Market Design for the Transition to Renewable Electricity Systems

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Christoph Fraunholz

Abstract

The research carried out in this thesis aims to shed light on the role of the European electricity market design in the transition to a target electricity system that combines sustainability, affordability, and reliability. While the ongoing expansion of fluctuating renewable electricity sources challenges the established structures and market mechanisms, governments across Europe have decided to phase-out certain conventional technologies like coal or nuclear power. Since traditional electricity systems rely on flexibility provided by controllable generation capacity, other flexibility options are needed to compensate for the decommissioned conventional power plants and support the system integration of renewables.

Against this background, the dissertation extends an established large-scale agent-based electricity market model in order to account for the developments towards an integrated European electricity market and the characteristics of storage technologies. In particular, the representation of cross-border effects is enhanced by integrating approaches from the fields of operations research, non-cooperative game theory, and artificial intelligence in the simulation framework. The extended model is then applied in three case studies to analyze the diffusion of different flexibility options under varying regulatory settings. These case studies cover some central aspects of the European electricity market, most importantly capacity remuneration mechanisms, the interaction of day-ahead market and congestion management, and the role of regulation for residential self-consumption.

Results of the case studies confirm that by designing the regulatory framework, policymakers and regulators can substantially affect quantity, composition, location, and operation of technologies – both, on the supply side and the demand side. At the same time, changes and amendments to market design are frequent and will continue to be so in the years ahead. Moreover, given the increasing level of market integration in Europe, the role of cross-border effects of national market designs will gain further in importance. In this context, agent-based simulation models are a valuable tool to better understand potential long-term effects of market designs in the interconnected European electricity system and can therefore support the European energy transition.

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Part I

Overview

Chapter 1

Introduction

1.1 Motivation

The European electricity system is currently undergoing a major transformation towards more sustainability. This process is associated with a strong expansion of renewable electricity sources which – due to their fluctuating character – challenge the established structures and market mechanisms. At the same time, governments across Europe have decided to phase-out certain conventional technologies for electricity generation, e.g., German is planning to shut down all nuclear power plants by the end of 2022. These developments may endanger the secure supply with electricity which is crucial for any industrialized country.

Since traditional electricity systems rely on flexibility provided by *controllable* generation capacity, other flexibility options are needed to compensate for the decommissioned conventional power plants and support the system integration of renewables. However, it is not clear how the required *firm* generation, storage, and flexible demand capacity can be incentivized both effectively and efficiently. Price signals reflecting regional scarcity are another key aspect in this context, since the zonal European market design does not adequately account for intra-zonal grid restrictions. Moreover, on the demand side, an increasing share of households uses photovoltaics with batteries to cover part of their electricity demand. To this end, incentives for a system-friendly operation of these systems need to be established.

1.2 Objective and Research Questions

The aim of this dissertation is to analyze the role of the European electricity market design in the transition to a target electricity system that combines sustainability, affordability, and reliability. By setting the regulatory framework, policymakers and regulators can substantially affect quantity, composition, location, and operation of technologies – both, on the supply side and the demand side. The thesis concentrates on some central elements of the European electricity market, namely capacity remuneration mechanisms, the interaction of day-ahead market and congestion management, and the role of regulation for residential self-consumption. The overall objective is to derive policy implications with regard to an adequate European electricity market design, and thus, to contribute to a successful transition of the European electricity system. More specifically, the following energy economic research questions are central to the dissertation:

(1) How does the parametrization of *capacity remuneration mechanisms* affect the future technology mix and long-term generation adequacy?
(2) How efficient is a market splitting in Germany from a long-term system perspective?
(3) In which way can regulation and retail electricity pricing be used to govern the diffusion, operation, and system impact of residential battery storages?

When investigating electricity market design, it is important to model transformation pathways of the system in order to account for path dependencies and lock-in effects arising from long investment horizons. At the same time, the developments towards an integrated European electricity market and the important future role of electricity storage need to be considered. Given these requirements, the thesis aims to extend an established agent-based electricity market model in terms of both, the short-term market operation perspective and the long-term investment planning perspective. For this purpose, approaches from the fields of operations research, non-cooperative game theory, and artificial intelligence are developed and integrated in the simulation framework. The extended model can then be used to carry out a number of *explorative* scenario analyses in order to investigate long-term system developments under varying regulatory settings.

1.3 Structure of the Thesis

The cumulative dissertation is structured in two parts (see Fig. 1.1). Part I starts with this introductory Chapter 1. In the following Chapter 2, the relevant background on the flexibility requirements in future electricity systems as well as the design of the European electricity market is provided. Chapter 3 introduces the agent-based electricity market model PowerACE, which is the central tool used in this thesis, and describes the methodological model extensions that are carried out. In Chapter 4, the scope and major results of the three case studies are summarized. Chapter 5 provides a critical reflection, while the final Chapter 6 concludes and derives a set of policy implications. Part II contains the following scientific publications:

Paper A This contribution was presented at the *16th International Conference on the European Energy Market (EEM)* and is published in the peer-reviewed conference proceedings. The article focuses on the long-term perspective of the PowerACE model and develops a novel approach for the generation and storage expansion planning problem, which adequately takes into account cross-border effects.

Paper B This article is published as a preprint in the *Working Paper Series in Production and Energy* and currently under review with a scientific journal. The paper is dedicated to the short-term model perspective of PowerACE and deals with advanced methods for the model-endogenous day-ahead price forecasting. For this purpose, artificial neural networks are implemented in order to adequately capture the complex non-linear cross-border relationships in spot market price formation.

Paper C This paper is published in the journal *Energy Policy* and investigates the role of electricity storage in capacity remuneration mechanisms. Both, a theoretical analysis and a complementary simulation study are carried out to provide insights on the impact of different parametrizations of capacity remuneration mechanisms on the future technology mix and long-term generation adequacy.

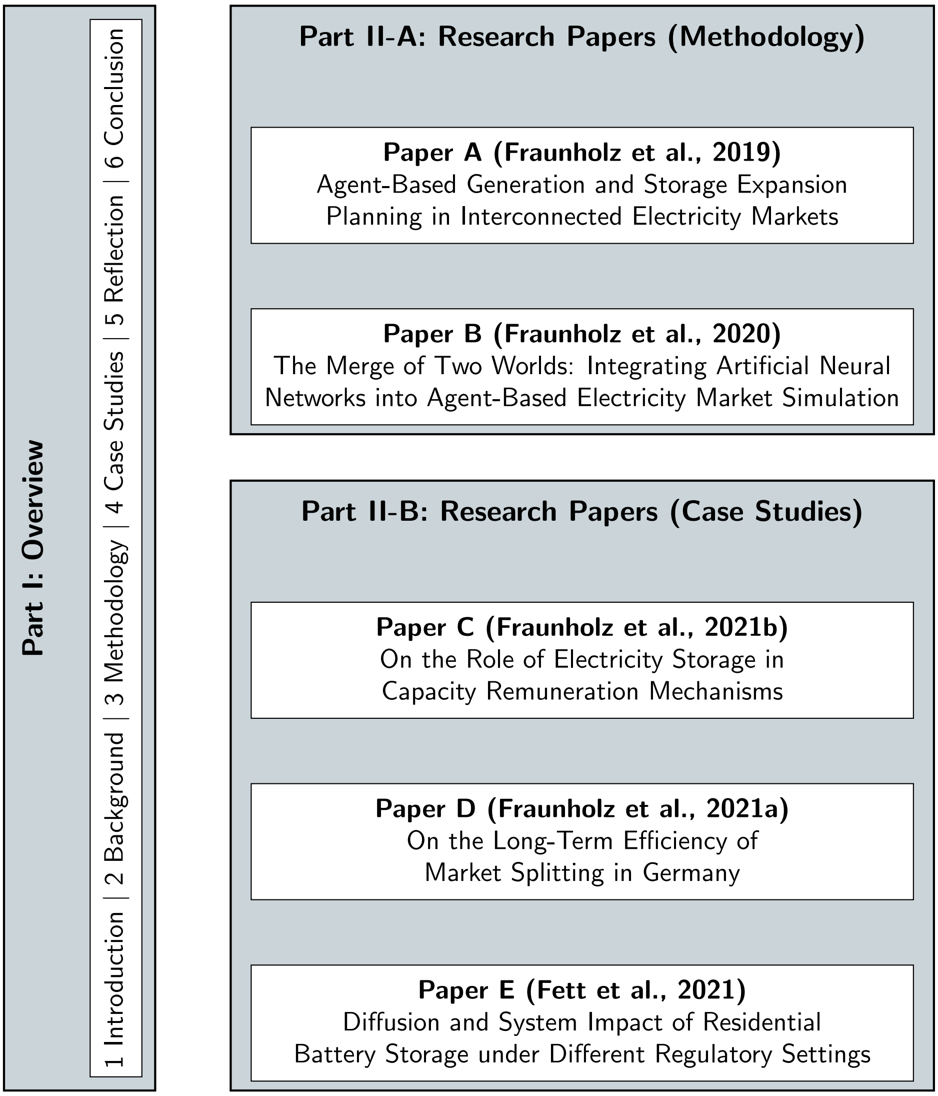


Figure 1.1: Structure of the cumulative dissertation. In Part I, relevant background and an overview of the research papers included in the thesis is provided. Part II contains five articles, two with a methodological focus and three presenting case studies.

Paper D This article is published in the journal *Energy Policy* and deals with the long-term efficiency of splitting the German market area in two price zones. To this end, a new modeling framework is developed which jointly applies the electricity market model PowerACE and an optimal power flow model. This approach allows to carry out a holistic analysis in which both market and grid aspects can be considered.

Paper E This paper is in press as a preprint in the *Working Paper Series in Production and Energy* and has been submitted to a scientific journal for peer-review. The article analyzes the system impacts arising from a diffusion of residential battery storage systems in Germany under different regulatory frameworks. For this purpose, the electricity market simulation model PowerACE is coupled with a prosumer simulation model focusing on investment and operation of batteries.

Chapter 2

Background

The trend towards ever-increasing shares of fluctuating renewables in electricity generation challenges the established structures and market mechanisms in Europe. The following Section 2.1 presents the status quo of renewable expansion and discusses flexibility requirements in future electricity systems as well as available flexibility options. Building on this, Section 2.2 provides an overview of the current European electricity market design and delves into the elements that are central to this thesis.

2.1 Flexibility Requirements in Future Electricity Systems

2.1.1 Status Quo of Renewable Expansion

In the European Union, the share of renewables in gross electricity demand has grown from 12 % in 1990 – almost entirely provided by hydro power – to 33 % in 2019 – with fluctuating photovoltaics and wind power accounting for about half of the generation (Eurostat, 2021a,b). For 2030, current European climate targets foresee at least 40 % cuts in greenhouse gas emissions from 1990 levels, which translates into a 57 % share of renewables in the power sector (Agora Energiewende, 2019). As part of the *European Green Deal*, the European Commission (2021a,b) has proposed to raise the 2030 target to a 55 % emission reduction and to strive for climate neutrality by 2050. However, these new targets are yet to be written

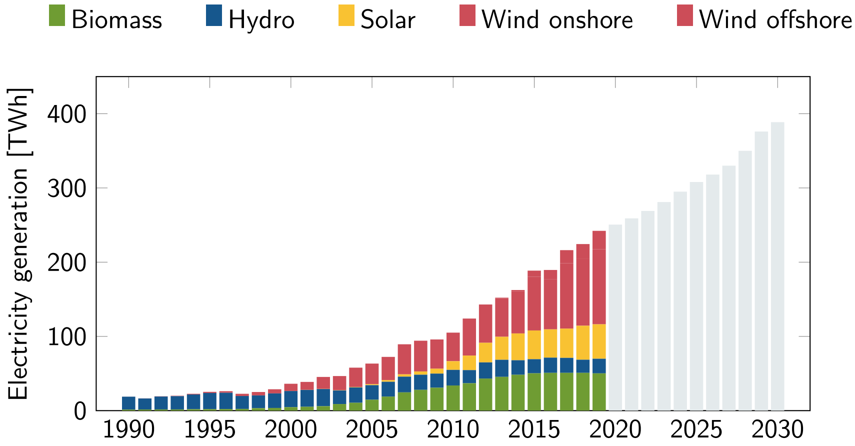


Figure 2.1: Renewable electricity generation in Germany. Since the introduction of the Renewable Energy Sources Act (EEG) in 2000, the electricity production from biomass, photovoltaics, and wind power has increased sharply. By 2030, Germany aims to further raise the share of renewables in total electricity demand from today's 42 % to 65 %. *Source:* own illustration using historical data from Bundesministerium für Wirtschaft und Energie (2020) and targets from § 4a EEG 2021.

into law and are therefore not legally binding (European Commission, 2021c). Developing concrete plans on how to achieve the required emission reductions lies in the responsibility of the individual Member States which are required to develop respective national long-term strategies.

Germany, which is widely recognized as a European leader in terms of renewables, has introduced the *Renewable Energy Sources Act* (EEG) in 2000 in order to foster renewable electricity generation. This has particularly led to a substantial rise of electricity production from solar and wind power over the past 20 years (see Fig. 2.1). In 2019, more than 240 TWh of renewable electricity was produced in Germany, corresponding to a 42 % share in total electricity demand. By 2030, this share shall be increased to 65 % or almost 400 TWh of renewable electricity, with the ultimate objective of a completely emission-free electricity production by 2050 (§ 1 EEG 2021).

In order to achieve these targets, Germany plans to build an additional 50 GW of photovoltaics and 30 GW of wind power (thereof some 12 GW offshore) by 2030 (§ 4 EEG 2021 and § 1 WindSeeG). This would increase today's roughly 125 GW of installed renewable capacity to more than 200 GW (see Fig. 2.2). Although these

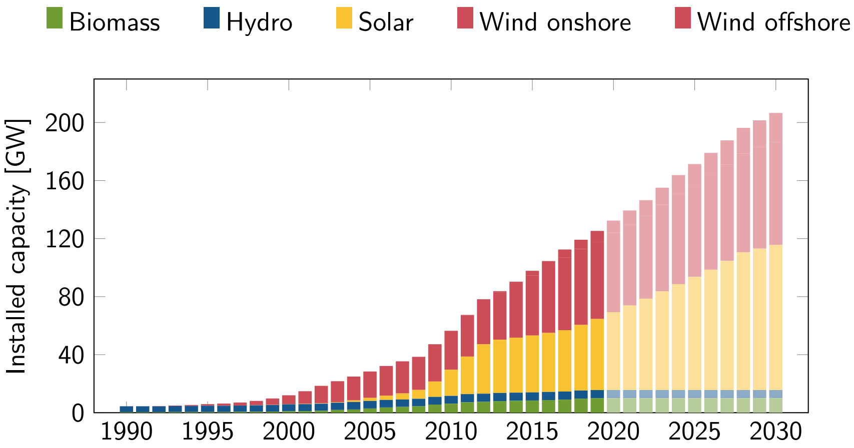


Figure 2.2: Capacity expansion of renewable energies in Germany. Photovoltaics and wind power account for the most significant share of new installations. In the coming decade, Germany plans to build an additional 50 GW of photovoltaics and 30 GW of wind power. *Source:* own illustration using historical data from Bundesministerium für Wirtschaft und Energie (2020) and targets from § 4 EEG 2021, § 1 WindSeeG.

expansion targets seem rather ambitious, it is doubtful whether they are indeed sufficient to reach the desired 65 % renewable share by 2030. This is because the electricity demand might grow significantly in the next decade driven by the diffusion of new electric applications from the heat and transport sector. Either way, the strong expansion of fluctuating renewables will have a strong impact on the electricity market and call for additional system flexibility, as outlined in the following.

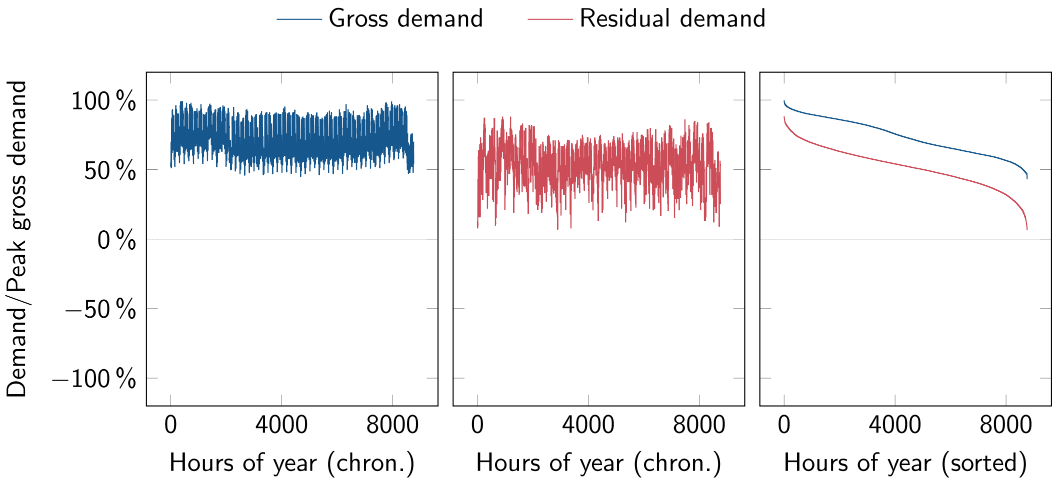
2.1.2 Market Impact of Fluctuating Renewables

In the context of electricity systems, Ma et al. (2013) define *flexibility* as the degree to which a system can *"cope with variability and uncertainty in both generation and demand, while maintaining a satisfactory level of reliability at a reasonable cost, over different time horizons"*. Due to the fluctuating character of renewable electricity sources such as wind and solar power, future electricity systems will require substantially higher amounts of flexibility than traditional electricity systems, where the flexibility is almost entirely provided by controllable generation capacities. In this section, the market impact of fluctuating renewables is illustrated and arising challenges are outlined in more detail.

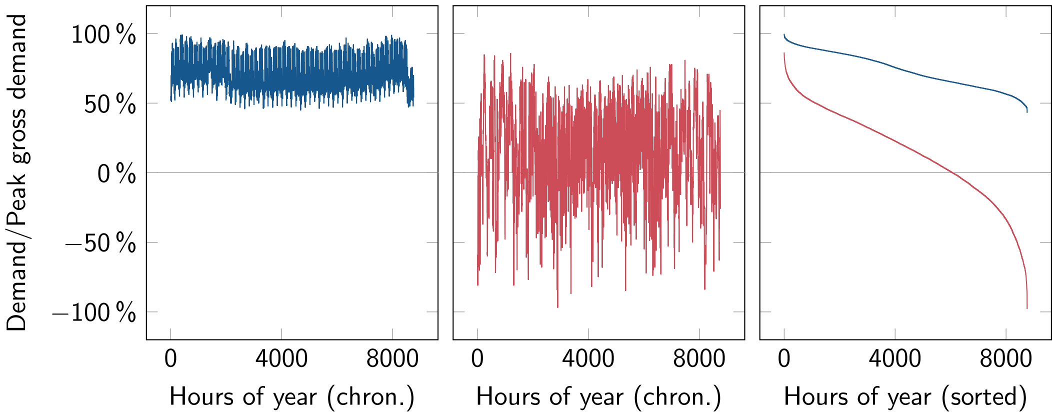
Using real-world data of the German electricity market, Fig. 2.3 presents the market impact arising from high shares of fluctuating renewables in a stylized setting[1]. For this purpose, the time series of gross electricity demand is normalized by its peak value and shown in the left panel. The middle panel shows the *residual demand*, which can be calculated by subtracting the hourly feed-in of wind and solar power from the respective gross demand. The hourly residual demand is again normalized by the peak gross demand. Obviously, higher shares of fluctuating renewables go hand in hand with strong fluctuations of the residual demand. Sorting the chronological time series of gross and residual demand in descending order leads to the *(residual) load duration curve*, which is depicted in the right panel. Here, three important market impacts arising from increasing levels of fluctuating renewables become apparent (Ueckerdt et al., 2015), which are addressed in the following.

Low capacity credit Although wind and solar power generate large amounts of electricity, their generation is weather-dependent and exhibits strong seasonal as well as diurnal patterns. Thus, time periods with renewable generation do not necessarily correlate with periods of high electricity demand. For example, solar production is highest during daytime in summer, while the peak demand in Germany typically occurs in cold winter evenings. Contrary, other regions may face their peak demand in summer due to the extensive use of air conditioning. In this case, however, wind power may be of rather little benefit since its production

[1] Please note that the illustration is only intended to provide an insight on the general effects that can be expected under high shares of fluctuating renewables and is therefore simplified regarding both, the demand and the supply side. In reality, the shape of the electricity demand is likely to change in the future, e.g., driven by efficiency improvements as well as the electrification of heat and transport (Boßmann and Staffell, 2015). Depending on the flexibility of the new electric applications, the system challenges may either be reduced or intensified. The patterns of the fluctuating renewable electricity generation may also change as compared to today, e.g., due to photovoltaic systems with east-west orientation or system-friendly wind turbines (May, 2017). These developments are likely to support the system integration of additional fluctuating renewables. It is also important to mention that both, electricity demand and renewable electricity production, follow different patterns in countries other than Germany. Thus, other countries can be either more or less affected by high shares of fluctuating renewables than shown in the stylized German setting.



(a) ∼30 % fluctuating renewables (8 % solar, 18 % wind onshore, 4 % wind offshore)



(b) ∼80 % fluctuating renewables (22 % solar, 48 % wind onshore, 10 % wind offshore)

Figure 2.3: Stylized illustration of the market impact arising from high shares of fluctuating renewables. From left to right, the gross electricity demand, the residual demand and the (residual) load duration curves are depicted. In part (a), a moderate share (∼30 %) of fluctuating renewable generation with respect to total gross electricity demand is assumed. Part (b) shows the same setting, yet with a significantly higher renewable share (∼80 %). While intermittent renewables have a low capacity credit, they reduce the full-load hours of conventional power plants and may lead to a negative residual demand in many hours. *Source:* based on similar illustrations in Ueckerdt et al. (2015); gross demand and renewable feed-in of part (a) are 2018 real-world data from Germany (ENTSO-E, 2020), the renewable feed-in is linearly scaled to reach an 80 % share of total gross demand in part (b).

is typically highest in the winter months. Thus, it is crucial to consider the mix between wind and solar as well as regional peculiarities (for a detailed analysis, see Ueckerdt et al., 2015). Fluctuating renewables have relatively low *capacity credits*, meaning that they can only provide little securely available capacity. This implies that these technologies need to be complemented by substantial amounts of *firm* capacity like dispatchable power plants or electricity storage in order to handle situations with simultaneous non-availability of solar and wind power. Relevant publications on the complementarity of renewable electricity generation across technologies and regions include Berger et al. (2020), Heide et al. (2010), Jessen-Thiesen et al. (2019), Miglietta et al. (2017).

Reduced full-load hours Higher penetrations of wind and solar power reduce the utilization of conventional generation units, typically referred to as *full-load hours*. In consequence, the specific generation costs per unit of electricity – known as *levelized cost of electricity* (LCOE) – increase for conventional power plants. At the same time, the near-zero marginal generation cost of renewables depresses electricity prices due to the *merit-order effect* (Sensfuß et al., 2008). These effects lower the profitability of conventional power plants and reduce investment incentives for additional *firm* capacity. As outlined in detail in Section 2.2.2, the expansion of renewables has therefore intensified the discussion on whether the traditional *energy-only market* (EOM) – in which generators are only remunerated for their produced electricity – is an appropriate market design or whether the introduction of *capacity remuneration mechanisms* (CRMs) is inevitable (e.g., Batlle and Rodilla, 2010; Cramton et al., 2013; Joskow, 2008; Newbery, 2016; de Vries, 2007).

Overproduction In electricity systems with high shares of intermittent renewables, the combined wind and solar generation may exceed the current demand for electricity in certain hours, resulting in a negative residual demand. Both, the number of such hours as well as the magnitude of the surplus generation are likely to increase as the share of wind and solar power grows. If this overproduction cannot be mitigated by means of flexibility options, the utilization of the renewable-based power plants decreases, which in turn increases their LCOE. Nevertheless, a recent analysis by Zerrahn et al. (2018) shows that allowing for a certain amount of renewable curtailment is more efficient from an overall economic perspective than aiming to integrate all renewable production. Please note that apart from the described market-based curtailment of renewables, insufficient grid capacities can lead to additional grid-related curtailment (see Section 2.2.3).

Several publications are available in the literature that deal with the need and the provision of flexibility in electricity systems with high shares of intermittent renewables (please refer to Zöphel et al., 2018, for an overview with a focus on Europe). It is also important to mention that flexibility has many additional dimensions to the market impacts introduced in detail (see, e.g., Lund et al., 2015). Against this background, Bertsch et al. (2016) provide a quantitative long-term analysis of the European electricity markets, covering both, the wholesale electricity market and the control reserve market. The authors find that in a market design ensuring a cost-efficient capacity mix, requirements in terms of ramping and balancing energy provision are never binding constraints. Thus, the generation and storage units needed as backup capacity provide sufficient ramping and balancing capabilities as a by-product. This important finding is closely related to the fact that open cycle gas turbines are – due to their comparably low capital cost and high variable cost – the most cost-efficient conventional technology for a low number of realizable full-load hours. At the same time, open cycle gas turbines possess the highest ramping flexibility among the available conventional power plant technologies. Backed up by these results, this thesis puts an explicit focus on the three introduced market impacts (low capacity credit, reduced full-load hours, overproduction) and the arising challenges in terms of generation adequacy and system integration. In contrast, other important aspects of system flexibility – like ramping requirements and short-term balancing of supply and demand – are not investigated.

2.1.3 Classification of Flexibility Options

A wide range of flexibility options exists to mitigate the challenges of electricity systems dominated by fluctuating renewable generation. Michaelis et al. (2017) provide a categorization of various technologies and compare them with regard to four criteria, namely (1) activation time, (2) duration of flexibility provision, (3) number of activations, and (4) activation costs. The authors find that these techno-economic characteristics vary strongly across the different technologies, such that a mix of options is likely to be best suited to fulfill the flexibility requirements of future electricity systems. In the following, an own classification of flexibility options is proposed, which builds on the categories identified by Lund et al. (2015), Michaelis et al. (2017), Schill (2020), and Zöphel et al. (2018). Please note that the attribution of technologies to the different categories is sometimes ambiguous. Therefore, other classifications can be considered just as valid as the provided one.

Power-to-Power (temporal shifting flexibility) This category comprises a range of technologies that allow for a temporal load shifting from times of high residual demand to times with low – or even negative – residual demand. As of today, shifting flexibility is mostly provided by pumped storage power plants. However, in the future, new storage technologies like batteries (e.g., lithium-ion, redox-flow) as well as demand side technologies (e.g., air conditioning, industrial processes) may play a more pronounced role. While the flexibility provision of storage units is mainly restricted by the available storage volume, demand side management additionally needs to consider the properties of the underlying processes. On the other hand, electricity storage always comes along with conversion losses, which need to be compensated by sufficient spreads between the electricity prices for charging and discharging. In contrast, demand processes typically do not suffer from conversion losses.

X-to-Power (downward flexibility) In times of low wind and solar production, other technologies are needed to serve the residual demand. The supply side can traditionally provide this type of flexibility at the lowest cost by activating dispatchable power plants fired with fossil fuels, biomass or synthetic gas. On the demand side, certain industrial processes (e.g., electric arc and induction furnaces, electrolysis) can also contribute through load shedding, i.e., a short-term reduction of electricity demand. The flexibility provision with conventional power plants is not restricted in time and has relatively low activation costs. In contrast, load shedding can be activated faster than a power plant that is cold-started, but at a higher cost. Moreover, demand reductions are limited to process-specific, typically rather short time spans.

Power-to-X (upward flexibility) The straightforward option of dealing with negative residual loads caused by a surplus of electricity generation is curtailment of wind and solar power, which is quickly activated and theoretically unlimited in time. However, curtailment comes along with welfare losses, which can be considered as artificial activation cost. On the demand side, sector coupling technologies like Power-to-Heat (e.g., heat pumps), Power-to-Gas (e.g., hydrogen production via electrolysis) or smart charging of electric vehicles offer new opportunities. These processes can be quickly ramped up, yet are restricted by the underlying demand for heat and gas as well as the vehicle battery capacities. Importantly, in contrast to curtailment, the activation cost is negative. This is because the consumers are willing to pay for electricity, as long as they can produce heat or gas at cost below the respective market price. Please note that if Power-to-Gas is combined with a subsequent reconversion of the produced gas to electricity, this technology falls into the category Power-to-Power.

Electricity grid (spatial shifting flexibility) The electricity generation by wind and solar power is highly weather-dependent. Transmission and distribution grids can therefore support the system integration of these technologies by allowing for a geographical balancing between regions with different meteorological conditions. Like this, surplus renewable electricity can be exported to interconnected countries and imports may help to cover peaks of the national residual demand. For a fully renewable European electricity system, Rodríguez et al. (2014) determine significant benefits of strongly increased or even unconstrained interconnector capacities. On the other hand, insufficient transmission capacities (within or across countries) can hinder a further expansion of renewables as discussed for Germany in Section 2.2.3. Apart from enabling the integration of larger shares of fluctuating renewables, increasing the interconnector capacities between different market areas also yields positive welfare effects as explained in Section 2.2.1.

This dissertation covers flexibility options from all of the introduced categories, namely utility-scale and residential short-term electricity storage (temporal shifting), conventional power plants (downward flexibility), curtailment of renewables (upward flexibility) and cross-border transmission (spatial shifting). Other flexibility options on the demand side are out of the scope of this thesis and subject to future research.

Please note that most of the literature related to flexibility options focuses on the *theoretical* or the *economic* potential of flexibility options, whereas analyses on the *market* potential[2] are scarce and typically neglect saturation effects, i.e., the diminishing marginal value of additional flexibility (Kondziella and Bruckner, 2016). In contrast, this thesis takes an *explorative* approach, i.e., aims to investigate the diffusion of flexibility options under different market conditions and regulatory settings, and with a system development that emerges from the aggregated behavior of several individual actors. Thus, to provide the relevant background, the following section delves into the design of the European electricity market.

2.2 Designing the Future European Electricity Market

Following Ockenfels (2009), *market design* can be defined very generally as the art of creating *"real-world institutions and mechanisms that align individual incentives and behavior with the underlying goals"*. In the context of electricity markets, these goals are best summarized by the *energy trilemma* which comprises sustainability, affordability, and reliability of electricity supply. While the design of electricity markets differs around the world, the European setting is particularly interesting due to the tight interconnection of diverse national markets and the corresponding cross-border effects. The European electricity market consists of several market design elements, the most important of which are shown schematically in Fig.

[2]For the context of renewable energy sources, Edenhofer et al. (2012) define the different levels of potential as follows. The *theoretical* potential is derived from natural and physical parameters (e.g., the total irradiation on the surface of the Earth) and represents an upper limit on the production from a given (energy) resource. More relevant from a practical perspective is the *technical* potential, which takes into account additional technological constraints and therefore provides an estimate of the achievable (energy) output under a full implementation of demonstrated technologies. The *economic* potential considers all technological and social costs/benefits as well as competition between different technologies and is therefore a subset of the *technical* potential. Finally, the *market* potential describes the (energy) output of a resource expected under forecasted market conditions, i.e., emerging from private economic agents' decisions (business case perspective). Please note that the *market* potential is not necessarily a subset of the *economic* potential, since political technology support may foster the diffusion of a technology beyond the economically rational level.

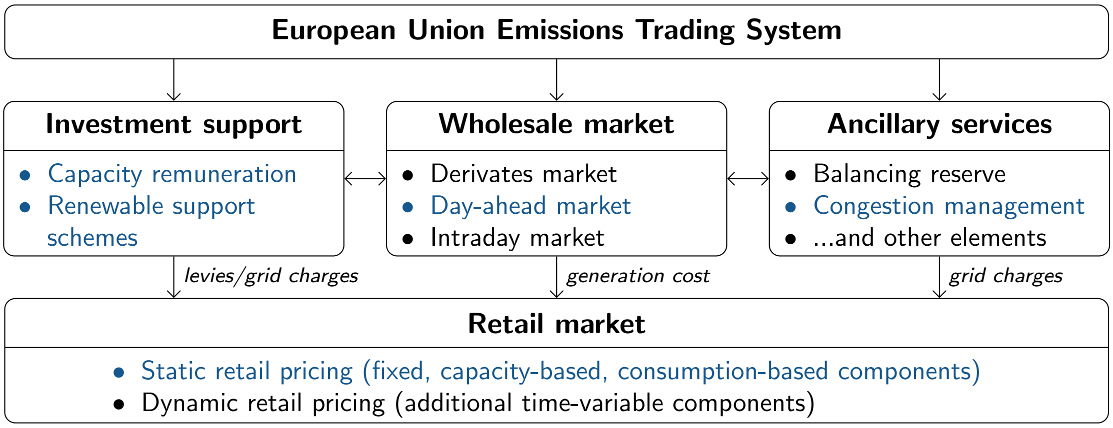


Figure 2.4: Schematic overview of the major electricity market design elements in Europe. A variety of instruments exist which aim to (1) reduce carbon emissions, (2) provide investment support, (3) arrange the trade of electricity, and (4) guarantee system stability. The costs of all instruments are mostly levied to the end consumers. Aspects which are being dealt with in this dissertation are highlighted in blue.

2.4. This variety of instruments offers several possibilities to align the market participants' behavior with the objectives of the energy trilemma or – in other words – to steer quantity, composition, location, and operation of technologies.

Newbery et al. (2018) state that an ideal future electricity market design should efficiently price all products and services to reflect their economic cost and value with regard to time, space, and emissions. Inspired by Newbery et al. (2018), the following sections delve into a number of important electricity market design issues. Section 2.2.1 takes a higher-level perspective and discusses the overarching political goal of creating a single European electricity market. In Section 2.2.2, the challenge of securing long-term generation adequacy is outlined, while Section 2.2.3 is dedicated to the short-term market clearing and alternative congestion management techniques. Finally, Sections 2.2.4 and 2.2.5 introduce investment support mechanisms for renewables and discuss the role of regulation for residential self-consumption.

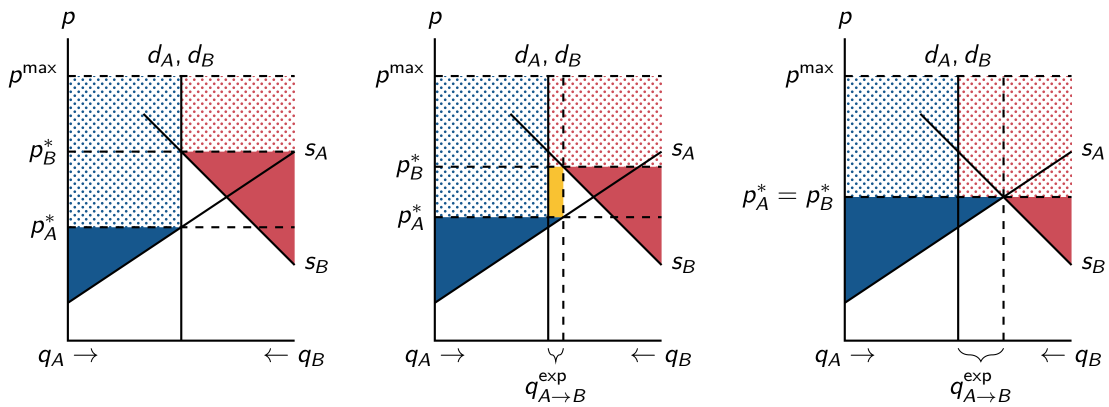
2.2.1 Fostering the European Market Integration

Creating a single European electricity market – also known as *Internal Electricity Market* – is a major strategic goal of the European Commission (2011). Increasing the level of interconnection across Europe is expected to come along with a number of benefits, amongst others (Turvey, 2006; Newbery et al., 2018; Ringler et al., 2017): (1) decrease of generation cost and price volatility, (2) higher level of generation adequacy, (3) lower need for back-up conventional generation capacity, (4) simplified system integration of fluctuating renewables, (5) higher level of market competition.

Some of these aspects were already addressed in Section 2.1.3, where the electricity grid was introduced as an important flexibility option. Additionally, Fig. 2.5 explains the positive welfare effects of coupling two market areas in a stylized example with a static electricity demand and different levels of interconnection capacity. Clearly, overall welfare increases substantially alongside an increase of the interconnection capacity. Yet, since the marginal benefit decreases with additional transmission capacity, the socially optimal capacity level is the one where the total welfare gain equals the investment cost of the interconnector (Spiecker et al., 2013). Thus, a certain price difference between the adjacent market areas is likely to persist, which reflects the value of capacity on the respective link (Newbery et al., 2018).

Before the introduction of market coupling in Europe, cross-border capacities were traded *explicitly* and prior to the actual electricity trading (Newbery et al., 2016). In contrast, market coupling uses *implicit auctions*, such that market participants only bid for the electricity on the exchange and the market clearing prices are then determined while accounting for the available cross-border capacities (EPEX SPOT, 2020). The coupling of the European day-ahead markets started in 2006 with the introduction of the *Tri-Lateral Market Coupling* (TLC) between France, Belgium and the Netherlands and has made significant progress since. In November 2010, the *Central Western European* (CWE) market coupling was launched, which additionally included the German-Austrian-Luxembourg market area. As of 2020, the current pan-European day-ahead market coupling initiative called *Price Coupling of Regions* (PCR) covers a total of 24 European countries and the ultimate goal is to develop a single price coupling solution to calculate electricity prices across Europe. For further details, please refer to EPEX SPOT (2020).

In 2015, the European Commission (2015) established a guideline on capacity allocation and congestion management (CACM), which prescribes, amongst others, the use of flow-based capacity calculation methods in highly meshed networks



(a) no interconnection **(b) limited interconnection** **(c) unlimited interconnection**

Figure 2.5: Welfare effects of market coupling in a stylized example with two markets areas and a static electricity demand. Shaded areas depict the producer rents (blue for market area A, red for market area B), dotted areas the consumer rents (same color code). The maximum price $p^{\max}$ can either refer to an artificial price limit or the consumers' maximum willingness to pay. In the isolated case without any interconnection capacity (a), the market clearing prices p_A^*, p_B^* are determined by the intersection of the demand curves d_A, d_B with the respective supply curves d_A, d_B. Under a limited interconnection capacity (b), market area A increases its generation and exports an amount $q_{A\rightarrow B}^{\text{exp}}$ to market area B. This leads to an increase of the producer rent and a decrease of the consumer rent in A, while the opposite is true in B. In this setting, the owner of the interconnector can make an arbitrage profit (the congestion rent, shaded in yellow) by buying electricity in A and selling it at a higher price in B. If the interconnection capacity is unlimited (c), full price convergence is reached. Total welfare increases from setting (a) over (b) and finally (c). *Source:* based on similar illustrations in Ringler et al. (2017) and Spiecker et al. (2013).

as well as a regular monitoring and review of the bidding zone configuration in Europe. So far, the calculation of the cross-border capacities for the day-ahead market coupling had been based on *net transfer capacities* (NTC), where the link between commercial transactions and the physical characteristics of the grid is strongly simplified (van den Bergh et al., 2016). While this procedure is still used in most of Europe, *flow-based market coupling* (FBMC) was introduced in the CWE area in May 2015 (Felten et al., 2019). This new method uses an improved representation of the physical transmission constraints and therefore allows for less conservative restrictions in the market coupling procedure (van den Bergh et al., 2016). Consequently, FBMC offers more trading opportunities and likely comes along with substantial welfare gains as compared to the previous NTC approach (Plancke et al., 2016b).

In an attempt to avoid undue discrimination between intra- and inter-zonal electricity exchange, ACER (2019) specified a minimum amount of interconnector capacities to be made available for trading in 2019. For this purpose, the *minimum remaining available margin* (minRAM)[3] is linearly increased from today's 20 % to 70 % by 2025. Early research on this new regulation suggests that not only would welfare gains be achieved through better trading opportunities on the day-ahead market, but also might the need for curative congestion management measures increase, potentially overcompensating for the positive market effects (Matthes et al., 2019; Schönheit et al., 2021). Also ACER and CEER (2020) share these concerns and expect the amount of remedial measures carried out in Europe to stabilize the grid to further increase in the coming years.

This has revived the debate about an adequate bidding zone configuration as stipulated by the CACM regulation (see above). Recent insights in this regard are provided by Felling and Weber (2018), Felling et al. (2019) and Voswinkel et al. (2019), who find welfare gains under adjusted European price zones. However, establishing a long-term stable bidding zone configuration is challenging in a highly dynamic environment with phase-out decisions for conventional power plant tech-

[3] The remaining available margin (RAM) is the line capacity that can be used for day-ahead trading and is obtained by deducing certain margins from the thermal line limit, e.g., a margin accounting for the reference flow caused by commercial transactions outside the day-ahead market and a safety margin to compensate for simplifications made in the FBMC methodology (van den Bergh et al., 2016).

nologies and ever-increasing shares of renewable electricity generation as shown for the case of a German market splitting in Paper D.

Despite the challenges, ACER and CEER (2020) report substantial progress towards the European electricity market integration and the European Commission is likely to put significant effort in further fostering these developments. It is therefore crucial for any European electricity market model to adequately take into account cross-border effects. Papers A and B provide important contributions in this regard for the long-term perspective (expansion planning) and the short-term perspective (day-ahead market simulation), respectively.

2.2.2 Securing Long-Term Generation Adequacy

A secure supply with electricity is crucial for any industrialized country. This thesis takes a long-term perspective, therefore the focus is on *generation adequacy*, which can be defined as the *"ability of the generation in the power system to match the load on the power system at all times"* (Poncela Blanco et al., 2016). In contrast, the short-term dimension of supply security deals with operational aspects of the electricity system. The generation adequacy issue is closely related to the question of whether a given electricity market design provides sufficient incentives to invest in *firm* generation, storage, and flexible demand capacity. In the following, a very condensed overview of the academic discussion on generation adequacy in electricity markets is provided. For further details, please refer to the review paper by Bublitz et al. (2019) – co-authored by the author of this thesis.

In an ideal electricity market with sufficient demand elasticity and no price caps, the market always clears, a corresponding market clearing price is obtained, and no involuntary load shedding occurs even in times of supply scarcity (Cramton and Ockenfels, 2012). In such an EOM, generators are solely remunerated for their produced electricity but not for the provision of *firm* capacity.

However, in most of today's electricity markets, a large portion of the demand is inelastic, since consumers are isolated from wholesale market prices but rather pay a fixed tariff per unit of consumption (Vàzquez et al., 2002). Thus, since most consumers have little (if any) incentive to reduce their electricity consumption in times of peak demand, situations may occur in which the demand cannot be fully covered by the available generation or storage capacity and the market clearing fails. In the absence of a competitive market price, the price paid to generators then *must* be administratively set (Cramton et al., 2013). Please note that in competitive markets, capacity only has a price when it is scarce. Thus, as stated by Cramton and Ockenfels (2012), EOMs come along with an inherent tendency to produce scarcity situations at some point.

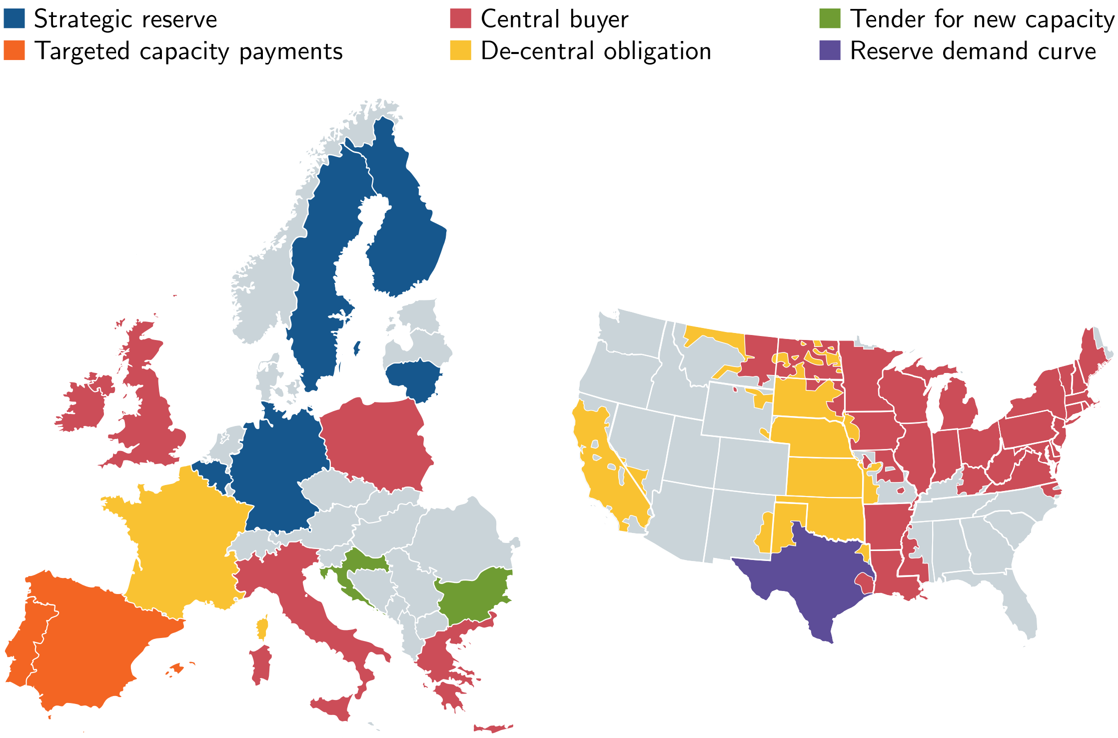
Moreover, price caps are usually applied in real-world electricity markets, since it seems impossible to distinguish efficient scarcity prices from prices indicating the abuse of market power (Cramton and Ockenfels, 2012; Vàzquez et al., 2002). Optimally, the price cap should be set at the *value of lost load* (VoLL)[4], which is however difficult if not impossible to determine (Cramton et al., 2013). In practice, price caps are often set much lower for political reasons, leading to the *missing-money problem*, which describes the lost earnings of (peak load) power plants beyond the price cap (Bublitz et al., 2019). The issue is further intensified by the ongoing expansion of renewables for two reasons (cf. Section 2.1.2). Firstly, the near-zero marginal generation cost of renewables depresses electricity prices. Secondly, higher shares of renewables drastically reduce the load factor of thermal capacities. Clearly, these two effects have strong negative impacts on the contribution margins of conventional power plants.

Apart from the described market imperfections, it is crucial to consider that investors are usually rather risk-averse and therefore build less capacity than a risk-neutral investor would (Vàzquez et al., 2002). More specifically, even if the earnings from infrequently occurring price spikes *were* sufficient to cover fixed and capital costs, investors might be reluctant to bear the associated risks and refrain from building sufficient amounts of generation and storage capacity (Newbery, 2016). Then again, if investors *were* willing to take the risk of relying on infrequent price spikes, they would additionally have to cope with what Cramton and Ockenfels (2012) call the *"risk of political and regulatory opportunism"*. Once prices reach levels that are considered not acceptable, policymakers and regulators are likely to intervene. Finally, investors are also confronted with uncertainties regarding fuel and electricity prices, and the regulatory framework – e.g., the nuclear phase-out decision in Germany or carbon emission targets (Bublitz et al., 2019).

[4]The VoLL describes the average willingness of customers to pay for the reliability of their electricity supply.

Against the described background, it is doubtful, whether an EOM is able to incentivize sufficient amounts of *firm* capacity to guarantee long-term generation adequacy. Such considerations have led to the introduction of CRMs around the world. While different variants of such mechanisms exist (for an overview, see European Commission, 2016b), all have in common the major objective of incentivizing investments and ultimately ensuring generation adequacy. For this purpose, capacity providers are offered a supplementary income on top of the earnings from selling electricity on the market in order to reduce their investment risk (Hawker et al., 2017). However, CRMs are sometimes considered as hidden subsidies to operators of conventional power plants whereas alternative capacity providers like electricity storage or flexible demand barely face any chance of successfully participating in the mechanisms. Recent numbers from ACER and CEER (2020) support this view, since roughly three quarters of the capacity remunerated under European CRMs in 2019 and 2020 were conventional power plants. Against this background, Paper C investigates in more detail, how the design of CRMs may create a bias towards conventional power plants or storage technologies, and ultimately affect the future technology mix as well as long-term generation adequacy.

