
| Share hydro storage*Load | -113.12 (.022) | -59.41 (.171) | -96.22 (.021) |
| Share hydro storage*Load² | 0.71 (.069) | 0.27 (.428) | 0.69 (.050) |
| Share hydro storage*Wind | 15.39 (.637) | -31.23 (.296) | -1.87 (.945) |
| Share hydro storage*Wind² | -0.75 (.039) | -0.55 (.081) | -0.72 (.012) |
| Share hydro storage*Solar | 427.96 (.000) | -34.62 (.801) | 162.45 (.208) |
| Share hydro storage*Solar² | -20.76 (.009) | -4.47 (.530) | 10.87 (.097) |
| Share hydro storage*Load var | -2.33 (.001) | -2.69 (.000) | -4.26 (.000) |
| Share hydro storage*VRE var | -5.41 (.000) | -4.66 (.000) | -4.39 (.000) |
| Share hydro storage*VRE Load cov | 6.52 (.000) | 7.01 (.000) | 7.73 (.000) |
| Share hydro storage*(Load*Wind) | 0.41 (.455) | 0.72 (.158) | 0.46 (.287) |
| Share hydro storage*(Load*Solar) | -2.91 (.088) | -0.03 (.983) | -4.03 (.015) |
| Share hydro storage*(Wind*Solar) | -3.88 (.098) | 3.30 (.141) | 2.41 (.185) |
| Share export import*Load | -22.46 (.040) | -2.30 (.810) | -8.41 (.361) |
| Share export import*Load² | 0.12 (.131) | -0.02 (.782) | 0.06 (.360) |
| Share export import*Wind | -3.11 (.568) | -20.77 (.000) | -9.29 (.064) |
| Share export import*Wind² | -0.23 (.000) | -0.17 (.002) | -0.18 (.001) |
| Share export import*Solar | 19.16 (.413) | -24.05 (.323) | -13.85 (.569) |
| Share export import*Solar² | -4.20 (.004) | -4.31 (.003) | 0.72 (.586) |
| Share export import*Load var | -0.38 (.008) | -0.87 (.000) | -1.12 (.000) |
| Share export import*VRE var | -1.19 (.000) | -1.08 (.000) | -1.15 (.000) |
| Share export import*VRE Load cov | 1.64 (.000) | 1.85 (.000) | 2.02 (.000) |
| Share export import*(Load*Wind) | 0.21 (.016) | 0.33 (.000) | 0.20 (.012) |
| Share export import*(Load*Solar) | 0.60 (.079) | 0.58 (.062) | 0.05 (.864) |
| Share export import*(Wind*Solar) | -1.22 (.000) | 0.09 (.765) | -0.07 (.792) |
| Share oil gas | 744.97 (.529) | | |
| Share hydro storage | 3756.20 (.018) | | |
| Share export import | 770.31 (.039) | | |
| Observations | 14266 | 14266 | 14258 |
| R² | 0.183 | 0.162 | 0.109 |
| Joint Significances | | | |
| Load, Load² | 5.48 (.000) | 80.12 (.000) | 42.94 (.000) |
| Wind, Wind², Load*Wind, Wind*Solar | 7.72 (.000) | 227.82 (.000) | 152.13 (.000) |
| Solar, Solar², Load*Solar, Wind*Solar | 5.52 (.000) | 57.83 (.000) | 37.20 (.000) |
| Load, Load², Wind, Wind², Solar, Solar², Load*Wind, Load*Solar, VRE Load cov | 12.37 (.000) | 613.77 (.000) | 575.18 (.000) |
| Load var, VRE var | 21.46 (.000) | 130.84 (.000) | 118.88 (.000) |
| Share oil gas interactions | 3.22 (.000) | 51.67 (.000) | 57.64 (.000) |
| Share hydro storage interactions | 11.47 (.000) | 123.08 (.000) | 184.19 (.000) |
| Share export import interactions | 9.86 (.000) | 161.19 (.000) | 165.38 (.000) |

Note: p values in parenthesis based on HAC robust (Pooled), clustered (FE), and Newey West (FD) standard errors. Joint significances report the F-statistics with respective standard errors in parenthesis. Dummies for weekdays and months are included in all models but not shown.

Table A.7: Basic model results for individual countries, absolute values.

| Basic Model | Austria/ Germany | Denmark | GB | Greece | Italy | Portugal | Romania | Spain | Sweden |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | 929.12 (.000) | 87.29 (.000) | 42.27 (.982) | 930.14 (.007) | 565.57 (.000) | 74.82 (.000) | 393.38 (.170) | 106.19 (.000) | 1036.15 (.015) |
| Residual Load | -38.66 (.000) | -66.25 (.000) | -84.70 (.504) | -385.06 (.004) | -40.06 (.000) | 14.10 (.055) | -116.81 (.214) | -1.61 (.574) | -171.45 (.011) |
| Residual Load² | 0.41 (.000) | 19.37 (.000) | 2.77 (.190) | 40.06 (.004) | 0.69 (.000) | -2.82 (.002) | 14.01 (.119) | -0.10 (.152) | 6.55 (.010) |
| Residual Load var | 1.56 (.000) | 49.34 (.000) | 7.91 (.089) | 158.71 (.001) | 2.88 (.000) | 14.84 (.000) | 162.83 (.000) | 4.19 (.000) | 8.15 (.005) |
| Gas Price | 28.91 (.000) | 13.30 (.017) | -115.76 (.466) | 25.54 (.058) | 10.81 (.026) | 5.74 (.006) | 25.85 (.055) | 6.07 (.018) | 11.20 (.558) |
| Lagged Gas Price | -11.50 (.043) | 6.36 (.233) | -44.10 (.599) | -34.68 (.044) | -1.80 (.762) | -0.18 (.943) | -8.53 (.561) | -0.87 (.762) | -10.52 (.431) |
| Market split dummy | 3.16 (.795) | | | | | | | | |
| Observations | 1785 | 1818 | 1820 | 1786 | 1779 | 1698 | 1815 | 1826 | 1759 |
| $R^2$ | 0.43 | 0.19 | 0.03 | 0.11 | 0.26 | 0.40 | 0.26 | 0.54 | 0.17 |
| Joint significance of Residual Load and Residual Load² | 25.39 (.000) | 15.82 (.000) | 3.98 (.019) | 4.27 (.014) | 13.99 (.000) | 26.39 (.000) | 4.85 (.008) | 52.72 (.000) | 4.08 (.017) |

Note: p values in parenthesis based on HAC robust standard errors. Joint significances report the F-statistics with clustered standard errors in parenthesis. Dummies for weekdays and months are included in all models but not shown.