While the first CRMs in the US were already implemented in the 1990s, these mechanisms have only recently gained popularity in Europe, leading to a number of uncoordinated national implementations (for an overview on the current status, see Fig. 2.6). However, in a highly interconnected electricity system like the European one (see Section 2.2.1), national attempts to increase generation adequacy might lead to a number of potentially undesirable cross-border effects (Bublitz et al., 2019; Hawker et al., 2017). In this context, Bucksteeg et al. (2019) provide a comprehensive model-based analysis on the impacts of different levels of coordination with respect to CRMs. The authors find substantially lower capacity requirements under a European-wide solution, but also a higher dependency on import capabilities for some countries. Moreover, it is shown that under asymmetric market designs, countries without a CRM benefit from additional capacity in their neighboring countries in the short-term and free-riding occurs. However, in the long-term, the missing-money problem in these countries increases, as generation investments are shifted to the countries using CRMs. In another model-based analysis, Fraunholz et al. (in press) also find substantial cross-border effects of CRMs and come to similar conclusions. For the particular case of Switzerland,



(a) Europe **(b) United States**

Figure 2.6: Overview of (a) the future situation of capacity remuneration mechanisms in Europe when all planned mechanisms are implemented and (b) the current situation in the US. The situation is more diverse in Europe due to uncoordinated national approaches and diverging policy targets. Whereas only two different types of capacity remuneration mechanisms are found in the US, a specific case is the Texas ERCOT market, where the energy-only market is supported by an artificial reserve demand curve that produces high price signals to incentivize new investments or demand side management. *Source:* reproduced from Bublitz et al. (2019) (with the following primary sources: ACER and CEER, 2017; Chow and Brant, 2018; EirGrid plc and SONI Limited, 2017; European Commission, 2014b, 2016a,b; U.S. Government Accountability Office, 2017; Midcontinent Independent System Operator, Inc., 2019; Hancher et al., 2015; Roques et al., 2016).

Zimmermann et al. (2021) can show that the large share of flexible hydro power dampens adverse cross-border effects caused by CRMs in the surrounding market areas. In conclusion, while a lot depends on the respective setting, the introduction of CRMs in neighboring countries may create considerable pressure on the national regulator to also take measures to ensure generation adequacy (Bhagwat et al., 2017).

Another point of criticism regarding CRMs is their potential inefficiency. ACER and CEER (2020) state that in 2020, the costs of CRMs per unit of electricity demand were very high in Ireland (approx. 9 EUR/MWh), but also in Great Britain, France, and Greece (all roughly 3 EUR/MWh). Thus, although these figures do not account for potential long-term benefits of CRMs on electricity prices, there are still reasonable doubts about the efficiency of several European CRMs.

2.2.3 Alternative Congestion Management Regimes

Electricity markets differ in the degree to which trading and transmission are integrated in the market clearing process (Ländner et al., 2019). This in turn directly affects the resulting equilibrium electricity prices, which are a major driver for investment decisions. Moreover, the way the market clearing is carried out has an immediate impact on the required congestion management. Whereas *preventive* congestion management techniques aim to account for grid restrictions at the market clearing stage and thereby avoid or reduce grid congestion, *curative* measures come into play after the market clearing process in order to relieve the remaining congestion (Plancke et al., 2016a).

In this context, *nodal pricing* – also named *locational marginal pricing* (LMP) – is commonly considered as the most efficient mechanism, since prices in this market design directly reflect not only marginal generation costs but also transmission constraints (Stoft, 1997). The concept implies that a locational marginal price is determined for each grid node. This price represents the marginal cost of delivering an additional unit of electricity to the respective node. Price differences between two nodes then reflect the respective transmission cost. Thus, adjacent nodes with identical prices are not affected by congestion between each other. Consequently, by fully considering grid restrictions at the market clearing stage, nodal pricing does not require any additional curative congestion management (Plancke et al., 2016a). This market design concept is currently implemented in several US markets as well as in New Zealand, Singapore, and Russia (Newbery et al., 2018; Plancke et al., 2016a).

Since the market liberalization in Europe was initiated by European legislation, but implemented through national regulation, mostly national bidding zones with no further regional price differentiation emerged (Egerer et al., 2016). Another reason for this development may also be that a nationwide uniform electricity price is considered more acceptable from a political perspective (Ambrosius et al., 2019). In contrast to a nodal system, a zonal system only takes into account *inter*-zonal transmission restrictions at the market clearing stage, whereas *intra*-zonal restrictions are neglected. This concept is typically referred to as a *copperplate* assumption. While zonal pricing used to work rather well in the strongly interconnected European electricity system with generation located near the load centers, it is recently being challenged by the increasing shares of distributed renewable electricity generation. If intra-zonal congestion prevents the market result from being realized, curative congestion management needs to be carried out. This includes measures like *redispatching* of conventional power plants or *curtailment* of renewable generation. A prominent example is the German market, where the strong expansion of wind power in the North – with the demand centers being located in the South and West – has led to a substantial increase of congestion management measures and related cost in the past years (see Fig. 2.7).

Despite the drawbacks of the zonal pricing approach, a short-term implementation of nodal pricing in Germany or even Europe is unlikely, as it would require a complex adaption of market players and institutions, most notably the establishment of a German or European-wide *independent system operator* (ISO)[5] (Trepper et al., 2015; Felling and Weber, 2018). The risk of reduced market liquidity and increasing market power are further obstacles (Newbery et al., 2018). However, Newbery et al. (2018) suggests that nodal and zonal pricing systems might also be mixed in order to better reflect the variation of grid conditions in different countries. Bjørndal et al. (2018) recently investigated such a hybrid system and conclude that although some wrong price signals occur, the zonal pricing concept is outperformed by the hybrid system.

[5]In Europe, dispatching of generation units and grid operation are carried out by independent parties. Contrary, in North America, ISOs combine these two roles in a single organization.

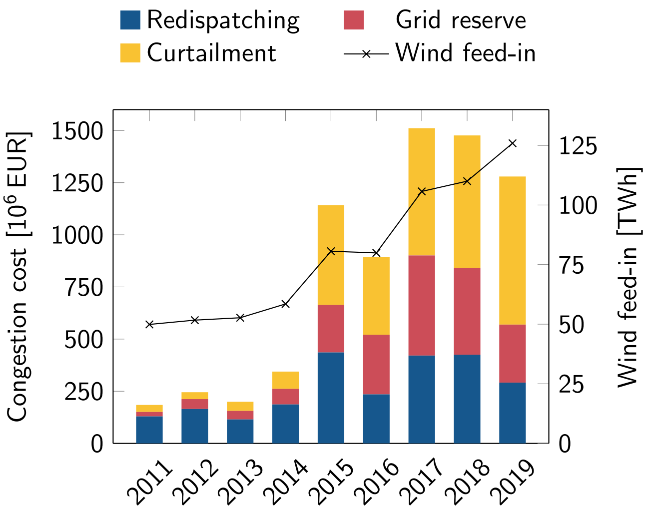


Figure 2.7: Development of the wind feed-in and the cost of congestion management in Germany between 2011 and 2019. Alongside the strong expansion of wind power, also the amount and related cost of different congestion management measures has significantly increased over the past years. *Source:* own illustration using data from Bundesministerium für Wirtschaft und Energie (2020); Bundesnetzagentur and Bundeskartellamt (2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020).

Alternatively to a nodal or hybrid model, existing bidding zones could also be reconfigured, e.g., by splitting existing countrywide zones into multiple zones. Such a market splitting is already used in the Nordic electricity market as well as in Italy, and also intensively discussed for Germany. Against this background, Paper D provides an in-depth analysis of potential long-term effects of a German market splitting on electricity prices, investment incentives, and required congestion management.

2.2.4 Efficient Support Schemes for Renewables

In the European Union, the first mechanisms to foster renewable electricity generation date back to the late 1970s and by 2011, all Member States had implemented such policy instruments (Kitzing et al., 2012). Renewable support mechanisms are typically classified in four categories (e.g., Kitzing et al., 2012; Newbery et al., 2018): (1) *feed-in tariffs*, which provide a guaranteed price for a specific period or predefined amount of production, (2) *feed-in premiums*, where a fixed add-on to the market price is provided, (3) *auctions*, where a certain amount of capacity is procured in a competitive way and remunerated for a certain period or generation, (4) *quota obligations with tradable green certificates*, where either producers or suppliers of electricity need to establish a specific share of renewables in their portfolio. Most countries do not apply a single instrument, but rather a combination, e.g., in order to discriminate between different installation sizes and technologies (Kitzing et al., 2012).

Two major metrics for renewable support instruments are their *effectiveness* (i.e., ability to foster sufficient amounts of investments) and their *efficiency* (i.e., their ability to limit the cost of diffusion to a reasonable level). In 2013, when many renewable technologies had not yet reached maturity, feed-in tariffs were predominant (Newbery et al., 2018). This instrument has advantages in terms of effectiveness, i.e., allows for a fast expansion, as feed-in tariffs provide a relatively predictable revenue stream and thus free the investors from market risks (Kreiss et al., 2017). On the downside, the renewable electricity producers have strong incentives to feed-in their generated electricity even in situations with an oversupply (cf. Section 2.1) since they lose their subsidies when not dispatched. This may lead to negative bidding up to the amount of the feed-in premium received (Newbery et al., 2018).

While feed-in tariffs are still in place for some technologies and particularly for small installation sizes (e.g., residential photovoltaics), the European Commission (2014a) has put an obligation on its Member States to conduct auctions for renewables from 2017 on. Due to its competitive character, the auction format offers a number of potential advantages as compared to other support schemes (Haufe and Ehrhart, 2018): (1) lower support levels and therefore higher efficiency, (2) better control of (technology-specific) expansion targets, (3) insights on cost-covering support levels, (4) incentives for innovation, ultimately leading to further cost reductions. In consequence, auctions are particularly suitable for mature markets where policymakers want to focus on volume control and competitive price setting rather than fostering diffusion at any price (Winkler et al., 2018).

However, auctions are also sensitive to the existing market and framework conditions and therefore need to be carefully and individually designed (Haufe and Ehrhart, 2018). In particular, auctions come along with a substantial non-realization risk mostly emerging from bidders' uncertainties concerning their project costs. In consequence, expansion targets and therefore the effectiveness may be threatened. Against this background, Kreiss et al. (2017) take an auction-theoretic perspective and investigate different measures to reduce the non-realization risk, namely financial prequalifications (securities), physical prequalifications (e.g., a feasibility study), and penalties (e.g., a reduced support level). The authors find that while having a positive impact on the expected realization probability, these measures are likely to have undesirable side-effects like reduced competition and an elevated support level.

Winkler et al. (2018) assess the outcomes of several real-world renewable auctions and contrast these with the outcomes of alternative support instruments. The authors find no evidence of a generally higher effectiveness or efficiency of auctions and speculate that this may be related to the level of competition on the market as well as non-economic barriers like land availability. Jansen et al. (2020) focus on offshore wind auctions and find strong evidence of near-zero effective subsidies in recent auctions. Yet, the authors also emphasize that policymakers should nevertheless carefully consider whether or not to discontinue renewable support, since the *contracts for difference* (CFDs)[6] typically associated with renewable auctions provide a revenue stabilization which is crucial for risk-averse investors.

While renewable support schemes are not central to the work presented in this thesis, feed-in tariffs for residential photovoltaics are part of the analyses carried out in Paper E.

2.2.5 Regulation for Residential Prosumage

Renewable support schemes as well as rapid technology cost declines have fostered the diffusion of decentralized electricity generation using small-scale photovoltaic (PV) systems. In some European countries, *grid parity* has already been reached, meaning that the LCOE for PV has fallen below the post-tax retail electricity prices (Dehler et al., 2017). In combination with decreasing feed-in remuneration, engaging in self-consumption has therefore become an attractive business case for many households, sometimes already justifying investments in battery storage (Klingler et al., 2019; Schill et al., 2017). The profitability threshold of batteries is – in analogy to *grid parity* – known as *battery parity* (Fett et al., 2019). In Germany, more than half of the recently installed residential PV systems were already equipped with battery storage (Fett et al., 2019).

Apart from increasing the share of renewable electricity generation, residential *prosumage*[7] comes along with at least two major benefits (Dehler et al., 2017; Schill et al., 2017). Firstly, consumers can actively participate in the energy transition, eventually leading to higher public acceptance as well as an improved awareness of energy usage. Secondly, if operated in a system-friendly way, residential battery storage could support the system integration of renewables (cf. Section 2.1.3) and relief the electric grid.

However, there are also critical aspects associated with residential prosumage. Firstly, local balancing of fluctuations in demand and renewable generation using small-scale batteries may be less efficient from a system perspective than wide-area

[6] CFDs are used to close the gap between a market reference price and the successful bid price of an auction for a predefined period of time. In one-sided CFDs, only a lower-bound price for the revenues is defined, whereas two-sided CFDs additionally establish an upper-bound price above which revenues have to be returned by the investors (Jansen et al., 2020).

[7] While the term *prosumer* refers to an entity that is both a *pro*ducer and con*sumer* of electricity, *prosumage* adds the dimension of energy storage used to increase self-consumption, i.e., covers *pro*duction, con*sum*ption and stor*age* of electricity (Schill et al., 2017).

balancing (Schill et al., 2017). Secondly, direct battery charging strategies may result in unpredictable PV production peaks and therefore bring more harm than good to the electric grid and the overall system (Dehler et al., 2017). Thirdly, and maybe most importantly, increasing levels of prosumage could have strong distributional impacts (Dehler et al., 2017; Fett et al., 2019; Schill et al., 2017). These arise from an indirect support of self-consumption through the current retail pricing schemes, which charge taxes and levies – such as grid charges or the renewable energy levy – on a volumetric basis, i.e., per kilowatt hour (kWh) of electricity consumption (Fett et al., 2019; Schill et al., 2017). Consequently, as stated by Newbery et al. (2018), self-consumption offers the chance to gain *"tax-free returns on investment by reducing post-tax expenditure on energy"*. However, increasing shares of self-consumption imply that the fixed grid costs and feed-in remuneration need to be allocated to a smaller amount of consumption, thus resulting in higher retail prices (Fett et al., 2019). Obviously, this creates stronger incentives to engage in self-consumption. Eventually, a self-enforcing *utility death spiral* could materialize (Costello and Hemphill, 2014). However, mostly more privileged households have the opportunity to bring up the necessary investment for prosumage, whereas poorer consumers would typically have to rely on the utilities and are therefore more affected by the increase in electricity prices (Newbery et al., 2018).

Fett et al. (2019) show that policymakers can strongly influence the levels and patterns of PV feed-in and self-consumption by making adjustments to the regulatory framework. Against this background, Paper E investigates in detail, how aspects like system-friendly operation, fixed grid charges, and a feed-in limit for residential PV could affect the diffusion and system impact of residential battery storage.

Chapter 3

Methodology

In order to represent real-world electricity systems at a sufficient level of detail, large-scale models depicting the electricity market are required. Optimization and agent-based simulation are the two most established approaches in this domain, which is likely due to the detailed bottom-up character of these model types (Bublitz, 2019). The following Section 3.1 presents the key characteristics of both model classes and explains the choice of a simulation approach for this dissertation. Subsequently, Section 3.2 introduces the basic principles of the established PowerACE model and provides an overview of the extended version developed in this thesis. Sections 3.3 and 3.4 then describe the major model extensions that are carried out in more detail. Moreover, references to the corresponding research papers in Part II are provided.

3.1 Large-Scale Electricity Market Modeling

Traditional optimization models take the perspective of a central planner and aim to minimize total system costs subject to certain constraints like an emission reduction target. Thus, these models typically follow a *normative* approach and determine optimal systems under given framework conditions. Some well-known optimization models for European electricity systems include DIMENSION (Bertsch et al., 2016), E2M2s (Spiecker et al., 2013), ELMOD (Leuthold et al., 2012), and PERSEUS (Möst and Fichtner, 2010).

In contrast, agent-based simulation models take an *explorative* perspective. These models implement different software agents to represent certain actors in the real-world. The agents follow their own goals based on predefined decision rules and in some cases additional learning algorithms. Ultimately, the system behavior emerges from the individual agents' decisions. The most relevant agent-based simulation models for the analysis of European electricity markets include AMIRIS (Deissenroth et al., 2017), EMLab (Chappin et al., 2017), and PowerACE (Genoese, 2010).

In order to allow for a better comparison of optimization models and agent-based simulation models, Table 3.1 provides an overview of some key characteristics of both model types. As previously indicated, this thesis aims to analyze transformation pathways rather than the design of optimal future systems. More specifically, the objective is to determine how the electricity system *could* develop under certain market designs and regulations, not how it *should* develop. It is therefore essential to consider, amongst others, the individual behavior of market players under imperfect foresight and path dependencies in terms of investment decisions. The characteristics of agent-based simulation models stand well in line with these requirements, making them an appropriate methodology for the planned analyses on market design. Against this background, the established agent-based electricity market model PowerACE is used as the main research tool in this thesis. In the following, the basic principles of the model are introduced and an overview of the extended version developed for this dissertation is provided.

3.2 Overview of the Simulation Model PowerACE

3.2.1 Base Version

The initial version of the electricity market simulation model PowerACE was jointly developed by researchers from University of Karlsruhe, Fraunhofer Institute for Systems and Innovation Research, and University of Mannheim between 2004 and 2007. The original model has a focus on the German day-ahead electricity market and includes several agents which represent the associated market participants such as utility companies, regulators, and consumers. The modeled utility compa-

Table 3.1: Characteristics of agent-based simulation and optimization models for electricity markets. Due to their explorative character, agent-based simulation models are useful to investigate transformation pathways. *Source:* based on Bublitz (2019).

Characteristics	Agent-based simulation models	Optimization models
Model objective	Realistic simulation of the development of the market, e.g., wholesale prices	Determination of the optimal outcome under a given objective
Market perspective	Real, imperfect markets with strategic actors	Markets with perfect competition and complete transparency
Information	Myopic and imperfect	Myopic or perfect foresight
Market prices	Result of supply and demand, including possible mark-ups	Marginal costs of electricity demand (shadow prices)
Strengths	Considering strategic behavior and imperfect information, well extensible and adaptable	Optimal results, established methodology, transparency through concise mathematical notation
Weaknesses	Decision rules determine outcome but in some cases hard to validate	Deviations between optimal results and real market events, neglecting of the participants' perspectives

nies decide on both the short-term dispatch of their conventional power plants as well as long-term capacity expansion, i.e., investments in additional power plants.

The original model version of PowerACE was applied to a range of research questions, e.g., the merit-order effect of renewables (Sensfuß et al., 2008) and potential market power in Germany (Möst and Genoese, 2009). More details of the original model and additional analyses can be found in the dissertations of the involved researchers (Genoese, 2010; Sensfuß, 2008; Weidlich, 2008). Since its origins, several additional researchers have substantially extended PowerACE and a variety of different model versions with different focuses therefore exist. In the following paragraphs, some key elements and characteristics of the model that were already implemented prior to this dissertation are described in more detail.

Day-ahead market A key element of PowerACE is the representation of the day-ahead market, which is cleared on an hourly basis by the market operator. For this purpose, the agents representing utility companies submit bids for their power plant units and an aggregated supply curve is constructed by sorting all sell bids according to their price in ascending order. The market outcome is then determined as the intersection between this supply curve and the exogenously given static electricity demand. Please note that in this context, the electricity demand refers to the residual demand to be covered by the conventional power plants, i.e., feed-in of renewables and electricity exchange with neighboring countries are considered.

Market coupling Given the European Commission's goal of creating an Internal Electricity Market (cf. Section 2.2.1), cross-border effects between interconnected market areas are a major aspect to be considered in electricity market models. Against this background, Ringler et al. (2017)[8] embedded a simplified representation of *EUPHEMIA* (NEMO Committee, 2019) – the algorithm used for the real-world day-ahead market clearing process across multiple interconnected market areas – into PowerACE. Formally, the market coupling in PowerACE is implemented as a linear optimization problem which is solved independently for each simulation hour.

Investment planning At the end of each simulation year, the agents representing utility companies carry out their investment planning. For this purpose, model-endogenous long-term price forecasts are created in order to estimate the profitability of different investment options. Taking into account the decisions of the other players, each utility company then decides on type and amount of investments in new conventional power plants. Importantly, investments are only carried out if expected to be profitable and scarcity situations without sufficient generation capacity to cover the demand may occur. This distinguishes the approach from optimization models which typically enforce a minimum capacity to satisfy demand at all times. Moreover, a continuous time period is considered, whereas optimization models usually only investigate selected years to reduce computational complexity.

Capacity remuneration mechanisms Several European countries have recently introduced uncoordinated national CRMs in order to incentivize sufficient invest-

[8]For a more detailed German description, see also the corresponding dissertation (Ringler, 2017).

ments in *firm* capacity and thereby ensure generation adequacy (cf. Section 2.2.2). Given the crucial impact of these mechanisms on the investment planning of utility companies, electricity market models should account for the different market designs. Against this background, three types of CRMs have been implemented in PowerACE and analyzed in the past: capacity payments (Genoese et al., 2012), a central buyer (Renz et al., 2014), and a strategic reserve (Bublitz et al., 2015). Moreover, a comparison of different design options for the German electricity market is provided in Keles et al. (2016).

Input and output data PowerACE is a detailed bottom-up simulation model featuring a typical time horizon of 30–40 years and a temporal resolution of 8760 h/a. Consequently, the model requires substantial amounts of input data, most importantly a list of existing conventional power plants and investment options with their techno-economic characteristics, assumptions on the development of fuel and carbon prices as well as hourly time series for the feed-in of renewables and the electricity demand. In order to illustrate these data requirements, Table 3.2 presents an exemplary overview for a typical long-term simulation covering ten market areas. Details on the respective sources used to compile the required data sets are provided in the research papers included in Part II of the thesis. The output of PowerACE includes hourly day-ahead electricity prices, the corresponding electricity generation by technology as well as changes in the long-term composition of the conventional power plant fleet.

3.2.2 Extended Version

The existing model version of PowerACE provides a good basis to investigate the research questions of this dissertation. However, in order to adequately account for the important future role of flexibility options and particularly electricity storage (cf. Section 2.1.3) as well as the European market integration (cf. Section 2.2.1), some major model extensions have to be carried out. The subsequent paragraphs briefly introduce these extensions, while Fig. 3.1 shows a schematic overview of the extended model version of PowerACE. As outlined in more detail in Paper C, the developed electricity market model is the first agent-based simulation approach available in the literature to simultaneously consider dynamic aspects and

Table 3.2: Exemplary overview of the input data required for a PowerACE simulation covering ten European market areas and a time horizon of 2015–2050. In order to reduce complexity and solution time, many optimization models in the literature consider fewer market areas, only selected years or typical days instead of full hourly resolution. Due to its simulation-based character, PowerACE remains tractable even when using the full regional, temporal, and technological resolution.

Input data type	Resolution	Dimension of data
Conventional power plants	unit level	ca. 1600 units
Fuel and carbon prices	yearly (daily)	36x6 values[1]
Investment options	yearly	36x13 technologies[2]
Transmission capacities	yearly (hourly)	36x10x10 values[3]
Electricity demand	hourly, market area	36x8760x10 values
Renewable feed-in	hourly, market area, technology	36x8760x10x6 values[4]

[1] Five fuel types (uranium, lignite, coal, gas, oil) and carbon emission certificates.
[2] Seven conventional power plant options and six storage options.
[3] Each pair of market areas with transmission capacities per direction of flow. Not all values are non-zero, since some market areas are not directly interconnected.
[4] Six renewable technologies (biomass, geothermal, hydro, solar, wind off-/onshore).

interdependencies in terms of (1) time (multiple investment decision periods), (2) space (multiple interconnected countries), (3) technologies (different conventional power plants and types of storage), and (4) market designs (EOM and different types of CRMs).

Cross-border effects (spatial coupling dimension) The interconnector capacities in Europe are expected to be substantially increased in the upcoming years. Thus, adequately considering cross-border effects in electricity market models becomes even more relevant. However, the long-term investment perspective of PowerACE so far took an almost exclusively national perspective. Paper A therefore introduces a novel algorithm to solve the generation expansion planning problem in interconnected electricity markets by iteratively determining a stable Nash-equilibrium of investment decisions across all modeled market areas (see also Section 3.3). Moreover, while an algorithm for the coupling of the day-ahead markets has already been implemented in PowerACE (see above), cross-border effects have thus far only been rudimentally considered in another essential part of the day-ahead market simulation, namely the model-endogenous electricity price fore-

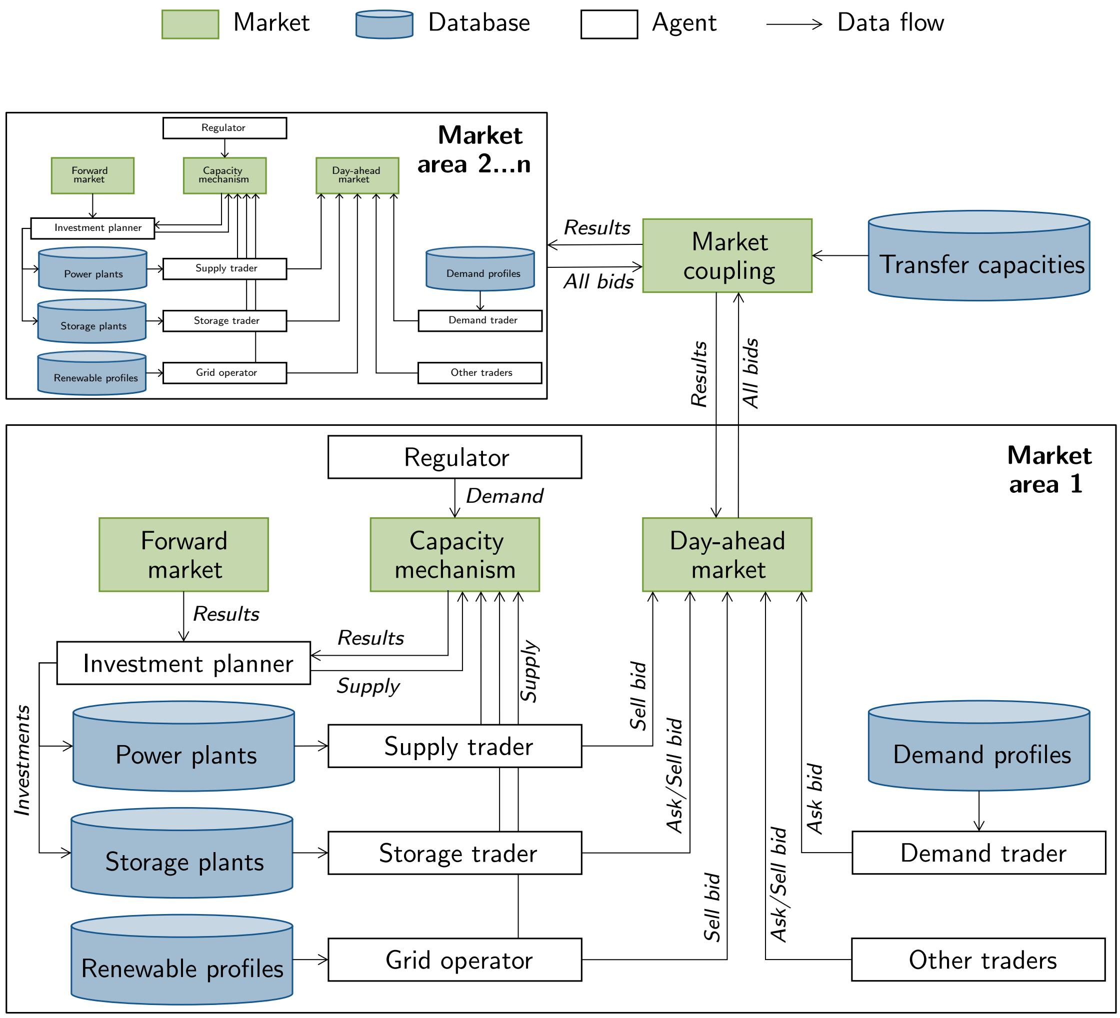


Figure 3.1: Schematic overview of the extended electricity market simulation model PowerACE. The focus lies on the short-term simulation of the day-ahead markets and long-term investment decisions under consideration of different capacity remuneration mechanisms as well as cross-border effects. *Source:* Paper C (Fraunholz et al., 2021b).

casting of the agents. Thus, in Paper B, a methodology is developed which uses model-endogenously trained artificial neural networks to create day-ahead price forecasts (see also Section 3.4).

Electricity storage (temporal coupling dimension) Given the ongoing expansion of fluctuating renewables like wind and solar power, the importance of electricity storage as a flexibility option increases. As storage technologies add a time-coupled component, this aspect adds substantially to the model complexity. In order to fully integrate short-term electricity storage into PowerACE, a number of extensions need to be carried out. In Fraunholz et al. (2017), a bidding algorithm for the participation of storage units in the day-ahead market is developed. The general idea of this algorithm is to optimally schedule the charging and discharging given a model-endogenous day-ahead price forecast for the next 72 hours (rolling horizon). Moreover, storage technologies are included as additional investment options in the expansion planning methodology of Paper A. Finally, storage technologies are also integrated in the central buyer CRM described above. For this purpose, some new regulatory parameters have to be added, as described in detail in Paper C.

Model coupling interfaces New technologies on the demand side are expected to strongly affect the shape of the electricity demand over the course of a day, week or even year (Boßmann and Staffell, 2015). At the same time, the increasing share of renewable electricity generation challenges the transmission grid, which in turn leads to higher interdependencies between electricity market outcomes and required congestion management (cf. Section 2.2.3). Since it is hardly possible to include all of these aspects within a single model while maintaining the desired level of detail, the joint application of different models with a specific focus is a viable alternative. Thus, approaches and data interfaces need to be developed which allow for a model coupling of PowerACE with demand side and optimal power flow models. An example of such a methodology is described in Hladik et al. (2018), while different applications can be found in Paper D, Paper E, and Hladik et al. (2020).

Extended geographical scope Six additional market areas are integrated in PowerACE (highlighted in italics) and the model now covers the following ten countries: *Austria*, Belgium, *Czech Republic*, *Denmark*, France, Germany, *Italy*, Netherlands, *Switzerland*, *Poland*. This selection of countries represents a significant portion of the European electricity market and moreover offers a variety of different design options (cf. Section 2.2.2). The extended geographical scope therefore allows for analyses on market design under consideration of the respective cross-border effects.

3.3 Generation and Storage Expansion Planning

As previously outlined, it is essential to consider cross-border effects when analyzing the long-term investment planning of utility companies in interconnected electricity markets. Against this background, Paper A introduces a novel algorithm to solve the *generation expansion planning* problem, in which the future technology mix needs to be determined subject to the expected future electricity demand, renewable feed-in, and cross-border transmission capacities. The new approach takes an individual investor's perspective and expands the general idea of the baseline model version of PowerACE (cf. Section 3.2.1) to a multi-country setup. Furthermore, storage technologies are included as additional investment candidates (typically referred to as *storage expansion planning*). Please note that this aspect is particularly challenging since storage adds a time-coupled component to the problem (Haas et al., 2017).

Given a list of available technology options, each investor's profit is maximized by choosing type and quantity of investments to carry out under given assumptions on the actions of all other investors. For this purpose, the investors rely on a model-endogenous long-term price forecast. Yet, these price forecasts are influenced by the investment decisions of all investors in all considered market areas. Thus, a complex game with multiple potential strategies opens up. Ideally, the problem at hand would be modeled as an *equilibrium problem with equilibrium constraints* (EPEC). Unfortunately, given the nonconvex nature of EPECs, such problems are extremely challenging to solve and hardly tractable for real-world applications with multiple players and investment periods (Conejo et al., 2016). Thus, an iterative

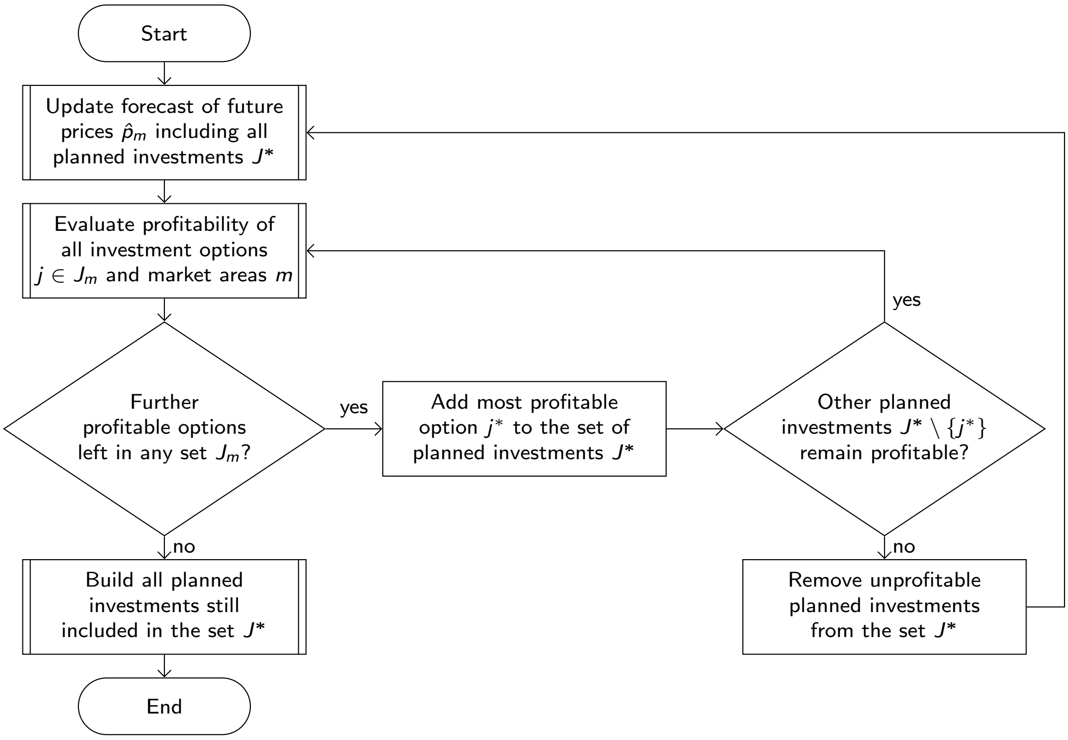


Figure 3.2: Simplified overview of the developed expansion planning algorithm. Starting with an initial model-endogenous long-term price forecast, the profitability of all investment candidates is evaluated. Potential investments are then gradually added to and removed from the – initially empty – set of planned investments until a Nash-equilibrium has been found. During the process, the price forecast is updated numerous times to account for the respective price impact of the currently planned investments. For more details, please refer to Paper A.

procedure is applied in order to find a stable outcome for the described setting, which is illustrated in simplified form in Fig. 3.2.

The algorithm starts with an initial price forecast, which is implemented as a time-coupled linear optimization problem. In the objective function, total generation costs across all market areas are minimized subject to the energy balance in each market area and a number of techno-economic constraints like generation bounds for all power plants, limited cross-border transmission capacities, and some constraints for the storage units. The hourly price forecasts are then derived from the dual variable of the energy balance in the respective market area.

Using this price forecast, the profitability of all investment candidates in all market areas is evaluated and potential investments are gradually added to and removed from the – initially empty – set of planned investments. During this process, the price forecast needs to be updated numerous times to account for the respective price impact of the currently planned investments. The iterative procedure terminates once a *Nash-equilibrium* has been found. This implies that all planned investments are profitable and at the same time none of the investors is able to improve his expected payoff by carrying out further or less investments. In consequence, there exists no incentive for any investor to unilaterally deviate from the equilibrium outcome.

The developed algorithm assumes an EOM design. However, several European countries have either already implemented some kind of CRM or are currently in the process of evaluating appropriate solutions (cf. Section 2.2.2). Since these mechanisms are likely to bring along substantial cross-border effects, it is crucial to consider their impact in the expansion planning. Thus, the centralized capacity auction algorithm developed by Renz et al. (2014) is integrated into the new methodology. This is realized by first computing an initial future price forecast and then carrying out annual descending clock auctions in the market areas using the mechanism, in order to contract a specific amount of secured generation, and storage capacity. Subsequently, the usual investment planning procedure shown in Fig. 3.2 is run while considering the investment decisions resulting from the centralized capacity auctions. For some additional details on the basic principles of the central buyer mechanism, please also see the Appendix of Paper C.

In summary, the developed expansion planning approach is the first in the field of long-term agent-based simulation models to adequately consider cross-border effects, storage technologies, CRMs, and technological learning at the same time (see also the literature section of Paper C).

Paper A is complemented by an illustrative case study covering ten interconnected European market areas with their respective current real-world market design (EOM, strategic reserve, centralized capacity auctions) and a time horizon from 2020 until 2050. On the one hand, results of the case study clearly show high investment incentives in countries applying CRMs, such as France. On the other hand, related (negative) cross-border effects can be observed, which reduce investment incentives in other countries that rely on an EOM (e.g., the Netherlands). These findings confirm both the essential need to adequately model and consider cross-border effects in multi-country long-term electricity market models as well as the suitability of the developed methodology to do so.

3.4 Model-Endogenous Day-Ahead Price Forecasting

Electricity price forecasts are an essential element of the decision making processes in liberalized electricity markets, which is reflected by the enormous body of literature on this topic (for a thorough review, see Weron, 2014). Since PowerACE aims to represent real-world electricity markets in a realistic fashion, model-endogenous price forecasting is also a crucial aspect of the day-ahead market simulation. Before delving into the issue of price forecasting, some context is provided by introducing the major steps of the day-ahead market simulation with PowerACE (Fig. 3.3).

Firstly, all agents participating in the day-ahead market create a model-endogenous price forecast, which is essential, e.g., in order to estimate the running hours of a conventional power plant and distribute the expected start-up costs accordingly. Secondly, the different traders prepare hourly bids consisting of type (sell/ask), volume, and price which are submitted to the central market operator. The bid prices for the conventional power plants are based on the respective variable costs, distributed start-up costs, and a potential scarcity mark-up. Further price-inelastic bids for demand, renewable feed-in, and storage units are prepared by a single trader per market area, respectively. Thirdly, the market operator matches supply bids and demand bids across all market areas and carries out the market clearing. In this step, welfare is maximized subject to the limited interconnector capacities between the different market areas. Finally, the information about accepted and declined bids is returned to the different traders and processed. The utility agents can now plan the dispatch of their generation units accordingly. Moreover, the day-ahead market simulation returns a market clearing price and corresponding electricity volume for each market area and simulation hour.

Creating accurate model-endogenous price forecasts is both essential and challenging, as these forecasts have a direct impact on the bidding behavior of the agents, which in turn affects the outcomes of the market clearing process. At the same time, the price forecasting approaches can be continuously updated through-

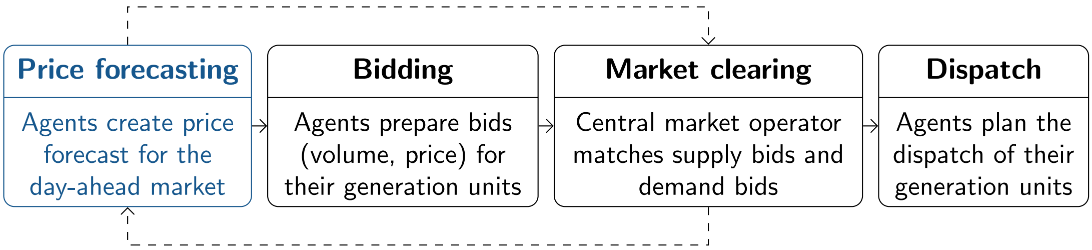


Figure 3.3: Steps of the day-ahead market simulation with PowerACE. Accurate price forecasts are essential, as they have a direct impact on the bidding of the agents, and thus an indirect impact on the outcomes of the market clearing process. The market outcomes of previous auctions in turn affect the price forecasting of the agents. *Source:* Paper B (Fraunholz et al., 2020).

out a simulation by using the market outcomes of previous auctions as input data. A mutual dependency between price forecasts and market outcomes then exists. In consequence, poor price forecasts are likely to result in distorted market outcomes. Since the simulated day-ahead market electricity prices are a key result of an electricity market model, this aspect is particularly crucial.

As outlined in Section 3.2.1, PowerACE was originally developed to analyze the German electricity market. In such a single-country setup, only a limited number of price drivers exists and model-endogenous price forecasts can therefore be implemented relatively simple. For example, in the base version of the model (cf. Section 3.2.1) a basic merit order model is used. This involves sorting the conventional power plants according to their variable generation costs in ascending order. The intersection of the resulting aggregated supply curve with the respective residual demand would then determine the expected market price. However, the model extension to a multi-country setup heavily increases the complexity of creating reasonably accurate price forecasts, since the non-linear effect of cross-border electricity exchange (cf. Section 2.2.1) needs to be considered.

Against this background, novel approaches for model-endogenous price forecasting are developed, implemented, and evaluated in Paper B. The new method relies on an innovative combination of machine learning and agent-based modeling. More specifically, different feed-forward neural networks are continuously trained with the auction results of previously simulated day-ahead market periods and then applied to forecast the day-ahead prices of the next simulation day. While artificial neural networks have previously been extensively used for real-world electricity price forecasting, such a model-endogenous application in a long-term multi-country setup brings along a number of additional challenges and is unique in the literature to date.

The new forecasting approach is benchmarked against a simpler linear regression approach and a naive forecast in a case study covering ten interconnected European market areas and a time horizon from 2020 until 2050 at hourly resolution. Results of the case study confirm that the developed model-endogenous price forecasting approaches perform well and are highly suitable for the agent-based simulation of multiple interconnected electricity markets.

Chapter 4

Case Studies

The extended agent-based simulation model PowerACE described in the previous Chapter 3 is applied in three case studies, which are all related to challenges introduced in Chapter 2. The chapter at hand summarizes the case studies by briefly describing the respective background, applied methodology, and major results. The corresponding research papers are included in Part II of the dissertation.

4.1 Role of Electricity Storage in Capacity Remuneration Mechanisms

As outlined in Section 2.2.2, the substantial increase of highly intermittent renewable electricity generation has driven the implementation of CRMs around the world. All these mechanisms share the basic concept of providing additional income to capacity providers on top of the earnings from selling electricity on the market. Like this, the investment risk for new *firm* generation, storage or demand side management capacity should be reduced, ultimately incentivizing sufficient amounts of *firm* capacity to ensure generation adequacy, i.e., avoid scarcity situations. At the same time, CRMs are sometimes considered as hidden subsidies to operators of conventional power plants while other alternative capacity providers, such as electricity storage or demand side management, are confronted with major barriers for a successful participation in these mechanisms.

Both in Europe and the US, the respective regulators aim to establish full technology neutrality of any CRM to be implemented (European Commission, 2013; Sakti et al., 2018). Yet, the concrete rules applied for the participation of storage and demand side units differ substantially (Chen et al., 2017; National Grid, 2017; Sakti et al., 2018; Single Electricity Market Committee, 2016, 2018; Usera et al., 2017). A major aspect in this regard is the non-trivial question of whether and how much *firm* capacity such units can contribute to system adequacy. This is because – in contrast to conventional power plants – the energy-limited nature of storage units hinders this technology from providing full power output throughout scarcity periods of whatever length. In consequence, although it is generally agreed that storage technologies have some kind of capacity value, the specific rules of participation in CRMs can affect the competitiveness of storage units against conventional resources.

Against this background, Paper C provides an in-depth analysis on how the design of a CRM may create a bias towards or against storage technologies, and ultimately affect the future technology mix as well as long-term generation adequacy. For this purpose, a twofold methodology is applied. Firstly, a generic capacity auction mechanism is set up and important design parameters are derived and analyzed in a rigorous theoretical discussion. Secondly, the theoretical findings are further investigated by applying the agent-based electricity market model PowerACE and running a number of multi-country long-term simulations.

In the theoretical discussion, it can be derived that essentially only three drivers decide on which technology is able to bid the lowest price in a capacity auction. Thus, these drivers ultimately affect the auction outcome and in particular the resulting technology mix in the electricity market. This important finding is shown in Eq. (4.1), where k_1, k_2 denote two constants, c_p^{invest} the investment expenses of technology option p, CM_p the respective contribution margin of participating in the day-ahead market, f_p^{derate} the *derating factor*[9], and p^{CRM} the capacity price bid into the auction. Please note that the investment expenses c_p^{invest} are primarily technology-specific and cannot be directly influenced by the regulator of the capacity auction. While the contribution margins CM_p are also technology-specific, the regulator can still steer them by implementing call options with a certain strike price p^{limit} on the electricity market. Similarly, the technology-specific der-

[9]Derating factors are applied in order to base the remuneration on the capacity credit of a given technology, i.e., the units are only remunerated for the amount of *firm* capacity they are able to provide rather than for their *nameplate* (or *nominal*) capacity.

ating factor f_p^{derate}, which is particularly relevant for storage technologies, can be directly set by the regulator.

$$p_p^{\text{CRM}} = \frac{k_1}{f_p^{\text{derate}}} \cdot \max\left(k_2 \cdot c_p^{\text{invest}} - CM(p^{\text{limit}})_p, 0\right) \tag{4.1}$$

A stylized example of a future situation on the day-ahead market is then used to show that bundling a CRM with call options (including a strike price) can increase the competitiveness of storage units against conventional power plants. This is because under high shares of renewables, storage units can charge at very low cost and are therefore less affected by a price limit than conventional power plants with high variable costs. Consequently, the storage units can bid lower prices in the capacity auctions.

In another stylized example, a lowest-cost frontier is derived for the *difference costs*[10] of a conventional power plant, a small storage unit, and a large storage unit under different storage duration requirements (i.e., different derating factors). Quite intuitively, increasing the storage duration requirements comes along with a stronger derating and consequently higher difference costs of the storage units. Thus, while the small storage unit may be the most profitable option under low storage duration requirements, higher requirements will result in a shift towards the larger storage unit and ultimately the conventional power plant, which is not affected by derating at all. Please note, however, that apart from the described impact on technology choice, the derating factor also has another somewhat inverse effect. Since the total amount of *firm* capacity to be procured in a capacity auction is often predefined, stronger derating of storage technologies leads to lower capacity contributions of these units and consequently a higher amount of *nameplate* capacity to be contracted in order to fulfill the desired *firm* capacity target. Thus, under certain circumstances, stronger derating of storages may counterintuitively lead to more storage investments being carried out despite the higher capacity prices that are bid into the auction.

In order to illustrate and confirm the theoretical findings, a number of simulations with the agent-based electricity market model PowerACE are run. As

[10]The difference costs describe the delta between the income needed for an investment to reach profitability and the net present value if the unit was optimally operated on the electricity market. This delta therefore corresponds to the additional income needed from a CRM if the investment should be built.

a benchmark, a European EOM is first analyzed. Subsequently, additional simulations are carried out to show the impact of implementing capacity auctions with call options as well as different storage derating factors in these auctions on investments in storage units.

The results of the simulations stand well in line with those of the theoretical discussion. It can be confirmed that a CRM without call options creates an implicit bias towards conventional power plants, while a mechanism with call options and a strike price increases storage profitability in direct comparison with conventional power plants. Moreover, stronger derating of storage technologies is found to generally create a bias towards larger storages and ultimately conventional power plants. At the same time, the higher amounts of *nameplate* capacity to be procured may overcompensate this effect and lead to more storage investments despite stronger derating. The simulations also confirm that due to their limited storage volume, the storage units are not able to provide sufficient *firm* capacity to cover all peak demand periods.

Overall, it can be concluded, that the concrete design of a CRM has strong impacts on both, the resulting technology mix and the achieved level of generation adequacy. More specifically, in order to account for the capacity value of electricity storage, such technologies should be allowed to participate in any CRM, yet with their *nameplate* capacity adequately derated to reflect the *firm* capacity they can actually provide.

4.2 Long-Term Efficiency of Market Splitting in Germany

As briefly introduced in Section 2.2.3, the German electricity market is currently facing challenges associated with the massive expansion of renewable electricity generation, which is – in the case of wind power – to a large extent located in the Northern part of the country. In contrast, the historical demand centers of Germany are located in the South and West. This locational mismatch between generation and consumption has already led to increasing amounts of congestion management in the past years. Yet, the situation is even expected to intensify due to the German government's decisions on phasing out nuclear power by 2022 and coal-fired generation by 2038, which will lead to a large-scale reduction of dispatchable generation capacities. Given the delays in the planned grid extension between Northern and Southern Germany, the idea of splitting the German market area into a Northern and a Southern part – although undesired – has therefore come back to the political agenda. Due to the potentially strong consequences of such a zonal split, the topic is highly relevant not only from an academic and political perspective, but also for generation companies, grid operators, and industry. While the short-term impacts of a German market splitting have been extensively analyzed by several authors (Burstedde, 2012; Breuer et al., 2013; Breuer and Moser, 2014; Trepper et al., 2015; Egerer et al., 2016; Plancke et al., 2016a), only one group of authors has also tackled the long-term perspective (Ambrosius et al., 2019; Grimm et al., 2016a,b, 2017, 2018). Yet, as emphasized by Grimm et al. (2016b), the long-term effects of a zonal splitting are an essential aspect for the political discussion on such a measure.

In order to investigate all relevant long-term aspects of a zonal split in Germany, the decisions of different actors need to be considered. This includes (1) a regulator who decides on the actual zonal split, (2) different generation firms who carry out long-term investment and short-term market decisions, and (3) a transmission system operator (TSO) who carries out the required congestion management measures. Against this background, Paper D introduces an innovative modeling framework consisting of two established energy-related models: the optimal power flow model ELMOD and the electricity market simulation model PowerACE.

Fig. 4.1 illustrates the interaction of the two models and the different decision levels involved. In a first step (bottom-left box), the regulator decides on an optimal splitting of the German price zone and corresponding inter-zonal transmission capacities available to the market. For this purpose, hourly nodal prices[11] for the base year 2020 are simulated with ELMOD and clustered in two zones. Next, $|Y|$ periods covering one year at hourly resolution are simulated. In each period, three different steps are carried out. Firstly, the day-ahead market is simulated with PowerACE under consideration of the new zonal delimination. Secondly, the

[11]The nodal price or locational marginal price (LMP) of an electricity grid node represents the marginal cost of delivering an additional unit of electricity to this specific node. The LMP therefore includes information on both, marginal generation costs and the transmission grid. Since diverging nodal prices are an strong indicator for grid congestion, clustering nodes with similar LMPs is a promising approach to determine stable zones with low intra-zonal congestion.

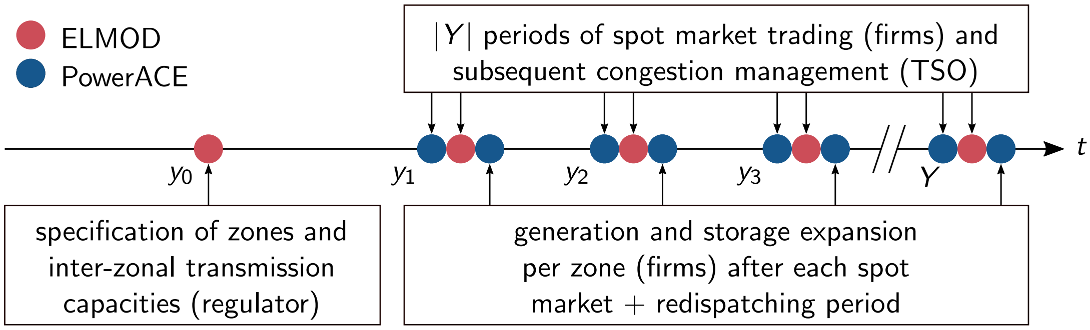


Figure 4.1: Timeline of the joint application of the models ELMOD and PowerACE. By considering the decision levels of all relevant actors, the novel modeling approach enables a holistic long-term analysis of a potential German market splitting. *Source:* Paper D (Fraunholz et al., 2021a).

hourly power plant and storage dispatch originating from the market simulation is used as an input for ELMOD, which is now applied to determine required congestion management measures. These two steps correspond to the top-right box of Fig. 4.1. Thirdly, the generation firms represented in PowerACE decide on potential investments in new generation and storage units to be used in subsequent periods (bottom-right box).

Contrary to other approaches in the literature (most notably Ambrosius et al., 2019), the developed *explorative* approach does not assume perfect anticipation of all actors, but allows capturing long-term investment and short-term market behavior in a multi-period setting and under imperfect information. The applied methodology is therefore very well suited to analyze dynamic impacts of a market splitting in Germany in a closer-to-real-world fashion than any publication available to date.

Results of Paper D show strong impacts of a market splitting on day-ahead electricity prices, investment planning of generation companies, required congestion management and, ultimately, system costs and social welfare.

Under a zonal split, the day-ahead prices are initially significantly higher in the Southern German price zone (DES) as compared to the Northern German price zone (DEN). Mostly driven by the ongoing grid extension, the price differences then decline between 2020 and 2035, yet rise again slightly between 2035 and 2050 due to the ongoing strong expansion of renewables without additional grid extension. The price divergence between DEN and DES also proves to have a direct impact on investment incentives: under the zonal split, much more new power plants are built in DES than DEN as compared to the reference case of a single price zone.

As regards the grid perspective, less congestion management measures need to be carried out under the zonal split in the short term (2025). Yet, in the medium term (2035), the required congestion management increases as compared to the reference, since the bidding zone delimination has become outdated given the completely different setup regarding location of (new) power plants, grid extension, and renewable expansion as compared to the base year 2020.

The described results are ultimately reflected in system costs, which rise under the market splitting, mainly driven by the significantly higher wholesale prices for electricity as compared to the status quo of a single German price zone. Regarding social welfare, despite the strong increase of the producer rents in DES, the zonal split results in an overall negative welfare effect in Germany.

These findings clearly show that a zonal delimination optimal from today's perspective is likely to become outdated over time in a dynamic environment with grid extension, renewable expansion as well as power plant investments and decommissioning. In consequence, policymakers and regulators should regularly re-assess and potentially adjust bidding zone configurations. Yet, if investors cannot rely on stable price zones, locational investment incentives may no longer be given. Adequately setting up stable bidding zones therefore remains a major challenge, which is reflected by most of the European electricity market still being organized in countrywide price zones.

4.3 Diffusion and System Impact of Residential Battery Storage

As outlined in Section 2.2.5, the current German retail pricing schemes charge taxes and levies on a volumetric basis, thus providing strong incentives to engage in self-consumption. In combination with rapid technology cost reductions and decreasing feed-in remuneration, installing residential photovoltaic systems with battery storage has become an attractive business case for many German households. However, a large-scale diffusion of residential battery storage may come along with substantial – and not necessarily beneficial – system impacts. For this

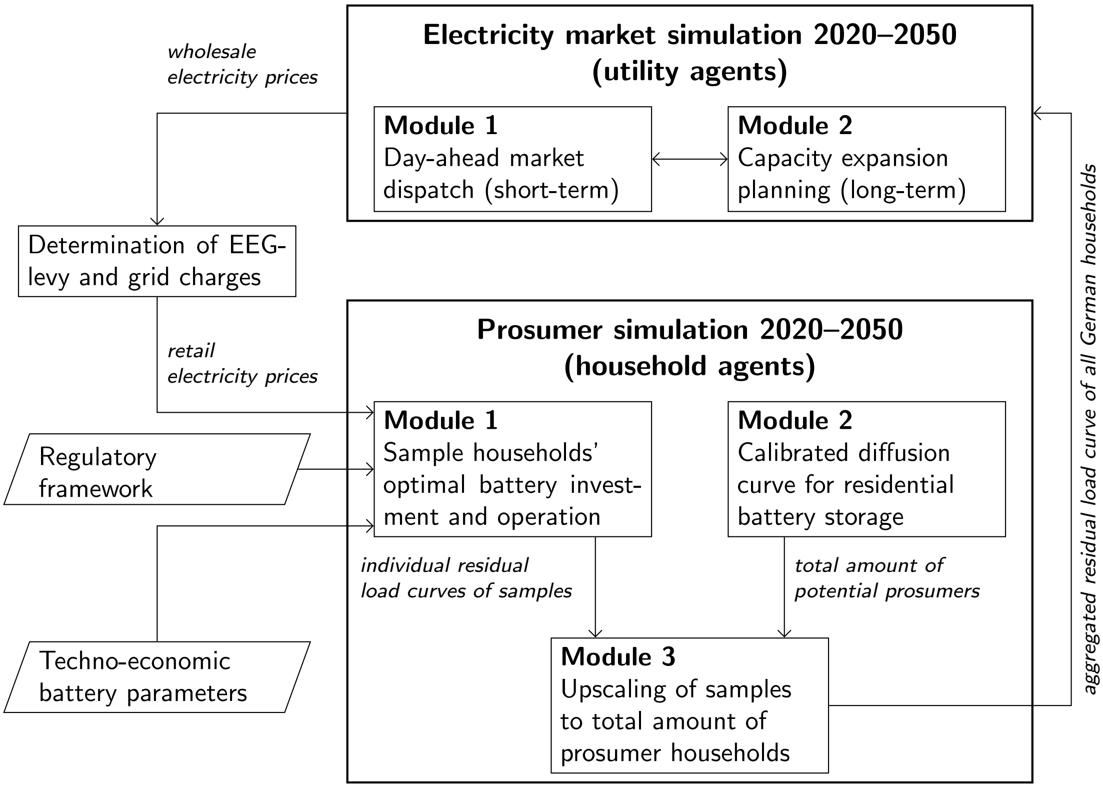


Figure 4.2: Overview of the applied simulation framework to investigate residential battery diffusion and related long-term system impacts. By combining a prosumer simulation and an electricity market simulation, the interdependencies between households' and utilities' decisions can be adequately accounted for. *Source:* Paper E (Fett et al., 2021).

reason, policymakers and regulators are confronted with the difficult task of designing an adequate regulatory framework for self-consumption in order to govern the diffusion, operation, and system impact of the residential batteries.

Against this background, a novel modeling framework is developed in Paper E, which is based on the joint application of a prosumer simulation and an agent-based electricity market simulation (see Fig. 4.2). This methodology is then used to investigate the long-term impacts of residential battery storage diffusion in Germany with a particular focus on the regulatory framework. Apart from the status quo of the German regulation for self-consumption, a more system-friendly operational strategy, and a restrictive regulation comprising fixed grid charges as well as a self-consumption charge are analyzed.

The proposed approach is the first in the literature to consider bidirectional dependencies between the decisions of households and utilities, the technology diffusion process, and alternative operational strategies for the residential batteries. Moreover, the total household electricity consumption is approximated by several empirically measured household load profiles. This allows to account for the diversity of households' load curves and avoid biases resulting from aggregated or synthesized data.

The results of Paper E show that under a more restrictive regulation, households invest in substantially smaller photovoltaic and storage systems in the medium term up to 2030. However, in the long run, this effect gradually diminishes and self-consumption becomes profitable for most households despite the unfavorable regulation. This effect is, amongst others, driven by decreasing cost of photovoltaics and battery storage as well as increasing retail electricity prices. In terms of battery operation, a forecast-based dynamic strategy proves to align photovoltaic generation and battery charging significantly better than a default strategy following the sole objective of maximizing self-consumption. Importantly, if reasonably accurate forecasts on photovoltaic generation and electricity demand are available, the self-sufficiency of households would only slightly suffer from this dynamic strategy. However, driven by relatively high feed-in remuneration, households are likely to invest in large photovoltaic systems, such that substantial amounts of photovoltaic generation are fed into the grid regardless of the operational strategy of the battery.

Despite the strong impacts of residential battery storage on an individual household level, the simulations reveal only moderate system impacts. There are three major reasons for this result, all of which are related to the innovative modeling approach applied. Firstly, the use of a diffusion model leads to a gradual battery expansion over time. Thus, even by 2050, only a fraction of the households invests in photovoltaic and storage systems. Secondly, the diffusion process of the residential batteries also affects the electricity market simulation. Since the utilities plan their investments in multiple decision periods, lock-in effects may occur: if a certain amount of power plants is built at a time with little residential storage, it will remain in the system even if the residential storage capacity increases later on. Thirdly, other flexibility options like utility-scale storage and electricity exchange with the German neighboring countries have a tremendous balancing effect. Nevertheless, the positive impact of a dynamic operational strategy for the residential battery storages is also visible on the system level. The more system-friendly operation strongly reduces the curtailment of renewables and therefore contributes to a better system integration of residential photovoltaics.

These findings have important policy implications. Even if restrictive regulatory frameworks for self-consumption are set up, the diffusion of residential battery storage seems difficult to steer in the long term. However, on a system level, the way the residential batteries are operated appears to be more crucial than the amount of storage installed. Fortunately, relatively simple regulatory adjustments, such as a reduction of the maximum feed-in limit for residential photovoltaics, are suitable to incentivize a more system-friendly operation of the residential storages.

Chapter 5

Critical Reflection

Despite substantial modeling effort, the analyses of this dissertation have certain limitations, which are addressed in the following. Moreover, an outlook regarding promising future research directions is given for each of the discussed aspects.

Risk aversion of investors Given the capital intensity of investments in large-scale generation or storage capacity as well as regulatory uncertainty, investors in the field of energy usually behave risk-averse rather than risk-neutral. Consequently, it can be reasonably assumed that they would build less capacity than a theoretical risk-neutral investor. Due to the complex setting with multiple market areas and decision periods considered in this thesis, this aspect is not accounted for. The developed expansion planning algorithm relies on a single model-endogenous price forecast and assumes perfect foresight regarding, e.g., expansion of renewables, evolution of the electricity demand, and development of fuel and carbon prices. In future work, the existing algorithm should therefore be extended to consider these uncertainties. This could be achieved by carrying out multiple price forecasts with varying assumptions on future developments and then applying risk metrics to decide on the investments.

Additional market segments The dissertation puts an explicit focus on capacity remuneration mechanisms and the day-ahead market. While these are two of the most relevant market segments when carrying out long-term electricity market analyses, other important elements exist that are not considered. Firstly, renewable auctions could be integrated in the agent-based simulation framework rather than using exogenous assumptions on the expansion of renewables. Secondly, due to the increasing share of fluctuating renewables, short-term markets, i.e., intraday and control reserve markets, have become more important in the past years. These market segments should therefore also be considered in future work. Thirdly, the European Union Emissions Trading System is not modeled in detail, but an exogenous price path for carbon emission certificates is set. While it seems difficult to model a cross-sectoral emission trading mechanism, even a simplified model-endogenous representation may already provide additional insights.

Future role of flexible electricity demand The shape of the electricity demand is likely to undergo substantial changes in the future, e.g., driven by efficiency improvements as well as the electrification of heat and transport. This aspect is only partly considered in the thesis by modeling the diffusion of residential battery storage as an exemplary novel technology. Other technological changes on the demand side are however not considered. Thus, it is generally recommended to foster the joint application of models with a focus on the supply side and on the demand side (for an example of such a methodology, see Hladik et al., 2018, 2020). Importantly, the role of demand flexibility is likely to increase in the future, which needs to be adequately accounted for – both, in the short-term day-ahead market simulation and in the long-term expansion planning. A first approach to consider demand side management model-endogenously in PowerACE has been developed by Zimmermann et al. (2016). This methodology should be extended to also allow for the participation of flexible demand resources in capacity remuneration mechanisms.

Extended geographical scope The current model version of PowerACE covers a total of ten European market areas. The represented countries offer a variety of different market design options such that analyses on market design under consideration of cross-border effects can be carried out (cf. Section 3.2.2). Nevertheless, additional countries should be modeled in future work, e.g., to account for the flexible hydro power capacities in Scandinavia, which may contribute significantly to the integration of fluctuating renewables located in the rest of Europe.

Flow-based market coupling As outlined in Section 2.2.1, flow-based market coupling was introduced in Central Western Europe in 2015 and replaced the previously used approach based on net transfer capacities. PowerACE does not yet account for this development, but still uses net transfer capacities for the coupling of all considered market areas. In the years ahead, additional European countries will be implementing flow-based market coupling. Since this comes along with less conservative restrictions in the market coupling procedure, respective modeling approaches for both, the short-term and long-term perspective, should be developed in future work. Amongst others, this will require a reasonably accurate representation of the European transmission grid.

Chapter 6

Conclusion and Policy Implications

The research carried out in this thesis aims to shed light on the role of the European electricity market design in the transition to a target electricity system that combines sustainability, affordability, and reliability. For this purpose, the dissertation first provides the relevant background on the flexibility requirements in future electricity systems as well as the design of the European electricity market. In this context, three important market impacts arising from increasing levels of fluctuating renewables are identified: (1) the *low capacity credit* of these technologies, which leads to substantial requirements for additional dispatchable capacity, (2) the *reduced full-load hours* of conventional power plants, which threatens their profitability, (3) the challenge of renewable *overproduction*, which calls for complementary flexibility options like storage or higher levels of interconnector capacity. Subsequently, the principles of the European electricity market design with regard to investment support, wholesale market operation, ancillary services, and retail pricing are outlined and the pivotal role of market design in the transition to a renewable electricity system is illustrated.

When investigating electricity market design, it is important to model transformation pathways of the system rather than to derive optimal future systems. This is mostly due to the capital intensity of investments in large-scale generation or storage capacity and resulting long investments horizons. Thus, path dependencies and lock-in effects need to be adequately accounted for. Given their *explorative* character, simulation models are a particularly suitable method in the research field of electricity market design. For this reason, the thesis extends an established large-scale agent-based electricity market model in order to adequately account for the developments towards an integrated European electricity market and the characteristics of storage technologies. These extensions substantially increase the model complexity due to the more pronounced coupling of the spatial and temporal model dimensions. On the methodological side, approaches from the fields of operations research, non-cooperative game theory, and artificial intelligence are integrated in the agent-based simulation framework. To the best knowledge of the author, the developed electricity market model is the first agent-based simulation approach available in the literature to simultaneously consider dynamic aspects and interdependencies in terms of (1) time (multiple investment decision periods), (2) space (multiple interconnected countries), (3) technologies (different conventional power plants and types of storage), and (4) market designs (energy-only market and different types of capacity remuneration mechanisms).

The extended model is applied in three case studies to analyze the diffusion of different flexibility options under varying regulatory settings. These case studies cover some central aspects of the European electricity market, most importantly capacity remuneration mechanisms, the interaction of day-ahead market and congestion management, and the role of regulation for residential self-consumption. In the following, the main findings and policy implications are summarized.

Role of electricity storage in capacity remuneration mechanisms In electricity markets around the world, the substantial increase of intermittent renewable electricity generation has intensified concerns about generation adequacy, ultimately driving the implementation of capacity remuneration mechanisms. Although formally technology-neutral, substantial barriers often exist in these mechanisms for non-conventional capacity such as electricity storage. Against this background, both a rigorous theoretical analysis and a simulation study regarding relevant design parameters of capacity remuneration mechanisms are carried out. Results show that the design of such mechanisms inevitably creates a bias towards one technology or the other. Most importantly, linking the capacity auctions with call options proves to increase the competitiveness of storages against conventional power plants. Although this is generally desirable as it may support the system integration of renewables, it remains challenging to determine the amount of *firm* capacity that electricity storages can provide. While it seems impossible to establish completely technology-neutral capacity remuneration mechanisms, policymakers should generally reconsider the design of these mechanisms and allow for an adequate participation of non-conventional resources under consideration of their respective capacity value.

Long-term efficiency of market splitting in Germany In Europe, the ongoing renewable expansion and delays in the planned grid extension have intensified the discussion about an adequate electricity market design. Against this background, this thesis jointly applies an agent-based electricity market model and an optimal power flow model to investigate the long-term impacts of splitting the German market area into two price zones. While the current German government is strongly in favor of staying with a single German price zone, existing literature suggests that a potential market splitting might have positive short-term impacts. This is because the zonal split may reduce the required congestion management by accounting for transmission grid restrictions already at the market clearing stage. The analyses carried out in this dissertation reveal strong impacts of a German market splitting on electricity prices, expansion planning of generators, and required congestion management. While the congestion volumes indeed decrease significantly under a market split in the short term, the optimal zonal configuration for 2020 is found to become outdated over time due to dynamic effects like grid extension, renewable expansion as well as power plant investments and decommissioning. Policymakers and regulators should therefore regularly re-assess bidding zone configurations. Yet, this stands in contrast to the major objective of price zones to create stable locational investment incentives.

Diffusion and system impact of residential battery storage The current German retail pricing schemes charge taxes and levies on a volumetric basis, which provides strong incentives to engage in self-consumption. Given the rapidly declining costs of rooftop photovoltaics and battery storage, many German households install such systems to increase their self-sufficiency rates. Designing an adequate regulatory framework may help to govern the diffusion, operation, and system impact of the residential batteries. Against this background, a prosumer simulation and an agent-based electricity market simulation are jointly applied to investigate the long-term impacts of a residential battery storage diffusion on the electricity market. The analysis of different regulatory frameworks shows significant effects on the household level, yet only moderate system impacts. In the long run, the diffusion of residential battery storage seems difficult to govern, even under a restrictive regulation. In contrast, the way the batteries are operated may be easier to regulate. Policymakers and regulators should focus on this aspect, since a system-friendly battery operation supports the system integration of residential photovoltaics while having little impact on the households' self-sufficiency.

Overall, the dissertation shows the important role of European electricity market design in the transition to a renewable electricity system. Since policymakers and regulators do not trust the pure energy-only market to satisfy all aspects of the *energy trilemma* (sustainability, affordability, reliability), changes and amendments to market design are frequent and will continue to be so in the years ahead. Moreover, given the increasing level of market integration in Europe, the role of cross-border effects of national market designs will gain further in importance. In this context, agent-based simulation models are a valuable tool to better understand potential long-term effects of market designs in the interconnected European electricity system and can therefore support the European energy transition.

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Part II

Research Papers

Paper A

Agent-Based Generation and Storage Expansion Planning in Interconnected Electricity Markets

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Abstract

This paper introduces a novel algorithm to solve the generation expansion planning problem in interconnected electricity markets. Starting from an individual investor's perspective, a stable Nash-equilibrium is determined by iteratively adjusting the investment decisions of all players. Both, generation technologies and storage units using arbitrage trading can be considered as investment options. The new method also allows for consideration of capacity remuneration mechanisms and technological learning. In an illustrative case study, the developed algorithm is embedded into the agent-based simulation model PowerACE and applied to a multi-country long-term scenario analysis. Results show high investment incentives in countries using a capacity remuneration mechanism as well as related cross-border effects in other countries that rely on an energy-only market design. These findings confirm the suitability of the methodology for long-term analyses of interconnected electricity markets.

A.1 Introduction

In light of the European Commission's goal of creating a Single European Market for electricity, the appropriate consideration of cross-border effects in long-term electricity market models covering multiple market areas gains in importance. This affects in particular the generation expansion planning problem (GEP), in which the future technology mix needs to be determined subject to the future electricity demand, renewable feed-in and cross-border transmission capacities.

In this paper, a novel GEP algorithm is presented, which is based on an individual investor's perspective. All investors have a list of technology options available and maximize their individual profit by choosing type and quantity of investments to carry out under given assumptions on the actions of all other investors. Finding a stable outcome for this game is achieved by determining a Nash-equilibrium[12] in an iterative procedure.

[12] In a Nash-equilibrium, each player maximizes its profit under given assumptions on the actions of all other players. Further, in the equilibrium state, each player acts exactly as expected by the respective other players. Therefore, none of the players has the possibility to further increase its profit by unilaterally deviating from the equilibrium. For details refer to, e.g., Varian (2014).

The remainder of this paper is structured as follows. In Section A.2, a brief overview of existing literature on GEP is provided to outline the novelty of this contribution. Section A.3 presents the general idea of the developed algorithm as well as methodological details. In Section A.4, the algorithm is embedded into an existing agent-based simulation model and an illustrative case study is then carried out, in which multiple interconnected electricity market areas act as the different players. Section A.5 concludes and gives an outlook.

A.2 Literature Review

An in-depth survey on traditional modeling techniques developed for the GEP problem under monopoly as well as in competitive electricity markets is, e.g., provided by Kagiannas et al. (2004). In the following, some literature particularly relevant for this contribution is briefly reviewed.

Chuang et al. (2001) develop a GEP game based on the Cournot model. They present an iterative solution algorithm as well as numerical results for a test system. Filomena et al. (2014) also adopt a Cournot model, in which uncertainty is exemplary considered in terms of the marginal cost. They further provide a formal discussion of open-loop and closed-loop models. Haikel (2011) applies a Cournot model formulated as a stochastic dynamic program to compare three different capacity remuneration mechanisms (CRMs).

Pereira and Saraiva (2011) formulate and solve the GEP problem using an iterative procedure. A system dynamics approach is applied to simulate the long-term behavior of the electricity market. Based on these results, the generation agents pursue individual profit maximization using genetic algorithms.

Contray to the above-mentioned publications, Heuberger et al. (2017) tackle the GEP problem from a system planner perspective and consider endogenous technology cost reductions in their model. Moreover, case studies on the power system of the United Kingdom are carried out.

Ringler (2017) uses an agent-based simulation framework, in which an iterative procedure to determine an equilibrium state is embedded. Although this approach is close to the one presented in this contribution, his GEP algorithm only considers cross-border effects in a simplified fashion.

To the best knowledge of the authors, the methodology developed in this paper is the first in the literature to allow for adequate consideration of cross-border effects in multi-country long-term agent-based simulation models. Moreover, additional to conventional generation technologies, electricity storage technologies can be considered as investment options by evaluating their maximum arbitrage profit. Due to the simulative approach, the new method also allows for a straightforward integration of CRMs and technological learning.

A.3 Methodology

A.3.1 Overview of the Expansion Planning Algorithm

The overall investment planning procedure is depicted in Fig. A.1. The decisions of the different investors are primarily based on their expectations regarding future electricity prices. As these, vice versa, are influenced by the investment decisions of all investors in all interconnected market areas, a complex game with multiple possible strategies opens up. To find a stable outcome for this game, a Nash-equilibrium needs to be determined.

Therefore, the developed algorithm terminates when all planned investments are profitable and at the same time none of the investors is able to improve his expected payoff by carrying out further or less investments, i.e., there is no incentive for any investor to unilaterally deviate from the equilibrium outcome. In the following as well as in the case study carried out in Section A.4, for the sake of simplicity, the different market areas are defined as the players interacting with each other[13] and the planned investments are then distributed among the investors within each market area[14]. Following this approach, it is possible to consider the mutual impact of investments in one market area on the electricity prices and consequently investments in the interconnected market areas.

In a first step, the future electricity prices $\hat{p}_{m,y,h}$ are estimated for all market areas m, several future years y and hours h (see Section A.3.2). Using this electric-

[13] If the investors within each market area are differently parameterized, it would also be possible to extend the proposed algorithm and have the single investors instead of the market areas play against each other.

[14] Distributing the planned investments within a given market area is achieved by first randomizing and then iterating over the different investors after each investment being carried out.

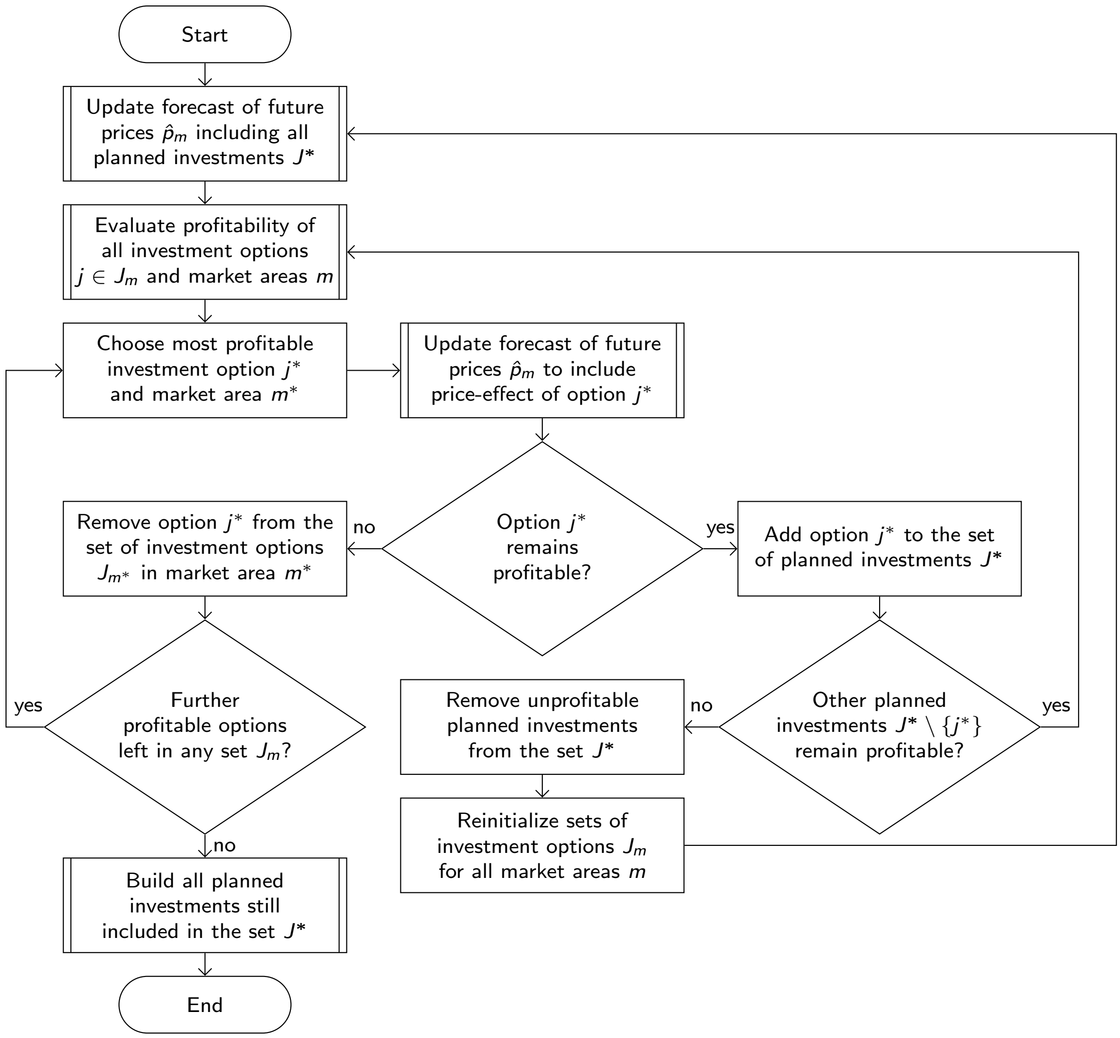


Figure A.1: Overview of the Expansion Planning Algorithm.

ity price forecast, the profitability $\pi_{m,j}$ of all investment options $j \in \boldsymbol{J_m}$ – with $\boldsymbol{J_m}$ denoting the set of available investment options in the respective market area m – is determined for all market areas under a price-taker assumption[15] (see Section A.3.3).

Across all market areas, the most profitable investment option j^* in the corresponding market area m^* is then chosen and the price forecast is updated in order to include the respective price-effect if option j^* were actually built. Adequately estimating this price effect across all market areas is essential to guarantee convergence of the GEP algorithm. More formally, the price forecast needs to be constructed in such a way that Eq. (A.1) holds (where $\boldsymbol{J^*}$ is the set of planned investments and n and k denote two different iterations), i.e., an additional investment always needs to have a negative or at least neutral impact on the profitability $\pi_{m,j}$ of all other planned or potential investments.

$$\boldsymbol{J_n^*} \subseteq \boldsymbol{J_k^*} \Rightarrow \pi_{m,j,n} \geq \pi_{m,j,k} \quad \forall n,k,m,j \tag{A.1}$$

After updating the price forecast, two cases can be distinguished:

Case (1): If j^* remains profitable under the new price forecast, the option is added to the set $\boldsymbol{J^*}$. Contrary, other planned investments in the set $\boldsymbol{J^*}\backslash\{j^*\}$, which are becoming unprofitable under the new price forecast, are gradually removed from $\boldsymbol{J^*}$. Further, the sets of available investment options $\boldsymbol{J_m}$ are reinitialized for all market areas m, since formerly removed options might have become profitable again by removing planned investments. Ultimately, the next iteration of the algorithm begins by updating the price forecast to consider the impact of removing formerly planned investments.

Case (2): If j^* becomes unprofitable under the new price forecast, the option is removed from the set of available investment options $\boldsymbol{J_{m^*}}$ in market area m^*. Further, once again two cases can be distinguished:

Case (2a): There are still other profitable investment options left in any of the sets $\boldsymbol{J_m}$. The algorithm then continues by evaluating the most profitable remaining investment option.

[15] The impact of an investment decision on future electricity prices is considered at a later stage in the expansion planning algorithm.

Case (2b): No further profitable investment options are left in any of the sets $\boldsymbol{J_m}$. This implies that no investor in any of the market areas could increase his profit – neither by carrying out additional investments, nor by reducing his planned investments, which would lead to another investor carrying out this respective investment. Therefore, there exists no incentive for any investor to unilaterally deviate from the achieved outcome and a Nash-equilibrium has been found. Consequently, all planned investments currently included in the set $\boldsymbol{J^*}$ are being built and the algorithm terminates.

A.3.2 Forecast of Future Electricity Prices

In general, all techniques used to forecast electricity prices (e.g., time series analysis, machine learning, optimization) could be implemented into the proposed methodology. However, techniques relying on patterns detected from past simulation data seem rather unsuitable to adequately estimate the potential price-effect of new investments. For the case study presented in Section A.4, the price forecast is therefore carried out by solving a time-coupled linear optimization problem over all market areas, which minimizes total generation costs as shown in Eq. (A.2), where c_p^{var} denotes the variable generation costs of the conventional power plant $p \in \boldsymbol{P^{\text{con}}}$ and the product $c^{\text{voll}} \cdot l_m^{\text{dump}}$ describes the costs of curtailed load in market area m. The cost minimization is carried out subject to

- the energy balance of every market area m, Eq. (A.2b), with l_m^{gross} denoting the respective gross electricity demand,
- lower and upper bounds for the electricity generation g_p of all power plants $p \in \boldsymbol{P}$, Eq. (A.2c),
- lower and upper bounds for the charging l_p^{charge} of the storage units $p \in \boldsymbol{P^{\text{stor}}} \subseteq \boldsymbol{P}$, Eq. (A.2d),
- constrained storage levels s, Eq. (A.2e),
- initial and final storage levels $s_{h_0}, s_{h_{\max}}$, Eq. (A.2f),
- the energy balance of the storage units with charge efficiency η_p^{charge} and discharge efficiency $\eta_p^{\text{discharge}}$, Eq. (A.2g),
- limited interconnector capacities f_{m_1,m_2} between the different market areas, Eq. (A.2h).

The optimization problem is solved for multiple years depending on the desired forecast period. Yet, for better readability, the corresponding index y is omitted in Eqs. (A.2)–(A.2h).

$$\text{minimize} \quad \sum_{m} \sum_{h} \left(\sum_{p \in \boldsymbol{P_m^{\mathbf{con}}}} c_{p,h}^{\text{var}} \cdot g_{p,h} + c^{\text{voll}} \cdot l_{m,h}^{\text{dump}} \right) \tag{A.2a}$$

subject to

$$l_{m,h}^{\text{gross}} + \sum_{p \in \boldsymbol{P_m^{\mathbf{stor}}}} l_{p,h}^{\text{charge}} - l_{m,h}^{\text{dump}} = \sum_{p \in \boldsymbol{P_m}} g_{p,h} + \sum_{m'} \left(f_{m',m,h} - f_{m,m',h} \right) \quad \forall m, h \tag{A.2b}$$

$$0 \leq g_{p,h} \leq g_p^{\max} \qquad \forall p \in \boldsymbol{P}, h \tag{A.2c}$$

$$0 \leq l_{p,h}^{\text{charge}} \leq l_p^{\text{charge,max}} \qquad \forall p \in \boldsymbol{P^{\mathbf{stor}}}, h \tag{A.2d}$$

$$0 \leq s_{p,h} \leq s_p^{\max} \qquad \forall p \in \boldsymbol{P^{\mathbf{stor}}}, h \tag{A.2e}$$

$$s_{p,h_0} = s_{p,h_{\max}} = 0.25 \cdot s_p^{\max} \qquad \forall p \in \boldsymbol{P^{\mathbf{stor}}} \tag{A.2f}$$

$$s_{p,h} = s_{p,h-1} + \eta_p^{\text{charge}} \cdot l_{p,h}^{\text{charge}} - 1/\eta_p^{\text{discharge}} \cdot g_{p,h} \qquad \forall p \in \boldsymbol{P^{\mathbf{stor}}}, h \neq h_0 \tag{A.2g}$$

$$0 \leq f_{m_1,m_2,h} \leq f_{m_1,m_2,h}^{\max} \qquad \forall m_1, m_2, h \tag{A.2h}$$

For the price forecast, information on future electricity demand, renewable feed-in and expected decommissioning of power plants is required. All of this data is considered assuming perfect foresight. The hourly price forecasts $\hat{p}_{m,y,h}$ then correspond to the dual variable of the energy balance of the respective market area m, Eq. (A.2b).

A.3.3 Profitability Analysis of the Investment Options

Using the electricity price forecast, the profitability $\pi_{m,j}$ of all investment options $j \in \boldsymbol{J_m}$ is determined for all market areas m by first calculating the annual contribution margins $CM_{m,j,y}$. These can be computed according to Eq. (A.3), where Δt denotes the time step length of 1 h. For conventional power plants $j \in \boldsymbol{J}^{\mathbf{con}}$, the contribution margin is calculated in a simplified fashion as the sum of call options on the respective hourly contribution margins. Please note that start-up costs are neglected when using this approach.

$$CM_{m,j,y} = \begin{cases} \Delta t \sum_h \max\left(0, \hat{p}_{m,y,h} - c^{\text{var}}_{j,y,h}\right) & \text{if } j \in \boldsymbol{J}^{\mathbf{con}} \\ \dfrac{\Delta t}{g^{\max}_j} \sum_h \left(g^*_{j,y,h} - l^{\text{charge},*}_{j,y,h}\right) \hat{p}_{m,y,h} & \text{if } j \in \boldsymbol{J}^{\mathbf{stor}} \end{cases} \tag{A.3}$$

In order to determine the optimal hourly charging ($l^{\text{charge},*}$) and discharging ($g^*_{j,y,h}$) strategies of the storage technologies $j \in \boldsymbol{J}^{\mathbf{stor}}$, similarly as for the future price forecast, a time-coupled linear optimization problem is solved, in which the arbitrage profit is maximized, Eq. (A.4), subject to the standard storage constraints – analogous to Eqs. (A.2c)–(A.2g).

$$\text{maximize} \quad \sum_h \left(g_{j,y,h} - l^{\text{charge}}_{j,y,h}\right) \hat{p}_{m,y,h} \tag{A.4}$$

Next, specific net present values $NPV_{m,j}$ in EUR/kW$_{\text{el}}$ are derived as shown in Eq. (A.5), where c^{invest}_j denotes the investment expenses, δ_j the construction time in years, c^{fix}_j the fixed expenditures for operation and maintenance per year, i the discount rate and n_j the investment horizon in years.

$$NPV_{m,j} = -\sum_{y=0}^{\delta_j - 1} \frac{c^{\text{invest}}_j / \delta_j}{(1+i)^y} + \sum_{y=\delta_j}^{n_j+\delta_j} \frac{CM_{m,j,y} - c^{\text{fix}}_j}{(1+i)^y} \tag{A.5}$$

Finally, the net present values are converted to annuities $A_{m,j}$ as shown in Eq. (A.6) in order to account for the technology specific investment horizons (Konstantin and Konstantin, 2018). The annuities ultimately serve as indicator to compare the profitability $\pi_{m,j}$ of the different investment options. Alternatively, any other technique known from capital budgeting, e.g., the internal rate of return or the profit investment ratio, could also be implemented.

$$\pi_{m,j} := A_{m,j} = NPV_{m,j} \cdot \frac{(1+i)^{n_j} \cdot i}{(1+i)^{n_j} - 1} \tag{A.6}$$

A.3.4 Integration of Centralized Capacity Auctions

Several European countries have either already implemented some kind of CRM or are currently in the process of evaluating appropriate solutions (Bublitz et al., 2019). Since these mechanisms may bring along substantial cross-border effects, it is essential to consider their impact in the GEP.

For this reason, the centralized capacity auction algorithm developed in Keles et al. (2016) can optionally be combined with the methodology of this contribution. This is realized by first computing an initial future price forecast (see Section A.3.2), and then carrying out annual descending clock auctions in the respective market areas, in order to contract a specific amount of secured generation and storage capacity. Subsequently, the investment planning procedure shown in Fig. A.1 is run while considering the investment decisions resulting from the centralized capacity auctions.

A.4 Case Study

A.4.1 Modeling Framework

For the illustrative case study presented in the following, the new GEP algorithm has been embedded into PowerACE, an established agent-based simulation model developed for the analysis of European electricity markets in long-term scenario analyses. Previous applications of this model in different configurations include Keles et al. (2016), Genoese (2010), and Ringler et al. (2017).

PowerACE has a focus on the day-ahead market and different types of CRMs and runs at hourly resolution (8760 h/a) over a typical time horizon from 2015 up to 2050. Within the model, various agents represent the associated market participants, such as utility companies, regulators and consumers. The electricity suppliers can decide on the daily scheduling of their conventional power plants and storage units as well as once per year on the construction of new conventional generation or storage capacities – for which the newly developed algorithm is used. Thus, the short-term and long-term decision levels are jointly considered and their interactions can be investigated. Ultimately, the development of the markets emerges from the behavior of all agents.

A.4.2 Input Data and Key Assumptions

The regional scope of PowerACE currently covers ten countries (Central Western Europe, Poland, Czech Republic, Denmark and Italy), all of which are modeled under consideration of their current real-world market design[16] (see Fig. A.2). Power plant data for the model has been obtained from S&P Global Platts (2015). The characteristics of the investment options are based on Schröder et al. (2013) and Louwen et al. (2018). Fossil fuel prices are based on de Vita et al. (2016), while the CO_2 price development path is taken from the same source, yet scaled to reach 150 EUR/t_{CO_2} in 2050. Historical electricity demand profiles of 2015 obtained from ENTSO-E (2017) are used and scaled to the yearly demand according to de Vita et al. (2016). Electricity generation from renewables is based on historical profiles of 2015 (ENTSO-E, 2017), which are scaled such that an overall renewable share in relation to electricity demand of 80 % in 2050 is reached. The electrical grid is only considered in a simplified fashion by assuming maximum cross-border transmission capacities from ENTSO-E (2016), while intra-zonal restrictions are not accounted for.

A.4.3 Exemplary Results

In Fig. A.3, the development of the conventional power plant and utility-scale storage capacities is depicted for two exemplary countries. These results emerge from exogenously given decommissioning of power plants and endogenous investment

[16]For details on the different market designs see Bublitz et al. (2019). Due to the similarities of the different types of CRMs on an abstract level, the French mechanism is modelled using the central buyer implementation, although in reality, a de-central obligation mechanism is used in France.

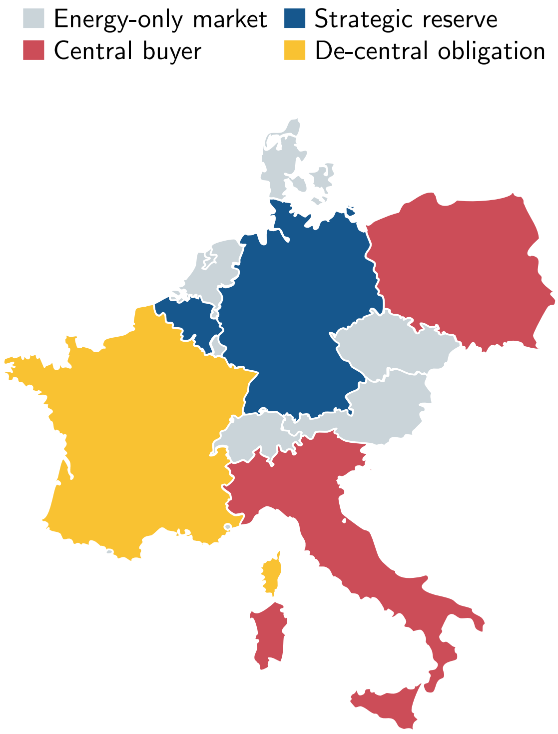
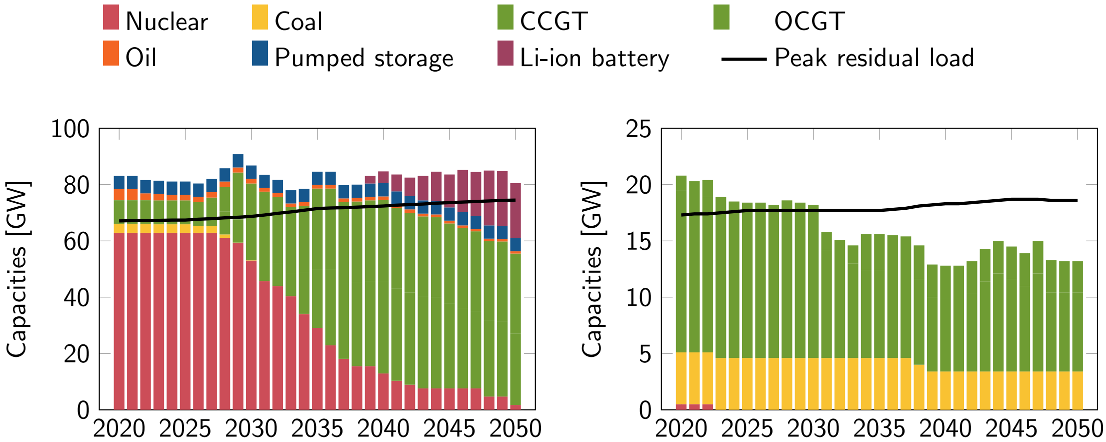


Figure A.2: Overview of the real-world electricity market designs implemented in the different countries covered by PowerACE.



(a) France, with an active capacity remuneration mechanism

(b) The Netherlands, which rely on an energy-only market

Figure A.3: Simulated development of the conventional power plant and utility-scale storage capacities for two exemplary market areas.

decisions of the different agents in PowerACE. As a reference, the peak residual load[17] is also shown.

Due to their CRM, substantial investments in new conventional generation and storage capacity are carried out in France (Fig. A.3a). This leads to the available capacity always exceeding the French peak residual load. Contrary, in the Netherlands (Fig. A.3b), which rely on an energy-only market, investment incentives are much lower. This finding is related to cross-border effects of the French CRM. With the high amount of newly installed capacity in France, the expected electricity prices in the Netherlands decline, resulting in relatively few investments being carried out there. As a consequence, the Dutch peak residual load cannot always be covered by the available capacity, making the Netherlands dependent on electricity imports.

These results illustrate the essential need to adequately model and consider cross-border effects in multi-country long-term electricity market models, for which the developed algorithm of this contribution is well suited.

[17]The peak residual load is defined as the highest hourly electricity demand of the respective market area, which is not covered by renewable generation.

A.5 Conclusion and Outlook

In this paper, a novel algorithm to solve the generation expansion planning problem in interconnected electricity markets was presented. The developed methodology allows for adequate consideration of cross-border effects in multi-country long-term agent-based simulation models, which could be confirmed by an illustrative case study covering a region of ten interconnected market areas.

Results of the case study showed high investment incentives in countries using a capacity remuneration mechanism (such as France) as well as related cross-border effects, which reduce investment incentives in other countries that rely on an energy-only market design (like the Netherlands).