Table A.8: Extended model results for individual countries, absolute values.

| Extended Model | Austria/ Germany | Denmark | GB | Greece | Italy | Portugal | Romania | Spain | Sweden |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | 390.19 (.154) | 281.04 (.316) | -3259.20 (.406) | 146.77 (.789) | 455.01 (.004) | 210.63 (.026) | 602.84 (.287) | 11.68 (.924) | 1324.78 (.018) |
| Load | -17.15 (.075) | -200.64 (.232) | 171.08 (.529) | -148.42 (.420) | -33.54 (.002) | -34.37 (.304) | -239.91 (.170) | 5.70 (.555) | -204.79 (.013) |
| Load² | 0.24 (.013) | 49.27 (.054) | -1.35 (.742) | 23.43 (.143) | 0.66 (.001) | 2.90 (.340) | 27.83 (.072) | -0.26 (.196) | 7.49 (.010) |
| VRE | 27.99 (.000) | 62.02 (.076) | -257.30 (.478) | 475.61 (.008) | 32.81 (.023) | -13.20 (.314) | -46.22 (.659) | -0.75 (.879) | 91.53 (.063) |
| VRE² | 0.54 (.000) | 17.54 (.000) | 23.26 (.103) | 100.10 (.040) | 2.92 (.063) | -2.35 (.056) | 20.20 (.150) | -0.01 (.969) | 11.45 (.013) |
| Load var | 0.67 (.119) | -226.16 (.000) | 16.75 (.151) | 184.69 (.000) | 2.16 (.000) | -26.31 (.002) | 34.02 (.734) | 5.00 (.000) | 2.85 (.808) |
| VRE var | 2.16 (.000) | 41.51 (.000) | 27.59 (.062) | 103.19 (.035) | 5.22 (.000) | 10.75 (.028) | 188.85 (.000) | 4.97 (.000) | -7.00 (.451) |
| VRE Load cov | -3.21 (.000) | -112.61 (.000) | -15.49 (.068) | -307.41 (.013) | -7.02 (.000) | -40.19 (.000) | -290.18 (.000) | -8.29 (.000) | -25.74 (.000) |
| Load*VRE | -0.75 (.000) | -35.09 (.001) | -4.74 (.362) | -116.05 (.000) | -1.67 (.002) | 5.27 (.020) | -2.33 (.878) | 0.22 (.186) | -9.18 (.034) |
| Gas Price | 23.06 (.000) | 11.49 (.013) | -126.10 (.451) | 23.21 (.072) | 11.03 (.024) | 5.72 (.002) | 14.47 (.245) | 6.41 (.012) | 8.94 (.615) |
| Lagged Gas Price | -11.31 (.021) | 6.20 (.197) | -55.74 (.496) | -34.94 (.044) | -3.26 (.602) | 2.70 (.234) | -4.82 (.732) | -0.90 (.747) | -8.41 (.493) |
| Market split dummy | -3.87 (.787) | | | | | | | | |
| Observations | 1785 | 1818 | 1820 | 1786 | 1779 | 1698 | 1815 | 1826 | 1759 |
| $R^2$ | 0.43 | 0.23 | 0.04 | 0.11 | 0.27 | 0.42 | 0.28 | 0.54 | 0.18 |
| Joint Significances | | | | | | | | | |
| Load, Load² | 6.17 (.002) | 18.26 (.000) | 2.89 (.056) | 4.03 (.018) | 6.12 (.002) | 0.58 (.560) | 3.56 (.029) | 8.20 (.000) | 3.71 (.025) |
| VRE, VRE² | 20.19 (.000) | 23.65 (.000) | 3.24 (.039) | 7.55 (.001) | 5.41 (.005) | 2.78 (.062) | 1.04 (.354) | 0.02 (.984) | 3.11 (.045) |
| | 11.27 (.000) | 16.30 (.000) | 2.07 (.082) | 4.89 (.001) | 4.77 (.001) | 1.75 (.136) | 4.87 (.001) | 6.87 (.000) | 3.25 (.011) |
| Load, Load², VRE, VRE², VRE Load cov, Load*VRE Load var, VRE var | 26.92 (.000) | 36.02 (.000) | 1.08 (.364) | 5.14 (.000) | 17.95 (.000) | 24.41 (.000) | 18.38 (.000) | 59.63 (.000) | 7.54 (.000) |

Note: p values in parenthesis based on HAC robust standard errors. Joint significances report the F-statistics with clustered standard errors in parenthesis. Dummies for weekdays and months are included in all models but not shown.

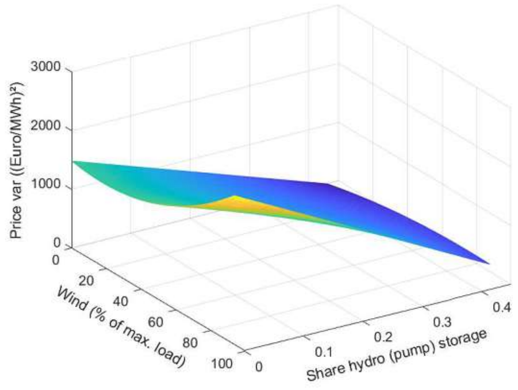
Table A.9: Wind & Solar Model results for individual countries, absolute values.