In future work, the new method will be applied to analyze in-depth the long-term impact of unilateral and coordinated capacity remuneration mechanisms as well as other market designs in Europe. From a methodological point of view, the algorithm could be extended to also allow for model-endogenous decommissioning of power plants as well as retrofit measures as an alternative to investments in new generation and storage capacity.

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Paper B

The Merge of Two Worlds: Integrating Artificial Neural Networks into Agent-Based Electricity Market Simulation

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Abstract

Machine learning and agent-based modeling are two popular tools in energy research. In this article, we propose an innovative methodology that combines these methods. For this purpose, we develop an electricity price forecasting technique using artificial neural networks and integrate the novel approach into the established agent-based electricity market simulation model PowerACE. In a case study covering ten interconnected European countries and a time horizon from 2020 until 2050 at hourly resolution, we benchmark the new forecasting approach against a simpler linear regression model as well as a naive forecast. Contrary to most of the related literature, we also evaluate the statistical significance of the superiority of one approach over another by conducting Diebold-Mariano hypothesis tests. Our major results can be summarized as follows. Firstly, in contrast to real-world electricity price forecasts, we find the naive approach to perform very poorly when deployed model-endogenously. Secondly, although the linear regression performs reasonably well, it is outperformed by the neural network approach. Thirdly, the use of an additional classifier for outlier handling substantially improves the forecasting accuracy, particularly for the linear regression approach. Finally, the choice of the model-endogenous forecasting method has a clear impact on simulated electricity prices. This latter finding is particularly crucial since these prices are a major result of electricity market models.

B.1 Introduction

Since the liberalisation of electricity markets, wholesale spot markets have steadily gained importance in determining the economics of generation, storage and demand units in the energy system. Even though a major share of final electricity generation – and likewise consumption – is still traded on the forward market or via bilateral contracts, the spot market price is the eventual realization that determines the opportunity and the future expectations on electricity prices. Typically, on a day-ahead basis, demand and supply bids are matched in auctions on electricity exchanges in many parts of the world to determine electricity prices. In understanding the complex techno-economic interdependencies in the price formation on electricity markets, many efforts have been made to model market logic and actors' behavior in both the long-term investment and the short-term operational perspective.

Besides approaches deploying mathematical optimization (e.g., Leuthold et al., 2008), system dynamics (e.g., Petitet, 2016) and equilibrium models (e.g., Just and Weber, 2008), simulation models depicting the individuals' behavior constitute one major research stream. After evolving in the early 2000s, so-called agent-based simulation models (ABM) are today widely applied to address research questions dealing with electricity price developments, energy policy measures, generation adequacy, generation expansion planning, market design and market performance. In ABMs, system effects emerge from depicting and simulating the individual agents' behavior. The most popular ABMs developed for the analysis of European electricity markets include AMIRIS (Reeg et al., 2012), EMLab (Chappin et al., 2017), and PowerACE (Genoese, 2010). For a broad overview on further applications of ABMs in the energy context, please refer to the several review papers available in the literature (Guerci et al., 2010; Hansen et al., 2019; Ringler et al., 2016; Weidlich and Veit, 2008; Zhou et al., 2007).

In ABMs, each agent derives its decisions model-endogenously. Thus, a key challenge in accurately modeling agents' behavior lies in providing adequate expectations for the future developments within the model. Hereby, agents typically base their decisions on fundamental factors, such as techno-economic investment parameters or variable costs of electricity generation, and on market price expectations. The need for the latter motivates the essential role of price forecasting in ABMs, as the price forecasts have crucial interdependencies with agents behavior and thus the plausibility of the simulation results.

However, hardly any methodology or evaluation of the quality of model-endogenous price forecasting has been presented in the literature in the past (see Section B.2). As this issue is crucial to model accuracy and has been treated only rudimentary, this contribution addresses the scope of developing adequate model-endogenous short-term price forecasts and to evaluate them using PowerACE, an established ABM developed at Karlsruhe Institute of Technology (KIT). PowerACE offers the opportunity to conduct case studies depicting the interconnected European electricity market with a time horizon until 2050. We investigate and report both, the forecasting accuracy and the emerging simulation results under different price forecasting approaches. In brief, the main highlights and contributions of this paper are:

- We describe the implementation and interdependencies of model-endogenous price forecasts in long-term ABMs for interconnected electricity markets.
- We assess the suitability and the performance of naive, linear regression and artificial neural network (ANN) based forecasting approaches.
- We evaluate the impact of improved price forecasts for the agents on the simulation results emerging on a European energy system level.

The remainder of the paper is structured as follows. Section B.2 provides a literature review on machine learning (ML) applications in the energy context in general and the integration of such methods in ABMs in particular. Section B.3 introduces the PowerACE model, outlines the challenges of model-endogenous price forecasting and explains the developed approaches as well as their implementation. In Section B.4, a case study of the interconnected European electricity market until 2050 is presented and the accuracy of the developed forecasting approaches is evaluated. Section B.5 comprises the main findings, draws conclusions and provides an outlook on future research fields in the further development of ABM.

B.2 Literature Review and Research Gap

Since literature matching the exact scope of this paper is scarce, the review provided in the following starts with a rather generic overview of ML approaches applied for (price) forecasting in the energy domain. Then, we present in more detail the few directly relevant publications and outline the research gap this paper aims to fill.

Forecasting is one of the most popular fields in energy economics. Herein, as in many other research fields, ML approaches gain more and more importance. Among the family of ML approaches, ANN can be considered the most popular and most widespread. As shown in a pioneering study by Adya and Collopy (1998), well-designed ANN approaches are capable to outperform traditional forecasting approaches from econometrics and were computationally manageable at the end of the last millennium. With increasing computational capacities in the past years, ML has conquered the forecasting domain with various algorithms fitted to even more various scopes.

In the energy context, major applications include load forecasting (pioneering studies by Lee et al., 1992; Liu et al., 1991; Park et al., 1991), renewable feed-in (see, e.g., Yadav and Chandel, 2014, for an extensive review on solar), redispatch forecasting (Staudt et al., 2018) or even more complex tasks such as photovoltaic potential assessment (Mainzer et al., 2017).

However, the most prominent field for ANN applications remains price forecasting and particularly the forecasting of electricity spot market prices (for conciseness, in the remainder referred to as *electricity prices*). Forecasting electricity prices with ANN has been pervasively studied (see, e.g., Catalão et al., 2007; Conejo et al., 2005; Pindoriya et al., 2008; Rodriguez and Anders, 2004, for early studies). The thorough review on electricity price forecasting by Weron (2014) provides the reader a well-elaborated chapter on different structures and applications of ANN. Since the publication of this review paper, literature on ANN applications in electricity price forecasting has further augmented. Ghoddusi et al. (2019) provide a review on ML in energy economics, with an updated review on ANN studies forecasting electricity prices. Among the most influencing studies are Bento et al. (2018), Dudek (2016), Keles et al. (2016b), Lago et al. (2018a,b), Peng et al. (2018), Singh et al. (2017) and Wang et al. (2017), which all apply ANN in methodological variations to forecast electricity prices in different market areas. In addition to the review by Ghoddusi et al. (2019), recent studies by Giovanelli et al. (2018), Oksuz and Ugurlu (2019) and Ugurlu et al. (2018) provide further investigations and case studies on how to accurately forecast electricity prices in national spot markets with the use of ANNs.

Apart from the electricity spot market, ANNs are as well deployed to other electricity-related prices, such as balancing reserve market prices (Kraft et al., 2019, 2020) and energy prices for commodities like carbon emission certificates (Fan et al., 2015; Sun et al., 2016) or crude oil (Ding, 2018; Huang and Wang, 2018; Jammazi and Aloui, 2012; Moshiri and Foroutan, 2006; Yu et al., 2017; Zhao et al., 2017).

Let us now move on to the more specific field of implementing forecasting and ML techniques into ABMs of electricity markets. In a recent review paper, Prasanna et al. (2019) differentiate between two use case categories in this context. Firstly, ML methods can be used to forecast external input data, which is subsequently being used in an ABM. Secondly, ML algorithms may be applied to implement the learning behavior of the agents.

An example of the first use case category is provided in Scheidt (2002), where an ANN is trained to forecast electricity prices. The forecasts created by the ANN are then used to derive trading strategies that are deployed in a subsequently applied ABM. However, unlike in our approach, the ANN is not retrained using simulation results but only used in a static way.

Most publications falling into the second use case category identified by Prasanna et al. (2019) apply relatively simple reinforcement learning approaches like Q-learning (e.g., Esmaeili Aliabadi et al., 2017) or Erev-Roth learning (e.g., Mengelkamp et al., 2018; Zhou et al., 2011). Still, some noteworthy exceptions using supervised learning exist, which are addressed next.

Wehinger et al. (2013) present an ABM covering four European countries (France, Germany, Italy, Switzerland) with model-endogenous adaptive price forecasting based on multiple linear regression. The agents use these price forecasts to determine optimal trading decisions. As the simulation moves on, the price forecasting model is continuously updated using the latest available simulation outcomes. Despite the proximity to our concept, there are four major distinctions. Firstly, the regression model mostly relies on autoregressive terms and only includes few exogenous variables (temperature, wind forecast and oil price). Secondly, a linear regression rather than an ANN is used. Thirdly, unlike in our approach, effects in the neighbouring countries are not explicitly considered in the price forecasts. Finally, only a relatively short time horizon of few years is covered, whereas the time horizon in our work covers 2020 through 2050.

Pinto et al. (2012, 2016) use an ABM of the Iberian electricity market and implement different adaptive price forecasting techniques, such as feedforward ANNs or support vector machines. Although their scope of work is closely related to ours, the paper at hand can be seen as an extension in terms of several aspects. Firstly, Pinto et al. only consider very short time periods of two months rather than a multi-decade setting as we do. Secondly, a very basic ANN configuration is applied and only the Iberian market is modelled whereas we consider a much more complex setup with ten interconnected market areas. Finally and most importantly, Pinto et al. do not provide statistical evidence of any forecast's superiority over the other benchmarks considered.

We can conclude that given the scarce literature on applying ML for model-endogenous price forecasting in ABMs of electricity markets, an important research gap with regard to improving such simulation models opens up. Against this background, the following Section B.3 introduces an innovative and unique methodology, that combines the two popular research streams of ML and ABM. Before we move on, let us outline that model-endogenous forecasting brings along a number of additional challenges in comparison to forecasting in the general sense. Firstly, the feedback on simulated electricity prices needs to be considered. Poor forecasting accuracy leads to poor agent bidding behavior, which then leads to implausible simulated prices in the consecutive simulation step. These erroneous prices influence the forecasting in the next simulation step, and so on. Secondly, both, the diversity and the change in the composition of the national energy systems and in interconnection capacities between market areas over time requires an approach, that is flexible and capable to adapt to new price formation mechanisms (Lago et al., 2018b). Thirdly, the computational limitation needs to be considered in the implementation into an ABM framework such as PowerACE. As the model training and forecasting is carried out numerous times within a simulation run until 2050, each single forecasting procedure must remain computationally lean. Therefore, a trade-off between ANN architecture and training on one side and the computational performance on the other side needs to be carried out.

B.3 Methodology

This section starts with an overview of PowerACE, the existing ABM framework applied in this paper. Next, we describe in detail the developed ANN forecasting approach and its integration into PowerACE. Finally, some additional forecasting approaches are introduced, which are used as benchmarks to evaluate the performance of the developed ANN-based methodology.

B.3.1 Simulation Framework

Overview

PowerACE is an established agent-based simulation model, which was originally developed for the analysis of the German electricity market in long-term scenario analyses (see Keles et al., 2016a; Ringler et al., 2017; Fraunholz et al., 2021b, for some exemplary applications). The model covers different electricity market segments with a focus on the day-ahead market and different types of capacity remuneration mechanisms and runs at an hourly resolution (8760 h/a) over a typical time horizon from 2015 up to 2050.

Within PowerACE, several agents represent the associated market participants such as utility companies, regulators and electricity consumers (see Fig. B.1). Most notably, the modelled electricity suppliers can decide on the daily dispatch of their conventional power plants and storage units as well as once per simulation year on the investment in new such facilities. Thus, the short-term and long-term decision levels are considered jointly and their interactions can be investigated. Ultimately, the development of the markets emerges from the simulated behavior of all agents.

In light of the European Commission's goal of creating a Single European Market for electricity, the importance of adequately considering cross-border effects in electricity market models increases. Thus, recent advancements of PowerACE focus on expanding the geographical scope to cover multiple countries, which obviously significantly increases the model complexity. In this context, Fraunholz et al. (2019) concentrated on the long-term investment perspective of the model and developed a novel algorithm to solve the generation expansion planning problem in interconnected electricity markets. Ringler et al. (2017) focused on the short-term perspective and embedded a linear optimization approach into PowerACE. This optimization is a simplified representation of EUPHEMIA (NEMO Committee, 2019), the algorithm used for the real-world day-ahead market clearing process across multiple interconnected market areas.

Yet, to-date, cross-border effects are only rudimentally considered in an essential part of the day-ahead market simulation, namely the model-endogenous short-term electricity price forecasting of the agents in PowerACE. To provide some more context, we next introduce the different steps of the day-ahead market

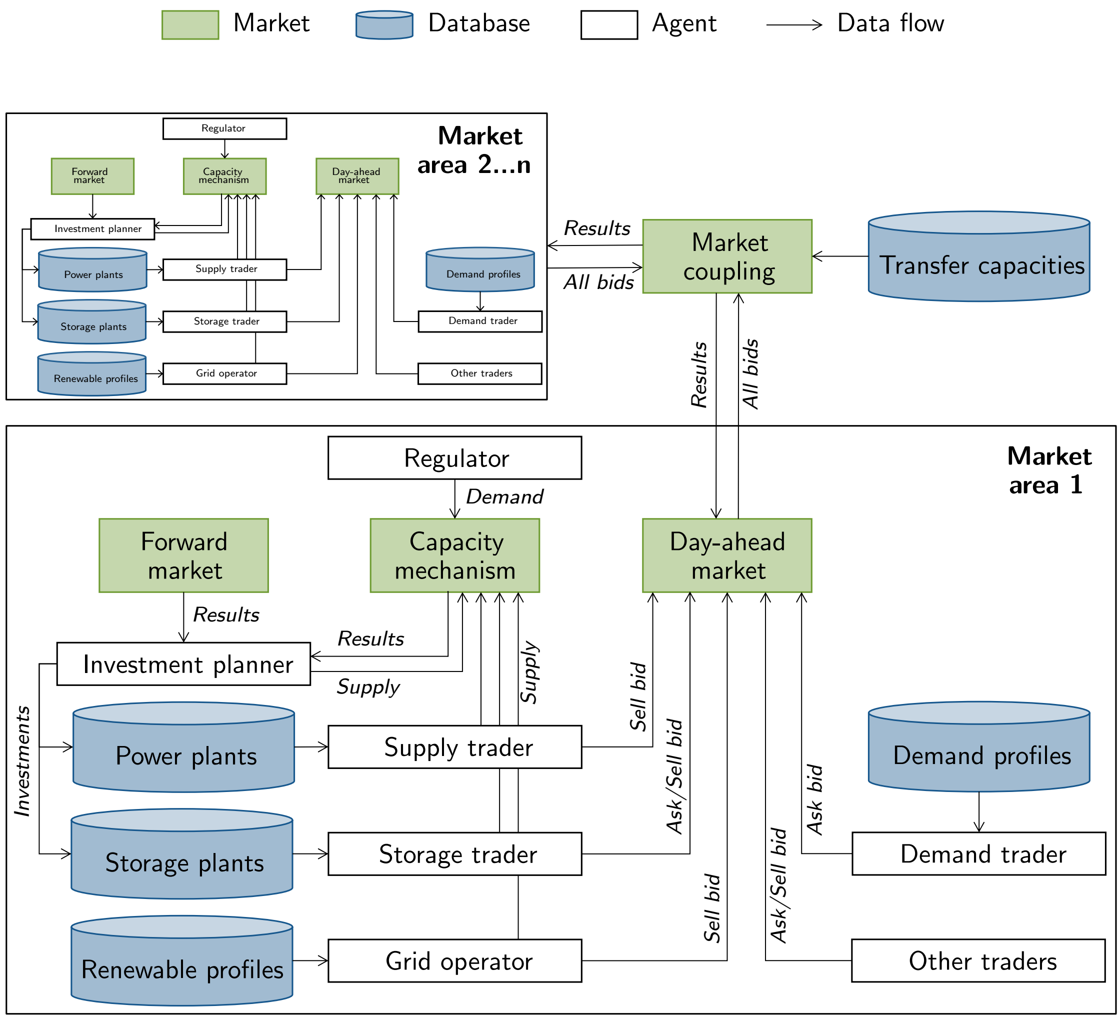

Figure B.1: Schematic overview of the agent-based electricity market model PowerACE. The focus lies on the short-term simulation of the day-ahead markets and long-term investment decisions in a multi-country setup.

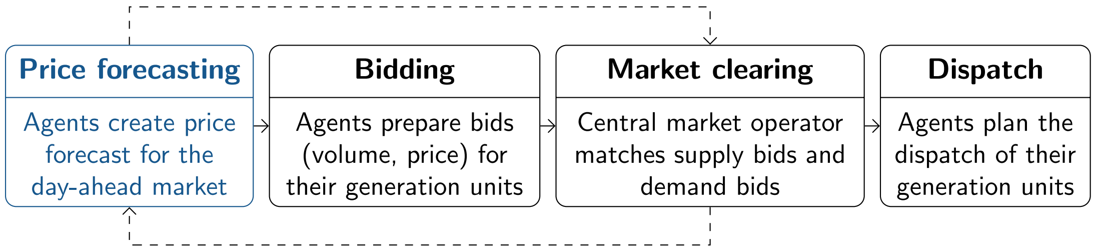

Figure B.2: Steps of the day-ahead market simulation with PowerACE. Accurate price forecasts are essential, as they have a direct impact on the bidding of the agents, and thus an indirect impact on the outcomes of the market clearing process. The market outcomes of previous auctions in turn affect the price forecasting of the agents.

simulation with PowerACE. As the long-term investment perspective of the model is not in the focus of this paper, it is not further addressed.

Day-Ahead Market Simulation

Multiple traders per market area participate in the day-ahead market simulation with PowerACE. Most importantly, *supply traders* representing the major utility companies in a given market area prepare individual bids for each of their conventional power plants. Additionally, price-inelastic bids for demand, renewable feed-in and (optionally) pumped storage units are prepared by agents representing a single trader per market area, respectively. We concentrate on the procedure from the supply traders' point of view, for which the different steps in the day-ahead market simulation are illustrated in Fig. B.2 and briefly described as follows.

Price forecasting According to theory, electricity generators in a competitive market environment are willing to offer electricity at the marginal generation cost. However, starting up a power plant leads to additional costs related to a higher fuel consumption and a reduced lifetime caused by material wear and tear. In order to account for this and prepare bids accordingly, it is important for the generators to estimate the running hours of a specific power plant on the next (simulation) day. Thus, the supply traders prepare a price forecast for all hours of the following day.

Bidding Based on the price forecast and their respective bidding strategies, the different supply trader agents now prepare bids for each of their power plants

p and hour h of the following day. These bids consist of volume (MWh) and price (EUR/MWh). The bid volumes are determined by the installed capacity and under consideration of an exogenously given availability factor as well as a potential balancing reserve provision. In contrast, the bid prices depend both, on the type of the power plant and whether it is expected to run in the respective hour (i.e., $h \in \boldsymbol{H}_p^{\text{on}} \subseteq \boldsymbol{H}$) or expected not to run (i.e., $h \in \boldsymbol{H}_p^{\text{off}} \subseteq \boldsymbol{H}$). Table B.1 provides an overview of the bidding strategies for the different situations. Please note that in all cases, the variable costs c_p^{var} of a power plant p play a crucial role. These are determined by the fuel price p_p^{fuel}, the power plant's net electrical efficiency η_p, the price of CO_2 emission allowances p^{CO_2}, the CO_2 emission factor of the fuel e^{fuel} and the costs for operation and maintenance $c_p^{\text{O\&M}}$ as shown in Eq. (B.1).

Market clearing All bids prepared by the supply trader agents are then submitted to a central market operator, which uses a clearing algorithm – formulated as a linear optimization problem – to determine electricity prices and cross-border electricity flows (Ringler et al., 2017). In the objective function, the economic welfare in the coupled electricity system is maximized (Eq. (B.2)). Constraints include the energy balance in all market areas (Eq. (B.2b)) as well as a limitation of the acceptance rates of demand bids (Eq. (B.2c)), supply bids (Eq. (B.2d)) and exchange flows between the different market areas (Eq. (B.2d)). The optimization problem is solved for each simulation hour, yet, we omit the index h for better readability. After the market has been cleared, the market outcome – in particular the information on which bids have been accepted – is returned to the different supply trader agents.

Dispatch Finally, all supply trader agents calculate the sum of their accepted hourly bid volumes, which results in their individual hourly load curve to serve. The agents then determine a cost-minimal dispatch of their power plant fleet, which serves this load curve under consideration of variable generation costs and start-up costs[18].

[18] Formally, this step requires to solve a mixed-integer linear optimization problem. However, to save computational resources, a heuristic approach is applied, such that only close-to-optimal solutions can be guaranteed.

$$c_p^{\text{var}} = \frac{p_p^{\text{fuel}} + p^{\text{CO}_2} \cdot e^{\text{fuel}}}{\eta_p} + c_p^{\text{O\&M}} \tag{B.1}$$

$$\max_{x_d, x_s, x_{m_1,m_2}} \sum_{m \in \boldsymbol{M}} \left(\sum_{d \in \boldsymbol{D_m}} (p_d \cdot q_d \cdot x_d) - \sum_{s \in \boldsymbol{S_m}} (p_s \cdot q_s \cdot x_s) \right) \tag{B.2a}$$

subject to

$$\underbrace{\sum_{d \in \boldsymbol{D_m}} (q_d \cdot x_d)}_{\text{Demand}} - \underbrace{\sum_{s \in \boldsymbol{S_m}} (q_s \cdot x_s)}_{\text{Supply}} + \underbrace{\sum_{m' \in \boldsymbol{M'_m}} \left(q^{\max}_{m,m'} \cdot x_{m,m'} - q^{\max}_{m',m} \cdot x_{m',m} \right)}_{\text{Exchange flows}} = 0 \quad \forall m \in \boldsymbol{M} \tag{B.2b}$$

$$0 \le x_d \le 1 \quad \forall d \in \boldsymbol{D_m}, \forall m \in \boldsymbol{M} \tag{B.2c}$$

$$0 \le x_s \le 1 \quad \forall s \in \boldsymbol{S_m}, \forall m \in \boldsymbol{M} \tag{B.2d}$$

$$0 \le x_{m_1,m_2} \le 1 \quad \forall m_1, m_2 \in \boldsymbol{M} \tag{B.2e}$$

where

(Decision variables)

x	bid acceptance rate [–]
(Parameters)	
p	bid price [EUR/MWh]
q	bid volume [MWh]
(Indices)	
d	demand bid
s	supply bid
m	market area

Table B.1: Overview of power plants' hourly bidding prices $b_{p,h}$ depending on the type of the power plant and the expected online hours. *Source:* Fraunholz et al. (2021a).

Case (1):	Power plant p (base-/medium-/peak-load) is in the market in all hours h[1]	
	$b_{p,h} = c_p^{\text{var}}$	$\forall h \in H_p^{\text{on}} = H$
Case (2):	Power plant p (base-load) is in the market in some hours h[2]	
	$b_{p,h} = c_p^{\text{var}}$	$\forall h \in H_p^{\text{on}} \subseteq H$
	$b_{p,h}^{\text{min}} = c_p^{\text{var}} - c_p^{\text{start}}/t_p^{\text{off}}$	$\forall h \in H_p^{\text{off}} \subseteq H$
	$b_{p,h}^{\text{rest}} = c_p^{\text{var}}$	$\forall h \in H_p^{\text{off}} \subseteq H$
Case (3):	Power plant p (medium-/peak-load) is in the market in some hours h[3]	
	$b_{p,h} = c_p^{\text{var}} + c_p^{\text{start}}/t_p^{\text{on}}$	$\forall h \in H_p^{\text{on}} \subseteq H$
	$b_{p,h} = c_p^{\text{var}} + c_p^{\text{start}}/\Delta t$	$\forall h \in H_p^{\text{off}} \subseteq H$

[1] If a power plant is expected to always be in the market, no start-up costs occur and the hourly bids $b_{p,h}$ therefore only consist of the variable costs c_p^{var}.

[2] Base-load power plants are expected to temporarily accept market prices below their marginal generation costs in order to avoid start-up costs in subsequent hours. Thus, variable costs are bid for the expected running hours H_p^{on} and two different bids are created for each hour $h \in H_p^{\text{off}}$ – the minimum running load of the power plant is bid at variable costs minus avoided start-up costs c_p^{start}, while the remaining load is bid at variable costs. The avoided start-up costs are evenly distributed among the expected offline time t_p^{off}.

[3] If a medium- or peak-load power plant is expected to be in the market only in few hours or never, the hourly bids consist of variable costs and start-up costs. For expected online times t_p^{on} longer than one hour, start-up costs are distributed evenly.

(Sets)

$\boldsymbol{M}$ simulated market areas

$\boldsymbol{M'_m}$ market areas connected to market area m

$\boldsymbol{D_m}$ demand bids submitted in market area m

$\boldsymbol{S_m}$ supply bids submitted in market area m

It is important to realize that the model-endogenous price forecasts have a direct impact on the bidding of the different supply trader agents, which in turn drives the outcome of the market clearing process (cf. Fig. B.2). At the same time, the price forecasting approaches applied in this paper are continuously updated during the simulation. For this purpose, the market outcomes of previous auctions are used as input data. In other words, there exists a mutual dependency between price forecasts and market outcomes. Thus, poor price forecasts lead to distorted, unsound bidding behavior and ultimately distorted market outcomes. This aspect is crucial, since simulated day-ahead market electricity prices are typically one of the major results of electricity market models.

As previously mentioned, PowerACE was originally developed to analyze the German electricity market. If only a single market area is considered, model-endogenous price forecasts are relatively simple to implement due to the limited number of price drivers. However, extending the model to a multi-country setup heavily increases the complexity of creating reasonably accurate price forecasts for all considered market areas. Thus, this paper aims to develop, implement and test novel approaches in this regard. To the best knowledge of the authors, this crucial aspect with regard to model accuracy is mostly overlooked to date by simulation-based electricity market models in the scientific literature (cf. Section B.2).

Before delving into the methodological details of the proposed new price forecasting approaches, we have to mention that a single price forecast is created in each simulated market area, which is then used by all supply traders allocated to a given market area. We choose this approach first and foremost to reduce the computational burden. Moreover, the scope of this paper is to highlight the general suitability of ANNs in the context of electricity market simulation models. However, extending our approach to a separate price forecast for each supply trader is straightforward, since multiple instances of an ANN can easily be created by using different random number seeds. Moreover, network architecture and training strategies could be varied to further diversify the price forecasts.

B.3.2 Artificial Neural Network Model

Preparation of Input Data

The objective of the implemented ANNs is to find model-endogenous relationships between different input variables and the target variable, i.e., the simulated market prices. Since the day-ahead electricity markets are cleared such that a balance between supply and demand is ensured, drivers of both the supply and the demand side are relevant. Moreover, the market results in a given market area are crucially affected by the situation in directly or even indirectly interconnected market areas.

We aim to keep our ANNs as simple as possible and therefore base them solely on fundamental factors, used in similar form, e.g., by Keles et al. (2016b): expected electricity demand, expected feed-in of renewables, fuel prices, carbon prices, and available generation capacities. Please note that we always consider the variables of all modelled market areas, regardless of the market area for which the price forecast is carried out. This is because the electricity markets of the European countries are interconnected and therefore mutually influence each other. This is particularly relevant in the price formation process and therefore also in price forecasting as recently confirmed by Lago et al. (2018b). Given the model-endogenous character of our price forecasts and the fact that simulations up to 2050 are carried out, a few additional particularities need to be considered:

- As is common practice in electricity market models, renewables are assumed to bid their generation at 0 EUR/MWh. The feed-in of 1 MW renewable electricity is therefore essentially equivalent to a reduction in electricity demand of 1 MW. Thus, we combine electricity demand and renewable feed-in to a single variable per market area, the residual demand.

- Due to the non-availability of hourly resolved projections up to 2050 in the literature, we assume constant fuel and carbon prices over the course of a single year. In consequence, the simulated electricity prices do not contain intra-annual fluctuations caused by level variations of the fuel and carbon prices. We can therefore omit fuel and carbon prices from the list of input variables used in our price forecasting ANNs.

- PowerACE allows for investment decisions and decommissioning of old generation capacity at the end of each simulation year. Throughout a year, however, constant availability factors are used for all technologies except for nuclear power plants[19]. Thus, only the available generation capacities of market areas with substantial shares of nuclear power are included in the set of explanatory variables.

[19]Nuclear power plants are base-load power plants and therefore rely on as many running hours as possible. These units therefore typically carry out their annually required revisions in times of low electricity demand. Thus, seasonal patterns can be observed regarding the available capacities of nuclear power plants

- The day-ahead price cap in European electricity markets is currently set at 3000 EUR/MWh. In practice, this limit is (almost) never reached. Contrary, due to the simulation horizon of PowerACE up to 2050, scarcity situations with extreme price spikes may well occur in our model. The same is true for hours with a surplus of renewable electricity generation and prices reaching 0 EUR/MWh or even becoming negative. These situations are still relatively rare in reality, yet are likely to occur substantially more often in future simulation years. Thus, unlike present real-world day-ahead price forecasts, our ANN approach needs to be able to consider such situations adequately.

Apart from time series for the residual demand in all modelled market areas and the available capacities in market areas with substantial shares of nuclear power, we also consider the first differences of the residual demand time series to account for auto-correlation in load and thus electricity prices (cf. Weron, 2014). Moreover, since the operation of pumped storage plants does not only depend on the level of the residual load in a given hour, but also on the load level throughout the day, the input data for our ANNs also includes the daily arithmetic mean of the residual load in the respective market area under consideration.

Model Configuration and Training

For the price forecast using ANNs we apply a two-stage modeling approach, which is schematically illustrated in Fig. B.3.

Firstly, a feedforward neural network is used for a regression[20] aiming to explain the simulated prices in dependence of the residual demands, their first differences and daily mean as well as the available capacities in all market areas. For the training of this model (Fig. B.3a, red boxes), the input data is filtered to exclude outlier prices resulting from the must-run capacity exceeding the residual demand[21] (i.e., a price of 0 EUR/MWh) or a scarcity situation (i.e., a price of

[20]Please note that we use the term *regression* to describe the general process of finding relationships between a set of input variables and a set of output variables, regardless of the specific method applied. Whenever we refer to *regression* in the meaning of a particular statistical method, we use the exact name of this method, e.g., *linear regression*, *logistic regression* or *non-linear regression*.

[21]In reality, even negative prices often occur in such situations. This is because some heat-controlled conventional power plants need to stay online to fulfill their heat delivery agreements. Moreover, renewable feed-in is often subsidized such that it can still operate profitably, even

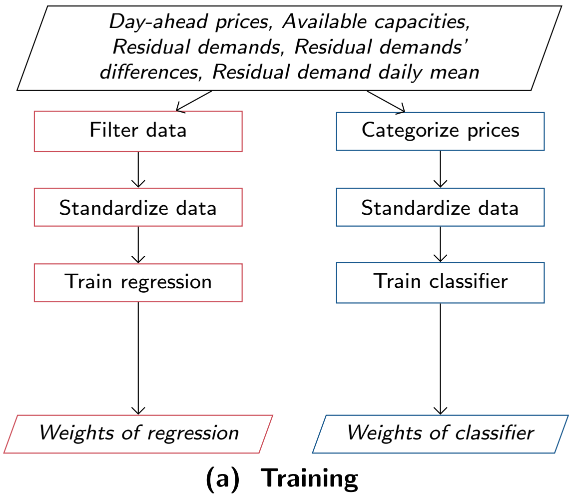

Figure B.3: Overview of the training (a) and forecasting (b) process of the artificial neural networks. Two different models are applied, one for price regression (red) and one for classification to consider extreme situations (blue), i.e., surplus generation setting the price at 0 EUR/MWh and scarcity resulting in a price of 3000 EUR/MWh.

3000 EUR/MWh). Next, the explanatory variables and the response variable are standardized as shown in Eq. (B.3), where z denotes the standardized variable, x the non-standardized variable, $\overline{x}$ the mean of the sample and S the standard deviation of the sample. Standardization is a common procedure in machine learning to improve training speed and performance. The network is then trained with the standardized data.

$$z = \frac{x - \overline{x}}{S} \tag{B.3}$$

Secondly, another feedforward neural network is used to classify the simulated prices into 1) situations with a renewable surplus setting the price at 0 EUR/MWh, 2) regular situations with the price being set by any conventional power plant or storage unit, and 3) scarcity situations with peak prices of 3000 EUR/MWh as shown in Eq. (B.4). Please note, that the residual demands' differences do not have an impact on whether a renewable surplus or a scarcity situation occurs and

under (slightly) negative prices. In PowerACE, must-run conditions of conventional power plants are not modelled and all renewables offer their production at 0 EUR/MWh. Thus, prices of 0 EUR/MWh can only occur in our model, if the feed-in of renewables exceeds the residual demand.

are therefore omitted. For the training of the model (Fig. B.3a, blue boxes), the simulated prices are first categorized and transformed using one-hot encoding. Then, as for the first ANN, the explanatory variables are standardized and the ANN is trained to obtain the weights of the classification network.

$$c = \begin{cases} 1, & \text{if } p = 0\,\text{EUR/MWh} \\ 2, & \text{if } p > 0\,\text{EUR/MWh} \wedge p < 3000\,\text{EUR/MWh} \\ 3, & \text{if } p = 3000\,\text{EUR/MWh} \end{cases} \tag{B.4}$$

The ANNs are trained with random initial weights once every simulation month to adequately consider recent simulation outcomes. After being trained, the ANNs are applied to provide day-ahead electricity price forecasts to the trading agents for every simulation day until the next training is carried out. The forecasting process is shown in Fig. B.3b. The input data is first standardized using the respective time series characteristics (mean and standard deviation) of the training process. Using the same standardization in training and forecasting is essential to obtain reasonable forecasts, since the situations to be forecasted need to follow the same statistical process as the training data. Both the regression ANN and the classification ANN are then simultaneously applied to obtain forecasts of prices and price classifications.

After prediction, the forecasts are destandardized or set to the fixed value of the predicted class according to Eq. (B.5), respectively. If the classification predicts a regular situation ($\hat{c} = 2$), the price forecast of the regression ANN $\hat{p}_{\text{prelim}}$ determines $\hat{p}$. Yet, if according to the classification, a surplus of generation is predicted to set the price ($\hat{c} = 1$) or a scarcity situation is predicted to occur ($\hat{c} = 3$), the price forecast $\hat{p}$ is set to 0 EUR/MWh, or 3000 EUR/MWh, respectively. In the literature, this applied algorithm is also known as a regime-switching model (e.g., Keles et al., 2012; Swider and Weber, 2007).

$$\hat{p} = \begin{cases} 0\,\text{EUR/MWh}, & \text{if } \hat{c} = 1 \\ \hat{p}_{\text{prelim}}, & \text{if } \hat{c} = 2 \\ 3000\,\text{EUR/MWh}, & \text{if } \hat{c} = 3 \end{cases} \tag{B.5}$$

Table B.2 provides an overview of the applied hyperparameters in the regression and classification ANNs. These parameters were found after intense testing and satisfy the trade-off between computational burden and forecasting accuracy. Most notably, we use a relatively large batch size of 512 to increase the chance of all three price classes being included in the majority of the batches. In order to avoid overfitting, we apply a L2-regularization. This means that the loss term to be minimized during training is supplemented by a regularization term r, which is calculated as the squared Euclidean norm of the weight vector $\boldsymbol{w}$, multiplied by a small coefficient ε as shown in Eq. (B.6). Moreover, early stopping helps to reduce the risk of overfitting and at the same time limits the time required for the model training. The training data consists of simulation results from the previous 8760 hours of the simulation and is adjusted for each new model training using a rolling horizon approach.

$$r = \varepsilon \cdot \|\boldsymbol{w}\|_2^2 = \varepsilon \cdot (w_1^2 + w_2^2 + ... + w_n^2) \tag{B.6}$$

We are well aware that other and more sophisticated types of ANN than simple feedforward networks exist. Yet, as also stated by Prasanna et al. (2019), in the context of ABMs with multiple agents interacting dynamically, computationally efficient lean algorithms are preferable for model-endogenous tasks. We apply two ANNs (classification and regression, as described above) in each of the ten market areas, which are trained monthly over a simulation period of 31 years (2020 until 2050). Consequently, we end up with $2 \cdot 10 \cdot 12 \cdot 31 = 7440$ model trainings to be carried out. Thus, despite acknowledging the potential improvements that recurrent neural networks or other advanced types of ANN may bring along, we refrain from implementing such approaches.

Technical Implementation

The agent-based simulation model PowerACE is programmed in Java. For this reason, we use *Deeplearning4J*[22], an established deep learning programming library written for Java to embed the novel price forecasting approaches based on ANNs into the existing modeling framework.

[22] `https://deeplearning4j.org/`

Table B.2: Overview of the applied hyperparameters in the regression and classification ANNs.

Hyperparameter	Regression ANN	Classification ANN
Model class	Feedforward network	Feedforward network
Input variables[1]	22	12
Output variables[2]	1 (day-ahead price)	3 (price categories)
Hidden layers	2	1
Neurons in hidden layers	20/15	10
Activation functions	Rectified linear unit/Rectified linear unit/Identity	Rectified linear unit/Softmax
Weight initialization	Xavier uniform (Glorot and Bengio, 2010)	Xavier uniform (Glorot and Bengio, 2010)
Updater	Adam (Kingma and Ba, 2017) with $\alpha = 0.001$, $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 10^{-8}$	Adam (Kingma and Ba, 2017) with $\alpha = 0.001$, $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 10^{-8}$
Loss function	Mean squared error	Multiclass cross-entropy
Regularization	L2 with coefficient 10^{-4}	L2 with coefficient 10^{-4}
Training data size	8760 (rolling horizon)	8760 (rolling horizon)
Batch size	512	512
Number of epochs	200	200
Early stopping	10 epochs w/o improved loss	10 epochs w/o improved loss

[1] As shown later in Section B.4.1, ten market areas are modelled. The regression ANN uses residual demands, their first differences and the available capacities in all market areas. Moreover, the daily arithmetic mean of the residual load in the respective market area under consideration is included. Please note, however, that only the available capacities in France are considered, since it is the only modelled country with a substantial share of nuclear power installed and constant availabilities are assumed for all other technologies. Contrary, the classification ANN omits the first differences of the residual demands, as they do not have an impact on whether a renewable surplus or a scarcity situations occurs.

[2] Since separate forecasting models are created for each market area, the only output variable of the regression ANN is the day-ahead electricity price in the respective market area. Contrary, the classification ANN predicts the probabilities of an hour belonging to one of three classes, thus it has three output variables.

PowerACE considers multiple market areas, for each of which a separate price forecast needs to be carried out. Since these forecasts can be calculated fully independent of each other, we use multi-threading to speed-up the training process. We run PowerACE on a machine with an *AMD Ryzen Threadripper 2950X* CPU (16 cores at 4.0 GHz) and 128 GB main memory (RAM). As we want to ensure deterministic behavior, the ANNs are initialized with an identical random number seed in all simulations carried out.

B.3.3 Benchmark Models

In order to assess the accuracy of the implemented price forecasts based on ANNs, it is necessary to compare the outcomes with those of some benchmarks. For this purpose, we implement a naive approach as well as a linear regression approach, which are briefly described in the following paragraphs.

Naive Price Forecast

The basic idea of the naive price forecast is to use a potential correlation between prices in a given hour and those of the same hour on the previous day. Alternatively, it is also common to use the hour of the same weekday in the previous week, to account for differences between different types of days. More precisely, the price forecasts $\hat{p}_h$ in hour h are calculated very simply as $\hat{p}_h = p_{h-x}$, where x denotes the respective lag of 24 or 168 hours. Please note that despite the obvious simplicity of this approach, more advanced but insufficiently calibrated models often fail to outperform the naive benchmark (Conejo et al., 2005).

Linear Regression Model

A linear regression model is a reasonable additional benchmark, as it ranges between the naive forecast and the ANN approach with regard to model complexity. Analogously to the ANN approach, the implemented linear regression approach consists of the two separate steps previously introduced in Section B.3.2.

However, the regression part is carried out as a multiple linear regression rather than as an ANN. The corresponding relationship is shown in Eq. (B.7), where $\boldsymbol{\beta}$ denotes the vector of regression coefficients, $\boldsymbol{x_h}$ the vector of explanatory variables in hour h, and p_h the independent variable, i.e., the price in hour h.

$$p_h = \boldsymbol{\beta} \cdot \boldsymbol{x_h} \tag{B.7}$$

Similarly, a multinominal logistic regression is applied for classification instead of the second ANN. With K denoting the number of price categories (in our case $K = 3$), $\boldsymbol{\beta_k}$ the vector of regression coefficients for price category k, and $\boldsymbol{x_h}$ the vector of explanatory variables in hour h, Eq. (B.8) presents the probability of a given hour h falling into price category k. For the forecast, the category with the highest estimated probability ultimately determines the expected category $\hat{c}_h$ of the hour h.

$$\Pr(c_h = k) = \begin{cases} \dfrac{e^{\boldsymbol{\beta_k} \cdot \boldsymbol{x_h}}}{1 + \sum_{k'=1}^{K-1} e^{\boldsymbol{\beta_{k'}} \cdot \boldsymbol{x_h}}}, & \text{for } k \neq K \\ \dfrac{1}{1 + \sum_{k'=1}^{K-1} e^{\boldsymbol{\beta_{k'}} \cdot \boldsymbol{x_h}}}, & \text{for } k = K \end{cases} \tag{B.8}$$

Please note that individual models are used in each considered market area, yet we omit the index m for better readability. Since a linear predictor function is used in both, the regression and the classification part, we can interpret this benchmark as a linear approach, contrary to the non-linear character of the ANNs.

Please note that the type of relationship between electricity prices and the various explanatory variables is likely to change throughout the simulation in an a priori unknown fashion. Consequently, we refrain from applying non-linear regression models as an additional benchmark.

Models Without Classifier

Finally, in order to assess the benefit of handling outliers separately by means of a classifier, both, the ANN approach and the linear regression approach are additionally tested in configurations without classifiers, i.e., only the red parts of Fig. B.3 are applied for these cases.

B.4 Evaluation of the Forecasting Approaches

In this section, we conduct a multi-country long-term case study using PowerACE with the newly implemented price forecasting methods. To start with, we provide an overview of the data used and the scenarios under investigation. Then, we compare the forecasting performance of the ANN approach and the benchmarks. Finally, we show how the forecasting accuracy affects the eventual simulated market outcomes, i.e., the day-ahead electricity prices.

B.4.1 Data Sources and Scenario Setup

As introduced in Section B.3.1, PowerACE is a detailed bottom-up simulation model and therefore requires substantial amounts of input data. Table B.3 provides an overview of the data used in all simulations presented in the following as well as the respective sources. Since a major objective of the developed price forecasting methodologies is the adequate consideration of cross-border effects, the applied version of PowerACE covers ten interconnected European countries, all of which are modelled considering their respective real-world market design[23] (see Fig. B.4).

We run a total of five simulations with identical input data and only vary the applied day-ahead price forecasting methodology. The simulations are carried out with an hourly resolution and cover the time horizon from 2020 to 2050. The different forecasting approaches investigated are as follows:

- Naive persistence forecast with lag of 24 hours (*Naive24*),
- Multiple linear regression with multinominal logistic regression classifier (*LRw/C*),
- Feedforward neural network with feedforward neural network classifier (*ANNw/C*),
- Multiple linear regression without classifier (*LRw/oC*),
- Feedforward neural network without classifier (*ANNw/oC*).

In the remainder of this paper, we focus on the first three approaches, while the additional model runs without classifier are only briefly addressed. However, the complete results of all simulations are included in Appendix B.6.

B.4.2 Forecasting Performance

In order to compare the forecasting performance of the different approaches under investigation, we apply two common error metrics in the field of forecasting.

[23] For details on the different market design options see Bublitz et al. (2019).

Table B.3: Overview of the input data used in all simulations carried out with PowerACE. The table has been adopted from a previous study (Fraunholz et al., 2021b) since we make use of the exact same data sets.

Input data type	Resolution	Sources and comments
Conventional power plants	unit level	S&P Global Platts (2015), and own assumptions
Fuel prices	yearly	EU Reference Scenario (de Vita et al., 2016)
Carbon prices	yearly	EU Reference Scenario (de Vita et al., 2016), scaled to reach 150 EUR/t_{CO_2} in 2050
Investment options	yearly	Louwen et al. (2018); Schröder et al. (2013); Siemens Gamesa (2019), and own assumptions
Interconnector capacities	yearly	Ten-Year Network Development Plan (ENTSO-E, 2016)
Electricity demand	hourly, market area	historical time series of 2015 (ENTSO-E, 2017), scaled to the yearly demand given in the EU Reference Scenario (de Vita et al., 2016)
Renewable feed-in	hourly, market area	historical time series of 2015 (ENTSO-E, 2017), scaled to reach an overall renewable share in relation to electricity demand of 80 % in 2050

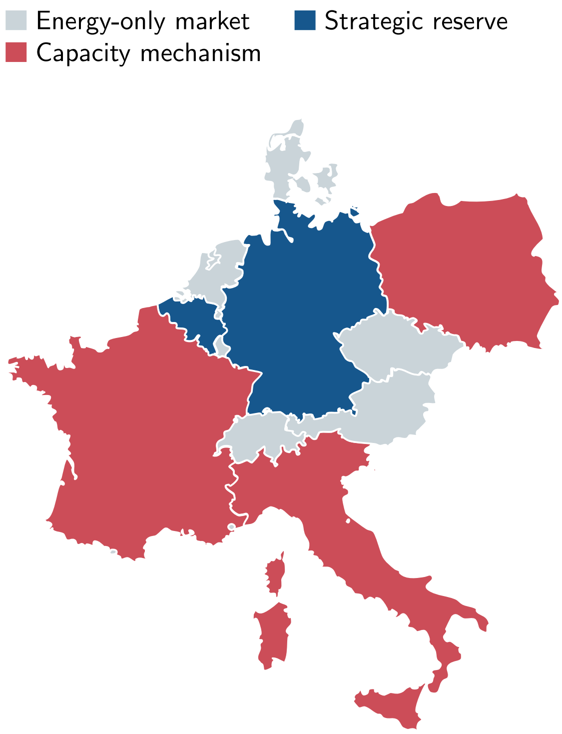

Figure B.4: Overview of the real-world electricity market designs implemented in the different countries covered by PowerACE. Only the grey market areas rely on an energy-only market, whereas the other market areas use different long-term investment support schemes, either a strategic reserve (blue) or a capacity mechanism (red). However, as theory suggests no impact of these mechanisms on the short-term bidding behavior is modelled.

Firstly, we consider the *mean absolute error* (MAE) between the forecasted hourly electricity prices $\hat{p}$ and their simulated realizations p. For a given year y and market area m, the MAE can be calculated according to Eq. (B.9). Secondly, in order to account for the general increase of the price level over the course of the simulation (cf. Section B.4.3), we also calculate the *mean absolute percentage error* (MAPE) according to Eq. (B.10). Please note that we choose the yearly mean prices $\overline{p}_{m,y}$ as the denominator rather than using the hourly realizations $p_{m,y,h}$ in order to avoid the adverse effect of dividing by very low values close to zero in case of very low simulated prices.

$$e_{m,y}^{\text{MAE}} = \frac{1}{8760} \sum_{h=1}^{8760} |p_{m,y,h} - \hat{p}_{m,y,h}| \tag{B.9}$$

$$e_{m,y}^{\text{MAPE}} = \frac{1}{8760} \sum_{h=1}^{8760} \frac{|p_{m,y,h} - \hat{p}_{m,y,h}|}{\overline{p}_{m,y}} \quad \text{with} \quad \overline{p}_{m,y} = \frac{1}{8760} \sum_{h=1}^{8760} p_{m,y,h} \tag{B.10}$$

While metrics like the MAE or the MAPE are useful to get a first impression of one forecast's superiority over another, they do not provide any notion of the statistical significance of such a conclusion. Many electricity price forecasting papers in the literature neglect this aspect. In contrast, as recommended by Weron (2014), we run one-sided Diebold-Mariano tests (Diebold and Mariano, 1995) on the time series of *absolute errors*. Given the structure of the Diebold-Mariano test, we conduct one-on-one tests for each of the combinations of two forecasting approaches in our set. As we test the hypothesis that one approach is better than the other in both directions, this leads to 20 tests per country and a total of 200 tests. Due to the large amount of data available (31 years from 2020 until 2050 at hourly resolution, i.e., a total of $31 \cdot 8760 = 271560$ data points), these hypothesis tests should then be able to state at a high significance level, whether the mean of the compared time series of *absolute errors* is statistically different from zero (i.e., one forecast is superior to the other).

In Tables B.4–B.6, we provide the MAEs and MAPEs in all countries and years for the naive persistence approach (*Naive24*), the linear regression approach with classifier (*LRw/C*) and the ANN approach with classifier (*ANNw/C*), respectively. For a quick visual overview, the same data are presented as heatmaps for selected simulation years in Figs. B.5 and B.6. The results of the additional simulations without classifier (*LRw/oC*, *ANNw/oC*) are provided in Tables B.7 and B.8 in Appendix B.6.

The first thing to observe is that the MAEs increase over the course of the simulation for all forecasting approaches considered. However, this finding is mostly related to the general increase of the price level as previously mentioned and shown in the subsequent Section B.4.3. Thus, it is reasonable to focus on the MAPEs instead, which remain more stable throughout the simulation period.

Moreover, we find that unlike in a usual electricity price forecasting context, the naive method (*Naive24*) performs very poorly with MAPEs (averaged over all simulated years) ranging between 0.40 and 0.53 for the different countries. This important result is due to the mutual dependencies between price forecasts and simulated prices as described in Section B.3.1, such that no stable outcome can be achieved. The linear regression approach (*LRw/C*) and the ANN approach (*ANNw/C*), both equipped with an additional classifier, clearly outperform the naive approach with MAPEs ranging from 0.17 to 0.32 and 0.17 and 0.21, respectively.

Please note, however, that these results are strongly affected by very few wrongly classified outlier prices. To show this, we additionally remove the 0.25% worst forecasts of each approach and for each country and recalculate the MAEs and MAPEs for the remaining 99.75% of the forecasted prices. The results for all five approaches are shown in Tables B.9–B.13 in Appendix B.6. We can observe that, although only very few data points have been removed, the error metrics improve substantially. The adjusted MAPE for the *ANNw/C* approach decreases to values between 0.12 and 0.16 for the different countries, and the *LRw/C* approach improves to values between 0.13 and 0.26. Given the complex dynamic setup with several mutual dependencies, we therefore consider the forecasts of the *ANNw/C* approach to be sufficiently accurate.

Regarding the benefit of using an additional classifier, we can state that this is much more relevant for the linear regression than for the ANN. This finding is rather straightforward: While the ANN approach is capable of handling outlier prices quite well even without a classifier, the linear regression approach is strongly distorted when fit to data sets including few, but extreme outliers. This is because not the entire value space is covered by observations and linear relationships fail to

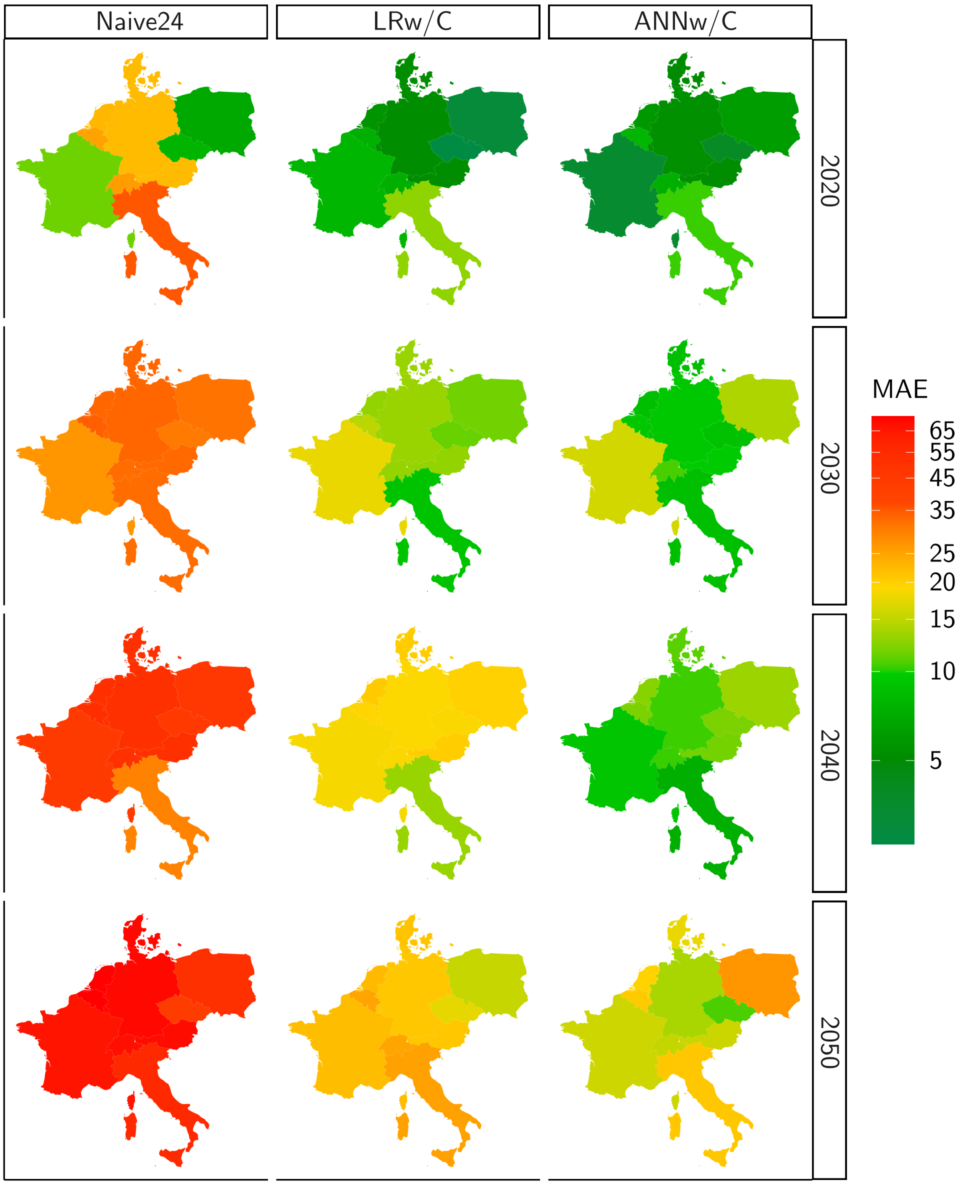

Figure B.5: Mean absolute errors (MAEs) of the different price forecasting approaches in selected simulation years. The linear regression (*LRw/C*) and even more so the artificial neural network approach (*ANNw/C*) clearly outperform the persistence forecast (*Naive24*). Driven by the general increase of the price level (cf. Section B.4.3), the MAEs increase over the course of the simulation for all forecasting approaches considered.

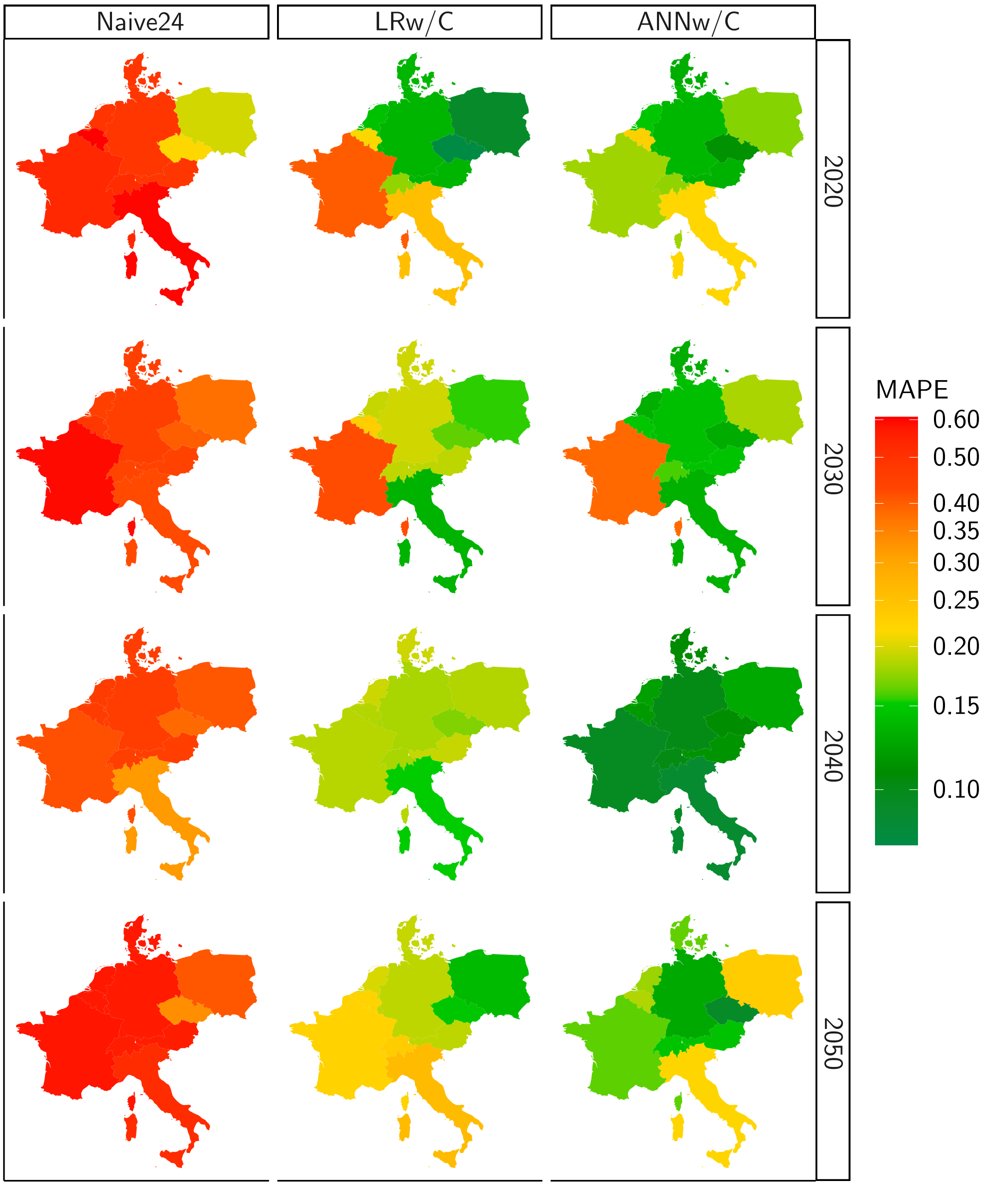

Figure B.6: Mean absolute percentage errors (MAPEs) of the different price forecasting approaches in selected simulation years. The linear regression (*LRw/C*) and even more so the artificial neural network approach (*ANNw/C*) clearly outperform the persistence forecast (*Naive24*). In contrast to the MAE, the MAPE accounts for the general increase of the price level (cf. Section B.4.3) and therefore remains more stable over the course of the simulation.

Year	Mean absolute error (MAE) [EUR/MWh]										Mean absolute percentage error (MAPE) [–]									
	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL
2020	22.2	25.2	7.8	22.2	11.5	22.2	35.2	22.7	6.9	26.0	0.49	0.61	0.22	0.49	0.53	0.49	0.60	0.50	0.20	0.52
2021	23.7	26.8	13.1	23.8	11.9	23.7	34.7	24.2	7.7	27.1	0.49	0.61	0.31	0.49	0.54	0.49	0.58	0.49	0.20	0.51
2022	24.5	28.0	20.0	24.5	12.3	24.4	34.7	24.8	11.5	27.5	0.48	0.62	0.41	0.48	0.54	0.48	0.56	0.48	0.27	0.50
2023	27.3	30.5	26.2	27.2	13.0	27.3	34.4	27.5	20.5	29.4	0.49	0.63	0.47	0.49	0.56	0.49	0.54	0.49	0.39	0.50
2024	45.8	44.4	45.4	45.8	18.7	45.9	33.4	44.5	39.8	46.7	0.64	0.75	0.63	0.64	0.69	0.64	0.50	0.63	0.58	0.64
2025	55.4	54.0	55.0	55.3	19.6	55.4	33.7	54.8	50.9	55.8	0.68	0.69	0.67	0.68	0.67	0.68	0.49	0.68	0.63	0.68
2026	42.4	43.2	41.8	42.2	22.1	42.4	33.1	42.4	39.1	42.3	0.57	0.60	0.56	0.57	0.73	0.57	0.47	0.57	0.51	0.56
2027	30.2	32.0	29.2	30.2	15.3	30.3	33.3	30.4	28.5	29.9	0.45	0.50	0.43	0.45	0.60	0.45	0.46	0.45	0.39	0.44
2028	30.6	32.3	29.2	30.7	17.5	30.7	32.6	30.7	29.4	30.1	0.44	0.49	0.41	0.44	0.62	0.44	0.45	0.45	0.39	0.43
2029	31.5	33.4	29.8	32.0	20.3	32.0	32.8	31.9	30.6	31.5	0.44	0.49	0.41	0.45	0.63	0.45	0.44	0.45	0.38	0.43
2030	32.9	34.1	30.6	33.3	26.8	33.3	32.4	33.3	31.5	32.4	0.44	0.48	0.40	0.45	0.59	0.45	0.42	0.45	0.38	0.43
2031	37.6	37.9	35.1	37.9	37.1	37.9	32.3	38.0	36.7	37.4	0.47	0.49	0.42	0.48	0.57	0.48	0.41	0.48	0.40	0.47
2032	41.4	41.7	38.9	41.7	41.9	41.7	31.8	41.9	36.0	41.1	0.48	0.49	0.44	0.48	0.57	0.48	0.40	0.49	0.39	0.47
2033	40.7	40.8	38.1	40.9	41.1	40.9	31.0	41.2	38.0	40.5	0.47	0.47	0.43	0.47	0.52	0.47	0.38	0.48	0.40	0.47
2034	41.8	41.2	39.4	42.0	41.3	42.0	33.1	42.1	38.0	41.9	0.45	0.45	0.41	0.45	0.46	0.45	0.38	0.45	0.38	0.45
2035	43.8	44.6	41.3	44.1	43.8	44.1	34.2	44.1	39.9	43.9	0.44	0.45	0.41	0.45	0.45	0.45	0.38	0.45	0.39	0.44
2036	45.0	45.8	41.8	45.2	44.0	45.2	32.0	45.1	42.1	45.1	0.43	0.44	0.39	0.43	0.43	0.43	0.35	0.43	0.39	0.43
2037	47.4	48.6	43.2	47.7	43.3	47.7	30.9	47.7	44.1	47.4	0.44	0.45	0.39	0.44	0.41	0.44	0.34	0.44	0.40	0.44
2038	55.4	55.2	50.5	55.7	43.4	55.7	30.1	55.9	54.0	55.3	0.47	0.47	0.41	0.47	0.40	0.47	0.32	0.47	0.44	0.47
2039	44.3	45.8	38.9	44.6	42.3	44.6	29.7	44.9	40.7	44.0	0.42	0.43	0.35	0.43	0.41	0.43	0.32	0.43	0.37	0.42
2040	51.2	52.7	45.3	51.6	44.5	51.6	29.3	52.0	46.6	51.0	0.46	0.46	0.39	0.46	0.42	0.46	0.32	0.46	0.41	0.45
2041	52.3	53.5	45.7	52.9	45.7	52.9	30.7	53.4	45.4	51.9	0.46	0.47	0.38	0.47	0.42	0.47	0.33	0.47	0.38	0.46
2042	60.9	61.3	53.6	61.5	47.6	61.6	33.4	62.2	53.4	60.1	0.50	0.50	0.41	0.51	0.43	0.51	0.35	0.51	0.44	0.49
2043	63.9	64.7	55.6	64.6	50.6	64.7	42.7	65.5	62.3	63.0	0.51	0.51	0.41	0.52	0.44	0.52	0.41	0.52	0.46	0.50
2044	56.8	58.7	44.6	57.3	52.3	57.3	41.3	58.4	50.3	55.8	0.49	0.50	0.36	0.50	0.47	0.50	0.40	0.50	0.40	0.48
2045	61.3	63.1	49.2	61.8	53.2	61.9	41.5	62.6	55.1	59.9	0.51	0.51	0.38	0.52	0.46	0.52	0.40	0.51	0.42	0.50
2046	63.6	65.3	53.0	63.8	56.0	63.9	48.4	64.6	49.3	62.2	0.52	0.52	0.39	0.52	0.49	0.52	0.45	0.52	0.39	0.51
2047	64.6	66.8	48.6	64.7	58.1	64.7	51.4	65.6	48.7	63.3	0.55	0.55	0.37	0.55	0.53	0.55	0.48	0.55	0.39	0.54
2048	68.4	71.3	42.8	69.1	63.8	69.2	49.5	70.6	50.1	66.4	0.55	0.55	0.34	0.55	0.54	0.55	0.47	0.55	0.40	0.54
2049	65.6	69.4	40.4	66.6	61.3	66.6	49.2	68.3	51.0	63.5	0.55	0.56	0.32	0.56	0.56	0.56	0.48	0.56	0.41	0.54
2050	69.4	72.4	43.4	70.3	66.6	70.3	55.6	72.1	51.2	68.2	0.56	0.57	0.34	0.57	0.58	0.57	0.52	0.57	0.41	0.56
Mean	46.5	47.9	39.3	46.8	37.6	46.8	36.4	47.2	39.7	46.5	0.49	0.53	0.41	0.50	0.52	0.50	0.43	0.50	0.40	0.49

Table B.4: Error metrics of the persistence forecast (Naive24). Unlike in a usual electricity price forecasting context, this simple approach performs very poorly with MAPEs (averaged over all simulated years) ranging between 0.40 and 0.53 for the different countries.

Year	Mean absolute error (MAE) [EUR/MWh]										Mean absolute percentage error (MAPE) [–]									
	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL
2020	5.2	7.4	2.6	5.3	7.9	5.2	12.7	5.6	3.1	7.4	0.14	0.21	0.08	0.14	0.40	0.14	0.26	0.14	0.09	0.17
2021	4.2	7.3	3.6	4.2	7.8	4.2	9.1	4.6	4.2	6.1	0.10	0.20	0.09	0.10	0.40	0.10	0.19	0.11	0.11	0.14
2022	4.2	7.7	4.0	4.2	8.3	4.2	11.3	4.5	3.3	6.9	0.10	0.20	0.10	0.10	0.42	0.10	0.21	0.10	0.08	0.15
2023	6.4	9.8	6.3	6.4	9.3	6.4	10.5	6.5	6.9	8.1	0.13	0.24	0.13	0.13	0.45	0.13	0.19	0.13	0.15	0.16
2024	20.5	20.3	18.8	20.4	13.5	20.4	9.8	18.8	18.5	21.0	0.31	0.38	0.29	0.31	0.54	0.31	0.17	0.29	0.29	0.32
2025	17.4	21.7	18.3	17.1	14.0	16.1	8.1	17.8	18.1	18.3	0.24	0.32	0.26	0.24	0.54	0.23	0.14	0.25	0.25	0.25
2026	13.2	16.3	13.3	13.2	13.9	13.2	8.1	14.0	14.7	13.8	0.20	0.26	0.20	0.21	0.52	0.21	0.14	0.22	0.22	0.21
2027	12.8	15.4	12.3	12.8	13.9	12.9	8.7	12.2	14.1	13.0	0.21	0.27	0.20	0.22	0.62	0.22	0.14	0.21	0.22	0.22
2028	8.9	11.1	7.9	9.0	12.7	9.1	7.9	8.7	9.1	9.0	0.14	0.19	0.13	0.15	0.51	0.15	0.13	0.14	0.14	0.15
2029	11.3	13.6	10.1	11.5	14.7	11.6	8.5	11.2	10.3	11.7	0.17	0.22	0.15	0.18	0.50	0.18	0.13	0.17	0.15	0.18
2030	12.8	14.8	11.4	13.1	17.7	13.2	9.0	12.9	11.7	13.0	0.19	0.23	0.16	0.19	0.42	0.20	0.13	0.19	0.16	0.19
2031	15.9	17.5	14.4	16.0	21.7	16.1	9.1	16.1	16.1	16.0	0.21	0.25	0.19	0.22	0.36	0.22	0.13	0.22	0.19	0.22
2032	19.9	20.5	18.1	20.0	22.7	20.4	9.8	20.6	17.3	19.4	0.24	0.26	0.22	0.25	0.33	0.25	0.14	0.25	0.20	0.24
2033	17.1	18.2	15.1	17.2	19.9	16.6	11.4	17.1	16.3	16.3	0.20	0.22	0.18	0.21	0.26	0.20	0.15	0.20	0.18	0.20
2034	17.4	17.7	16.5	18.1	18.8	18.1	10.7	18.0	16.6	17.9	0.20	0.20	0.19	0.21	0.23	0.21	0.14	0.20	0.18	0.20
2035	22.3	23.1	21.0	21.6	22.4	21.0	14.6	21.5	20.2	22.0	0.23	0.24	0.22	0.23	0.24	0.22	0.17	0.23	0.20	0.23
2036	19.7	17.9	18.1	19.5	19.2	18.9	11.7	20.1	18.2	19.8	0.20	0.18	0.18	0.20	0.20	0.19	0.14	0.20	0.18	0.20
2037	19.9	18.7	19.2	19.9	17.7	18.0	12.8	19.5	18.8	20.0	0.19	0.18	0.18	0.19	0.18	0.17	0.15	0.19	0.17	0.19
2038	23.5	21.0	20.0	22.9	19.6	22.5	15.3	23.8	22.7	23.3	0.21	0.19	0.17	0.21	0.19	0.20	0.18	0.21	0.20	0.21
2039	21.8	22.4	19.9	22.7	16.7	22.3	13.5	21.8	19.1	22.5	0.22	0.22	0.19	0.23	0.17	0.22	0.16	0.22	0.18	0.22
2040	20.2	19.5	18.9	20.4	18.6	19.1	13.0	20.5	19.8	18.9	0.19	0.19	0.17	0.19	0.19	0.18	0.15	0.19	0.18	0.18
2041	19.8	21.3	17.5	20.5	18.5	20.1	11.8	19.7	19.5	19.4	0.19	0.20	0.16	0.20	0.19	0.19	0.14	0.19	0.18	0.19
2042	25.4	25.0	22.2	25.2	20.8	23.9	13.0	25.9	24.4	24.2	0.22	0.22	0.18	0.22	0.20	0.21	0.15	0.23	0.21	0.22
2043	22.2	22.9	21.3	20.4	22.2	19.5	18.9	21.8	23.9	22.6	0.19	0.20	0.17	0.18	0.21	0.17	0.20	0.19	0.19	0.20
2044	21.9	23.2	22.8	19.9	19.7	19.8	16.8	21.4	23.1	21.9	0.21	0.22	0.20	0.19	0.19	0.19	0.18	0.20	0.20	0.21
2045	22.4	24.9	24.7	22.4	21.9	22.0	21.4	23.0	24.1	23.2	0.20	0.22	0.20	0.20	0.21	0.20	0.22	0.21	0.20	0.21
2046	26.5	26.4	27.6	23.1	22.9	23.3	25.4	25.9	15.7	26.5	0.24	0.23	0.22	0.21	0.22	0.21	0.26	0.23	0.14	0.24
2047	19.3	20.3	21.6	18.6	21.5	18.8	21.5	19.2	14.2	20.8	0.18	0.19	0.18	0.18	0.22	0.18	0.22	0.18	0.13	0.20
2048	29.6	31.2	20.0	28.5	25.8	28.9	26.4	28.9	14.5	30.9	0.26	0.27	0.17	0.25	0.25	0.26	0.27	0.25	0.13	0.28
2049	18.7	20.9	16.8	18.4	21.8	17.6	22.3	19.9	14.3	19.6	0.17	0.19	0.15	0.17	0.22	0.16	0.23	0.18	0.13	0.18
2050	21.0	25.1	17.4	21.2	22.0	21.0	25.4	22.4	15.4	24.9	0.19	0.22	0.15	0.19	0.22	0.19	0.26	0.20	0.14	0.23
Mean	17.5	18.8	16.2	17.2	17.7	16.9	13.8	17.5	15.7	18.0	0.20	0.23	0.18	0.20	0.32	0.19	0.18	0.20	0.17	0.21

Table B.5: Error metrics of the approach using multiple linear regression with a multinominal logistic regression classifier (LRw/C). With MAPEs ranging from 0.17 to 0.32, this approach clearly outperforms the naive approach. Please note that the results are strongly affected by very few wrongly classified outlier prices. Thus, Table B.10 in Appendix B.6 additionally presents the results with the 0.25% worst forecasts in each country being removed from the data sets.

Year	Mean absolute error (MAE) [EUR/MWh]										Mean absolute percentage error (MAPE) [–]									
	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL
2020	5.2	7.9	3.9	5.1	3.5	5.3	10.3	5.8	6.1	7.4	0.13	0.23	0.11	0.13	0.18	0.14	0.22	0.15	0.17	0.17
2021	5.6	6.3	5.1	5.3	2.8	5.4	10.2	5.9	5.7	7.3	0.13	0.17	0.13	0.13	0.15	0.13	0.20	0.14	0.15	0.16
2022	5.9	6.3	6.3	6.1	3.5	6.1	12.2	6.1	7.2	8.0	0.13	0.16	0.15	0.14	0.18	0.14	0.23	0.14	0.17	0.17
2023	8.8	8.5	8.9	8.8	3.8	8.7	12.1	8.8	8.9	10.4	0.18	0.20	0.18	0.18	0.18	0.18	0.22	0.18	0.18	0.20
2024	21.6	16.9	20.2	21.7	7.3	21.5	10.3	20.8	21.2	22.6	0.33	0.31	0.31	0.33	0.29	0.32	0.18	0.32	0.33	0.33
2025	15.4	19.5	16.1	15.5	5.5	14.7	9.4	14.5	14.9	16.2	0.22	0.28	0.22	0.22	0.22	0.21	0.16	0.20	0.21	0.22
2026	14.5	16.0	15.9	15.4	5.7	16.6	9.9	14.7	17.2	16.5	0.22	0.26	0.25	0.24	0.21	0.26	0.17	0.23	0.25	0.25
2027	16.2	15.9	16.3	16.3	8.0	16.1	13.3	16.2	17.5	18.2	0.26	0.28	0.26	0.27	0.36	0.26	0.21	0.27	0.26	0.29
2028	11.0	19.4	18.7	9.4	4.8	11.5	15.0	11.2	14.9	9.8	0.19	0.35	0.31	0.16	0.20	0.20	0.24	0.19	0.23	0.16
2029	11.0	10.4	10.8	10.4	7.4	11.0	11.3	10.3	14.5	12.3	0.16	0.17	0.16	0.16	0.25	0.17	0.17	0.16	0.19	0.18
2030	9.7	9.3	8.9	8.6	16.1	9.4	8.6	8.6	14.1	10.6	0.14	0.15	0.13	0.13	0.39	0.14	0.13	0.13	0.18	0.16
2031	10.4	11.1	9.1	9.1	19.5	9.5	7.2	10.2	12.5	10.8	0.14	0.16	0.12	0.13	0.33	0.13	0.11	0.14	0.15	0.15
2032	11.0	13.3	10.4	9.6	13.0	10.7	9.0	11.7	13.8	10.6	0.14	0.17	0.13	0.12	0.19	0.14	0.13	0.15	0.17	0.13
2033	10.7	10.6	10.7	9.5	13.1	9.2	10.1	9.4	16.9	9.9	0.13	0.13	0.13	0.12	0.18	0.11	0.14	0.11	0.19	0.12
2034	10.7	11.0	12.2	11.4	13.6	11.9	8.8	13.6	17.9	12.1	0.13	0.13	0.14	0.13	0.17	0.14	0.12	0.16	0.19	0.14
2035	14.3	15.0	15.0	14.0	15.1	13.8	10.3	15.8	15.2	15.1	0.15	0.16	0.16	0.15	0.17	0.15	0.13	0.17	0.16	0.16
2036	12.7	13.5	14.9	13.9	14.4	12.1	9.1	15.4	13.5	12.9	0.13	0.14	0.15	0.14	0.15	0.13	0.11	0.16	0.14	0.13
2037	13.4	12.3	13.6	12.7	12.1	12.9	9.7	13.3	17.2	12.2	0.13	0.12	0.13	0.13	0.13	0.13	0.12	0.13	0.16	0.12
2038	15.3	14.8	15.3	14.7	11.8	12.7	7.4	14.9	16.6	14.4	0.14	0.14	0.14	0.14	0.12	0.12	0.09	0.14	0.15	0.13
2039	14.1	17.0	13.2	15.1	11.4	14.1	7.4	12.9	15.8	14.8	0.15	0.18	0.13	0.16	0.12	0.14	0.09	0.13	0.15	0.15
2040	11.7	12.0	12.0	11.0	9.1	10.4	7.4	12.4	13.2	10.3	0.11	0.12	0.11	0.11	0.10	0.10	0.09	0.12	0.13	0.10
2041	19.1	17.6	21.9	20.1	20.9	17.4	10.8	17.7	15.3	19.3	0.18	0.17	0.19	0.19	0.20	0.16	0.12	0.17	0.14	0.18
2042	21.8	22.2	20.9	20.3	19.5	20.2	13.1	22.5	19.9	20.3	0.19	0.19	0.17	0.18	0.19	0.18	0.15	0.20	0.17	0.18
2043	31.8	36.0	35.2	31.2	36.0	31.9	25.3	34.8	34.3	28.9	0.27	0.31	0.28	0.27	0.33	0.28	0.26	0.30	0.28	0.25
2044	18.0	18.7	22.7	15.3	16.1	16.7	12.3	20.1	20.9	21.9	0.17	0.18	0.20	0.15	0.16	0.16	0.13	0.19	0.19	0.21
2045	16.3	18.5	18.7	15.6	18.9	13.8	16.7	14.8	18.1	18.2	0.15	0.16	0.15	0.14	0.18	0.13	0.17	0.13	0.15	0.17
2046	22.5	26.3	24.6	26.2	19.0	20.8	20.0	28.9	36.8	23.4	0.21	0.24	0.20	0.24	0.19	0.19	0.21	0.26	0.32	0.22
2047	14.0	15.3	16.8	12.5	16.5	13.4	15.0	14.4	18.2	14.4	0.13	0.14	0.14	0.12	0.17	0.13	0.16	0.14	0.16	0.14
2048	30.8	33.8	19.2	31.9	39.9	29.0	27.5	30.7	58.5	31.0	0.27	0.29	0.16	0.28	0.38	0.25	0.27	0.27	0.50	0.28
2049	16.4	25.8	17.5	13.8	17.4	18.4	17.2	17.6	16.3	15.0	0.15	0.23	0.15	0.13	0.18	0.17	0.18	0.16	0.15	0.14
2050	15.7	20.5	10.7	17.7	15.8	13.9	21.0	19.6	26.9	15.3	0.14	0.18	0.09	0.16	0.16	0.13	0.22	0.18	0.23	0.15
Mean	14.7	16.2	15.0	14.5	13.6	14.2	12.5	15.3	18.1	15.2	0.17	0.20	0.17	0.17	0.21	0.17	0.17	0.18	0.20	0.18

Table B.6: Error metrics of the approach using a feedforward neural network with a feedforward neural network classifier (ANNw/C). With MAPEs ranging from 0.17 to 0.21, this approach clearly outperforms both, the naive approach and the linear regression. Please note that the results are strongly affected by very few wrongly classified outlier prices. Thus, Table B.11 in Appendix B.6 additionally presents the results with the 0.25% worst forecasts in each country being removed from the data sets.

replicate large variations in the dependent variable with only moderate variations in explaining variables. For the detailed results of the approaches without classifier, please refer to Appendix B.6.

What remains to be proven is whether the differences between the forecasting approaches are statistically significant. For this purpose, Fig. B.7 presents the results of the Diebold-Mariano tests, which allow us to assess whether there is a clear rank of the approaches. We find the *ANNw/C* method to outperform both, the *LRw/C* approach and the *Naive24* approach, at a very strong significance level $p \leq 0.01$. Moreover, *LRw/C* is superior to *Naive24*, also at a significance level $p \leq 0.01$. The only exception from these results is Poland, where *LRw/C* is able to outperform *ANNw/C*.

When it comes to the benefit of the additional classifier, the Diebold-Mariano tests confirm the previously described findings (see Fig. B.9 in Appendix B.6): While the linear regression with classifier (*LRw/C*) clearly outperforms the approach without classifier (*LRw/oC*) in all considered countries (significance level $p \leq 0.01$, as before), this does not apply for the ANN approach. However, also the ANN approach with classifier (*ANNw/C*) is statistically significantly better than the one without classifier (*ANNw/oC*) in six out of ten countries, with one draw (no significantly better approach in Switzerland) and three defeats. Thus, while the focus of our paper is not on whether or not classifiers should be used, we can still state that the practice of doing so seems leads to preferable outcomes. Yet, the use of a classifier is clearly much more relevant when working with linear rather than non-linear approaches.

B.4.3 Impact of Forecasting Accuracy on Market Outcomes

Instead of solely focusing on the forecasting performance, we now want to inspect another key aspect of model-endogenous price forecasting: the impact on the eventual market outcomes of the simulation. For this purpose, Fig. B.8 shows the development of the volume-weighted average prices in all simulated market areas.

Firstly, we can observe a notable increase of the general price level as the simulation moves on. This is related to the model assumptions described in Section B.4.1, most notably the assumed increase of the carbon price to 150 $\mathrm{EUR/t_{CO_2}}$ in

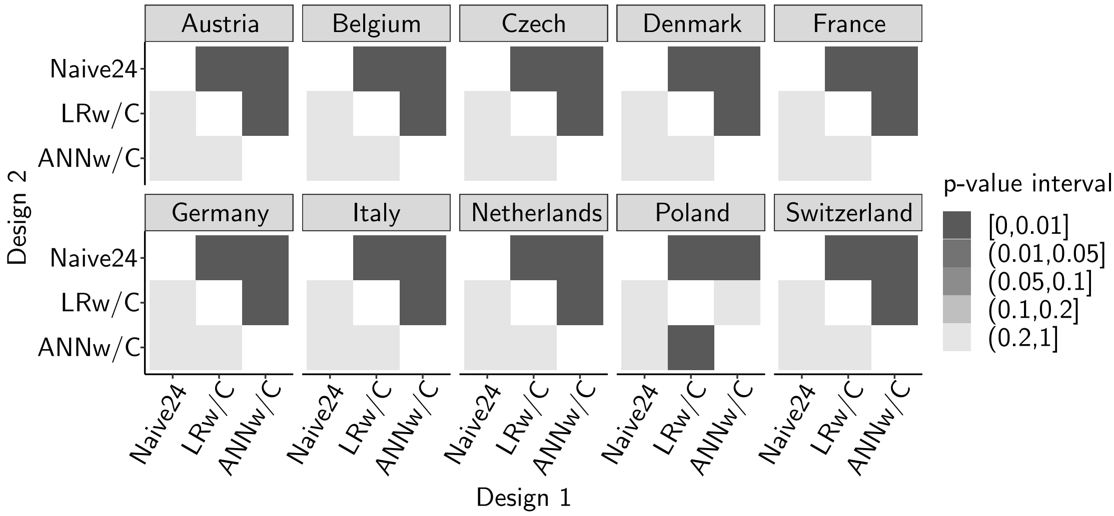

Figure B.7: Results of the Diebold-Mariano tests conducted to evaluate the statistical significance of the superiority of one forecasting approach over another. Reading example: *ANNw/C* (Design 1) is superior to *Naive24* (Design 2) in all countries at a significance level $p \leq 0.01$ as depicted by the respective grey tone.

2050 with 20% of the electricity demand remaining to be covered by non-renewable generation in this year.

Secondly, however, we can also observe that the price curves of the *LRw/C* and the *ANNw/C* approaches appear to be quite similar, while the price level using the *Naive24* method is elevated. This is an important finding as it directly highlights the crucial importance of sufficiently accurate model-endogenous price forecasts in ABMs of electricity markets. Otherwise, distorted bidding behavior may occur, e.g., if agents incorrectly assume that start-up costs occur and integrate these into their bids. Ultimately, this may result in distorted market outcomes. In that sense, the prices simulated under the more accurate price forecasts can be expected to be closer to reality, since real-world electricity price forecasting is a very advanced field with high levels of accuracy. This aspect is crucial, since simulated day-ahead market electricity prices are typically one of the major results of electricity market models.

An interesting side result of our analyses is that we indirectly confirm the statement of Ghoddusi et al. (2019), who claim that real-world electricity markets have already become much more efficient through the use of more sophisticated

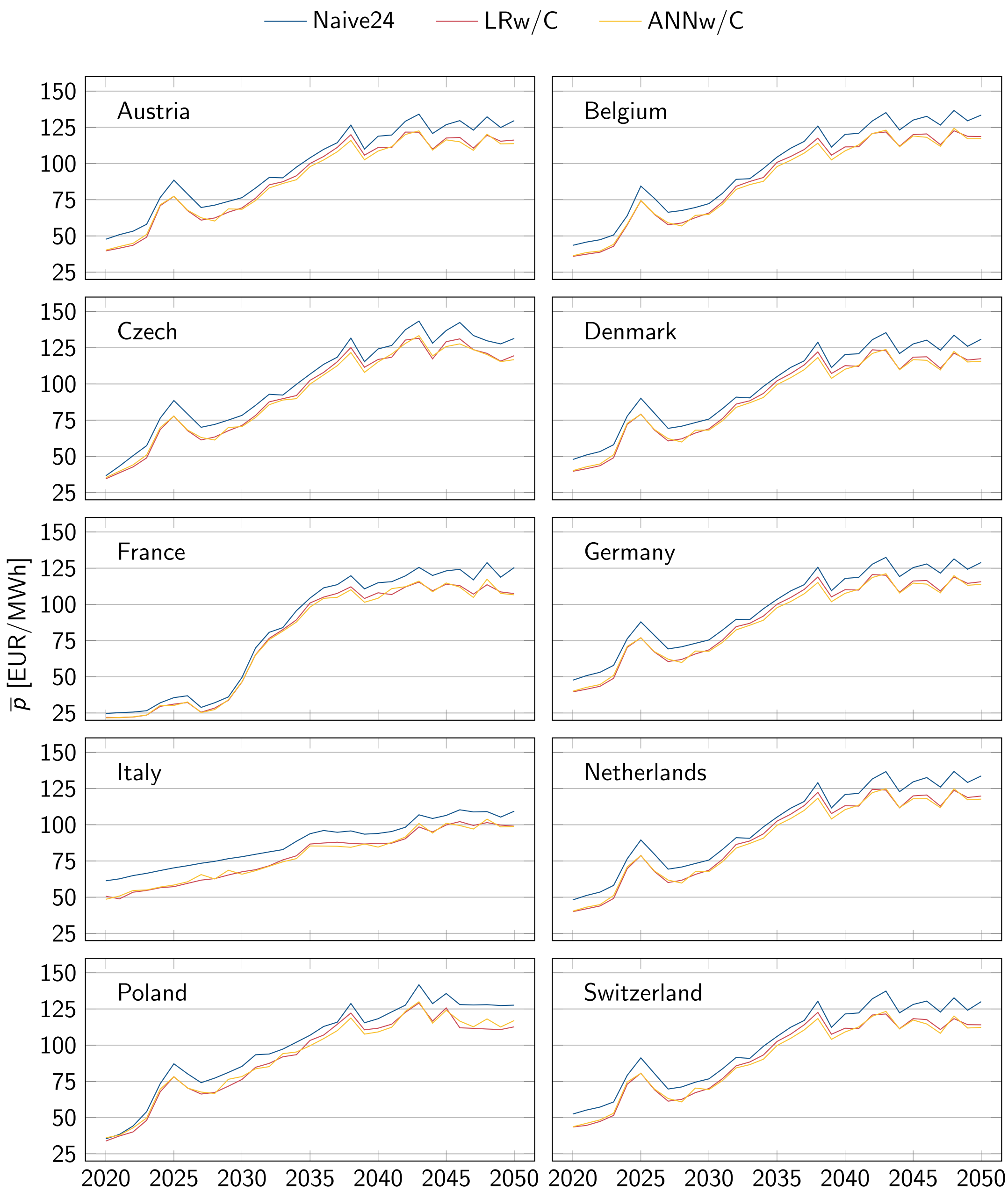

Figure B.8: Simulated development of the volume-weighted average day-ahead prices. Due to model assumptions like an increase of the carbon price to 150 EUR/t_{CO_2} in 2050, the price level generally rises strongly. However, also a strong impact of the price forecasting approach can be observed. The persistence forecast (*Naive24*) clearly leads to higher simulated prices than the other two approaches, which highlights the crucial importance of forecasting accuracy.

price forecasting methods. Thus, the benefit of increasing forecasting performance even further may be limited.

Yet, our most important finding is that while ANN approaches are found to be very useful in the context of ABMs and are increasing the quality and reliability of the model results, simpler approaches, e.g., based on linear regression, can be considered as a feasible alternative in future work. In our particular case, a linear regression with logistic classifier, too, performs reasonably well (only slightly worse than the ANN), but reduces the computational time required for the price forecasts by roughly 60% as compared to the ANN approach.

B.5 Conclusion and Outlook

In this article, we developed an electricity price forecasting technique using artificial neural networks and successfully integrated the novel approach into the established agent-based electricity market simulation model PowerACE. Our proposed methodology combines the fields of machine learning and agent-based modeling, both of which are very popular in the field of energy research.

In a case study covering ten interconnected European countries and a time horizon from 2020 until 2050 at hourly resolution, we benchmarked the new forecasting approach against a more simple linear regression model as well as a naive persistence forecast. Using Diebold-Mariano hypothesis tests, we then evaluated the statistical significance of the superiority of one approach over another. The major results of our simulations can be summarized as follows. Firstly, in contrast to real-world electricity price forecasts, we found naive approaches to perform very poorly when deployed model-endogenously in an agent-based framework. Secondly, although the linear regression performs reasonably well, it is outperformed by the neural network approach, which we could prove with strong statistical significance. Thirdly, the use of an additional classifier for outlier handling substantially improves the forecasting accuracy, particularly when linear approaches are deployed. Fourthly, the choice of the model-endogenous forecasting method has a clear impact on simulated electricity prices, which is crucial since these prices are a major results of electricity market models. Please note that this finding does not only apply to our particular simulation model, but is relevant for any agent-based approach in the field of electricity market simulation that relies on a price forecast to define agents' actions.

On the one hand, we can conclude that despite the superiority of the neural network approach, less computationally expensive approaches, e.g., based on linear regression, should always be considered as an alternative. If well fit to the scope, such approaches may – as in our particular case – come close to the accuracy of more advanced methods, yet at a much lower computational burden.

However, on the other hand, we are also well aware that far more sophisticated types of neural networks exist than simple feedforward networks we used. While the objective of our study was mostly on showing the potential of integrating neural networks into an agent-based modeling framework, we can well imagine that more advanced methods may bring additional benefits. In particular, recurrent neural networks may help to better account for time dependencies caused by electricity storage. Yet, the trade-off between accuracy and computational performance always needs to be considered.

Although our analysis focused on one particular field of application, we also see great potential in the joint application of methods from machine learning and agent-based modeling in other research contexts. Thus, we hope that our paper serves as a starting point and encourages fellow researchers to adapt our approach to their respective field of application.

B.6 Additional Results

Tables B.7 and B.8 show the MAEs and MAPEs in all countries and years for the linear regression approach without classifier (LRw/oC) and the ANN approach without classifier ($ANNw/oC$), respectively. In Fig. B.9, the results of the Diebold-Mariano tests are depicted for all investigated forecasting approaches. Moreover, in Tables B.9–B.13, adjusted MAEs and MAPEs with the 0.25% worst forecasts per country and approach being filtered are presented. This highlights the strong impact of few wrongly classified extreme outlier prices.