| **Wind & Solar Model** | Austria/ Germany | Denmark | GB | Greece | Italy | Portugal | Romania | Spain | Sweden |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | 134.88 (.660) | 551.56 (.162) | -3537.62 (.404) | -438.20 (.427) | 490.72 (.006) | 146.13 (.205) | 1789.49 (.021) | 66.47 (.559) | 1324.78 (.018) |
| Load | -8.85 (.372) | -337.58 (.122) | 185.19 (.525) | -73.05 (.654) | -33.98 (.002) | -14.99 (.690) | -555.22 (.016) | 3.37 (.710) | -204.79 (.013) |
| Load² | 0.17 (.059) | 64.46 (.037) | -1.55 (.728) | 29.20 (.079) | 0.62 (.001) | 1.91 (.548) | 47.37 (.011) | -0.24 (.206) | 7.49 (.010) |
| Wind | 25.68 (.000) | 66.29 (.108) | -286.37 (.505) | 399.52 (.012) | 37.87 (.010) | -12.52 (.392) | 44.49 (.728) | 0.21 (.966) | 91.53 (.063) |
| Wind² | 0.54 (.000) | 17.27 (.000) | 23.27 (.111) | 95.87 (.080) | 4.44 (.002) | -2.83 (.030) | 14.85 (.310) | -0.06 (.657) | 11.45 (.013) |
| Solar | 49.57 (.000) | -390.47 (.510) | -129.25 (.894) | 2065.65 (.032) | -6.14 (.886) | 155.72 (.620) | -2811.50 (.015) | -36.34 (.108) | |
| Solar² | 0.31 (.561) | -285.28 (.673) | 30.74 (.840) | -5.21 (.990) | 6.49 (.187) | -73.17 (.902) | 674.02 (.706) | 1.53 (.625) | |
| Load var | 0.74 (.094) | -184.89 (.000) | 17.14 (.135) | 116.06 (.010) | 2.62 (.000) | -23.67 (.003) | 44.14 (.620) | 4.96 (.000) | 2.85 (.808) |
| VRE var | 2.04 (.000) | 42.74 (.000) | 18.44 (.149) | 191.97 (.025) | 2.73 (.159) | 9.10 (.064) | 168.51 (.001) | 5.15 (.000) | -7.00 (.451) |
| VRE Load cov | -3.10 (.000) | -112.30 (.000) | -15.28 (.061) | -250.39 (.030) | -8.60 (.000) | -42.35 (.000) | -325.24 (.000) | -8.36 (.000) | -25.74 (.000) |
| Load*Wind | -0.73 (.000) | -35.50 (.002) | -4.08 (.536) | -106.57 (.000) | -1.89 (.001) | 4.72 (.044) | -8.30 (.596) | 0.25 (.140) | -9.18 (.034) |
| Load*Solar | -1.11 (.000) | 155.28 (.288) | -6.87 (.614) | -416.50 (.029) | -0.08 (.949) | -71.02 (.162) | 462.04 (.021) | 1.33 (.039) | |
| Wind*Solar | 1.42 (.000) | 18.08 (.711) | 54.41 (.270) | 238.35 (.158) | 3.94 (.333) | 33.20 (.318) | -223.83 (.353) | -0.93 (.257) | |
| Gas Price | 25.10 (.000) | 11.83 (.010) | -127.47 (.453) | 21.84 (.081) | 11.97 (.015) | 4.81 (.010) | 17.93 (.154) | 6.08 (.019) | 8.94 (.615) |
| Lagged Gas Price | -11.88 (.021) | 5.94 (.219) | -53.07 (.516) | -36.06 (.037) | -3.75 (.543) | 2.27 (.305) | -9.42 (.519) | -0.78 (.777) | -8.41 (.493) |
| Market split dummy | -7.38 (.594) | | | | | | | | |
| Observations | 1785 | 1818 | 1820 | 1786 | 1779 | 1698 | 1815 | 1826 | 1759 |
| $R^2$ | 0.44 | 0.23 | 0.04 | 0.12 | 0.28 | 0.44 | 0.30 | 0.55 | 0.18 |
| Joint Significances | | | | | | | | | |
| Wind, Wind², Load*Wind, Wind*Solar | 11.59 (.000) | 11.90 (.000) | 1.67 (.154) | 5.17 (.000) | 8.35 (.000) | 10.82 (.000) | 0.98 (.415) | 33.71 (.000) | 133.42 (.000) |
| Solar, Solar², Load*Solar, Wind*Solar | 5.96 (.000) | 1.59 (.173) | 1.16 (.324) | 1.61 (.170) | 1.06 (.374) | 8.42 (.000) | 2.40 (.048) | 1.45 (.215) | |
| Load, Load², Wind, Wind², Solar, Solar², Load*Wind, Load*Solar, VRE Load cov | 21.44 (.000) | 16.53 (.000) | 1.02 (.420) | 3.94 (.000) | 14.38 (.000) | 15.73 (.000) | 19.51 (.000) | 33.06 (.000) | 324.45 (.000) |
| Load var, VRE var | 24.76 (.000) | 43.99 (.000) | 1.44 (.238) | 8.87 (.000) | 18.86 (.000) | 6.84 (.001) | 6.41 (.002) | 56.00 (.000) | 0.71 (.493) |

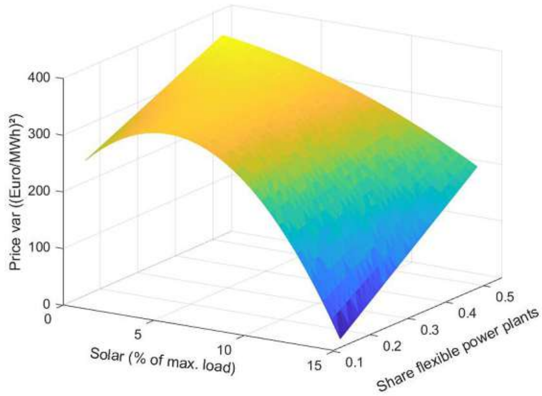
Note: p values in parenthesis based on HAC robust standard errors. Joint significances report the F-statistics with clustered standard errors in parenthesis. Dummies for weekdays and months are included in all models but not shown.

Table A.10: Panel unit root tests as described in Maddala and Wu (1999). P values in parentheses (alternative hypothesis: stationarity).

| | Individual intercepts | Individual intercepts and trends |
|---|---|---|
| | Exogenous variables | |
| Price var | 518.11 (.000) | 470.99 (.000) |
| Residual Load | 495.03 (.000) | 447.97 (.000) |
| Residual Load² | 490.83 (.000) | 442.21 (.000) |
| Residual Load var | 256.70 (.000) | 217.04 (.000) |
| Gas Price | 30.94 (.014) | 16.26 (.435) |
| Lagged Gas Price | 26.26 (.050) | 12.97 (.675) |
| Load | 229.33 (.000) | 197.16 (.000) |
| Load² | 232.34 (.000) | 199.40 (.000) |
| VRE | 675.00 (.000) | 617.97 (.000) |
| VRE² | 715.79 (.000) | 624.82 (.000) |
| Load var | 192.28 (.000) | 172.87 (.000) |
| VRE var | 526.09 (.000) | 472.35 (.000) |
| VRE Load cov | 381.74 (.000) | 312.42 (.000) |
| Load*VRE | 556.88 (.000) | 504.28 (.000) |
| Wind | 590.80 (.000) | 547.98 (.000) |
| Wind² | 613.04 (.000) | 570.17 (.000) |
| Load*Wind | 518.96 (.000) | 478.30 (.000) |
| Solar | 68.05 (.000) | 46.28 (.000) |
| Solar² | 72.92 (.000) | 51.48 (.000) |
| Load*Solar | 82.54 (.000) | 59.79 (.000) |
| Wind*Solar | 398.05 (.000) | 366.38 (.000) |