Year	Mean absolute error (MAE) [EUR/MWh]										Mean absolute percentage error (MAPE) [–]									
	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL
2020	5.2	7.4	2.6	5.3	7.9	5.2	12.7	5.6	3.1	7.4	0.14	0.21	0.08	0.14	0.40	0.14	0.26	0.14	0.09	0.17
2021	4.2	7.3	3.6	4.2	7.8	4.2	9.1	4.6	4.2	6.1	0.10	0.20	0.09	0.10	0.40	0.10	0.19	0.11	0.11	0.14
2022	4.2	7.7	4.0	4.2	8.3	4.2	11.3	4.5	3.3	6.9	0.10	0.20	0.10	0.10	0.42	0.10	0.21	0.10	0.08	0.15
2023	6.4	9.8	6.3	6.4	9.3	6.4	10.5	6.5	6.9	8.1	0.13	0.24	0.13	0.13	0.45	0.13	0.19	0.13	0.15	0.16
2024	40.2	31.4	36.6	40.0	16.1	40.1	8.8	38.5	37.7	39.0	0.58	0.58	0.54	0.58	0.66	0.58	0.16	0.57	0.54	0.57
2025	59.4	52.9	58.4	59.4	18.0	59.4	8.6	56.6	59.9	59.3	0.79	0.74	0.78	0.79	0.73	0.79	0.15	0.76	0.77	0.79
2026	39.2	37.4	39.1	38.9	20.5	38.9	8.4	38.5	40.0	39.1	0.59	0.59	0.58	0.59	0.78	0.59	0.14	0.58	0.56	0.58
2027	10.3	12.0	9.8	10.3	13.3	10.3	8.6	10.1	11.7	10.4	0.18	0.22	0.17	0.18	0.59	0.18	0.14	0.18	0.19	0.18
2028	9.7	11.7	8.6	9.8	12.9	9.9	8.6	9.5	10.1	9.7	0.16	0.20	0.14	0.16	0.51	0.16	0.14	0.15	0.15	0.16
2029	11.9	13.8	10.4	12.0	14.0	12.1	8.9	11.9	11.2	12.1	0.18	0.23	0.16	0.19	0.48	0.19	0.14	0.19	0.16	0.19
2030	13.7	15.1	11.9	13.9	16.8	13.9	9.7	13.7	12.5	13.7	0.20	0.24	0.17	0.21	0.40	0.21	0.14	0.20	0.17	0.20
2031	19.2	19.3	17.7	19.2	21.1	19.3	9.5	19.2	19.3	18.2	0.26	0.28	0.24	0.26	0.36	0.27	0.14	0.26	0.23	0.25
2032	34.6	34.5	34.1	34.4	31.5	34.6	10.6	34.5	24.4	32.8	0.42	0.43	0.40	0.42	0.46	0.42	0.15	0.42	0.28	0.41
2033	39.1	39.0	38.5	38.8	36.9	38.9	17.2	39.0	33.9	37.4	0.46	0.46	0.44	0.46	0.49	0.46	0.22	0.46	0.37	0.44
2034	42.6	41.2	39.1	42.6	41.3	42.7	20.5	42.7	35.8	42.1	0.48	0.47	0.43	0.48	0.49	0.48	0.25	0.48	0.38	0.47
2035	55.3	55.1	53.8	55.9	53.9	56.0	33.3	56.0	47.8	55.0	0.56	0.56	0.53	0.57	0.57	0.57	0.38	0.57	0.46	0.56
2036	58.8	58.0	58.6	59.4	56.9	59.5	31.5	59.5	52.3	58.5	0.58	0.57	0.56	0.58	0.58	0.59	0.35	0.58	0.49	0.57
2037	69.0	65.4	69.1	69.0	59.7	69.1	33.1	69.0	61.2	68.6	0.64	0.62	0.62	0.64	0.59	0.64	0.36	0.64	0.55	0.64
2038	80.2	76.2	82.2	80.1	61.0	80.1	15.6	80.2	79.2	79.5	0.70	0.68	0.68	0.71	0.58	0.71	0.19	0.70	0.65	0.70
2039	65.0	62.7	65.1	64.6	52.4	64.8	16.7	65.0	61.8	63.5	0.62	0.60	0.58	0.62	0.52	0.62	0.19	0.62	0.55	0.61
2040	64.9	64.4	64.2	64.6	53.0	64.8	17.7	65.0	52.7	61.8	0.59	0.59	0.55	0.59	0.52	0.59	0.20	0.59	0.47	0.57
2041	62.8	63.1	62.4	62.0	51.0	62.1	17.6	62.5	50.3	58.5	0.58	0.58	0.53	0.58	0.50	0.58	0.20	0.58	0.44	0.55
2042	71.7	71.2	73.2	71.4	55.3	71.5	20.8	71.9	56.3	67.0	0.61	0.60	0.57	0.61	0.51	0.61	0.22	0.61	0.46	0.58
2043	77.8	77.3	80.6	77.9	61.5	78.0	37.0	78.5	73.4	75.9	0.66	0.65	0.62	0.67	0.57	0.67	0.36	0.66	0.56	0.65
2044	58.5	58.5	50.8	57.4	49.3	57.5	32.3	58.5	43.1	56.2	0.54	0.53	0.43	0.54	0.47	0.54	0.33	0.54	0.37	0.52
2045	60.9	62.3	55.8	60.4	53.3	60.5	38.7	61.2	47.3	57.8	0.52	0.53	0.43	0.52	0.48	0.53	0.37	0.52	0.37	0.51
2046	68.7	70.1	66.6	68.9	62.3	69.0	47.4	69.8	23.9	67.0	0.60	0.60	0.52	0.61	0.58	0.61	0.46	0.61	0.21	0.60
2047	53.0	54.1	44.5	52.2	48.0	52.3	41.0	53.1	16.6	50.2	0.48	0.48	0.36	0.48	0.47	0.48	0.40	0.48	0.15	0.46
2048	75.2	78.1	30.3	75.7	68.2	75.8	52.7	77.7	18.2	72.4	0.65	0.66	0.25	0.66	0.65	0.66	0.52	0.66	0.16	0.65
2049	63.6	65.1	16.4	63.2	54.2	63.1	44.6	64.5	19.0	57.1	0.58	0.57	0.15	0.57	0.54	0.57	0.45	0.57	0.17	0.53
2050	55.3	59.0	16.5	56.5	52.6	57.0	44.5	57.7	20.4	55.1	0.49	0.51	0.14	0.50	0.52	0.50	0.44	0.50	0.18	0.50
Mean	44.5	44.5	39.1	44.5	37.7	44.6	22.2	44.7	33.5	43.4	0.46	0.47	0.39	0.46	0.52	0.46	0.26	0.46	0.34	0.45

Table B.7: Error metrics of the approach using multiple linear regression without classifier (LRw/oC). This approach performs much worse than the corresponding one with classifier (*LRw/C*, cf. Table B.5), because the linear regression approach is strongly distorted when fit to data sets including few, but extreme outliers.

Year	Mean absolute error (MAE) [EUR/MWh]										Mean absolute percentage error (MAPE) [–]									
	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL
2020	5.2	7.9	3.9	5.1	3.5	5.3	10.3	5.8	6.1	7.4	0.13	0.23	0.11	0.13	0.18	0.14	0.22	0.15	0.17	0.17
2021	5.6	6.3	5.1	5.3	2.8	5.4	10.2	5.9	5.7	7.3	0.13	0.17	0.13	0.13	0.15	0.13	0.20	0.14	0.15	0.16
2022	5.9	6.3	6.3	6.1	3.5	6.1	12.2	6.1	7.2	8.0	0.13	0.16	0.15	0.14	0.18	0.14	0.23	0.14	0.17	0.17
2023	8.8	8.5	8.9	8.8	3.8	8.7	12.1	8.8	8.9	10.4	0.18	0.20	0.18	0.18	0.18	0.18	0.22	0.18	0.18	0.20
2024	21.2	19.8	24.6	22.2	11.2	21.4	10.7	20.5	22.0	23.7	0.32	0.36	0.38	0.33	0.44	0.32	0.19	0.32	0.34	0.35
2025	11.8	14.5	12.6	12.7	6.5	12.3	8.6	11.2	15.7	14.2	0.17	0.22	0.18	0.18	0.26	0.18	0.15	0.16	0.22	0.20
2026	14.9	15.0	16.5	16.2	8.0	15.9	11.1	15.6	18.0	17.2	0.23	0.24	0.25	0.25	0.30	0.24	0.18	0.24	0.26	0.26
2027	13.6	13.7	14.4	14.6	8.1	13.5	10.0	13.4	15.2	14.9	0.23	0.25	0.24	0.25	0.37	0.23	0.16	0.23	0.24	0.25
2028	7.2	8.1	7.5	7.3	4.5	7.1	9.4	7.1	7.5	7.9	0.12	0.14	0.12	0.12	0.18	0.12	0.15	0.12	0.11	0.13
2029	7.9	8.9	8.7	7.4	7.6	7.8	8.6	7.6	7.8	9.2	0.13	0.15	0.13	0.12	0.26	0.12	0.13	0.12	0.11	0.14
2030	8.3	9.4	12.2	7.9	14.8	7.9	10.0	7.7	10.3	9.8	0.12	0.15	0.18	0.12	0.35	0.12	0.15	0.12	0.14	0.14
2031	8.6	11.3	17.3	9.6	16.6	9.4	9.2	9.3	14.6	10.8	0.12	0.17	0.24	0.14	0.28	0.13	0.14	0.13	0.18	0.15
2032	14.7	15.9	37.1	16.9	16.1	16.9	8.7	14.5	18.4	15.9	0.18	0.20	0.45	0.21	0.23	0.21	0.12	0.18	0.22	0.20
2033	10.1	9.5	39.5	11.8	11.4	12.2	6.2	9.9	13.4	11.0	0.12	0.12	0.47	0.14	0.16	0.15	0.09	0.12	0.15	0.13
2034	9.9	9.3	41.2	12.6	11.4	10.7	10.3	10.1	12.7	11.3	0.12	0.11	0.48	0.15	0.14	0.13	0.13	0.12	0.14	0.13
2035	15.1	14.3	56.6	15.5	12.8	13.7	8.9	13.9	16.4	15.5	0.16	0.16	0.60	0.17	0.15	0.15	0.11	0.15	0.17	0.17
2036	13.0	10.7	66.0	16.4	10.1	11.9	7.1	11.7	17.2	13.1	0.13	0.11	0.66	0.17	0.11	0.12	0.09	0.12	0.17	0.14
2037	15.9	13.9	85.0	16.8	9.2	16.1	10.2	14.5	21.1	15.4	0.16	0.14	0.79	0.16	0.10	0.16	0.12	0.14	0.20	0.15
2038	19.5	14.1	91.0	18.6	11.0	15.5	8.3	20.2	21.8	17.7	0.18	0.13	0.78	0.17	0.11	0.14	0.10	0.19	0.19	0.16
2039	21.6	19.5	68.9	22.9	13.5	21.2	7.7	23.8	23.7	22.1	0.22	0.20	0.64	0.23	0.14	0.22	0.09	0.24	0.22	0.23
2040	15.1	13.1	71.6	20.2	6.8	13.6	6.1	15.5	19.3	14.2	0.15	0.13	0.64	0.20	0.07	0.13	0.07	0.15	0.18	0.14
2041	18.0	17.4	77.4	18.6	12.4	16.7	10.2	17.7	17.7	17.4	0.17	0.17	0.67	0.18	0.13	0.16	0.12	0.17	0.16	0.17
2042	20.6	16.6	77.7	20.6	12.9	18.4	12.9	20.4	21.5	18.8	0.19	0.15	0.63	0.19	0.13	0.17	0.14	0.18	0.19	0.17
2043	24.0	18.0	67.0	23.9	18.3	23.9	24.4	26.5	28.5	21.9	0.21	0.16	0.53	0.21	0.18	0.21	0.25	0.24	0.24	0.20
2044	21.9	19.8	29.2	23.6	14.2	17.6	17.9	23.0	24.1	16.8	0.21	0.19	0.26	0.23	0.14	0.17	0.20	0.22	0.21	0.16
2045	20.0	17.6	29.1	21.2	15.1	16.6	19.1	20.8	23.9	16.0	0.18	0.16	0.23	0.19	0.14	0.15	0.20	0.19	0.20	0.15
2046	26.7	21.6	34.7	31.4	21.2	23.7	25.2	26.2	24.4	19.4	0.24	0.19	0.28	0.29	0.20	0.22	0.26	0.23	0.21	0.18
2047	21.5	18.0	23.1	20.2	16.4	16.9	20.1	20.4	19.7	17.5	0.21	0.17	0.19	0.19	0.17	0.16	0.21	0.19	0.18	0.17
2048	29.8	25.6	34.6	35.7	28.4	25.4	26.8	27.1	21.9	27.9	0.26	0.22	0.28	0.31	0.27	0.22	0.27	0.23	0.20	0.25
2049	25.8	21.7	19.3	23.8	21.4	18.8	21.4	23.5	20.3	20.1	0.24	0.19	0.17	0.22	0.22	0.17	0.22	0.21	0.18	0.19
2050	25.1	20.4	18.4	18.8	21.2	17.4	23.8	21.8	21.6	19.7	0.23	0.18	0.15	0.17	0.21	0.16	0.25	0.19	0.19	0.18
Mean	15.7	14.4	35.7	16.5	12.1	14.4	12.8	15.5	17.0	15.2	0.18	0.18	0.36	0.19	0.20	0.17	0.17	0.18	0.19	0.18

Table B.8: Error metrics of the approach using a feedforward neural network without classifier (ANNw/oC). This approach performs only slightly worse than the corresponding one with classifier (*ANNw/C*, cf. Table B.6), because the non-linear character of the ANN allows to account for outliers relatively well even without classifier.

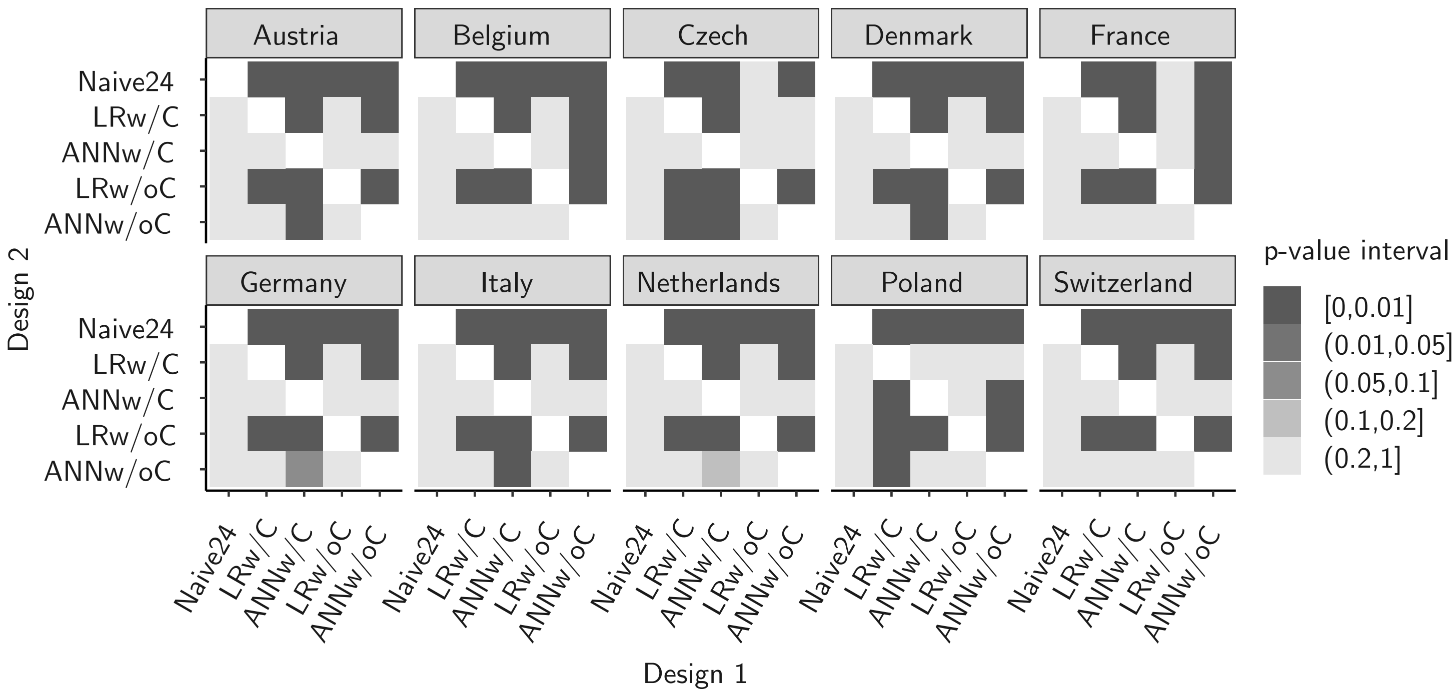

Figure B.9: Results of the Diebold-Mariano tests conducted to evaluate the statistical significance of the superiority of one forecasting approach over another. Reading example: *ANNw/C* (Design 1) is superior to *Naive24* (Design 2) in all countries at a significance level $p \leq 0.01$ as depicted by the respective grey tone. In contrast to Fig. B.7, this illustration additionally contains the two forecasting approaches without classifier (*ANNw/oC*, *LRw/oC*).

Year	Mean absolute error (MAE) [EUR/MWh]										Mean absolute percentage error (MAPE) [–]									
	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL
2020	22.0	24.9	25.7	7.6	22.0	22.0	11.2	35.0	22.5	6.7	0.48	0.60	0.52	0.21	0.48	0.48	0.52	0.60	0.49	0.19
2021	23.5	26.5	26.8	12.8	23.5	23.5	11.6	34.4	23.9	7.5	0.48	0.61	0.51	0.30	0.48	0.48	0.52	0.57	0.49	0.20
2022	24.2	27.7	27.2	19.8	24.2	24.2	11.9	34.4	24.6	11.3	0.47	0.61	0.50	0.41	0.47	0.47	0.53	0.55	0.48	0.26
2023	27.0	30.2	29.1	26.0	27.0	27.0	12.7	34.1	27.2	20.2	0.48	0.62	0.50	0.47	0.48	0.48	0.54	0.53	0.49	0.38
2024	38.2	36.8	39.1	37.8	38.3	38.2	13.3	33.1	36.9	32.1	0.53	0.62	0.54	0.53	0.53	0.54	0.49	0.50	0.52	0.47
2025	47.8	46.4	48.2	47.4	47.8	47.8	13.6	33.4	47.2	43.3	0.59	0.60	0.59	0.58	0.59	0.59	0.46	0.49	0.58	0.54
2026	34.8	35.7	34.7	34.3	34.9	34.6	15.0	32.7	34.9	31.6	0.47	0.50	0.46	0.46	0.47	0.47	0.49	0.47	0.47	0.41
2027	29.9	31.7	29.6	28.9	30.0	29.9	14.9	32.9	30.1	28.2	0.44	0.49	0.44	0.42	0.44	0.44	0.59	0.46	0.45	0.39
2028	30.3	32.0	29.9	28.9	30.4	30.3	17.1	32.2	30.4	29.1	0.44	0.49	0.43	0.41	0.44	0.44	0.60	0.44	0.44	0.38
2029	30.6	32.4	30.5	28.8	31.0	31.0	19.3	32.4	30.9	29.7	0.42	0.48	0.42	0.39	0.43	0.43	0.60	0.43	0.43	0.37
2030	31.3	32.5	30.9	29.0	31.7	31.6	25.2	31.9	31.7	30.6	0.42	0.46	0.41	0.38	0.43	0.43	0.56	0.42	0.43	0.37
2031	32.3	33.3	32.1	29.8	32.6	32.6	32.4	31.8	32.7	31.5	0.40	0.43	0.40	0.36	0.41	0.41	0.50	0.41	0.41	0.35
2032	33.9	34.2	33.6	31.4	34.2	34.2	34.4	31.4	34.4	30.7	0.39	0.40	0.39	0.35	0.40	0.40	0.47	0.39	0.40	0.33
2033	33.2	33.4	33.1	30.6	33.5	33.5	33.7	30.4	33.7	32.1	0.38	0.39	0.38	0.34	0.39	0.39	0.43	0.37	0.39	0.34
2034	34.3	33.7	34.4	31.9	34.5	34.5	33.8	29.5	34.6	30.8	0.37	0.36	0.37	0.33	0.37	0.37	0.38	0.34	0.37	0.31
2035	36.3	37.1	36.4	33.8	36.6	36.6	36.3	28.2	36.6	32.4	0.37	0.37	0.37	0.33	0.37	0.37	0.38	0.31	0.37	0.31
2036	37.5	38.2	37.5	34.3	37.7	37.7	36.5	26.6	37.6	34.6	0.36	0.37	0.36	0.32	0.36	0.36	0.36	0.29	0.36	0.32
2037	39.9	41.1	39.9	35.6	40.2	40.2	35.7	26.2	40.2	36.6	0.37	0.38	0.37	0.32	0.37	0.37	0.34	0.29	0.37	0.33
2038	47.9	47.7	47.8	43.0	48.2	48.2	35.9	27.2	48.4	46.5	0.41	0.41	0.40	0.35	0.41	0.41	0.33	0.29	0.41	0.38
2039	36.8	38.3	36.6	31.4	37.1	37.1	34.8	27.5	37.4	33.2	0.35	0.36	0.35	0.28	0.35	0.35	0.34	0.30	0.36	0.30
2040	43.7	45.2	43.5	37.8	44.2	44.1	37.0	28.3	44.5	39.1	0.39	0.40	0.39	0.32	0.39	0.39	0.35	0.31	0.40	0.34
2041	44.9	46.0	44.4	38.2	45.5	45.5	38.2	30.3	45.9	37.9	0.39	0.40	0.39	0.32	0.40	0.40	0.35	0.32	0.40	0.32
2042	53.5	53.8	52.7	46.1	54.1	54.1	40.1	31.7	54.8	45.9	0.44	0.44	0.43	0.36	0.45	0.45	0.36	0.33	0.45	0.37
2043	56.5	57.3	55.6	48.1	57.2	57.2	43.1	35.6	58.1	54.9	0.45	0.45	0.44	0.36	0.46	0.46	0.37	0.34	0.46	0.41
2044	49.4	51.3	48.4	37.2	49.9	49.9	44.9	37.2	51.0	42.9	0.43	0.43	0.42	0.30	0.44	0.44	0.40	0.36	0.44	0.34
2045	53.9	55.6	52.5	41.8	54.5	54.4	45.8	37.4	55.2	47.7	0.45	0.45	0.44	0.32	0.45	0.45	0.40	0.36	0.45	0.36
2046	56.2	57.9	54.8	45.6	56.5	56.4	48.6	41.4	57.2	46.4	0.46	0.46	0.45	0.33	0.46	0.46	0.42	0.39	0.46	0.37
2047	57.3	59.4	55.9	41.3	57.3	57.3	50.7	45.5	58.3	48.1	0.49	0.49	0.48	0.32	0.49	0.49	0.46	0.43	0.49	0.38
2048	61.1	63.9	59.0	41.1	61.8	61.7	56.4	43.0	63.2	49.6	0.49	0.49	0.48	0.32	0.49	0.49	0.48	0.41	0.50	0.39
2049	58.3	62.1	56.2	40.0	59.3	59.3	54.0	44.0	61.0	50.4	0.49	0.50	0.48	0.32	0.50	0.50	0.49	0.43	0.50	0.40
2050	62.1	65.1	60.9	42.9	63.0	63.0	59.2	48.6	64.8	50.5	0.50	0.51	0.50	0.33	0.51	0.51	0.51	0.45	0.52	0.40
Mean	40.9	42.3	40.9	34.3	41.2	41.2	32.2	33.8	41.6	35.2	0.44	0.47	0.44	0.36	0.44	0.44	0.45	0.41	0.44	0.36

Table B.9: Error metrics of the persistence forecast (Naive24) with the 0.25% worst forecasts per country being filtered. Although only very few data points have been removed, the metrics substantially improve as compared to the full data set (cf. Table B.4).

Year	Mean absolute error (MAE) [EUR/MWh]										Mean absolute percentage error (MAPE) [–]									
	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL
2020	5.1	7.3	7.1	2.5	5.1	5.1	7.8	12.5	5.4	3.0	0.13	0.21	0.17	0.07	0.13	0.13	0.40	0.25	0.14	0.09
2021	4.0	7.1	5.9	3.5	4.0	4.0	7.7	8.9	4.4	4.0	0.10	0.20	0.14	0.09	0.10	0.10	0.39	0.19	0.11	0.11
2022	4.0	7.5	6.6	3.9	4.0	4.0	8.1	11.0	4.3	3.2	0.09	0.20	0.14	0.09	0.09	0.09	0.41	0.21	0.10	0.08
2023	6.2	9.6	7.8	6.1	6.2	6.2	9.2	10.3	6.2	6.7	0.13	0.23	0.16	0.13	0.13	0.13	0.44	0.19	0.13	0.14
2024	12.8	12.6	13.4	11.1	12.8	12.8	9.9	9.6	11.1	10.8	0.19	0.24	0.20	0.17	0.19	0.19	0.40	0.17	0.17	0.17
2025	9.8	14.1	10.6	10.6	8.5	9.5	10.1	8.0	10.2	10.4	0.14	0.21	0.15	0.15	0.12	0.13	0.39	0.14	0.14	0.14
2026	7.6	9.4	8.2	7.4	7.7	7.7	10.8	8.0	7.4	8.5	0.12	0.15	0.13	0.11	0.12	0.12	0.40	0.14	0.12	0.13
2027	8.5	10.4	8.7	8.0	8.6	8.5	11.5	8.6	8.1	9.8	0.14	0.18	0.14	0.13	0.14	0.14	0.51	0.14	0.14	0.15
2028	8.7	10.9	8.9	7.7	8.9	8.9	12.6	7.7	8.5	8.9	0.14	0.19	0.14	0.12	0.15	0.15	0.50	0.12	0.14	0.13
2029	10.2	12.4	10.6	9.0	10.4	10.4	13.5	8.3	10.0	9.4	0.16	0.20	0.16	0.13	0.16	0.16	0.46	0.13	0.16	0.13
2030	11.7	13.6	11.8	10.2	12.0	11.9	16.5	8.8	11.7	10.5	0.17	0.21	0.17	0.15	0.18	0.18	0.39	0.13	0.17	0.14
2031	12.1	13.7	12.2	10.6	12.3	12.3	18.0	8.9	12.3	12.3	0.16	0.19	0.17	0.14	0.17	0.17	0.30	0.13	0.17	0.15
2032	12.4	13.6	12.4	10.9	12.8	12.4	15.8	9.0	13.0	10.9	0.15	0.17	0.15	0.13	0.16	0.15	0.23	0.13	0.16	0.13
2033	12.7	13.5	12.9	11.4	12.8	12.8	16.2	9.2	13.1	12.2	0.15	0.16	0.15	0.13	0.15	0.15	0.21	0.12	0.16	0.14
2034	13.6	13.9	13.7	12.4	13.7	13.6	16.3	9.1	13.8	12.5	0.15	0.16	0.16	0.14	0.16	0.15	0.20	0.12	0.16	0.14
2035	14.8	15.5	14.5	13.5	13.8	14.0	15.2	8.5	14.0	12.6	0.16	0.16	0.15	0.14	0.14	0.15	0.16	0.10	0.15	0.13
2036	14.0	14.5	14.2	12.5	13.9	13.9	14.8	9.2	14.1	12.9	0.14	0.15	0.14	0.12	0.14	0.14	0.15	0.11	0.14	0.13
2037	14.0	14.3	14.0	12.6	13.7	13.7	14.3	10.4	13.9	12.9	0.13	0.14	0.13	0.12	0.13	0.13	0.15	0.12	0.13	0.12
2038	16.0	15.4	15.8	13.8	15.0	15.4	15.3	12.9	16.3	15.1	0.14	0.14	0.14	0.12	0.13	0.14	0.15	0.15	0.15	0.13
2039	14.4	15.0	15.1	12.8	14.9	15.3	14.7	12.7	14.3	12.6	0.14	0.15	0.15	0.12	0.15	0.15	0.15	0.15	0.14	0.12
2040	14.9	15.2	14.9	13.9	14.4	14.5	15.2	12.8	14.9	12.9	0.14	0.14	0.14	0.13	0.14	0.14	0.15	0.15	0.14	0.12
2041	14.5	15.1	14.4	13.6	13.9	14.0	15.2	11.5	14.4	13.0	0.14	0.14	0.14	0.12	0.13	0.13	0.15	0.13	0.14	0.12
2042	17.9	17.6	16.7	14.7	16.4	17.7	15.9	12.4	18.5	16.9	0.16	0.15	0.15	0.12	0.14	0.16	0.15	0.14	0.16	0.14
2043	15.1	16.1	15.5	14.9	14.2	14.2	16.3	14.1	15.0	16.4	0.13	0.14	0.14	0.12	0.13	0.13	0.15	0.15	0.13	0.13
2044	15.1	16.4	15.5	15.4	14.3	14.4	16.0	14.9	15.3	15.7	0.14	0.15	0.15	0.14	0.14	0.14	0.16	0.16	0.14	0.14
2045	15.9	17.5	17.0	17.3	15.2	15.3	17.3	16.6	15.9	16.6	0.14	0.15	0.15	0.14	0.14	0.14	0.16	0.17	0.14	0.14
2046	19.1	19.0	19.1	20.2	15.9	15.6	17.7	18.2	18.5	14.5	0.17	0.17	0.17	0.16	0.14	0.14	0.17	0.18	0.16	0.13
2047	15.1	16.6	16.2	15.5	13.9	14.1	16.9	17.8	14.9	13.9	0.14	0.15	0.15	0.13	0.13	0.13	0.17	0.18	0.14	0.13
2048	22.2	23.7	23.6	16.6	21.5	21.1	18.4	19.6	21.5	14.2	0.20	0.20	0.21	0.14	0.19	0.19	0.18	0.20	0.19	0.13
2049	14.4	16.5	15.6	15.7	13.6	13.8	15.9	18.3	15.0	14.0	0.13	0.15	0.15	0.14	0.12	0.13	0.16	0.19	0.13	0.13
2050	14.9	17.7	17.6	17.2	13.9	14.2	14.9	19.2	15.7	15.1	0.13	0.16	0.16	0.15	0.13	0.13	0.15	0.20	0.14	0.14
Mean	12.6	14.1	13.2	11.8	12.2	12.3	14.1	11.8	12.6	11.7	0.14	0.17	0.15	0.13	0.14	0.14	0.26	0.15	0.14	0.13

Table B.10: Error metrics of the approach using multiple linear regression with a multinominal logistic regression classifier (LRw/C) with the 0.25% worst forecasts per country being filtered. Although only very few data points have been removed, the metrics substantially improve as compared to the full data set (cf. Table B.5).

Year	Mean absolute error (MAE) [EUR/MWh]										Mean absolute percentage error (MAPE) [–]									
	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL
2020	5.1	7.8	7.2	3.8	5.2	5.0	3.3	10.2	5.7	6.0	0.13	0.22	0.17	0.11	0.13	0.13	0.17	0.21	0.14	0.17
2021	5.5	6.2	7.2	4.9	5.3	5.2	2.7	10.0	5.7	5.6	0.13	0.17	0.16	0.13	0.13	0.12	0.14	0.20	0.14	0.15
2022	5.7	6.1	7.8	6.2	6.0	5.9	3.4	11.9	6.0	7.0	0.13	0.16	0.17	0.14	0.14	0.14	0.17	0.22	0.14	0.17
2023	8.6	8.3	10.2	8.7	8.5	8.6	3.6	11.9	8.6	8.7	0.17	0.19	0.20	0.17	0.17	0.17	0.17	0.22	0.17	0.18
2024	14.0	9.3	15.0	12.6	13.9	14.1	3.2	10.1	13.2	13.6	0.21	0.17	0.22	0.19	0.21	0.21	0.13	0.18	0.20	0.21
2025	8.1	12.1	8.8	8.7	7.7	8.1	3.4	9.3	7.8	7.8	0.11	0.18	0.12	0.12	0.11	0.11	0.14	0.16	0.11	0.11
2026	7.9	8.5	9.0	8.4	9.1	7.9	3.3	9.7	8.1	9.6	0.12	0.14	0.14	0.13	0.14	0.12	0.12	0.16	0.13	0.14
2027	9.6	9.6	11.2	9.7	9.8	9.7	4.0	13.2	9.3	10.9	0.16	0.17	0.18	0.16	0.16	0.16	0.18	0.20	0.15	0.16
2028	10.8	18.8	9.6	18.3	11.3	9.2	4.6	14.8	11.0	14.7	0.18	0.34	0.16	0.30	0.19	0.16	0.19	0.24	0.19	0.22
2029	9.6	9.0	10.9	9.4	9.6	9.0	5.9	11.1	8.9	13.4	0.14	0.14	0.16	0.14	0.14	0.14	0.20	0.16	0.14	0.18
2030	7.6	7.2	8.5	7.1	7.3	6.5	14.0	8.4	6.5	12.3	0.11	0.11	0.13	0.10	0.11	0.10	0.33	0.13	0.10	0.16
2031	6.7	7.0	7.1	6.7	6.4	6.3	16.1	7.0	6.2	9.7	0.09	0.10	0.10	0.09	0.09	0.09	0.27	0.10	0.09	0.12
2032	6.0	7.1	6.2	6.0	5.8	5.6	8.0	8.2	5.8	8.1	0.08	0.09	0.08	0.07	0.07	0.07	0.12	0.12	0.07	0.10
2033	8.2	7.9	8.5	8.7	7.1	7.4	11.3	9.5	7.0	13.2	0.10	0.10	0.10	0.10	0.09	0.09	0.15	0.13	0.08	0.14
2034	8.3	7.9	9.6	8.2	8.2	7.7	11.8	6.1	8.3	14.2	0.10	0.09	0.11	0.10	0.10	0.09	0.15	0.08	0.10	0.15
2035	9.7	10.1	9.9	10.7	9.5	9.7	11.1	6.7	9.3	12.2	0.10	0.11	0.11	0.11	0.10	0.10	0.12	0.08	0.10	0.13
2036	8.2	8.3	8.0	9.4	7.6	8.0	10.1	6.1	9.0	8.0	0.08	0.09	0.08	0.09	0.08	0.08	0.11	0.07	0.09	0.08
2037	7.8	8.0	7.3	9.0	7.3	8.1	9.1	6.3	7.4	9.8	0.08	0.08	0.07	0.08	0.07	0.08	0.10	0.08	0.07	0.09
2038	7.7	7.3	6.9	8.1	5.8	7.2	8.1	5.6	7.3	9.0	0.07	0.07	0.06	0.07	0.05	0.07	0.08	0.07	0.07	0.08
2039	6.6	9.5	7.2	5.7	6.5	7.6	7.4	5.6	5.4	8.3	0.07	0.10	0.07	0.06	0.07	0.08	0.08	0.07	0.06	0.08
2040	4.9	5.4	5.0	5.4	4.5	5.1	6.1	5.2	4.9	5.7	0.05	0.05	0.05	0.05	0.04	0.05	0.06	0.06	0.05	0.05
2041	13.9	13.3	15.3	16.7	12.8	15.9	18.5	10.6	13.1	9.7	0.13	0.13	0.15	0.15	0.12	0.15	0.18	0.12	0.12	0.09
2042	15.0	15.3	14.1	14.7	14.0	13.7	17.1	12.2	15.3	13.3	0.13	0.13	0.13	0.12	0.12	0.12	0.17	0.14	0.14	0.11
2043	24.4	28.6	23.9	27.8	24.4	23.8	31.7	19.7	28.3	26.8	0.21	0.25	0.21	0.22	0.21	0.21	0.29	0.20	0.24	0.22
2044	11.2	11.9	17.5	15.2	9.6	9.4	12.4	9.2	12.7	13.4	0.11	0.11	0.17	0.13	0.09	0.09	0.12	0.10	0.12	0.12
2045	12.3	13.5	13.9	14.7	10.4	11.0	14.9	12.9	11.4	14.9	0.11	0.12	0.13	0.12	0.09	0.10	0.14	0.13	0.10	0.12
2046	15.2	18.7	16.0	17.2	13.3	18.8	15.5	13.2	21.6	33.2	0.14	0.17	0.15	0.14	0.12	0.17	0.15	0.14	0.20	0.29
2047	9.7	10.7	10.3	10.9	8.2	8.5	11.8	11.8	9.5	16.3	0.09	0.10	0.10	0.09	0.08	0.08	0.12	0.12	0.09	0.15
2048	23.4	26.4	23.6	14.8	21.5	24.5	32.1	20.1	23.3	56.4	0.21	0.23	0.21	0.13	0.19	0.21	0.30	0.20	0.20	0.49
2049	11.8	18.4	11.3	16.9	11.0	10.8	14.3	12.9	11.1	15.9	0.11	0.17	0.11	0.15	0.10	0.10	0.15	0.13	0.10	0.14
2050	10.1	13.1	11.5	10.1	8.9	10.3	12.8	14.1	12.2	26.5	0.09	0.12	0.11	0.09	0.08	0.09	0.13	0.15	0.11	0.23
Mean	10.1	11.3	10.9	10.8	9.6	10.0	10.7	10.4	10.3	14.0	0.12	0.14	0.13	0.12	0.12	0.12	0.16	0.14	0.12	0.16

Table B.11: Error metrics of the approach using a feedforward neural network with a feedforward neural network classifier (ANNw/C) with the 0.25% worst forecasts per country being filtered. Although only very few data points have been removed, the metrics substantially improve as compared to the full data set (cf. Table B.6).

Year	Mean absolute error (MAE) [EUR/MWh]										Mean absolute percentage error (MAPE) [–]									
	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL
2020	5.1	7.3	7.1	2.5	5.1	5.1	7.8	12.5	5.4	3.0	0.13	0.21	0.17	0.07	0.13	0.13	0.40	0.25	0.14	0.09
2021	4.0	7.1	5.9	3.5	4.0	4.0	7.7	8.9	4.4	4.0	0.10	0.20	0.14	0.09	0.10	0.10	0.39	0.19	0.11	0.11
2022	4.0	7.5	6.6	3.9	4.0	4.0	8.1	11.0	4.3	3.2	0.09	0.20	0.14	0.09	0.09	0.09	0.41	0.21	0.10	0.08
2023	6.2	9.6	7.8	6.1	6.2	6.2	9.2	10.3	6.2	6.7	0.13	0.23	0.16	0.13	0.13	0.13	0.44	0.19	0.13	0.14
2024	32.6	23.9	31.4	29.0	32.5	32.5	12.2	8.7	30.9	30.1	0.47	0.44	0.46	0.43	0.47	0.47	0.50	0.15	0.46	0.43
2025	52.2	45.6	52.1	51.1	52.2	52.2	14.0	8.4	49.3	52.7	0.70	0.64	0.69	0.68	0.70	0.70	0.56	0.14	0.66	0.68
2026	32.1	30.3	32.0	32.0	31.8	31.8	15.2	8.3	31.3	32.8	0.48	0.48	0.48	0.48	0.48	0.48	0.58	0.14	0.47	0.46
2027	10.1	11.8	10.2	9.6	10.0	10.0	13.1	8.4	9.9	11.5	0.17	0.21	0.17	0.16	0.17	0.17	0.58	0.14	0.17	0.18
2028	9.5	11.5	9.5	8.4	9.7	9.6	12.7	8.5	9.3	10.0	0.15	0.20	0.15	0.13	0.16	0.16	0.51	0.13	0.15	0.15
2029	11.0	12.9	11.3	9.5	11.3	11.2	13.1	8.7	11.0	10.3	0.17	0.21	0.17	0.14	0.18	0.17	0.45	0.13	0.17	0.15
2030	12.5	14.0	12.6	10.8	12.8	12.7	15.6	9.5	12.6	11.4	0.18	0.22	0.18	0.15	0.19	0.19	0.38	0.14	0.19	0.15
2031	15.8	16.2	15.0	14.3	15.9	15.8	18.0	9.4	15.7	15.8	0.22	0.23	0.21	0.19	0.22	0.22	0.31	0.14	0.22	0.19
2032	27.2	27.1	25.4	26.6	27.2	27.0	24.2	10.4	27.2	19.1	0.33	0.34	0.31	0.32	0.33	0.33	0.35	0.15	0.33	0.22
2033	31.9	31.8	30.1	31.2	31.7	31.5	29.7	14.9	31.8	26.5	0.37	0.37	0.36	0.36	0.37	0.37	0.39	0.19	0.37	0.29
2034	35.4	34.0	34.9	31.9	35.5	35.3	34.1	17.1	35.4	28.4	0.39	0.39	0.39	0.35	0.40	0.39	0.40	0.21	0.39	0.30
2035	48.1	47.9	47.9	46.5	48.9	48.8	46.8	26.4	48.9	40.5	0.49	0.49	0.48	0.46	0.49	0.49	0.49	0.30	0.49	0.39
2036	51.8	50.9	51.4	51.5	52.5	52.3	49.9	25.4	52.4	45.1	0.51	0.50	0.51	0.49	0.52	0.51	0.50	0.29	0.51	0.42
2037	62.0	58.4	61.5	62.1	62.1	62.0	52.7	26.7	62.0	54.1	0.58	0.55	0.57	0.55	0.58	0.58	0.52	0.29	0.58	0.48
2038	73.3	69.2	72.6	75.3	73.2	73.2	54.0	15.1	73.3	72.2	0.64	0.61	0.64	0.62	0.64	0.64	0.52	0.18	0.64	0.59
2039	58.2	55.8	56.7	58.2	58.0	57.8	45.5	16.1	58.2	54.9	0.56	0.53	0.54	0.52	0.56	0.55	0.45	0.18	0.55	0.49
2040	57.9	57.4	54.7	57.1	57.8	57.6	46.0	16.9	58.0	45.5	0.53	0.52	0.51	0.49	0.53	0.53	0.45	0.19	0.53	0.40
2041	55.8	56.2	51.5	55.4	55.1	55.0	43.9	17.4	55.5	43.1	0.52	0.52	0.48	0.47	0.51	0.51	0.43	0.20	0.51	0.38
2042	64.8	64.3	60.0	66.2	64.5	64.4	48.2	20.3	64.9	49.1	0.55	0.54	0.52	0.51	0.55	0.55	0.45	0.22	0.55	0.40
2043	70.9	70.3	69.0	73.6	71.2	71.0	54.5	31.7	71.6	66.2	0.60	0.59	0.59	0.56	0.61	0.61	0.50	0.31	0.60	0.51
2044	51.7	51.7	49.3	43.9	50.6	50.6	42.3	28.4	51.7	36.4	0.48	0.47	0.46	0.37	0.47	0.47	0.40	0.29	0.48	0.32
2045	53.9	55.3	50.7	48.6	53.5	53.4	46.2	32.6	54.2	40.1	0.46	0.47	0.44	0.38	0.46	0.46	0.42	0.31	0.46	0.31
2046	61.7	63.1	60.0	59.4	62.0	61.9	55.3	40.2	62.8	22.1	0.54	0.54	0.54	0.46	0.55	0.55	0.52	0.39	0.55	0.20
2047	46.1	47.2	43.3	37.5	45.4	45.3	41.0	34.8	46.3	16.3	0.42	0.42	0.40	0.30	0.42	0.42	0.40	0.34	0.42	0.15
2048	68.1	71.1	65.4	26.3	68.8	68.6	61.2	45.6	70.6	17.9	0.59	0.60	0.58	0.22	0.60	0.60	0.58	0.45	0.60	0.16
2049	56.9	58.4	50.3	16.2	56.4	56.5	47.4	37.6	57.8	18.8	0.51	0.51	0.47	0.14	0.51	0.51	0.47	0.38	0.51	0.17
2050	48.4	52.1	48.2	16.2	50.1	49.6	45.7	37.4	50.7	20.1	0.43	0.45	0.44	0.14	0.44	0.44	0.45	0.37	0.44	0.18
Mean	39.3	39.3	38.2	34.3	39.3	39.3	32.7	19.6	39.5	29.3	0.40	0.42	0.40	0.34	0.41	0.40	0.46	0.23	0.40	0.30

Table B.12: Error metrics of the approach using multiple linear regression without classifier (LRw/oC) with the 0.25% worst forecasts per country being filtered. Although only very few data points have been removed, the metrics substantially improve as compared to the full data set (cf. Table B.7).

Year	Mean absolute error (MAE) [EUR/MWh]										Mean absolute percentage error (MAPE) [–]									
	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL
2020	5.1	7.8	7.2	3.8	5.2	5.0	3.3	10.2	5.7	6.0	0.13	0.22	0.17	0.11	0.13	0.13	0.17	0.21	0.14	0.17
2021	5.5	6.2	7.2	4.9	5.3	5.2	2.7	10.0	5.7	5.6	0.13	0.17	0.16	0.13	0.13	0.12	0.14	0.20	0.14	0.15
2022	5.7	6.1	7.8	6.2	6.0	5.9	3.4	11.9	6.0	7.0	0.13	0.16	0.17	0.14	0.14	0.14	0.17	0.22	0.14	0.17
2023	8.6	8.3	10.2	8.7	8.5	8.6	3.6	11.9	8.6	8.7	0.17	0.19	0.20	0.17	0.17	0.17	0.17	0.22	0.17	0.18
2024	13.6	12.2	16.0	17.0	13.7	14.6	7.2	10.5	12.9	14.4	0.20	0.22	0.24	0.26	0.21	0.22	0.28	0.19	0.20	0.22
2025	7.6	10.0	9.8	7.6	7.7	8.3	5.0	8.5	7.1	10.2	0.11	0.15	0.14	0.11	0.11	0.12	0.20	0.15	0.10	0.14
2026	8.6	8.2	10.5	10.2	8.8	9.4	5.1	11.0	8.6	10.9	0.13	0.13	0.16	0.15	0.13	0.14	0.19	0.18	0.13	0.16
2027	6.4	6.7	7.6	7.2	6.1	7.3	3.2	9.8	6.0	7.6	0.11	0.12	0.13	0.12	0.10	0.12	0.15	0.16	0.10	0.12
2028	6.6	7.2	7.3	7.1	6.6	6.8	4.3	9.2	6.7	7.0	0.11	0.13	0.12	0.11	0.11	0.11	0.17	0.15	0.11	0.11
2029	6.7	7.7	8.0	7.5	6.6	6.3	6.4	8.4	6.4	6.9	0.11	0.13	0.12	0.12	0.10	0.10	0.22	0.13	0.10	0.10
2030	7.5	8.6	8.9	10.4	7.1	7.1	13.9	9.8	6.9	9.3	0.11	0.14	0.13	0.15	0.11	0.11	0.33	0.15	0.10	0.12
2031	6.7	9.3	8.9	13.9	7.5	7.6	14.8	9.0	7.4	12.3	0.09	0.14	0.12	0.19	0.11	0.11	0.25	0.13	0.11	0.15
2032	8.4	10.0	10.1	29.8	10.7	10.7	10.5	7.5	8.3	12.7	0.10	0.13	0.13	0.36	0.13	0.13	0.15	0.11	0.10	0.15
2033	8.5	8.5	9.4	32.6	10.3	10.4	10.4	5.8	8.3	10.6	0.10	0.10	0.12	0.39	0.13	0.13	0.14	0.08	0.10	0.12
2034	8.6	7.6	9.1	34.2	8.3	10.3	10.1	7.6	8.0	9.7	0.10	0.09	0.11	0.40	0.10	0.12	0.13	0.10	0.09	0.11
2035	9.8	9.6	10.3	49.6	8.2	10.1	8.5	5.2	8.9	11.1	0.11	0.10	0.11	0.52	0.09	0.11	0.10	0.06	0.10	0.12
2036	9.5	8.4	9.8	59.2	8.1	12.6	7.9	5.3	8.3	11.9	0.10	0.09	0.10	0.59	0.08	0.13	0.09	0.06	0.09	0.12
2037	11.5	10.5	10.7	78.3	10.9	12.2	6.8	6.9	10.0	15.1	0.11	0.10	0.11	0.73	0.11	0.12	0.07	0.08	0.10	0.14
2038	14.1	9.3	13.0	84.3	10.2	13.5	7.6	6.2	14.7	15.0	0.13	0.09	0.12	0.73	0.09	0.12	0.08	0.07	0.13	0.13
2039	14.3	12.2	14.8	62.5	13.9	15.5	8.7	6.3	16.3	16.6	0.15	0.12	0.15	0.58	0.14	0.16	0.09	0.08	0.17	0.16
2040	11.3	9.4	11.0	64.8	9.4	16.1	6.1	5.2	11.5	13.2	0.11	0.09	0.11	0.58	0.09	0.16	0.06	0.06	0.11	0.13
2041	14.8	14.1	14.3	70.7	13.0	15.7	10.8	9.7	14.8	14.6	0.14	0.13	0.14	0.62	0.13	0.15	0.11	0.11	0.14	0.14
2042	16.0	12.9	14.7	71.0	13.8	15.8	11.1	12.0	16.0	16.0	0.14	0.12	0.13	0.57	0.13	0.14	0.11	0.13	0.14	0.14
2043	17.7	13.5	16.2	59.8	16.3	18.0	13.1	18.2	19.5	21.1	0.16	0.12	0.15	0.47	0.15	0.16	0.13	0.19	0.17	0.18
2044	16.5	13.6	10.9	23.6	12.6	18.4	10.6	14.6	16.8	17.6	0.16	0.13	0.10	0.21	0.12	0.18	0.11	0.16	0.16	0.16
2045	17.6	14.5	12.5	24.6	13.4	18.0	12.7	16.3	17.8	20.7	0.16	0.13	0.11	0.20	0.12	0.16	0.12	0.17	0.16	0.17
2046	19.8	16.7	14.5	27.9	16.2	24.8	15.1	18.7	19.5	20.9	0.18	0.15	0.13	0.22	0.15	0.23	0.15	0.19	0.17	0.18
2047	17.1	13.6	13.4	19.2	12.8	15.9	12.5	17.0	16.0	18.2	0.16	0.13	0.13	0.16	0.12	0.15	0.13	0.18	0.15	0.16
2048	22.4	20.2	21.7	28.1	18.1	28.3	21.3	19.6	20.8	21.6	0.20	0.17	0.19	0.23	0.16	0.25	0.20	0.19	0.18	0.19
2049	22.0	16.5	15.6	16.0	14.4	18.7	16.4	17.9	18.9	20.0	0.20	0.15	0.15	0.14	0.13	0.17	0.17	0.19	0.17	0.18
2050	22.3	17.6	16.2	17.5	14.6	16.8	16.2	20.3	19.6	21.3	0.20	0.15	0.15	0.15	0.13	0.15	0.16	0.21	0.17	0.19
Mean	12.0	10.9	11.5	30.9	10.5	12.7	9.3	11.0	11.7	13.4	0.14	0.14	0.14	0.31	0.12	0.15	0.15	0.15	0.13	0.15

Table B.13: Error metrics of the approach using a feedforward neural network without classifier (ANNw/oC) with the 0.25% worst forecasts per country being filtered. Although only very few data points have been removed, the metrics substantially improve as compared to the full data set (cf. Table B.8).

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Paper C

On the Role of Electricity Storage in Capacity Remuneration Mechanisms

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Abstract

In electricity markets around the world, the substantial increase of intermittent renewable electricity generation has intensified concerns about generation adequacy, ultimately driving the implementation of capacity remuneration mechanisms. Although formally technology-neutral, substantial barriers often exist in these mechanisms for non-conventional capacity such as electricity storage. In this article, we provide a rigorous theoretical discussion on design parameters and show that the concrete design of a capacity remuneration mechanism always creates a bias towards one technology or the other. In particular, we can identify the bundling of capacity auctions with call options and the definition of the storage capacity credit as essential drivers affecting the future technology mix as well as generation adequacy. In order to illustrate and confirm our theoretical findings, we apply an agent-based electricity market model and run a number of simulations. Our results show that electricity storage has a capacity value and should therefore be allowed to participate in any capacity remuneration mechanism. Moreover, we find the implementation of a capacity remuneration mechanism with call options and a strike price to increase the competitiveness of storages against conventional power plants. However, determining the amount of *firm* capacity an electricity storage unit can provide remains a challenging task.

C.1 Introduction

The substantial increase of renewable electricity generation in countries around the world brings along new challenges for the appropriate design of electricity markets. Due to the highly intermittent nature of solar and wind power, a certain amount of dispatchable capacity will likely also be required in the future, i.e., even under very high shares of renewables. At the same time, however, the reduced number of hours with scarcity and therefore price spikes leads to substantial risks for investments in this *firm* capacity.

Driven by such considerations, so-called capacity remuneration mechanisms (CRMs) have been implemented in several regions of the world as an extension to the energy-only market (EOM), in which capacity providers are solely compensated for the amount of electricity they sell on the markets. In the US, the earliest such mechanisms date back to the late 1990s. In recent years, also several European countries have started implementing different kinds of CRMs (Bublitz et al., 2019). All of these mechanisms typically aim to reduce the risks for new investments by offering capacity providers supplementary income on top of the earnings from selling electricity on the market. The additional generation, storage or demand side management (DSM) capacity may then in turn help to improve generation adequacy, i.e., avoid shortage situations.

Critical voices claim that CRMs are nothing but hidden subsidies to operators of conventional power plants while other alternative capacity providers, such as electricity storage or DSM, barely face any chance of successfully participating in these mechanisms. Formally, the European Commission requires full technology neutrality from any CRM to be implemented in Europe (European Commission, 2013). The situation is similar in the US, where the Federal Energy Regulatory Commission has recently directed grid operators to remove barriers that hinder storage from participating in wholesale energy, capacity and ancillary services markets and to define rules for their efficient remuneration taking into account physical and operational characteristics of such units (Sakti et al., 2018).

However, while most CRMs in Europe and the US generally allow the participation of storage and demand side units, the concrete rules applied differ substantially (Sakti et al., 2018; Usera et al., 2017). This is mostly due to the non-trivial question of whether and how much *firm* capacity such units can contribute to system adequacy. While conventional power plants can provide full power output throughout scarcity periods of whatever length, storage units are not able to do so due to their limited storage volume. The situation is similar for DSM, yet we exemplary focus on storage technologies in the remainder of this paper.

The rules defined for storage participation in a given CRM have a strong impact on the competitiveness of these technologies. For example, in the PJM[24] market area, storages are treated as conventional resources and therefore need to be available anytime PJM announces emergency conditions, no matter how long these situations may last (Chen et al., 2017; Usera et al., 2017). Consequently, storage operators need to fully manage the risk of their offers themselves and are subject to penalties if they fail to deliver their contracted capacity. Due to the energy-limited nature of electricity storage, this is a very rigorous requirement,

[24]Pennsylvania–New Jersey–Maryland Interconnection, a system operator in the US.

basically excluding storages from participation in the CRM. Contrary, CAISO[25] requires contracted capacity of its CRM to deliver their full output for at least four consecutive hours and to do so over three consecutive days (Usera et al., 2017).

A different approach has been chosen in Ireland and the United Kingdom, where methodologies to determine derating factors for storage technologies based on adequacy metrics have recently been developed (National Grid, 2017; Single Electricity Market Committee, 2016, 2018). These factors mostly depend on the individual storage volume of a given unit and are subject to future adjustments. Applying derating factors essentially aims to base the remuneration on the capacity credit of storages, i.e., these units are only remunerated for the amount of *firm* capacity they are able to provide rather than for their *nameplate* (or *nominal*) capacity. Such an approach is also suggested by Usera et al. (2017), as it may help electricity storage to compete in CRMs as compared to treating them in the same way as conventional resources.

These examples show, that there still exists no consensus about the role of electricity storage in CRMs. While it is generally agreed that these technologies have some kind of capacity value, the specific rules of participation in CRMs may hinder them from being competitive against conventional resources. It is thus the objective of this paper, to delve into the question how the concrete design of a CRM may create a bias towards or against storage technologies and thereby affect the future technology mix as well as long-term generation adequacy.

The remainder of this paper is structured as follows. Section C.2 provides an overview of the relevant literature and derives the research gap this paper aims to fill. In Section C.3, a generic capacity auction mechanism is first set up and a rigorous theoretical discussion is then provided, which highlights how bundling a CRM with call options[26] and the choice of a storage derating factor may affect the

[25] California Independent System Operator.

[26] More precisely, real-world CRMs typically apply *tolling agreements*, which are a series of hourly call options with varying strike prices. However, given the non-availability of hourly resoluted projections up to 2050 in the literature, we assume constant fuel and carbon prices over the course of a year throughout this paper. In consequence, we also apply constant strike prices in a given future year. We therefore refer to *call options* rather than using the technically more correct term *tolling agreements*. This does however not diminish the validity of our results, but rather makes the analyses more concise. Please also note that while CRM typically have a long-term focus (i.e., multiple years), *tolling agreements* can also be used independently from a CRM and may then cover shorter time periods, e.g., one year.

competitiveness of storage units against conventional power plants. In order to illustrate and confirm the theoretical findings, a multi-period long-term electricity market model is applied and a number of simulations are run in Section C.4. Ultimately, Section C.5 provides a summary of the findings, draws conclusions and derives relevant policy recommendations.

C.2 Literature Review and Research Gap

In the following, an overview of existing literature relevant for this article is provided. Although the article sets an explicit focus on electricity storage, some literature on DSM is also reviewed due to strong analogies between these technologies.

In a brief quantitative analysis, Schmitz et al. (2013) can show that excluding pumped storages from CRMs leads to a less efficient technology mix and ultimately welfare losses. The authors further provide a qualitative discussion on how the choice of CRM design parameters may create a bias against pumped storages. However, many of the parameters found to have an impact on pumped storages due to their capital cost intensity (contract duration, lag period, regional differentiation, market share) are much less relevant for novel storage technologies such as batteries.

Mays et al. (2019) very recently provided first evidence that bundling CRMs with call options has an asymmetric effect on different generation technologies and creates a bias towards resources with lower fixed costs and higher operating costs, i.e., peaker units. They conclude that current market structures might not be suitable to finance low-carbon resources, which are characterised by high fixed costs and near-zero operating costs. However, the authors use a rather stylistic setup and do not consider electricity storage, but only conventional and renewable generation technologies.

Another particularly relevant design parameter is the appropriate determination of so-called capacity credit metrics for storages. Different methods have been applied in this context, including approximations (Tuohy and O'Malley, 2009), dynamic programming (Sioshansi et al., 2014) and iterative algorithms coupled with Monte Carlo experiments (Borozan et al., 2019; Zhou et al., 2015, 2016).

Yet, none of these contributions looks into the role of the derived capacity credits in the context of a CRM.

There exist, however, also a few studies investigating the interdependencies between CRMs and electricity storage or DSM, which we present next.

Lynch et al. (2019) set up a mixed complementary problem to model an electricity system with energy and reserve markets as well as a quantity-based capacity market. They use their model in a case study for Ireland and find that DSM has an inherent capacity value. The authors conclude that DSM should be eligible to participate in CRMs since welfare losses would occur otherwise.

Opathella et al. (2019) introduce a capacity market model including a capacity demand curve as well as electrical storage and apply the developed model in a case study for Ontario. In doing so, they find derating factors to be a crucial factor deciding on the competitiveness of electricity storage.

Teng and Strbac (2016) evaluate different multi-service business cases for bulk electricity storage. In doing so, the authors also rudimentally consider storage participation in a CRM by reserving capacity during the peak periods and assuming a fixed capacity remuneration. They find that the restrictions due to the CRM only marginally reduce storage profits from the other markets and conclude that a CRM can contribute to a profitable business case for storages.

Askeland et al. (2019) apply a linear complementary model to analyze an EOM as well as a CRM in a European multi-country case study. The authors find that the CRM incentivizes substantial amounts of additional open cycle gas turbines, but also a little additional storage capacity as compared to the EOM. Moreover, they investigate the impact of different storage derating factors in the CRM and conclude that derating may lead to a substantial bias towards conventional power plants.

Khan et al. (2018) apply a hybrid electricity market model which uses optimization for short-term market operations and agent-based simulation of long-term investment decisions. The model is used to investigate an isolated and uncongested electricity market, which either relies on a pure EOM or has an additional CRM implemented. For both of these market designs, different settings with or without electricity storage and DSM are analyzed. The business case for storages is found to be better in the EOM setting than under a CRM, as scarcity prices allow for a larger arbitrage profit in this setting.

In the context of the existing literature, the contribution of this paper is as follows. To start with, for the first time, a rigorous theoretical discussion is presented on why and how bundling a CRM with call options and the choice of a storage derating factor may affect the competitiveness of storage units against conventional power plants.

Moreover, a multi-period long-term electricity market model is applied and a number of simulations are run to confirm the theoretical results. This contribution is therefore also the first in the literature to quantitatively analyze the impact of bundling a CRM and call options with a strike price on the competitiveness of storage units. Last but not least, our simulation approach differs from those presented in the literature to date in several important aspects.

Firstly, we consider a region covering several interconnected European market areas. Like this, we are able to adequately take cross-border effects into account, an aspect that we regard essential in light of the ongoing strong increase in cross-border transmission capacity. In the existing literature, either only a single country is considered (Khan et al., 2018; Lynch et al., 2019; Opathella et al., 2019; Teng and Strbac, 2016) or an unlimited interconnection capacity between the modeled countries is assumed (Askeland et al., 2019).

Secondly, we model multiple investment decision, capacity auction and day-ahead market periods, which is important due to potential path dependencies and lock-in effects. Most of the literature only considers a single capacity auction period (Askeland et al., 2019; Lynch et al., 2019; Opathella et al., 2019; Teng and Strbac, 2016). Moreover, Opathella et al. (2019) and Teng and Strbac (2016) do not model endogenous investment decisions at all, while Askeland et al. (2019) use a greenfield approach instead of considering the existing generation fleets.

Thirdly, electricity storage is fully integrated into the investment module of our model by determining its maximum future arbitrage potential and deriving expected future profits. Despite the computational burden of this approach, we consider it the only possibility to have a real trade-off between different investment options, i.e., conventional power plants and storages. In contrast, Khan et al. (2018) only very rudimentally implement storage investments by considering historical profits rather than expected future profits as for the conventional power plant technologies. This is not only a strong simplification but also an inconsistent approach.

Fourthly, we also fully integrate electricity storage into the CRM module of our model by considering different storage derating strategies. This is an essential aspect as the literature suggests that the *nameplate* capacity of storage is not identical with the amount of *firm* capacity that this technology can provide. In contrast, Khan et al. (2018) use the rather basic approach of having the storages bid their full *nameplate* capacity.

We can conclude that the applied simulation approach allows for the consideration of dynamic aspects and interdependencies in terms of time (multiple decision periods), space (multiple interconnected countries), technologies (different conventional power plants and types of storage) and markets (EOM and CRM) with an explicit focus on the development of the future technology mix as well as long-term generation adequacy. To the best of our knowledge, such an approach is unique in the literature available to date and highly suitable to investigate the role of electricity storage in CRMs.

C.3 Theoretical Discussion on Relevant Design Parameters

In this section, a theoretical discussion on CRM design and its impact on the competitiveness of electricity storage against conventional power plants is presented. For this purpose, a generic CRM is first set up (Section C.3.1) and it is then shown that bundling a CRM with call options and derating of storage capacity are essential drivers for the competitiveness of storages. These two drivers are ultimately analysed in more detail in Sections C.3.2 and C.3.3.

C.3.1 Generic Capacity Auction Mechanism

CRMs are typically designed to maintain generation adequacy and ultimately avoid shortage situations by offering capacity providers income on top of the earnings from selling electricity on energy markets. Although mechanisms may vary substantially in the way the required capacity and the corresponding capacity prices are determined, all types of CRMs should in theory lead to similar outcomes[27].

[27]For a detailed overview of different types of CRMs and their typical characteristics, please refer to Bublitz et al. (2019). Please note that apart from CRMs other instruments exist to

Therefore, without loss of generality, we assume a so-called central buyer mechanism with reliability options in the following. Such mechanisms are currently used by the US system operator ISO-NE[28] (Byers et al., 2018) as well as in Italy (Mastropietro et al., 2018; Perico et al., 2018) and Ireland (Single Electricity Market Committee, 2015). In a central buyer mechanism, a regulator first determines the total amount of *firm* capacity to be procured in a centralized auction and other auction parameters. All successful participants of the auction are then rewarded with the marginal capacity price of the auction.

In order to ensure that sufficient capacity is actually available when needed, the regulator may impose capacity derating factors f^{derate} in the auction, e.g., based on historical availability data or technology-specific considerations. We assume in the following that storage units are generally eligible to participate in the capacity auction, however need to be able to provide *firm* capacity over a predefined discharge duration[29].

Vàzquez et al. (2002) propose combining the capacity auctions with financial call options, so-called reliability options. In exchange for the earnings through the fixed capacity remuneration provided in the auctions, the earnings from the energy markets are then reduced by setting a price cap p^{limit} on the market prices. If the electricity price rises above the price cap, the so-called strike price of the call option, the generators will have to return the peak energy rent, which is the difference between market price and strike price, to the regulator. Like this, electricity consumers are protected from unreasonably high prices while at the same time the capacity remuneration provides a more secure income to the generators which no longer have to rely on infrequently occurring price spikes. Typically, capacity providers will have to return the peak energy rent to the regulator anytime there is a positive difference between market price and strike price, regardless of whether they were able to produce in the given period or not. This reflects an *implicit*

address the *missing money problem*, e.g., tolling agreements. The expected payoff of a one-year tolling agreement is then comparable to the capacity price of a CRM, both of which describe a revenue per capacity unit and year.

[28]Independent System Operator New England.

[29]Although a typical design parameter, we refrain from considering an *explicit* penalty for non-availability during scarcity periods, since electricity prices typically rise substantially in such situations and thus, there exists already a strong incentive to be available.

penalty for non-availability during scarcity periods, which is particularly crucial for electricity storage.

Imagine a multi-hour scarcity period with high market prices well above the strike price. Contrary to conventional power plants, storage units may then not be able to produce during the whole peak period, simply due to their limited energy content and consequently the storage running empty. Storage units may be exempt from the *implicit* penalty in such situations, as long as they were successfully providing their contracted capacity for the required discharge duration predefined by the regulator. This option implies that the risk of adequately derating storage capacity lies with the regulator. Alternatively, storage units may remain subject to the *implicit* penalty, even if their non-availability is caused by the storage running empty. Quite obviously, this latter option leaves a huge risk with the storage operators, basically excluding them from participation in the capacity auctions. This approach therefore seems not reasonable, if technology neutrality is to be achieved. Nevertheless, when looking at the impact of call options in more detail (Section C.3.2), we consider both variants.

Let us further define that generators receive the remuneration of the capacity auction for a fixed amount of years n^{CRM}. Under the described assumptions, we can now derive bidding strategies of an economically rational generator for a new generation or storage unit p. For this purpose, the so-called difference costs DC_p need to be computed, which describe the delta between the income needed for an investment to reach profitability and the net present value if the unit was optimally operated on the electricity market. This relation is shown in Eq. (C.1). Please note that the difference costs are only positive in case of negative net present values, while for investments already profitable without additional capacity remuneration, it is rational to bid into the capacity auction at zero cost to maximize the chances of being contracted and receiving additional capacity remuneration.

The calculation of the specific net present value for a new generation or storage unit p is shown in Eq. (C.2), where c_p^{invest} denotes the total investment expenses, δ_p the construction time in years, c_p^{fix} the fixed expenditures for operation and maintenance per year, i the discount rate, n_p the investment horizon in years and $CM(p^{\mathrm{limit}})_{p,y}$ the annual contribution margins on the electricity market. Please note that the contribution margins depend crucially on the level of the strike price p^{limit} of the call option, as will be discussed in Section C.3.2. Eq. (C.3) shows how the difference costs relate to the rational capacity bid price p_p^{CRM} for a unit p. Inserting Eqs. (C.2) and (C.3) into Eq. (C.1) and solving for p_p^{CRM}, we ultimately obtain the rational capacity bid price for investment option p as shown in Eq. (C.4).

$$DC_p = \max\left(-NPV_p, 0\right) \tag{C.1}$$

$$NPV_p = -\sum_{y=0}^{\delta_p-1} \frac{c_p^{\mathrm{invest}}/\delta_p}{(1+i)^y} + \sum_{y=\delta_p}^{n_p+\delta_p} \frac{CM(p^{\mathrm{limit}})_{p,y} - c_p^{\mathrm{fix}}}{(1+i)^y} \tag{C.2}$$

$$DC_p \overset{!}{=} f_p^{\mathrm{derate}} \cdot p_p^{\mathrm{CRM}} \cdot \sum_{y=\delta_p}^{n^{\mathrm{CRM}}+\delta_p} \frac{1}{(1+i)^y} \tag{C.3}$$

$$p_p^{\mathrm{CRM}} = \frac{\max\left(\sum_{y=0}^{\delta_p-1} \frac{c_p^{\mathrm{invest}}/\delta_p}{(1+i)^y} - \sum_{y=\delta_p}^{n_p+\delta_p} \frac{CM(p^{\mathrm{limit}})_{p,y}-c_p^{\mathrm{fix}}}{(1+i)^y}, 0\right)}{\left(\sum_{y=\delta_p}^{n^{\mathrm{CRM}}+\delta_p} \frac{1}{(1+i)^y} \cdot f_p^{\mathrm{derate}}\right)} \tag{C.4}$$

We now apply a few additional simplifications to bring Eq. (C.4) into a more concise form.

(1) The contribution margins only depend on the respective technology and an option strike price, but are otherwise constant through all years under investigation – see Eq. (C.5a).
(2) The fixed costs are set as a percentage k_0 of the investment expenses – see Eq. (C.5b).
(3) Construction time and investment horizon are identical for all technologies – see Eqs. (C.5c) and (C.5d).
(4) Two additional constants k_1 and k_2 are defined, which are independent of the technology as long as assumption (3) holds – see Eqs. (C.5e) and (C.5f).

$$CM(p^{\mathrm{limit}})_{p,y} = CM(p^{\mathrm{limit}})_p \quad \forall p, y \tag{C.5a}$$

$$c_p^{\mathrm{fix}} = k_0 \cdot c_p^{\mathrm{invest}} \quad \forall p \tag{C.5b}$$

$$\delta_p = \delta \quad \forall p \tag{C.5c}$$

$$n_p = n \quad \forall p \tag{C.5d}$$

$$k_1 = \sum_{y=\delta}^{n+\delta} \frac{1}{(1+i)^y} \Bigg/ \sum_{y=\delta}^{n^{\mathrm{CRM}}+\delta} \frac{1}{(1+i)^y} \tag{C.5e}$$

$$k_2 = k_0 + \sum_{y=0}^{\delta-1} \frac{1}{\delta(1+i)^y} \Bigg/ \sum_{y=\delta}^{n+\delta} \frac{1}{(1+i)^y} \tag{C.5f}$$

Applying the simplifications of Eqs. (C.5a)–(C.5f) to Eq. (C.4) finally leads us to the much more concise form presented in Eq. (C.6).

$$p_p^{\mathrm{CRM}} = \frac{k_1}{f_p^{\mathrm{derate}}} \cdot \max\left(k_2 \cdot c_p^{\mathrm{invest}} - CM(p^{\mathrm{limit}})_p, 0\right) \tag{C.6}$$

We can now see from Eq. (C.6) that the relation of investment expenses c_p^{invest}, contribution margins $CM(p^{\mathrm{limit}})_p$ and derating factor f_p^{derate} decides which technology option is able to bid the lowest capacity price p^{CRM}. To be more precise, there are essentially only these three drivers, on which ultimately the capacity auction outcome and in particular the resulting technology mix in the electricity market depends.

The investment expenses c_p^{invest} primarily depend on the specific technology p and cannot be directly influenced by the regulator of the capacity auction. However, particularly for emerging technologies, technological learning is likely to lead to substantial cost reductions in the future. For this reason, the simulation studies carried out later in this paper use dynamic investment expenses for all storage technologies.

Although the achievable contribution margins $CM(p^{\mathrm{limit}})_p$ largely depend on the respective technology, they can also be directly influenced by the regulator by implementing call options with a certain strike price on the electricity market. We will discuss the impact of this design parameter in more detail in Section C.3.2.

The derating factors f_p^{derate} are technology-specific and particularly relevant for storage technologies. This parameter can be directly set by the regulator. More theoretical details on this design choice are presented in Section C.3.3.

C.3.2 Impact of a Combination with Call Options

Fig. C.1 presents a stylized example of the day-ahead market in the future. In the first period $t_0, ..., t_1$, high feed-in of renewables results in a low price p^{low}, while

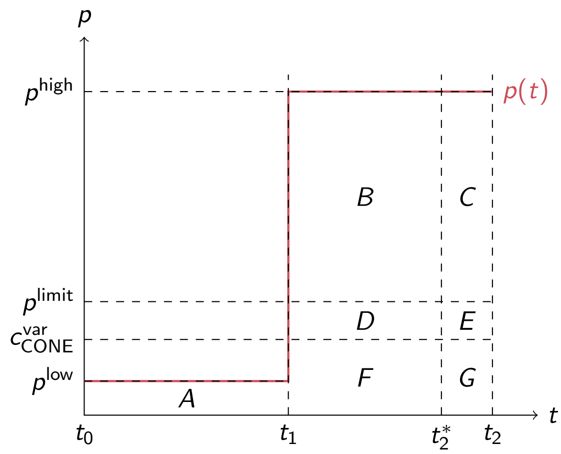


Figure C.1: Stylized example of the day-ahead market in the future with a low price period followed by a high price period.

in the subsequent second period $t_1, ..., t_2$, low feed-in from renewables and a lack of capacity leads to scarcity and high prices p^{high}. This is a situation as as it may frequently occur in the future under ongoing strong expansion of renewables. For the described setting, Table C.1 summarizes the contribution margins that a conventional power plant and a storage unit could make in different cases with and without a strike price.

A conventional power plant with total variable costs c^{var} would only operate when the market price $p(t)$ exceeds its variable costs, i.e., in the period $t_1, ..., t_2$. The corresponding specific contribution margins of the power plant if no strike price is set (Case 1) and if a strike price is set (Cases 2a and 2b) can be calculated using Table C.1 and are shown in Eq. (C.7), where $\Delta t = t_2 - t_1$.

$$\frac{CM^{\text{conv}}}{\Delta t} = \begin{cases} p^{\text{high}} - c^{\text{var}}, & \text{for Case 1} \\ p^{\text{limit}} - c^{\text{var}}, & \text{for Cases 2a/b} \end{cases} \tag{C.7}$$

A storage unit with round-trip efficiency η^{stor} could use the low prices in the period $t_0, ..., t_1$ to charge up to the maximum storage level and then discharge in the subsequent high price period $t_1, ..., t_2^*$. Please note that due to the limited storage volume as well as conversion losses, the unit can only sell electricity in a

Table C.1: Contribution margin of a conventional power plant and storage unit in the stylized example with a low price period followed by a high price period (cf. Fig. C.1).

Case	Strike price	Risk of empty storage	Power plant	Storage unit
1	No	Regulator	$B+C+D+E$	$B+D+F-A$
2a	Yes	Storage operator	$D+E$	$D+F-A-C$
2b	Yes	Regulator	$D+E$	$D+F-A$

certain share of the high price period[30]. The maximum revenues of the storage unit are therefore lower than those of the conventional power plant.

The specific contribution margins of the storage if no strike price is set (Case 1) and if a strike price is set (Cases 2a and 2b) can again be calculated using Table C.1 and are shown in Eq. (C.8), where $\Delta t = t_2 - t_1 = t_1 - t_0$. Please note, that, in case reliability options with a strike price are implemented, the margin depends on whether the storage operator (Case 2a) or the regulator (Case 2b) bears the risk of the storage running empty in a multi-hour scarcity period. In Case 2a, the storage operator would have to pay the difference between market price and strike price to the regulator during its non-availability in the period $t_2^*, ..., t_2$. Using $\Delta t^{**} = t_2 - t_{2^*} = \Delta t(1 - \eta^{\text{stor}})$, this is essentially an *implicit* penalty of $pen = \Delta t(1 - \eta^{\text{stor}})(p^{\text{high}} - p^{\text{limit}})$, corresponding to area C in Fig. C.1. Contrary, in Case 2b, the storage operator is exempt from the *implicit* penalty and can therefore achieve a higher contribution margin.

$$\frac{CM^{\text{stor}}}{\Delta t} = \begin{cases} \eta^{\text{stor}} p^{\text{high}} - p^{\text{low}}, & \text{for Case 1} \\ p^{\text{limit}} - p^{\text{low}} - p^{\text{high}}(1 - \eta^{\text{stor}}), & \text{for Case 2a} \\ \eta^{\text{stor}} p^{\text{limit}} - p^{\text{low}}, & \text{for Case 2b} \end{cases} \tag{C.8}$$

Whether a conventional power plant or a storage unit is better off in the given situation thus depends on different factors: the party bearing the risk of an empty storage, the absolute levels of p^{low}, p^{high}, c^{var} and p^{limit} (if applicable) as well as the storage volume $s^{\max}$ and round-trip efficiency η^{stor}. In systems with high shares

[30] Assuming an empty storage in t_0, the share can easily be computed as $\Delta t^* = t_2^* - t_1 = \eta^{\text{stor}}(t_2 - t_1)$. Alternatively, it would be possible to discharge at lower capacity throughout the period $t_1, ..., t_2$. Since the prices are assumed constant during $t_1, ..., t_2$, this storage operation would lead to the exact same profit.

of renewable electricity generation, it is reasonable to assume a lower price of $p^{\text{low}} = 0\,\text{EUR/MWh}_{\text{el}}$.

Eqs. (C.7) and (C.8) ultimately lead us to Eq. (C.9), which shows the condition that needs to hold for the storage unit to gain a competitive advantage over the conventional power plant in the different cases. We can see that the condition for Cases 1 and 2a is identical and independent of the strike price level p^{limit}. Therefore, if the storage operator itself has to bear the risk of an empty storage and is then subject to an *implicit* penalty, the introduction of a strike price does not lead to a discrimination of any technology. However, setting p^{high} to the typical European day-ahead price limit of $3000\,\text{EUR/MWh}_{\text{el}}$ and using a rather ambitious storage round-trip efficiency of $\eta^{\text{stor}} = 90\,\%$, we can derive that a storage unit would only be better off under very high variable costs of the conventional power plant $c^{\text{var}} > 300\,\text{EUR/MWh}_{\text{el}}$ (in this specific setting). This is a rather unrealistically high value from today's perspective, but may well become true in the future, if carbon emission allowances reach a sufficiently high price level.

$$CM^{\text{stor}} > CM^{\text{conv}} \Leftrightarrow \begin{cases} p^{\text{high}}(1-\eta^{\text{stor}}) < c^{\text{var}}_{\text{CONE}}, & \text{for Cases 1/2a} \\ p^{\text{limit}}(1-\eta^{\text{stor}}) < c^{\text{var}}_{\text{CONE}}, & \text{for Case 2b} \end{cases} \tag{C.9}$$

If, however, a strike price is introduced and the regulator bears the risk of the storage running empty (Case 2b), the condition for the storage unit to be better off than the conventional power plant becomes dependent on the strike price level p^{limit}. Consequently, in this setting, storage units would benefit from the introduction of reliability options with a certain strike price. If the strike price is set equal to the variable costs of a new conventional power plant, i.e., $p^{\text{limit}} = c^{\text{var}}_{\text{CONE}}$, the contribution margin of storage units would always be at least equal, but likely higher, than that of conventional power plant.

As previously mentioned, leaving the risk of a storage running empty during a long scarcity period with the storage operator, would basically exclude this technology from participation in the capacity auctions. In the remainder of this paper, and in particular for the simulations carried out in Section C.4, we therefore assume, that the regulator bears this risk and the storage operators are exempt from the *implicit* penalty.

C.3.3 The Role of Storage Derating

A relatively simple way of determining derating factors for storage technologies is the definition of a minimum discharge duration requirement by the regulator. Using this approach, also storage units with a small storage volume can participate in the capacity auctions, yet are only remunerated for a certain share of their capacity. The relation between derating factor f_p^{derate} for technology p, achievable discharge duration $t_p^{\text{discharge}}$ at full capacity $c_p^{\max}$ and required discharge duration t^{required} is shown in Eq. (C.10). The achievable discharge duration can also be expressed using storage volume $s_p^{\max}$, maximum discharge capacity $c_p^{\max}$ and discharge efficiency $\eta_p^{\text{discharge}}$. Please note that the derating factor is limited to 1, since large storage volumes might otherwise lead to a storage unit being remunerated for more than its maximum discharge capacity.

$$f_p^{\text{derate}} = \min\left(\frac{t_p^{\text{discharge}}}{t^{\text{required}}}, 1\right) = \min\left(\frac{s_p^{\max} \cdot \eta_p^{\text{discharge}}}{c_p^{\max} \cdot t^{\text{required}}}, 1\right) \tag{C.10}$$

Fig. C.2 illustrates the impact of varying the storage duration requirements t^{required} in a capacity auction. For this purpose, three exemplary technologies and their respective difference costs C^{diff} are presented, namely a conventional power plant (e.g., an open-cycle gas turbine), a small storage unit (e.g., a lithium-ion battery) and a large storage unit (e.g., an electric thermal storage[31]). Please note that the stylized example assumes a situation in the future, where storage technologies have reached cost-competitiveness with conventional power plants.

In this setting, the conventional power plant has constant difference costs since it is not affected by the required storage duration. Contrary, the capacity of the small storage unit is already derated under relatively low storage duration requirements due to its limited storage volume. Increasing the storage duration requirements comes along with stronger derating, ultimately resulting in a constant linear increase of the difference costs. Due to its larger storage volume and consequently longer achievable discharge duration $t^{\text{discharge}} = t'$, the difference costs of the large

[31] We base the characteristics of this technology on the concept presented by Siemens Gamesa (2019), which consists of a resistive heater for the charging process, volcanic stones as storage medium and a water steam cycle for the discharging process. Due to the large share of low-cost off the shelf components, we expect this technology to soon become one of the most cost-efficient large-scale electricity storage technologies available.

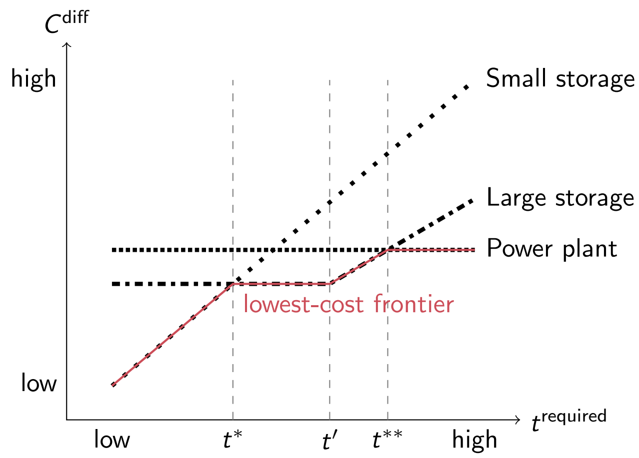


Figure C.2: Impact of different storage duration requirements on the difference costs of a conventional power plant, a small storage unit and a large storage unit in a stylized example.

storage unit remain constant for storage duration requirements of $t^{\text{required}} \leq t'$. Yet, for higher storage duration requirements, also the capacity of this technology is derated leading to a constant linear increase of its difference costs.

As a result, two tipping points regarding the lowest-cost technology to provide the required (equivalent) capacity can be observed in this specific setting (solid red line in Fig. C.2). For storage duration requirements of $t^{\text{required}} \leq t^*$, the small storage unit is the best of the three available options. Increasing the requirements to $t^* < t^{\text{required}} \leq t^{**}$, the large storage unit becomes preferable. Finally, under even higher requirements of $t^{\text{required}} > t^{**}$, the conventional power plant is the cheapest option, since it is the only technology not affected by derating factors.

Apart from the described impact on technology choice, the choice of the derating factors also has another somewhat inverse effect. Since the total amount of *firm* capacity to be procured in the capacity auctions is typically predefined, stronger derating of storage technologies leads to a lower capacity contribution of these units and therefore a higher amount of *nameplate* capacity to be contracted in order to fulfill the desired *firm* capacity target. Thus, depending on the relation of the different technologies' difference costs, stronger derating of storages may indeed even lead to more storage investments being carried out despite the higher capacity prices bid into the auction. In the stylized example, the highest amount of small storage investments could therefore be expected for storage duration requirements marginally below t^*, and analogously for large storages at requirements marginally below t^{**}. Please note that this effect only occurs as long as the capacity demand is fixed and not price sensitive. In many US markets (PJM, ISO-NE, NYISO[32]) this is not the case as they apply downward-sloping capacity demand curves in their auctions (Byers et al., 2018).

C.4 Simulation Study

In order to verify our theoretical findings regarding the impact of CRM design parameters on the competitiveness of storage, we now apply a multi-country long-term electricity market model to investigate these parameters in realistic and complex real-world settings. For this purpose, we first provide a brief introduction to the applied model (Section C.4.1) and the necessary input data (Section C.4.2). We then present developments under a European EOM, which serves as a benchmark (Section C.4.3). Subsequently, we set up a number of additional simulations illustrating the impact of implementing capacity auctions with call options (Section C.4.4) as well as different storage derating factors in these auctions (Section C.4.5) on investments in storage units.

Please note that the applied model has an explorative rather than a normative character. Thus, by simulating system behavior that emerges from individual actors' decisions, we want to analyze which technologies *would* be successful in the capacity auctions and receive support to come into the market under a specific setting. In contrast, we explicitly do not investigate which technologies *should* be supported to achieve a certain goal targeted by the regulator.

C.4.1 Model Overview and Relevant Extensions

PowerACE is an established agent-based simulation model developed for the analysis of European electricity markets in long-term scenario analyses. The initial model version is documented in Genoese (2010). Other previous applications of the model in different configurations include Bublitz et al. (2017), Keles et al. (2016) and Ringler et al. (2017). The model runs at hourly resolution (8760 h/a)

[32]New York Independent System Operator.

over a typical time horizon from 2015 up to 2050. PowerACE covers different market segments with a focus on the day-ahead market and different types of CRMs.

As shown in Figure C.3, various agents represent the associated market participants, such as utility companies, regulators and consumers. The electricity suppliers can decide on the daily scheduling of their conventional power plants and storage units as well as on the construction of new conventional generation or storage capacities based on expected future profits (see Appendix C.6.1). Thus, the short-term and long-term decision levels are jointly considered and their interactions can be investigated. Ultimately, the development of the markets emerges from the simulated behavior of all agents. A model validation is provided in Ringler et al. (2017).

PowerACE has been substantially extended for the analyses of this paper. Firstly, a bidding algorithm for the participation of storage units in the day-ahead market has been developed, which is described in detail in Fraunholz et al. (2017). Secondly, the existing investment planning procedure has been modified from a national perspective to a cross-border perspective and storage technologies have been included as additional investment candidates (for details, see Fraunholz et al., 2019). Thirdly, storage technologies have been integrated in the modeled CRMs. For this purpose, in particular the two new parameters *price cap* and *required storage duration* were implemented. Please note that the described consideration of storage technologies in all relevant parts of PowerACE is challenging, as it adds a time-coupled component to the model.

C.4.2 Data and Assumptions

Due to its nature as a detailed bottom-up simulation model, PowerACE requires substantial amounts of input data. Table C.2 provides an overview of the data used in all simulations presented in the following as well as the respective sources. Please refer to Appendix C.6.2 for details on the techno-economic characteristics of the different investment options as well as fuel and carbon prices. In the following paragraphs, additional assumptions are briefly described.

In order to adequately capture the variety of different electricity market designs in Europe, the regional scope of the applied version of PowerACE covers several

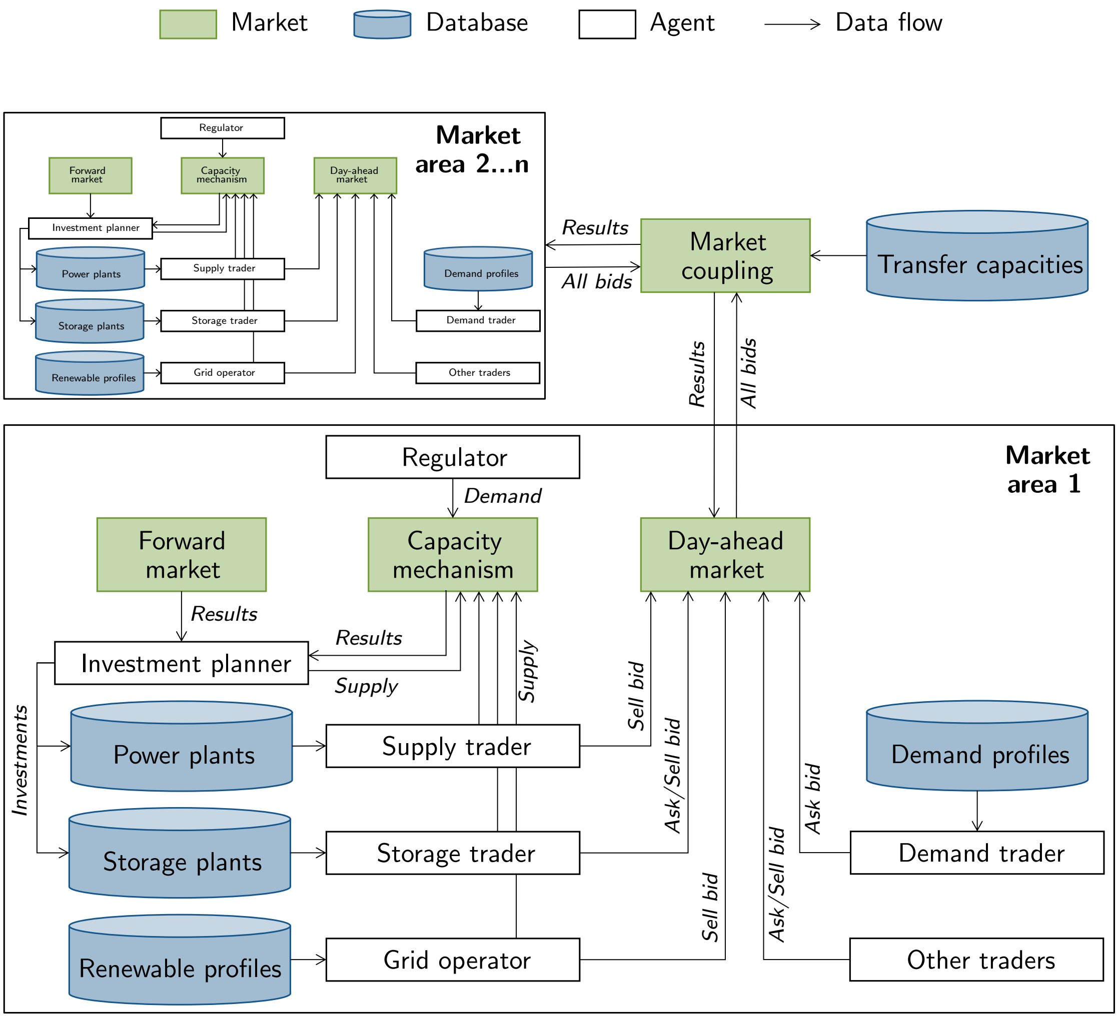


Figure C.3: Schematic overview of the electricity market model PowerACE. The focus lies on the short-term simulation of the day-ahead markets and long-term investment decisions under consideration of different capacity remuneration mechanisms as well as cross-border effects.

Table C.2: Overview of the input data used in all simulations carried out with PowerACE.

Input data type	Resolution	Sources and comments
Conventional power plants	unit level	S&P Global Platts (2015), and own assumptions
Fuel prices	yearly	EU Reference Scenario (de Vita et al., 2016), and own assumptions (cf. Fig. C.11)
Carbon prices	yearly	EU Reference Scenario (de Vita et al., 2016), scaled to reach 150 EUR/t_{CO_2} in 2050 (cf. Fig. C.11)
Investment options	yearly	Louwen et al. (2018); Schröder et al. (2013); Siemens Gamesa (2019), and own assumptions (cf. Tables C.8 and C.9)
Transmission capacities	yearly	Ten-Year Network Development Plan (ENTSO-E, 2016)
Electricity demand	hourly, market area	historical time series of 2015 (ENTSO-E, 2017), scaled to the yearly demand given in the EU Reference Scenario (de Vita et al., 2016)
Renewable feed-in	hourly, market area	historical time series of 2015 (ENTSO-E, 2017), scaled to reach an overall renewable share in relation to electricity demand of 80 % in 2050

European countries. We first run a benchmark simulation with a European EOM, which is then contrasted with several different configurations of national CRM policies, i.e., each of the ten countries is modeled under consideration of its current real-world market design[33] (see Fig. C.4). Please refer to Table C.3 for an overview of the scenarios investigated with PowerACE in the following sections.

All simulations are carried out at an hourly resolution and cover the time horizon from 2020 to 2050. Please note that as the focus of this paper is on market design issues, we do not model the electrical grid in detail, but only consider limited cross-border transmission capacities, while intra-zonal restrictions are not accounted for. This corresponds to the concept of zonal pricing which is used for the real-world market clearing process in Europe.

Contrary to the model endogenous expansion planning, decommissioning of existing power plants is exogenously defined based on the respective age and technical lifetime of the generation units, which remain unchanged for all scenarios under investigation. For two exemplary countries, France and Italy, the remaining capacities until 2050 without additional investments are shown on a technology aggregated level in Fig. C.5. As a reference, the peak residual demand[34] is also shown.

The developments of electricity generation from renewables and electricity demand are an exogenous input to PowerACE, which remains unchanged for all scenarios. Additional model endogenous investments in renewable technologies are therefore not considered. Moreover, DSM is out of the scope of this paper and not taken into account, i.e., the electricity demand is completely static. Fig. C.6 illustrates the assumed composition of the renewable electricity generation in France and Italy as well as the total yearly electricity demand.

[33]For details on the different market designs see Bublitz et al. (2019). Due to the similarities of the different types of CRMs on an abstract level, the French mechanism is modelled using the central buyer implementation, although in reality, a de-central obligation mechanism is used in France.

[34]The peak residual demand is defined as the highest hourly electricity demand of the respective market area, which is not covered by renewable generation.

Table C.3: Overview of all scenarios investigated with PowerACE. In Section C.4.3, a benchmark with a European EOM is analyzed. Section C.4.4 focuses on the impact of different strike price levels in a CRM. Finally, Section C.4.5 uses the most favorable strike price level for storages and then investigates varying storage duration requirements in more detail.

Section	Electricity market designs		Strike price[1]				Storage duration requirement[2]			
	European EOM	National CRM policies	n/a	none	high	low	n/a	low	medium	high
C.4.3	x		x				x			
C.4.4		x		x	x	x			x	
C.4.5		x				x		x	x	x

Abbreviations: CRM—capacity remuneration mechanism, EOM—energy-only market

[1] This additional price limit on the day-ahead market only applies to capacity that has been successfully contracted in the capacity auctions and should not be confused with the general day-ahead price limit of 3000 EUR/MWh_{el}, which is valid for all participants of the day-ahead market.

[2] Storage units with shorter discharge durations than required may still participate in the capacity auctions, but are derated and are only remunerated for a certain share of their maximum discharging capacity.

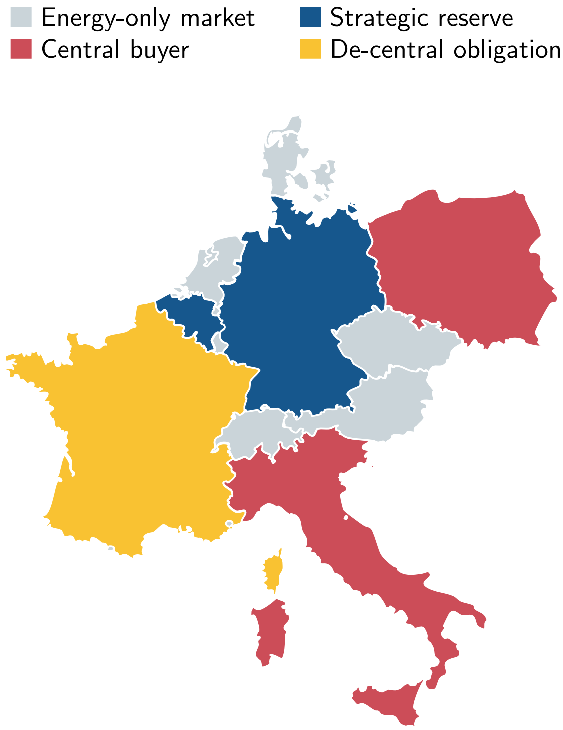


Figure C.4: Overview of the real-world electricity market designs implemented in the different countries covered by PowerACE.

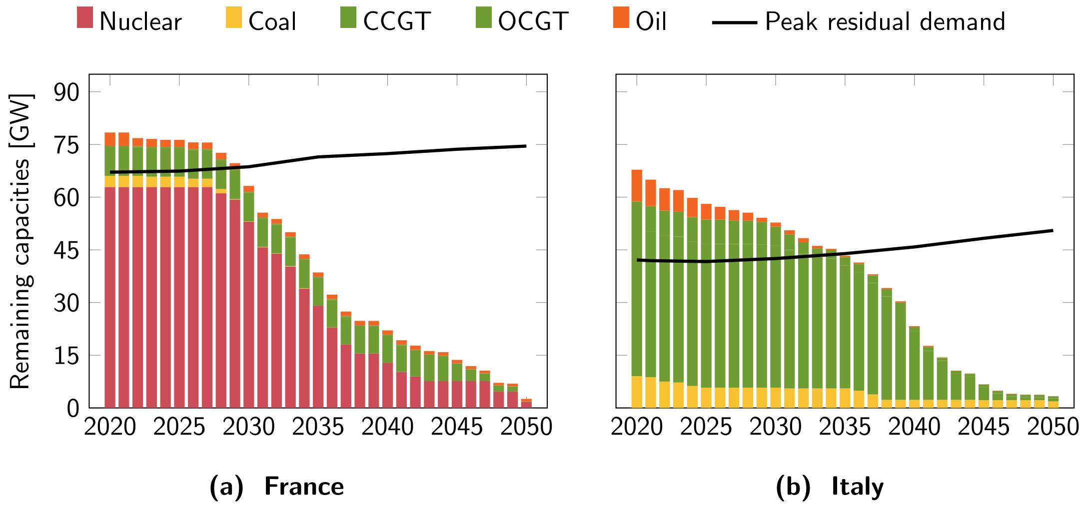


Figure C.5: Assumed conventional power plant capacities in France (a) and Italy (b) without additional new investments. *Source:* own illustration based on data from S&P Global Platts (2015), and own assumptions.