**(a)**




**(b)**

Figure A 1: Impact of wind generation and share of hydro (pump) storage (Panel (a)) and solar generation and share of flexible power plants (oil and gas, Panel (b)) on electricity price variance based on fixed effects estimates. Wind and solar generation and transmission capacities are depicted in % of maximal load, and flexible generation capacities are depicted in % of overall generation capacity.[28]

## A2. Appendix to Chapter 4

### Theoretical background on the solar-to-electricity efficiency of CSP

The optical efficiency $\eta_{optical}$ is the optical efficiency of the mirrors and receiver. The thermal efficiency describes the thermal efficiency of the receiver system, including the HTF $\eta_{thermal,receiver}$. The optical efficiency is the optical energy entering the projected area of the receiver $A_{projected}$ divided by the incident solar radiation in terms of DNI to the solar field.

$$Q_{optical} = DNI * A_{projected} * \eta_{optical} \tag{A. 7}$$

The thermal efficiency of the receiver $\eta_{thermal,receiver}$ is then obtained as the share of thermal energy $Q_{fluid}$ transferred to the HTF and finally to the power block.

$$\eta_{thermal,receiver} = \frac{Q_{fluid}}{Q_{optical}} \tag{A. 8}$$

Net solar-to-steam efficiency $\eta_{steam}$ of the system is the product of thermal and optical efficiency.

$$\eta_{steam} = \eta_{optical} * \eta_{thermal,receiver} \tag{A. 9}$$

[28] The unexpected positive effect of flexible power plants on the price variance (see Panel (b)) is caused by a statistical artifact: the insignificant coefficient of “Share oil gas * Load” has a magnitude of 40.10 (see Table A.6). In the first difference model, the respective coefficient is -3.97, and the figure shows a negative effect of flexible power plants on the price variance (see the figures included in the replication files).

Annual net solar-to-electricity efficiency $\eta_{CSP}$, which is the overall yearly net power generation divided by the incident DNI on the solar field, is the product of the power block efficiency $\eta_{power\ block}$ and the net solar-to-steam efficiency $\eta_{steam}$.

$$\eta_{CSP} = \eta_{steam} * \eta_{power\ block} \tag{A. 10}$$

# A3. Appendix to Chapter 6

**The applied Energy System Model HiREPS**

The power system model HiREPS (see Figure A 2) is used for modeling Austria's flexibility needs in accordance with the underlying assumptions and scenarios. As proven in numerous studies (e.g., Totschnig et al. (2015; 2017), Haas et al. (2017)), the model allows for detailed analyses of the possibilities and limitations of integrating renewable energies into electricity systems and markets.

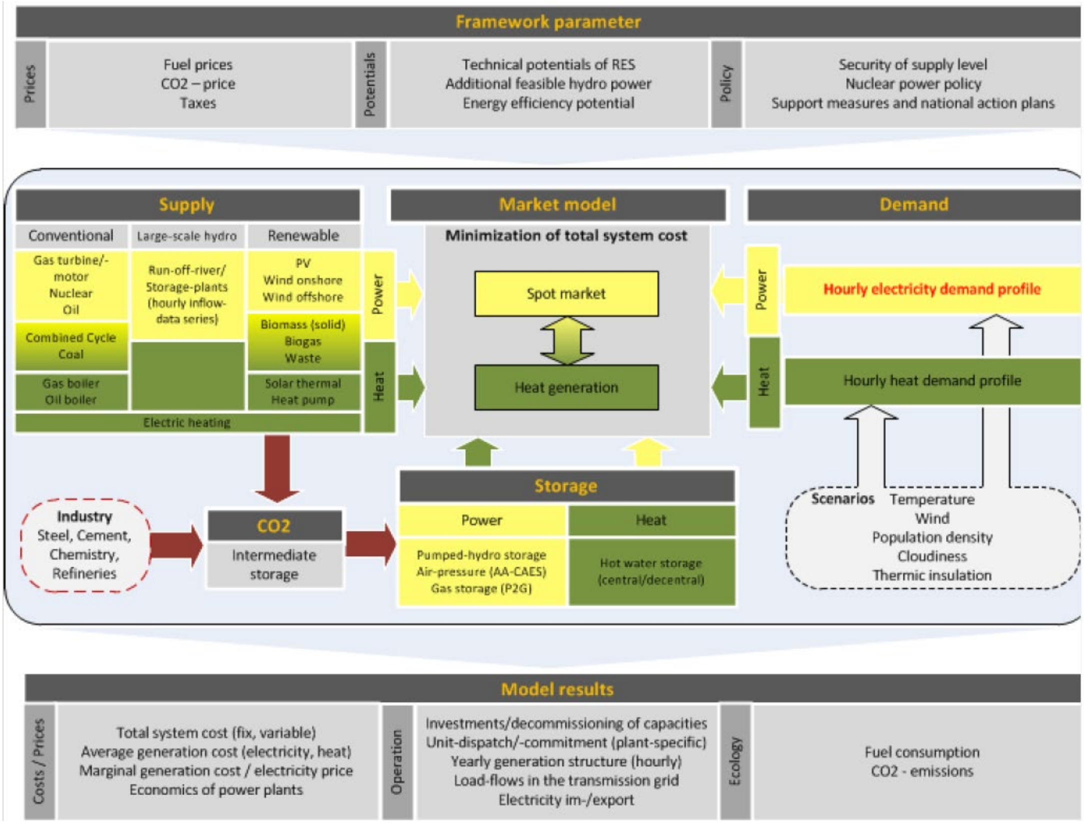


Figure A 2: Schematic overview of the power system model HiREPS

The model geographically covers Europe and incorporates key aspects of electricity systems with a high share of VRE, such as:

- temporal and spatial variations in renewable production

- thermal limits of the physical, electrical grid (incl. load flow calculations with a simplified European network model)
- technical limitations of the operation of thermal power plants
- detailed mapping of hydroelectric generation, including memory chains

**Identification of extreme weather events**

In order to ensure a high level of supply security, it is necessary to extend the model to extreme situations when determining the need for flexibility. In the context of the Austrian energy system, the consideration of "dark doldrums with low water" is of particular relevance.

Power generation from wind and solar power may be low for extended periods of time due to weak wind, slack periods, and darkness caused by weather or season. A situation in which these conditions are met over the course of several days is referred to as dark doldrum (Energieexperten 2018)]. When dark doldrums occur in winter, a long-term low supply of renewable energy meets a particularly high demand for energy due to the weather, a situation known as "cold dark doldrums" (Greenpeace Energy 2017).

The analysis of an extreme (weather) case undertaken within this study is based on a 2-week period of dark doldrums, equivalent to the dark doldrums of January 2017. The best-known cold dark doldrums in recent years occurred in Austria and Germany at this time. From 16$^{th}$ through 25$^{th}$ January 2017, the weather in Germany and Austria was characterized by fog and calm winds. Consequently, despite an installed capacity of 91 GW for wind and solar plants in Germany, only 4.6 GW were fed into the grid (Next Kraftwerke 2018). During this period, Austria was dependent on imports to cover its electricity needs (500 GWh imported during the winter days between 16$^{th}$ and 29$^{th}$ of January 2017), despite the full utilization of all available thermal capacities (E-Control 2018). Based on historical demand and generation time series – wind, PV, and RoR hydropower – (APG 2018), Figure A 3 shows the hourly development of residual load (*RL*) in 2017 as well as the symmetric (sym.) moving average of one, two, and three weeks. The longer the span of the average, the smoother the resulting series, thus providing an estimate of the trend cycle. A period with a very high *RL* can be observed during several weeks from late January to early February 2017. During this period, *RL* peaks at a weekly average of 6,959 MW, whereas the yearly average *RL* of 2017 is 3,291 MW.

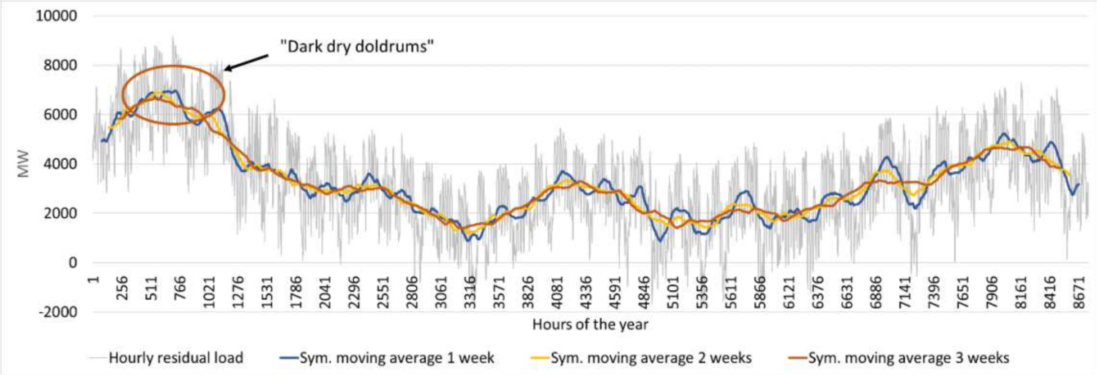



Figure A 3: Actual RL in 2017 in Austria (own illustration, based on APG (2018) and Eurostat (2018)) and moving averages for time windows of one, two, and three weeks. Dark, dry doldrum period at the beginning of the year.

Figure A 4, below, compares the *RL* of the years 2017 and 2018 with the weather years 2006 and 2007. Since the installed capacities of PV, wind, and RoR increased between 2006 and 2018, and because of data availability, the installed capacities of 2017 were used for the calculation of the residual load 2006 and 2007, thereby making the data comparable to 2017 and 2018. Figure A 4 shows the two-week average *RL* (symmetrically moving average) relative to the average *RL* of 2017. In this case, a value of 150% indicates that 150% of the average *RL* must be covered over the course of two weeks. The weather data for 2006 and 2017 both show two-week dark periods with more than 200% of the yearly average *RL*. A similar situation to 2017 can be observed in the weather data for 2006. Then, the peak value (of average weekly *RL*) was at 6,246 MW, while the yearly average *RL* amounted to 2,931 MW.

In the present study, the scenario "Extrema-LimitHydro" is dedicated to representing extreme weather conditions and shows the occurrence of "dark doldrums" based on the meteorological records of 2006. Huneke, Linkenheil, and Heidinger (2019) also conclude that 2006 best reflects the extreme situation of "cold dark doldrums" among the weather years from 1985 to 2016.

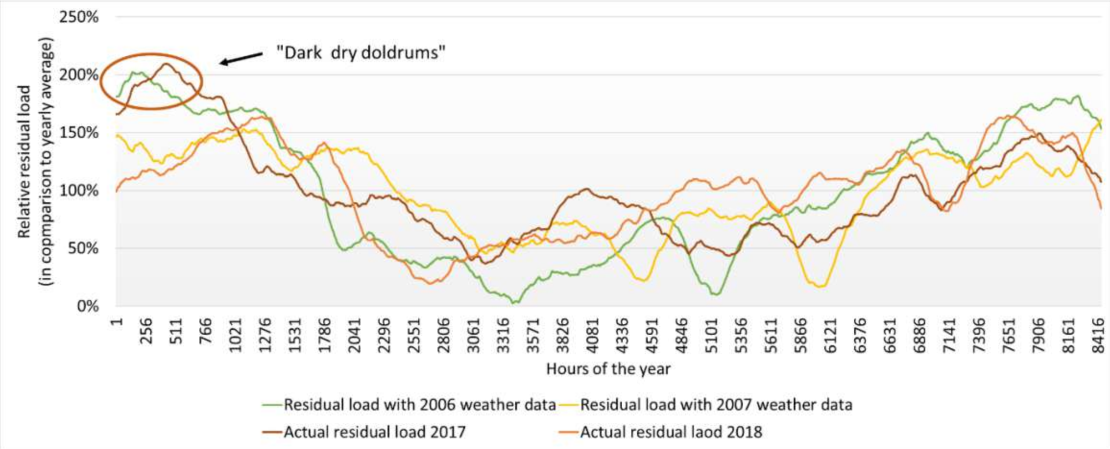



Figure A 4: RL (in relation to the average RL of the year) in a two-week symmetrically moving average for the weather years 2006 and 2007 (scaled at 2017 installed capacities) and actual residual load for the years 2017 and 2018 (own illustration based on APG (2018))

Also, Figure A 4 shows the actual *RL* of the year 2018, in which a very hot and dry summer was observed. This resulted in an exceptionally high *RL* in the late summer of 2018. Nevertheless, it was only slightly above the annual average *RL*. In contrast, the winter dark doldrum in 2017 and the dark doldrum modeled using 2006 weather data produce peaks of over 200% compared to the average *RL* of the given year.

Finally, it should be noted that the graphic representation and investigation in the context of this sub-chapter on dark doldrums only covers Austria and thus does not fully reflect European interactions in terms of weather years.

**Details on the scenario assumptions and model representation of the flexibility options**

This section describes the assumptions underlying the model-based analysis. Table A. 11 gives an overview of the main assumptions. The two main sources are the National Trends (NT) Scenario from the TYNDP 2020 for neighboring countries (ENTSO-E 2021d) and the WAM-NECP scenario for Austria (UBA 2019).

Table A. 11: Summary of scenario assumptions

| Topic | Assumption |
|---|---|
| **General data sources and assumptions for the rest of the EU (without Austria)** | |
| **Energy scenario (in general)** | NT2030 from ENTSO-E (2021d) |
| **Energy prices** | NT2030 in €/GJ (ENTSO-E 2021d)<br>Uranium 0.47<br>Lignite 1.1<br>Hard coal 4.3<br>Fracked oil 2.3<br>Natural gas 6.91<br>Heavy oil 14.63 |

| | |
|---|---|
| | Light oil 20.51 |
| **$CO_2$ price** | 60 €/t $CO_2$ |
| **Electricity demand** | According to NT2030 (ENTSO-E 2021d) on country level |
| **Installed power plant capacities** | According to NT2030 (ENTSO-E 2021d) on country level |
| **Electricity generation by renewables** | According to NT2030 (ENTSO-E 2021d) on country level |
| **Storage technologies (Power-to-$H_2$, batteries)** | According to NT2030 (ENTSO-E 2021d) on country level |
| **Transmission grid - NTC values** | 80% of the NT2030-NTC values (ENTSO-E 2021d) Exception: The 5400 MW between AT and DE are fully included. |
| **Interest rate** | 3.13% (before taxes, real) (Resch et al. 2021) |
| **Other data sources for Austria:** | |
| **Electricity demand (total)** | 85.2 TWh (UBA 2019) |
| Thereof: Industrial self-consumption covered by own plants (not in the public grid) | 8.1 TWh (UBA 2019) |
| **Electricity demand public grid** | 77.1 TWh (UBA 2019) |
| Thereof: Self-consumption power plants in the public grid | 1.2 TWh (UBA 2019) |
| Thereof: Electric conversion input (H2) | 1.2 TWh (UBA 2019) |
| Thereof: e-cars | 2.6 TWh |
| Thereof: Pumped storage losses | 1.3 TWh (simulation result) |
| **Electricity generation:** | Renewable electricity generation predefined based on (WAM-NECP) (UBA 2019); for the fossil-fueled capacities, only installed capacities were given as exogenous input |
| **District heating generation:** | 16.6 TWh based on (UBA 2017), includes heat losses in the transport networks. Biomass heat plants are deducted. |

In the following, details on the model representation of flexibility options in Austria in 2030 are presented.

**Renewable expansion in the European Context: Power generation fleet and network expansion by 2030**

Austria's electricity market is not an isolated system within Europe. From both a technical and a regulatory point of view, the international electricity systems are closely interconnected. Technically, this is done via the transmission grid, where the corresponding international exchange of electricity takes place. NTC values are used as a measure of how closely the grids of European countries are interconnected. The planned Austrian development, i.e., a massive expansion of renewable energies by 2030, is also embedded in the European context.

In this regard, Europe's TYNDP 2020 (ENTSO-E 2021d; 2021c) serves as a basis for determining European power sector trends until 2030. Data on electricity demand and the power generation fleet by 2030 is taken from the TYNDP 2020 scenario “National Trends”, characterized by reflecting national and EU climate targets (National Energy and Climate Plans (NECPs)) among ENTSO-E scenarios. The annual balance of electricity demand and supply is then modeled based on the capacity requirements of the underlying ENTSO-E scenario (ENTSO-E 2021c).

**Transmission network (cross-border exchange)**

The cross-border transmission expansion of the international transmission grids and their contribution to covering flexibility needs in the domestic energy market are based on the NTC values from ENTSO-E (2021d). Utilization of 80% of these capacities is allowed in the model, which takes a conservative approach regarding system requirements (e.g., n-1-rule), technical availability, and market limitations. For the NTC value between Germany and Austria (5400 MW), the full capacity is considered. With regard to the NTC value between Germany and Austria, it should be noted that the power plants of Illwerke (Federal State of Vorarlberg) and the Sellrain-Silz operated by TIWAG (Tyrol) (TIWAG 2022) are allocated to the German market area.

In the energy market modeling and the discussion of the results, the international electricity exchange is broken down in detail according to import and export or, if necessary, its contribution to the provision of flexibility is referred to as "cross-border exchange".

**Flexible generation technologies**

In the following, the assumptions related to flexible generation technologies are listed.

- The expansion of electricity production capacities and the corresponding flexibility potential is in line with UBA (2019). When modeling the energy market or discussing the results, generators are separated at the technology level and, if necessary, divided into relevant categories.
- The curtailment of wind, PV, and RoR hydro is a possible flexibility measure in the model (at a cost point of € 20/MWh, based on Resch at al. (2021))
- Thermal power plants are used flexibly, taking into account the heat requirement specifications for CHP plants. In the case of biomass, biogas, and waste incineration, flexibility is also limited by specifications for annual electricity generation (see UBA (2019)).
- In the model, additional gas capacities can be added to provide flexibility if required. The following assumptions were made for investment costs with a depreciation period of 20 years (Danish Energy Agency and Energinet 2016):
    - Combined Cycle (CC) Power Plant: 818 €/kW
    - CC with CHP: 859 €/kW
    - Gas turbine power plant: 507 €/kW

**Load management by P2H: Heat pumps & electric boilers for buildings and commercial load management**

The electricity demand for heat pumps and electric boilers can be shifted depending on the electricity price according to certain limitations. Their demand is modeled using the assumptions in Table A. 12 on installed capacities, storage size enabling the demand shift, as well as specific demand profiles. The assumptions for installed capacities for heat pumps and boilers are based on Hartl et al. (2016) and Biermayr et al. (2020), the assumptions of load shifting potential on Moser et al. (2015), Esterl (2016), Weiß (2019), and Austrian Energy Agency (2015). The assumptions on splitting between the residential and service sector are based on Kranzl et al. (2018). This category is referred to as "DSM (Residential + Service)" in the energy market modeling and the corresponding flexibility analysis.

For market modeling, each of the individual flexibility potentials was mapped using a fictitious replacement storage facility. For those parts of the system that can be operated flexibly, the installed capacity was multiplied by the maximum possible call-up time in order to derive a storage size in MWh (electric). For the heat pumps, a distinction was made between the two building types 'new building' and 'refurbished existing building'.

Table A. 12: Assumptions for the flexibility potential of heat pumps and electric boilers in the residential and service sector in Austria in 2030

| | Boiler (domestic water) | Heat pump (domestic water) | Heat pump (heating) | Commercial |
|---|---|---|---|---|
| **Installed capacity [$MW_{el}$]** | 1176 | 131 | 2909 | 692 |
| **Total annual energy demand [$GWh_{el}$]** | 2632 | 478 | 3163 | 2831 |
| **Controllable share [%]** | 10% | 30% | 30% | 34% |
| **Storage associated with the controllable units [$MWh_{el}$]** | 164 | 210 | 2494 | 599 |

It is worth mentioning that in the course of modeling the energy market, a certain contribution to making the electricity system more flexible was also assumed in the district heating sector. In addition to classic district heating generators, large heat pumps and electric heaters can also be used in the model if an investment in these technologies is economic under the given framework conditions. However, their use is comparatively low in 2030, as a look at the corresponding results reveals (see Table 19).

**E-Mobility**

As regards e-mobility, it is assumed that by 2030 25% of the total electric car (e-car) fleet will be charged in a controlled manner (others, e.g., e-car not plugged in, no participation in smart charging desired). For controlled charging, driving profiles are generated in the model based on previous mobility surveys and projected numbers of e-cars (BMVIT 2016; IEA 2016). From the point of view of the electricity market, in the model, 25% of the e-cars are therefore operated optimally in terms of charging behavior, i.e., charged depending on the electricity price. A simultaneity factor of 20% is assumed (Langrock et al. 2015; Österreichs Energie 2018).

**Industrial load management**

In the following, the assumptions related to industrial load management are described. A detailed analysis of the flexibility potential for the sectors pulp and paper, (petro-)chemicals, iron and steel, stone, earth and cement, as well as cross-sectional technologies, was conducted. Based on exhaustive pre-studies (Gruber 2017; S Moser et al. 2018; Berger et al. 2011; Schmidtthaler et al. 2014; Suhr et al. 2015; Ausfelder, Seitz, and Roon 2018; Blesl and Kessler 2013; Mauschitz 2021; Scalet et al. 2012; Sauer, Abele, and Buhl 2019), the different processes in each sector were analyzed, and their ability to shift demand was evaluated.

Based on the literature analysis, parts of the electricity demand of the industrial sector (paper/wood, cement, chlorine, air separation) was modeled as flexible, i.e., dependent on the electricity price according to the restrictions listed in Table A. 13. Industry's contribution to electricity system flexibility is referred to in the following as "DSM - Industry".

Table A. 13: Assumptions for flexibility potentials in 2030 in relevant industry segments

| | Mills | Stock preparation | Paper machine | Chlorine | Air separation |
|---|---|---|---|---|---|
| **Installed power [MW]** | 63 | 230 | 435 | 30 | 50 |
| **Storage size [MWh]** | 3915 | 1575 | 8874 | 1296 | 9589 |
| **Average demand [MW]** | 38 | 131 | 370 | 27 | 40 |
| **Remark** | Seasonally varying demand for cement (6-week winter break at temperatures below 0 °C), minimum operating time: 4 hours | Stock preparation | 70% minimum load | 50% minimum load | 50% minimum load |

**Power to Gas (Hydrogen)**

In the electricity market model, the future demand for hydrogen, on the one hand, results from the specification of the use of conversion ($H_2$ use in other sectors, flexible consumers) according to the underlying WAM-NECP scenario (UBA 2019). On the other hand, it becomes endogenous to the model with regard to use determined within the electricity sector (storage technology in the electricity system).

When using conversion, it is specified that at least 1.18 TWh of electricity per year is used for hydrogen production (UBA 2019). In order to ensure that the electrolyzers are used in a way that is beneficial to the system, an installed electrical output of min. 295 MW is assumed. It should be noted that a higher electrical output generally enables the electrolyzers to be operated in a way that is more beneficial to the system, but this tends to reduce their economic efficiency in return.

In addition, the model, with the existing capacity of 295 MW, can also convert more electricity into hydrogen or invest in additional electrolyzers if this is deemed economical. The underlying techno-economic assumptions are presented in Table A. 14. By producing more hydrogen than specified for conversion use, the need for fossil gas would be reduced, and consequently, savings in $CO_2$ costs (i.e., costs for emission allowances in the EU Emissions Trading Scheme (ETS)) would also be achieved.

Table A. 14: Assumed techno-economic characteristics of the electrolyzers installed by 2030 in the electricity market modeling

| CAPEX [€/kW$_{el}$] | OPEX [€/kW$_{el}$*a] | Depreciation period [a] | Efficiency [kWh$_{H2,HU}$/kWh$_{el}$] |
|---|---|---|---|
| **930** | 25 | 20 | 70% |

**(Pumped) hydropower storage plants**

In accordance with the WAM-NECP scenario (UBA 2019), the model assumes storage and pumped storage expansion until 2030. This scenario suggests hydropower will be expanded from currently around 39.5 TWh (standard energy capacity from natural inflow) to 44 TWh in 2030. The existing 2 TWh of RoR power plants and 1 TWh of storage hydropower are considered when dividing the expansion plan between the RoR and storage power plants. The expansion beyond this is assumed to be 40% RoR and 60% storage hydropower.

In addition, an increase in the output of existing systems seems possible at the cost of 1,125 €/kW. New asphalt storage tanks can be built at the cost of 1,000 €/kW in terms of electrical output and at the cost of 22 €/kWh in terms of storage size (Totschnig et al. 2015). A depreciation period of 40 years is assumed. However, the increase in output does not change the normal working capacity of hydropower.

In the following discussion of the results, the contribution of storage hydropower to electricity generation is, as far as possible, broken down into power plants with and without pumps and noted accordingly. The power consumed by pumped storage power plants is marked as “electricity for pumping of PHS”.

**Battery storage & Prosumers**

Battery storage is represented in the model as home battery (prosumer) and as large batteries on the market. However, large batteries as a flexibility option for grid applications are not expanded in the model in the assessed scenarios (Table 19).

Home batteries in connection with PV (prosumers) are assumed to be inflexible in the model (pure optimization of self-consumption).

In order to better depict prosumers (PV + home batteries) in the model, an upstream simulation was carried out in advance to generate corresponding PV generation and load profiles for the prosumer households. Seventy-five households were simulated, each with 4 $kW_{peak}$, with an average household electricity consumption of 4,500 kWh/a. All prosumer households contain batteries with an average storage capacity of 6 kWh (normal distribution). Furthermore, a single-phase charging and discharging power of 3.2 kW was assumed for the batteries, which from today's perspective, represents a standard market specification. The battery storage is not charged from the grid, but a pure self-consumption optimization is assumed. This means that the storage is fully charged in the morning with normal solar radiation and is discharged again in the course of the afternoon or evening.

The assumptions regarding the installed home battery capacity in 2030 are based on ENTSO-E (2021d) and D'Halluin, Rossi and Schmela (2020). The resulting installed capacity of PV systems and the installed capacity of home batteries are shown in Table A. 15.

Table A. 15: Assumptions about the prosumers in the electricity market model for 2030

| | Austria | Germany |
|---|---|---|
| **Capacity home batteries [GWh]** | 1.9 | 6.8 |
| **Charge/discharge power [MW]** | 1 013 | 3 627 |
| **Power PV of the prosumers [MW]** | 1 267 | 4 533 |

## Detailed results

In this section, tables are included as complementary information to Chapter 6.

Table A. 16 shows a detailed list of the status quo contribution of flexibility options by different time periods calculated based on ENTSO-E (2021a), while Table A. 17 summarizes the scenario-based results for the future (2030). Furthermore, a capacity and generation balance of the flexibility options is provided in Table A. 18, including the status quo (2020) and 2030, according to modeled scenarios, thus indicating the contribution of flexibility options in terms of peak capacity and yearly generation.

Table A. 16: Status quo (2020) of flexibility needs and contribution of flexibility options by different time periods (annual balance in TWh) (ENTSO-E, 2021a)

| | Daily (hourly fluctuations per day) | Weekly (daily fluctuations per week) | Monthly (weekly fluctuations per month) | Annual (monthly fluctuations per year) |
|---|---|---|---|---|
| **Flexibility needs (RL) (TWh)** | 3.6 | 3.1 | 2.0 | 4.8 |
| **Flexibility sources (TWh)** | | | | |
| Hard coal | 0.0 | 0.0 | 0.0 | 0.2 |
| Lignite | 0.0 | 0.0 | 0.0 | 0.0 |
| Gas | 0.6 | 0.7 | 0.4 | 2.6 |
| Waste and other fossils | 0.0 | 0.0 | 0.0 | 0.0 |
| Biomass and other RES | 0.0 | 0.0 | 0.0 | 0.0 |

| | | | | |
|---|---|---|---|---|
| (Pumped) storage hydropower | 2.8 | 2.0 | 0.1 | -0.7 |
| Cross-border exchange | 0.2 | 0.5 | 1.6 | 2.6 |
| Demand-side measures | 0.0 | 0.0 | 0.0 | 0.0 |

Table A. 17: Scenario-specific flexibility needs and contribution of flexibility options for 2030 (annual balance in TWh)

| | **Daily (hourly fluctuations per day)** | | **Weekly (daily fluctuations per week)** | | **Monthly (weekly fluctuations per month)** | | **Annual (monthly fluctuations per year)** | |
|---|---|---|---|---|---|---|---|---|
| | **Typical Year** | **Extreme Year** | **Typical Year** | **Extreme Year** | **Typical Year** | **Extreme Year** | **Typical Year** | **Extreme Year** |
| **Flexibility needs (RL) (TWh)** | 4.67 | 4.78 | 3.98 | 3.92 | 2.63 | 2.85 | 6.57 | 8.66 |
| **Flexibility sources (TWh)** | | | | | | | | |
| Waste incineration | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Biogas | 0.04 | 0.04 | 0.00 | 0.00 | 0.01 | 0.01 | 0.00 | 0.02 |
| Biomass | 0.02 | 0.02 | 0.00 | 0.00 | 0.01 | 0.02 | 0.02 | -0.02 |
| Gas-CHP | 0.38 | 0.13 | 0.69 | 0.27 | 0.92 | 0.24 | 1.81 | 3.03 |
| Gas Combined Cycle Power Plants | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Gas turbines | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Oil | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Hydropower storage (excl. PHS) | 1.71 | 1.47 | 0.11 | 0.45 | 0.72 | 0.53 | -0.45 | -1.08 |
| Pumped hydropower storage (PHS) | 4.50 | 4.91 | 0.77 | 2.33 | 2.30 | 2.28 | 0.92 | -0.12 |
| Large batteries on the market | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| DSM: Industry | 0.41 | 0.37 | 0.02 | 0.03 | 0.11 | 0.09 | 0.01 | 0.00 |
| DSM: Residential & Service | 0.64 | 0.62 | 0.00 | 0.00 | 0.03 | 0.04 | 0.00 | 0.00 |
| Cross-border exchange | -3.48 | -3.20 | 0.99 | -0.34 | -0.24 | 0.62 | 4.21 | 6.80 |
| Hydrogen | 0.22 | 0.18 | 0.04 | 0.09 | 0.10 | 0.07 | 0.03 | 0.04 |
| E-Mobility | 0.23 | 0.24 | 0.00 | 0.00 | 0.02 | 0.02 | 0.01 | 0.01 |
| DH-P2H | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Table A. 18: Key results on capacity and generation balance of flexibility options for meeting corresponding flexibility needs in 2020 (ENTSO-E 2021a) and for assessed scenarios in 2030

| **Flexibility Options** | **2020 Generation balance (TWh)** | **Typical year 2030 Generation balance (TWh)** | **Extreme year 2030 Generation balance (TWh)** | **Typical year 2030 Max. capacity balance (GW)** | **Extreme year 2030 Max. capacity balance (GW)** |
|---|---|---|---|---|---|
| Waste incineration | 1.1* | 1.0 | 1.0 | 0.11 | 0.11 |
| Biogas | | 0.5 | 0.5 | 0.07 | 0.07 |
| Biomass | 1.7** | 2.3 | 2.3 | 0.31 | 0.31 |
| Gas-CHP | | 9.3 | 6.4 | 2.55 | 2.55 |
| Gas turbines | 8.9 | 0.0 | 0.0 | 0.14 | 0.24 |
| Oil | | 0.0 | 0.0 | 0.01 | 0.01 |
| Hydropower storage incl. PHS | | 11.5 | 10.1 | 10.62 | 11.68 |
| Large batteries on the market | | 0.0 | 0.0 | 0.00 | 0.00 |
| DSM: Industry | | 0.0 | 0.0 | 0.28 | 0.28 |
| DSM: Residential & Service | | 0.0 | 0.0 | 1.11 | 1.10 |
| Cross-border exchange | 3.9 | -9.9 | -7.5 | 9.93 | 10.28 |
| Hydrogen | | -1.2 | -1.2 | 0.29 | 0.30 |
| E-mobility | | -2.6 | -2.6 | 1.12 | 1.19 |
| District heating-P2H | | -0.01 | -0.06 | 0.01 | 0.03 |
| Hard coal | 0.3 | | | | |

*Data for 2020 comprises waste and other fossils. **Data for 2020 includes biomass, biogas, and geothermal.