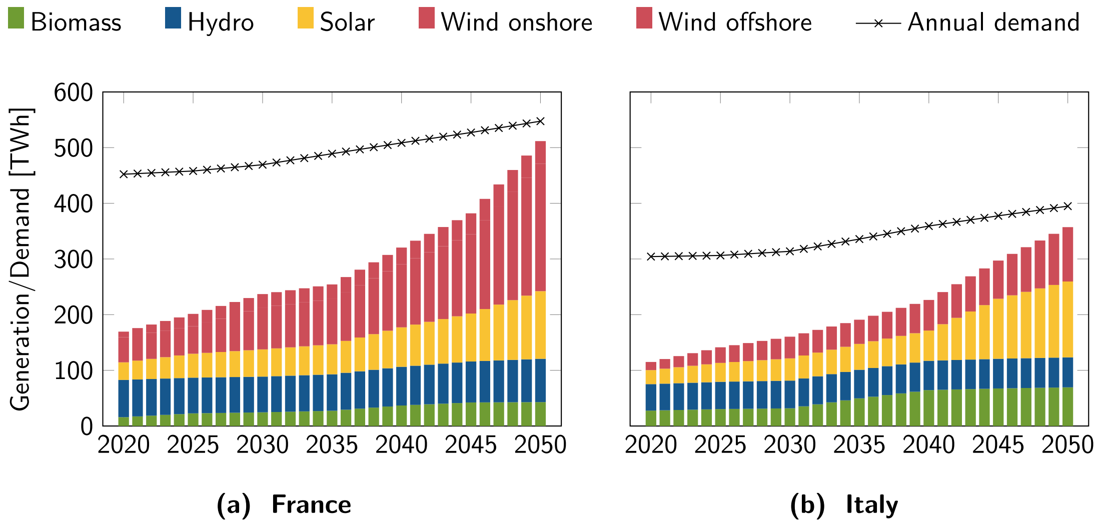


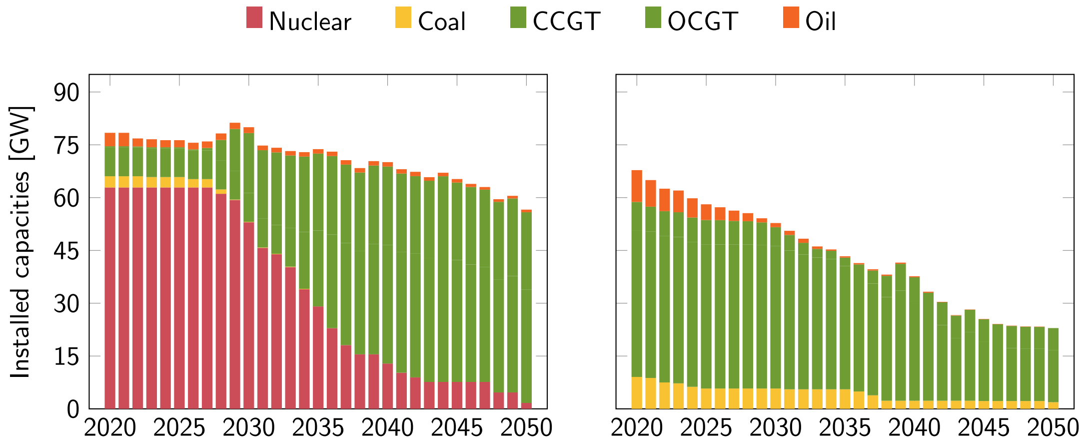
Figure C.6: Assumed renewable electricity generation and electricity demand in France (a) and Italy (b). *Source:* own illustration based on data from ENTSO-E (2017); de Vita et al. (2016), and own assumptions.

C.4.3 Reference Developments under a European Energy-Only Market

As a benchmark for the subsequent analyses on CRM design parameters in Sections C.4.4 and C.4.5, we now present the simulated long-term developments under a European EOM. For this purpose, Figs. C.7 and C.8 depict the conventional power plant and utility-scale storage capacities in France and Italy from 2020 to 2050. We choose these two countries for further analysis, since they have implemented a CRM in the current real-world setting and face substantial increases in future renewable electricity generation, therefore rendering storage investments attractive. The capacity developments emerge from exogenously given decommissioning of power plants (cf. Fig. C.5) and endogenous investment decisions of the different agents in PowerACE[35].

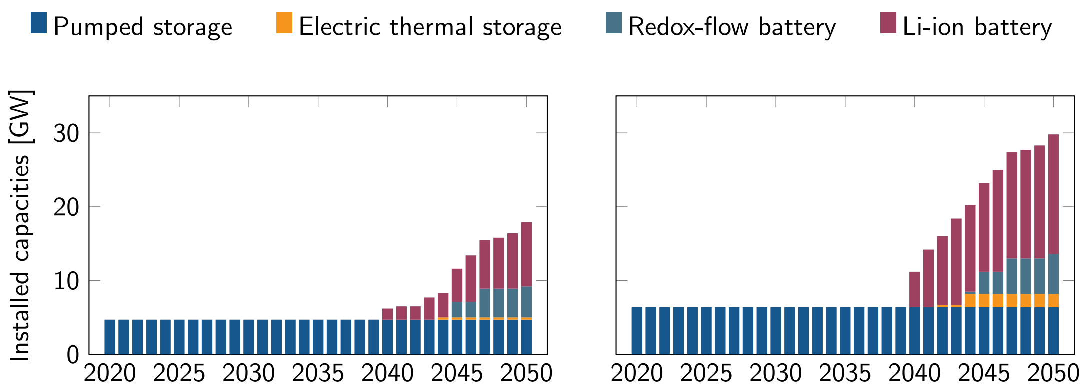
In France, the first thing to notice is the sharp (exogenously given) decline of nuclear generation capacities within a rather short period of time (47 GW between

[35]Please note that Figs. C.7 and C.8 do not show the *electricity generation* but the *installed capacities*, i.e., despite similar capacity levels as compared to today, the conventional power plants face significantly lower running hours in the future due to the assumed strong increase in renewable electricity generation (cf. Fig. C.6).



(a) France (b) Italy

Figure C.7: Simulated development of the conventional power plant capacities in France (a) and Italy (b) under a European energy-only market design.



(a) France (b) Italy

Figure C.8: Simulated development of the utility-scale storage capacities in France (a) and Italy (b) under a European energy-only market design.

2028 and 2038). Consequently, we can observe substantial amounts of substitute investments, mainly in combined cycle (CCGT) and open cycle gas turbines (OCGT). Since these technologies have a typical lifetime of 30 years (cf. Table C.8), once installed, they remain in the market until the end of the simulation period in 2050. As a result, only relatively few additional investments in storage technologies are carried out starting in 2040. This lock-in effect illustrates the high path dependence of the future technology mix. By using a dynamic multi-period model, we are able to properly take these effects into account. Ultimately, in 2050, we end up with 13.2 GW of new storages. Together with the 4.7 GW of pumped storage units, the total storage capacity in France makes up for some 24 % of the total flexible, i.e., conventional plus storage, capacity installed.

In Italy, the picture is somewhat different than in France. Due to the huge initial overcapacities, new investments are only carried out starting in 2037, i.e., 10 years later than in France. By this time, investment expenses for storage technologies have already strongly declined as compared to today (cf. Table C.9). In combination with the growing shares of renewable electricity generation towards 2050, this setting leads to some new conventional power plants, but also substantial investments in additional storage units. In 2050, a total of 23.4 GW of new storages is installed. Together with the 6.4 GW of pumped storage units, the total storage capacity in Italy makes up for some 56 % of the total flexible capacity installed. This share is substantially higher than in France, which will be a highly relevant finding for the subsequent analyses on CRM design parameters.

C.4.4 Capacity Auctions Bundled with Call Options

Scenario Setup

Let us now move on to the introduction of national CRM policies (cf. Fig. C.4) and more specifically the impact of bundling the capacity auctions with call options, which includes setting an additional day-ahead price limit for the capacity contracted in the capacity auctions. For this purpose, we set up three additional scenarios which we then compare with the European EOM scenario. An overview of the investigated scenarios is provided in Table C.4. All variables and parameters not mentioned there remain unchanged in all scenarios under investigation.

In scenario *CRM-08*, no strike price is set, i.e., only the general day-ahead price limit of 3000 $\mathrm{EUR/MWh_{el}}$ applies. Contrary, in scenario *CRM-08-limit_low*, we analyse the other extreme case, in which the strike price is set equal to $c^{\mathrm{var}}_{\mathrm{CONE},y}$, i.e., the variable cost of a new entry conventional power plant (typically an OCGT) in the given year y[36]. In order to limit the interference with the market evolution in normal conditions, Vàzquez et al. (2002) suggest to set the strike price at least 25 % above the most expensive generator expected to produce. For this reason, in scenario *CRM-08-limit_high*, we also investigate the case of a higher strike price set at 150 % of $c^{\mathrm{var}}_{\mathrm{CONE},y}$.

In all described CRM scenarios, we assume that the regulator bears the risk of a storage unit running empty during a multi-hour scarcity period, i.e., the storage operator is not subject to an *implicit* penalty in such situations (see also the discussion in Section C.3). Moreover, we set the required minimum storage duration to an intermediate value of 8 h for all scenarios. The impact of varying this parameter will then be analyzed in detail in the following Section C.4.5.

Long-Term Capacity Developments

For all described scenarios and the two countries under investigation (France and Italy), Fig. C.9 shows the simulated development of the conventional power plant and utility-scale storage capacities between 2020 and 2050. Please note that in order to make the differences between the scenarios more clearly visible, the respective deltas of installed capacities as compared to the European EOM are illustrated rather than presenting the absolute capacity values. Consequently, the zero-line represents the installed capacities in the European EOM. We also integrate a solid black line indicating the sum of the storage capacity deltas as well as a dashed black line for the total conventional capacity deltas.

[36]This stands in line with the way the strike price is determined in the recently implemented Italian CRM (Mastropietro et al., 2018; Perico et al., 2018). The Irish CRM also applies a similar methodology, in which the strike price is set a the maximum of two values: firstly, the fuel costs of a hypothetical reference peak generation unit and secondly, the variable costs of a reference demand side unit. This procedure is chosen to avoid discrimination against demand side management, which might face higher variable costs then a generation unit. Thus, under the Irish approach, typically a higher strike price than in Italy would evolve. For details please refer to Single Electricity Market Committee (2015).

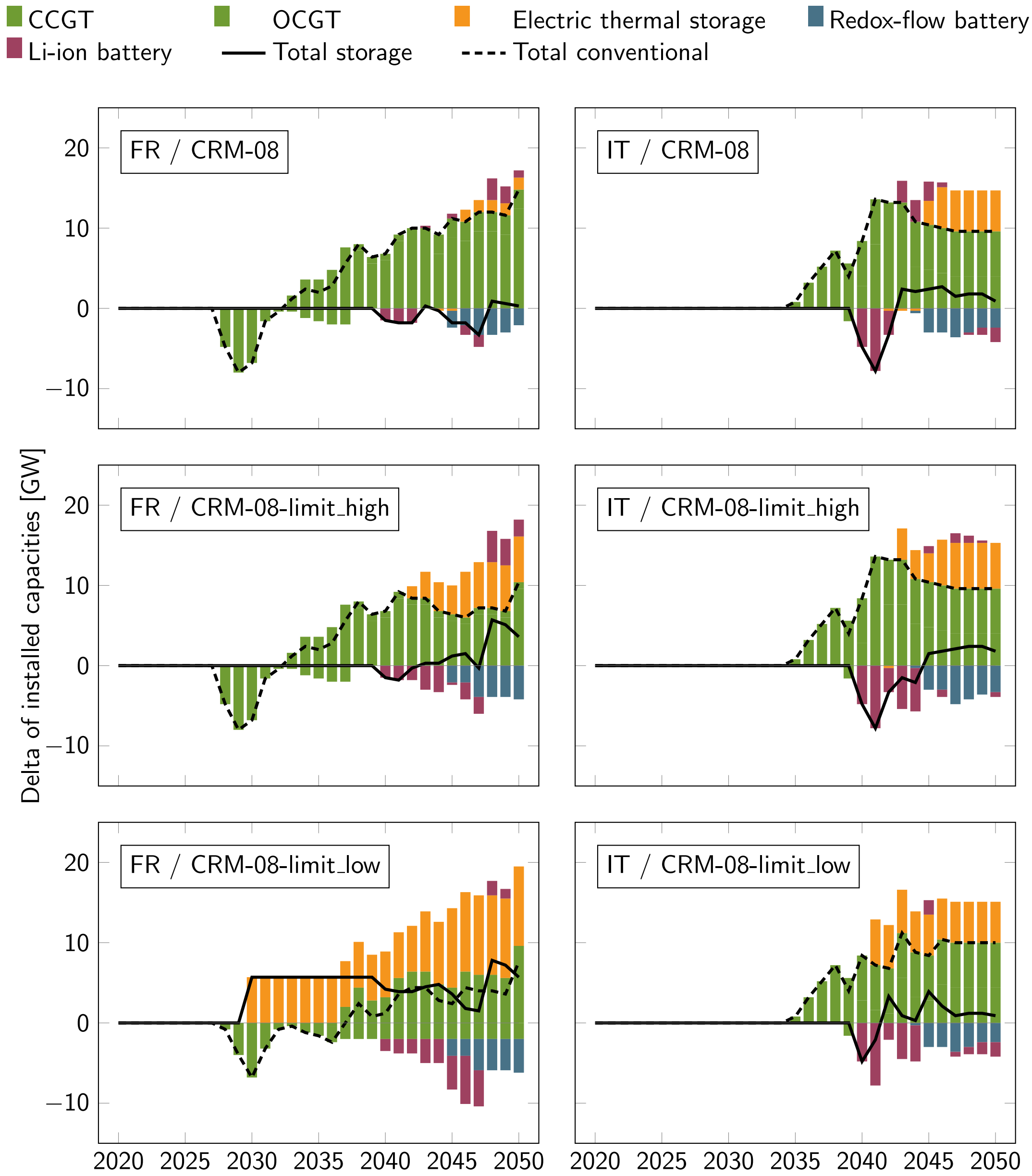


Figure C.9: Simulated development of the conventional power plant and utility-scale storage capacities in France (left) and Italy (right) under capacity remuneration mechanisms with different strike prices (from top to bottom: none, high, low). The values shown are the respective deltas of installed capacities as compared to the European energy-only market design.

Table C.4: Overview of the investigated scenarios regarding capacity remuneration mechanisms with call options and different strike prices.

Scenario	Electricity market designs	Strike price[1]	Storage duration requirement[2]
EOM	European EOM	n/a	n/a
CRM-08	National CRM policies	none	8 h
CRM-08-limit_high	National CRM policies	$1.5 \cdot c^{\mathrm{var}}_{\mathrm{CONE},y}$	8 h
CRM-08-limit_low	National CRM policies	$c^{\mathrm{var}}_{\mathrm{CONE},y}$	8 h

Abbreviations: CONE—cost of new entry, CRM—capacity remuneration mechanism, EOM—energy-only market

[1] This additional price limit on the day-ahead market only applies to capacity that has been successfully contracted in the capacity auctions and should not be confused with the general day-ahead price limit of 3000 EUR/MWh$_{\mathrm{el}}$, which is valid for all participants of the day-ahead market.
[2] Storage units with shorter discharge durations than required may still participate in the capacity auctions, but are derated and are only remunerated for a certain share of their maximum discharging capacity.

In France, we can observe that without implementing a strike price, the introduction of the French CRM mainly incentivises more investments in gas-fired power plants (both CCGTs and OCGTs) as compared to the European EOM (Fig. C.9, top left), while the total installed storage capacity remains relatively stable. It becomes obvious though, that storage investments are shifted to a later period, since the additional conventional power plants reduce their profitability. Results for Italy show similar trends (Fig. C.9, top right).

If a high strike price at 150 % of $c^{\mathrm{var}}_{\mathrm{CONE},y}$ is implemented, somewhat more storage capacity is built in France as compared to both the situation under a European EOM and that under a CRM without strike price (Fig. C.9, middle left). Contrary, in Italy, no such trend can be clearly identified (Fig. C.9, middle right). We will come back to the reasons for this finding later.

Finally, under a low strike price at $c^{\mathrm{var}}_{\mathrm{CONE},y}$, substantially more storages are built in France than in any other setting investigated thus far (Fig. C.9, bottom left). Moreover, the investments in storages are also carried out a lot earlier, starting already in 2030 rather than only after 2040. The higher installed storage capacities in turn replace some later investments in OCGTs due to the lock-in effect. In Italy, the trend of building storages earlier than in the other settings is similar, yet does not lead to a stable higher amount of installed storages in the long run (Fig. C.9, bottom right).

Summing up, we can conclude, that the findings of the simulations carried out generally stand in line with our theoretical discussion on the impact of implementing call options with a certain strike price in Section C.3.2. We can therefore confirm that if a CRM without call options is implemented, an implicit bias towards conventional power plants exists, while a CRM with call options and a strike price increases storage profitability in direct comparison with conventional power plants.

However, the effect in the simulations is much more pronounced in France than in Italy. This can largely be attributed to differences in the structure of the initial power plant fleets. As shown in Fig. C.5 and previously discussed in Section C.4.3, exogenously defined decommissioning of power plants starts earlier and at a much sharper rate in France than in Italy. The dominating driver for storage investments in Italy are the achievable arbitrage profits due to low investment expenses for storages in the period beyond 2040. Consequently, both the introduction of the Italian CRM and the optional bundling with call options have a rather small impact. In France, however, due to the stronger decommissioning rate, investments are needed earlier, when storages are still rather expensive to build. In this particular situation, implementing a CRM bundled with call options can shift investments towards storage technologies.

It is also important to mention that in none of the analyzed settings does the implementation of a strike price lead to all conventional power plant investments being replaced by storage units. This is because a strike price only affects the technology choice in situations where high price periods follow low price periods (as in our stylized example presented in Section C.3.2). If this situation is not given and storages are not able to charge at low or even zero cost, conventional power plants may remain the more profitable option to build, even if a strike price is implemented.

Our simulation results suggest that no straightforward answer can be given on whether an EOM or a CRM is more favorable for investments in storage technologies, but much depends on the country-specific drivers as well as the concrete design of the CRM. A CRM without call options has a rather small impact on storage investments as compared to an EOM, since lower revenues on the energy

Table C.5: Generation adequacy indicators in France and Italy under a European energy-only market and capacity remuneration mechanisms with different strike prices.

Scenario	No market clearing [∅ 2020–2050 in h/a]		Energy not served [∅ 2020–2050 in GWh/a]	
	France	Italy	France	Italy
EOM	10.7	8.4	60.5	50.0
CRM-08	–	1.4	–	1.7
CRM-08-limit_high	1.6	1.8	3.7	2.7
CRM-08-limit_low	5.1	2.1	16.2	2.6

markets are compensated by the additional capacity remuneration. If call options with a strike price are implemented, storage units gain a competitive advantage over conventional power plants in the capacity auctions. The additional capacity remuneration then leads to more storage investments as compared to an EOM. This effect is particularly important in countries with high capacity needs in the medium-term (2030–2040), where storage technologies are still rather expensive to build.

Impact on Generation Adequacy

An essential aspect when analyzing storage participation in CRMs is their ability to provide *firm* capacity. Although the model we apply for our simulations is deterministic, we can still draw some general conclusions on this issue by comparing the market outcomes in the different scenarios. For this purpose, Table C.5 shows two relevant adequacy indicators for all scenarios investigated thus far. Firstly, we present the mean amount of yearly hours with no successful market clearing, i.e., the situations in which the available generation and storage capacity plus potential imports were not sufficient to cover the residual demand. Secondly, we show the respective average yearly amounts of energy not served in these scarcity situations.

In France, for both indicators we can clearly identify that in all CRM scenarios, generation adequacy is substantially higher than in the European EOM. This is a rather straightforward finding since capacity targets in France are implemented in these settings. We do observe, however, that scarcity situations only fully vanish, if no strike price is implemented and consequently comparably few storages are built. Apparently, some scarcity situations with longer durations exist, in which the required storage duration of 8 h is not sufficient. Since the introduction of a strike price has a rather small impact on the technology composition in Italy as described before, we can also see from Table C.5 that the adequacy increases similarly in all CRM settings as compared to the European EOM. However, also in Italy some scarcity situations remain due to insufficiently large storage volumes.

In order to tackle the issue of storages running empty during scarcity periods, it is important to account for the energy-limited nature of storages in the capacity auctions. One way of doing so is to define a minimum discharge duration requirement and derate storage capacity accordingly, if a technology is not able to fulfill these requirements. The following section discusses this topic in more detail.

C.4.5 Storage Derating in the Capacity Auctions

Scenario Setup

We now stay with the CRM design determined as the most favorable one for storage investments, i.e., the setting with a low strike price set at $c^{\text{var}}_{\text{CONE},y}$. In order to investigate the impact of different storage derating factors, we re-use scenario *CRM-08-limit_low* from the previous section with a storage duration requirement of 8 h and run two additional simulations: *CRM-04-limit_low*, with a reduced requirement of 4 h and *CRM-12-limit_low*, with an increased requirement of 12 h[37]. These three scenarios are again all contrasted with the benchmark of a European EOM. Table C.6 summarizes all scenarios and their respective characteristics. All variables and parameters not mentioned there remain unchanged in all scenarios under investigation.

In our model, regardless of the storage duration requirements, all storage technologies are allowed to participate in the capacity auctions, yet their contracted

[37]The range of 4–12 h for the storage duration requirement is chosen according to the properties of the implemented storage investment options (see Table C.9). Moreover, for the CRM implemented in the UK a requirement of 4 h has recently been defined with derating applied for smaller storage discharge durations (National Grid, 2017).

Table C.6: Overview of the investigated scenarios regarding capacity remuneration mechanisms with different storage duration requirements.

Scenario	Electricity market designs	Strike price[1]	Storage duration requirement[2]
EOM	European EOM	n/a	n/a
CRM-04-limit_low	National CRM policies	$c^{\text{var}}_{\text{CONE},y}$	4 h
CRM-08-limit_low	National CRM policies	$c^{\text{var}}_{\text{CONE},y}$	8 h
CRM-12-limit_low	National CRM policies	$c^{\text{var}}_{\text{CONE},y}$	12 h

Abbreviations: CONE—cost of new entry, CRM—capacity remuneration mechanism, EOM—energy-only market

[1] This additional price limit on the day-ahead market only applies to capacity that has been successfully contracted in the capacity auctions and should not be confused with the general day-ahead price limit of 3000 EUR/MWh$_{\text{el}}$, which is valid for all participants of the day-ahead market.
[2] Storage units with shorter discharge durations than required may still participate in the capacity auctions, but are derated and are only remunerated for a certain share of their maximum discharging capacity.

capacity is derated according to Eq. (C.10) if their storage volume is not sufficient to fulfill the requirements[38].

Long-Term Capacity Developments

Fig. C.10 presents the simulated development of the conventional power plant and utility-scale storage capacities between 2020 and 2050 for all described scenarios and the two countries under investigation (France and Italy). As in the previous analysis focusing on call options, we illustrate the respective deltas of installed capacities as compared to the European EOM to emphasize the differences between the scenarios.

In both France and Italy similar trends can be observed. If we compare the settings with 4 h (Fig. C.10, top) and 8 h (Fig. C.10, middle) storage duration requirements, we can see a shift of investments from small li-ion batteries with 4 h discharge duration towards electric thermal storages[31] with 10 h discharge duration. The latter technology becomes the preferred option, as it is less affected

[38] While this procedure is similar to the CRMs in Ireland and the UK, our approach of using linear derating is somewhat simplified as compared to the more advanced methods used in the real-world cases (National Grid, 2017; Single Electricity Market Committee, 2016).

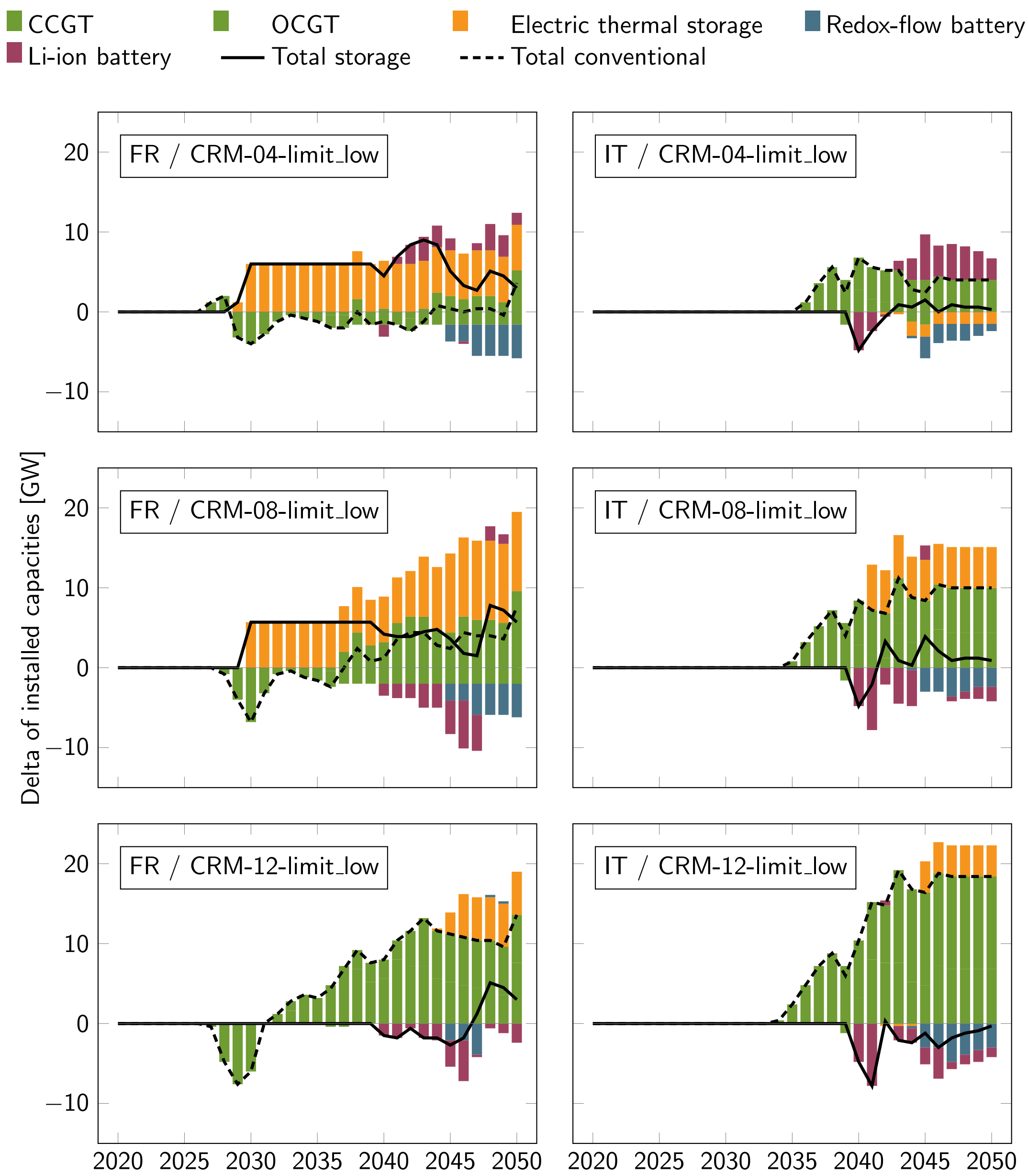


Figure C.10: Simulated development of the conventional power plant and utility-scale storage capacities in France (left) and Italy (right) under capacity remuneration mechanisms with different storage duration requirements (from top to bottom: 4 h, 8 h, 12 h). The values shown are the respective deltas of installed capacities as compared to the European energy-only market design.

by strong storage derating due to its larger storage volume. At the same time, the stronger derating of storages also leads to higher amounts of *nameplate* capacity to be contracted in the capacity auctions to fulfill the required *firm* capacity targets set by the regulator. This in turn leads to substantial amounts of additional gas-fired power plants (mostly CCGTs), but also to temporary phases with more storage investments carried out despite the stronger derating factor (see also Section C.3.3).

Moving on to the storage duration requirement of 12 h (Fig. C.10, bottom), we can see that storage technologies are becoming a lot less competitive than in the other settings. Consequently, fewer storage investments are carried out and those that remain are built at a later phase of the simulated period. In this setting, the higher amounts of *nameplate* capacity to be contracted in the capacity auctions lead to a strong increase in CCGTs and OCGTs, but no additional storage investments.

These simulation results stand perfectly in line with what we would expect from out theoretical discussion of the impact of storage derating in Section C.3.3. We can therefore confirm that stronger derating of storage technologies generally creates a bias towards larger storages and ultimately conventional power plants. However, we also find that the higher amounts of *nameplate* capacity to be procured in the capacity auctions may in some settings overcompensate this effect and even lead to more storage investments despite stronger derating.

Regarding the question whether an EOM or a CRM is more favorable for investments in storage technologies, we can confirm our findings from the previous section: While no straightforward answer to this issue can be given, it is rather the concrete design of the CRM that matters. The choice of the derating factors for storages is a strong driver deciding on whether more or less storage units are built than under a European EOM, and also which storage technology will be the dominant one. Moderate storage duration requirements are generally favorable for investments in small storages and may consequently lead to additional storage capacity under a CRM as compared to a European EOM. Higher storage duration requirements, i.e., stronger derating of storage capacity, makes small storages less attractive and shifts the technology mix towards larger storages or even conventional power plants. At the same time, stronger derating leads to higher *nameplate*

Table C.7: Generation adequacy indicators in France and Italy under a European energy-only market and capacity remuneration mechanisms with different storage duration requirements.

Scenario	No market clearing [∅ 2020–2050 in h/a]		Energy not served [∅ 2020–2050 in GWh/a]	
	France	Italy	France	Italy
EOM	10.7	8.4	60.5	50.0
CRM-04-limit_low	11.6	4.0	57.0	11.3
CRM-08-limit_low	5.1	2.1	16.2	2.6
CRM-12-limit_low	0.2	–	0.1	–

capacity targets in the capacity auctions, which are then typically reached through additional large storage units or ultimately conventional power plants.

Impact on Generation Adequacy

As previously discussed, the choice of the storage derating factors does not only affect the future technology mix, but in consequence also the ability of a CRM to fulfill its major objective of ensuring long-term generation adequacy. In order to get insights on this issue, Table C.7 presents the same two adequacy indicators as in the previous analysis of call options with varying strike prices.

In both France and Italy, we can see similar trends for the two indicators. Moderate storage derating leads to relatively high shares of storage units. Due to their limited storage volume, these units are not able to provide sufficient *firm* capacity to cover all peak demand periods. Consequently, scarcity situations can only be partly reduced (Italy) or even stay at a similar level as under a European EOM (France). This of course contradicts the actual goal of implementing a CRM in the first place.

If stronger storage derating factors are applied, fewer storage investments, but substantially more investments in conventional power plants are carried out. Since the conventional units are able to provide *firm* capacity at all times (neglecting forced outages), the scarcity situations vanish completely in this setting (Italy) or are at least reduced to a much lower level than in the European EOM setting (France). We can ultimately conclude that the appropriate choice of the storage derating factors in capacity auctions is essential in order to guarantee generation adequacy. At the same time, the resulting technology mix may be strongly affected by this design parameter.

C.5 Conclusion and Policy Implications

Both the theoretical discussion and the simulations carried out showed that there is no straightforward answer to whether an EOM or a CRM is the more beneficial market design for electricity storage technologies. Rather than the actual market design, much depends on the concrete specification of the CRM, which always creates a certain bias towards one technology or the other. We were able to show that bundling capacity auctions with call options and the choice of the storage derating factor are important drivers in this regard.

If storage units are not penalized for non-availability during scarcity situations caused by their storage volume running empty, they likely benefit from the introduction of call options with a certain strike price in direct comparison with conventional power plants. Contrary, if the storage units are indeed penalized even in these particular situations or if no call options with strike price are used, there exists a bias towards conventional power plants, as they do not face the risk of a storage running empty and can always provide *firm* capacity (neglecting forced outages).

We were also able to show that it is crucial to adequately estimate the *firm* capacity a storage unit can provide and to derive storage derating factors accordingly. Otherwise, the contribution of small storages may be overestimated, leading to issues regarding generation adequacy despite the implementation of a CRM.

At least to some extent, these results are also valid for DSM, which, much like electricity storage, is an energy-limited resource. However, each DSM technology differs regarding the underlying process, such that very individual restrictions need to be considered. Therefore a direct and general transfer of our results for electricity storage is not possible.

Overall, we can conclude, that the actual design of a CRM substantially impacts the future technology mix, even if all technologies are formally allowed to participate in the mechanism. The specification of the CRM may then in turn also have an impact on the goal of achieving long-term generation adequacy. More specifically, we could observe that electricity storage does indeed have a capacity value and should therefore be allowed to participate in any CRM, yet with its *nameplate* capacity adequately derated to reflect the *firm* capacity it can actually provide. Moreover, the simulation results suggest, that substantial need for investment in generation and storage capacity exists in Europe in the upcoming years due to decommissioning of old units.

Policymakers and regulators are therefore strongly recommended to design or re-specify their CRMs accordingly to allow for storage participation in an adequate manner. In this regard, the time to act is now. Otherwise, a lock-in effect may occur, i.e., once an undesired technology is built, it will likely remain in the system for a long time. While some European CRMs, e.g., Ireland and the United Kingdom, are already on the right path and have recently developed methods to determine storage derating factors, barriers are still very high in US markets like PJM, due to unnecessarily strict requirements (Chen et al., 2017; National Grid, 2017; Single Electricity Market Committee, 2016, 2018; Usera et al., 2017). Moreover, Ireland and Italy also combine their capacity auctions with call options and a certain strike price, which is generally favorable for storage units.

We are well aware that real-world CRMs are much more complicated than the simplified settings we have analyzed in our work and more research therefore needs to be carried out to confirm our findings. In particular, we refrain from modeling strategic behavior in the capacity auctions. To gain insights into this issue, it may be interesting to delve into the design and the auction outcomes of the different CRMs implemented around the world.

Moreover, in the simulations carried out, the storage derating factor has been determined by exogenously setting arbitrary required discharge durations rather than trying to choose optimal such values. It could therefore be a promising approach, to have the regulator agent determine adequate derating factors endogenously by implementing one of the methods from the literature (Borozan et al., 2019; Sioshansi et al., 2014; Zhou et al., 2015, 2016) into the simulation framework.

So far, we have focused on conventional power plants and short-term storage units. We could also extend our work by considering additional technologies like seasonal storage (power-to-X) or DSM to see whether the findings for short-term electricity storage also hold for these technologies. However, due to the large storage volume of power-to-X technologies, we expect its diffusion to mostly depend on the achievable reductions in capital expenditures rather than on the specific

CRM design. As regards DSM, the issue lies mostly with the availability of the necessary process-specific data.

Finally, we have to mention that electricity storage has many additional benefits to just the provision of *firm* capacity and arbitrage trading as we assume it in our paper. As we neglect this aspect, we probably underestimate the storage diffusion potential as compared to a real-world setting with multiple revenue streams. However, this does not diminish the relevance of our results.

C.6 Appendix

C.6.1 PowerACE Model Description

Day-Ahead Market Simulation

PowerACE is structured into different market areas, in each of which multiple traders are active on the day-ahead market. All agents participating in the market first create a price forecast, for which the behavior of the other market participants is anticipated, and then prepare individual hourly demand and supply bids.

The bid prices for the supply bids are primarily based on the variable costs of the respective power plant. In addition, the price forecast is used to estimate the running hours of each power plant and to distribute the expected start-up costs accordingly. Further price-inelastic bids for demand, renewable feed-in and storage units are prepared by a single trader per market area, respectively. For details on the determination of the bid volumes for the storage units, please refer to Fraunholz et al. (2017).

Once all bids have been prepared, they are submitted to the central market coupling operator. In the market clearing process, supply and demand bids are matched across all market areas, such that welfare is maximized subject to the limited interconnector capacities between the different market areas. For a formal description and details of the market coupling and clearing see Ringler et al. (2017).

As a result, the information about which bids have been partly or fully accepted is returned to the different traders. Final outcome of the day-ahead market simulation is a market clearing price and corresponding electricity volume for each simulation hour and market area. Please note that situations may occur, in which the available generation and storage capacity plus potential imports are not sufficient to cover the residual demand. The market clearing price in the respective market area is then set at the day-ahead price limit of 3000 EUR/MWh_{el}.

Generation and Storage Expansion Planning

In addition to the short-term decisions on the day-ahead market, the different utility companies modelled as agents in PowerACE can also perform long-term decisions on investments in new conventional power plant and storage capacities at the end of each simulation year. Contrary to the common approach of generation expansion planning with the objective of minimizing total future system costs, an actor's perspective is taken. Consequently, investments are only carried out if expected to be profitable by the investor agents. The expansion planning algorithm is introduced and described in detail in Fraunholz et al. (2019). A brief overview of the basic principles is given in the following.

In order to estimate the profitability of the different investment options, a model-endogenous long-term price forecast is first carried out. Using this forecast, annual contribution margins for all technologies are calculated and corresponding net present values are derived. These are ultimately converted to annuities to account for technology specific investment horizons.

For conventional power plant technologies, the contribution margins are calculated in a simplified fashion as the sum of call options on the respective hourly contribution margins. For storage technologies, the contribution margins correspond to their maximum arbitrage potential. Thus, in order to determine optimal hourly charging and discharging strategies based on the expected future prices, a time-coupled linear optimization problem is solved.

As previously mentioned, scarcity situations may occur in the model, if the available generation and storage capacities are not sufficient to cover the residual demand. The anticipation of the corresponding peak prices up to the day-ahead price limit of 3000 EUR/MWh_{el} is an important driver for investment decisions, both in our model and the theoretical concept of the energy-only market.

The decisions of the different investors are primarily based on their expectations regarding future electricity prices. As these, vice versa, are influenced by the investment decisions of all investors in all interconnected market areas, a complex game with multiple possible strategies opens up. To find a stable outcome for this game, a Nash-equilibrium needs to be determined.

Therefore, the expansion planning algorithm terminates when all planned investments are profitable and at the same time none of the investors is able to improve his expected payoff by carrying out further or less investments, i.e., there is no incentive for any investor to unilaterally deviate from the equilibrium outcome. The different market areas are defined as the players interacting with each other and the planned investments are then distributed among the investors within each market area. Following this approach, it is possible to consider the mutual impact of investments in one market area on the electricity prices and consequently investments in the interconnected market areas.

Capacity Remuneration Mechanism

The following paragraphs briefly introduce the central buyer mechanism implemented in PowerACE, which follows closely the generic mechanism introduced in Section C.3.1. For further details, please refer to Keles et al. (2016).

In the market areas with an active central buyer mechanism, annual descending clock auctions are carried out in order to contract a specific amount of *firm* generation and storage capacity. The auctions take place prior to the regular expansion planning as described above. Following this approach, it is possible to adequately consider the cross-border impacts of the capacity auctions[39].

For the auctions, the regulator first sets a targeted ratio between *firm* capacity and peak residual demand in the respective year, excluding imports. This ratio is an arbitrary value, which controls the desired level of generation adequacy and defines the amount of *firm* capacity to be procured in the auction. Since we only analyze deterministic cases in our simulations, we set the targeted ratio to 1.0, such that the residual load in the respective market area can always be covered by

[39]If the capacity auctions were carried out after the regular expansion planning, the investors in the other market areas could only react to the auction results in the subsequent investment planning periods. However, since capacity auctions are typically carried out with a certain lead time, it seems more plausible to assume that all investors possess a priori knowledge about the auction results before deciding on their investments. Please note that also in market areas with an active central buyer mechanism, additional investments driven by expected revenues from the EOM are always possible. Consequently, all modeled countries are considered in the regular expansion planning algorithm.

the domestically available conventional generation and storage capacity, without depending on electricity imports. Moreover, in order to analyze the impact of different mechanism designs, we have integrated the two parameters *price cap* and *required storage duration* as introduced in Section C.3.1 into the modeled mechanism.

Next, the different utility companies provide capacity bids consisting of volume and price. While existing capacity is offered at zero cost[40], the bids for potential new power plant and storage capacity are based on the respective difference costs. These are directly related to the regular investment planning procedure. Investments expected to be profitable even without additional capacity payments bid into the auction at zero cost. If the desired *firm* capacity is not yet guaranteed through these investments, additional bids of the technology with the lowest negative annuity, i.e. the best, yet not profitable investment option, are placed into the auction. The bid price of these additional investments is determined based on the additional income that would be needed to recover all cost related to the respective investment, the so-called difference costs.

For this contribution, storage technologies were integrated into the existing mechanism by using the concept of *firm* capacity. Thus, while conventional power plants can bid their full *nameplate* capacity in the auctions, storage units are derated according to the new mechanism design parameter *required storage duration* and can only bid their resulting *firm* capacity.

After receiving bids from all market participants, the auction is cleared and all successful participants are compensated with a uniform capacity price, which is paid to the existing power plants and storage units for one year and to new constructions for an arbitrary longer period.

C.6.2 Input Data

Fig. C.11 presents the assumed development of fuel and carbon prices over the time horizon of the simulation.

[40] In reality, existing capacity not able to operate profitably on the EOM would likely also bid with its respective difference costs. However, since we do not consider model endogenous decommissioning of power plant or storage capacity, investment expenses and fixed costs may be considered as sunk costs. Consequently, it is reasonable to assume that existing capacity would happily accept any additional capacity remuneration, regardless of how low it may be.

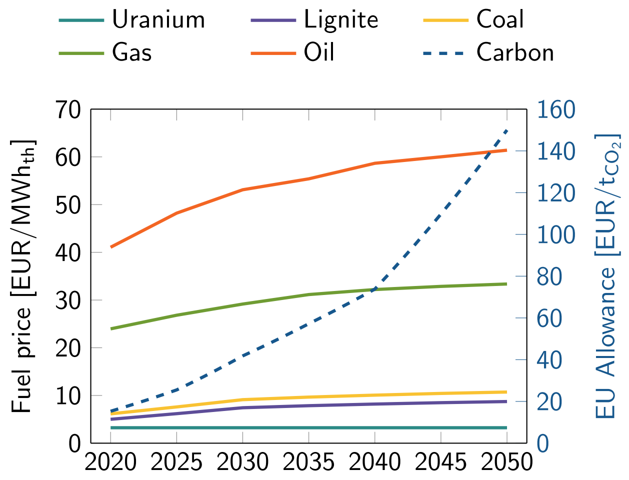


Figure C.11: Assumed development of fuel and carbon prices. *Source:* own illustration based on data from EU Reference Scenario (de Vita et al., 2016), and own assumptions.

An overview of the techno-economic characteristics of the different investment options modeled in PowerACE is provided in Tables C.8 and C.9.

Table C.8: Conventional power plant investment options modelled in PowerACE with their respective techno-economic characteristics. *Source:* Schröder et al. (2013); Louwen et al. (2018), own assumptions.

Technology	Block size [MW_{el}]	CCS	Net efficiency[1] [%]	Lifetime [a]	Building time [a]	Specific investment (2015–2050)[1] [$\frac{EUR}{kW_{el}}$]	O&M costs fixed [$\frac{EUR}{kW_{el}\,a}$]	O&M costs var.[2] [$\frac{EUR}{MWh_{el}}$]
Coal	600	no	45–48	40	4	1800	60	6
		yes	36–41			3143–2677		30
Lignite	800	no	43–47	40	4	1500	30	7
		yes	30–33			3840–3324		34
CCGT	400	no	60–62	30	4	800	20	5
		yes	49–52			1216–1078		18
OCGT	400	no	40–42	30	2	400	15	3

Abbreviations: CCGT—combined cycle gas turbine, CCS—carbon capture and storage, OCGT—open cycle gas turbine, O&M—operation and maintenance

[1] Resulting from technological learning, the net efficiency is assumed to increase over time. Since conventional power plants can generally be regarded as mature technologies, it is further assumed that only the specific investments of the CCS-technologies are declining.

[2] Including variable costs for carbon capture, transport and storage, where applicable.

Table C.9: Electricity storage investment options modelled in PowerACE with their respective techno-economic characteristics. *Source:* Louwen et al. (2018); Siemens Gamesa (2019), own assumptions.

Technology	Block size [MW_{el}]	Storage capacity[1] [MWh_{el}]	Round-trip efficiency[2] [%]	Life-time[2] [a]	Building time [a]	Specific investment (2015–2050)[2] [$\frac{EUR}{kW_{el}}$]	O&M costs fixed[2] [$\frac{EUR}{kW_{el}\,a}$]
Li-ion battery	300	1200	85–95	20–30	2	3149–572	63–11
		3000				7643–1388	153–28
RF battery	300	3000	75–85	20–30	2	4206–892	84–18
A-CAES	300	3000	60–75	30	2	1095	22
ETES	300	1200	50–60	40	2	600	12
		3000				672	13

Abbreviations: A-CAES—adiabatic compressed air energy storage, ETES—electric thermal energy storage, O&M—operation and maintenance, RF battery—redox-flow battery

[1] For RF batteries and A-CAES, a substantial share of the investment expenses is related to the converter units. Consequently, for economic reasons, only higher storage capacities of 3000 MWh_{el} are eligible as investment options for these technologies.

[2] Resulting from technological learning, round-trip efficiency and lifetime are assumed to increase over time for the emerging storage technologies. Analogously, specific investments and fixed costs for O&M are assumed to decline.

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Paper D

On the Long-Term Efficiency of Market Splitting in Germany

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Abstract

In Europe, the ongoing renewable expansion and delays in the planned grid extension have intensified the discussion about an adequate electricity market design. Against this background, we jointly apply an agent-based electricity market model and an optimal power flow model to investigate the long-term impacts of splitting the German market area into two price zones. Our approach allows capturing long-term investment and short-term market behavior under imperfect information. We find strong impacts of a German market splitting on electricity prices, expansion planning of generators and required congestion management. While the congestion volumes decrease significantly under a market split in the short term, the optimal zonal configuration for 2020 becomes outdated over time due to dynamic effects like grid extension, renewable expansion and new power plant investments. Policymakers and regulators should therefore regularly re-assess bidding zone configurations. Yet, this stands in contrast to the major objective of price zones to create stable locational investment incentives.

D.1 Introduction

Driven by the massive expansion of renewable electricity generation as well as political phase-out decisions of technologies such as nuclear or coal-fired generation, the design of the European electricity markets is in a state of constant evolution. An aspect of particular relevance in this respect is the design of the day-ahead markets and the closely related congestion management. Currently, following the concept of zonal pricing, the day-ahead market clearing of the interconnected European electricity system is carried out without considering any grid constraints within a price zone, which in most cases corresponds to a whole country. Only in a subsequent step, congestion management measures, such as redispatching and curtailment of generation from renewable energy sources (RES), are used if the market outcome is not realizable due to intra-zonal congestion. Due to recent and upcoming trends, congestion management becomes increasingly important in Germany:

- Large generation capacities, mainly located in Southern Germany, are dropping out of the market until 2022 due to the political decision of phasing-out nuclear

Nomenclature

Parameters

Δt	time step length [h]
η	efficiency [MWh_{el}/MWh_{th}]
$\overline{c}^{var}$	average variable costs [EUR/MWh_{el}]
c^{add}	specific costs of artificial load [EUR/MWh_{el}]
c^{curt}	specific costs of curtailment [EUR/MWh_{el}]
$c^{O\&M}$	operation and maintenance costs [EUR/MWh_{el}]
$c^{var,max}$	maximum variable costs [EUR/MWh_{el}]
$c^{var,rev}$	reverted variable costs [EUR/MWh_{el}]
c^{var}	variable costs [EUR/MWh_{el}]
c^{voll}	specific costs of lost load [EUR/MWh_{el}]
e^{fuel}	emission factor [t_{CO_2}/MWh_{th}]
l^{gross}	gross load [MWh_{el}]
l^{net}	net/residual load [MWh_{el}]
p^{CO_2}	CO_2 price [EUR/t_{CO_2}]
p^{fuel}	fuel price [EUR/MWh_{th}]

Sets and Indices

e	transmission line
h	hour
h^{off}	offline hour
h^{on}	online hour
m	market area
n	grid node
p	power plant
p^{con}	conventional power plant
p^{ren}	renewable power plant
p^{stor}	storage power plant
s	scenario
y	year

Variables

Δp	relative day-ahead price difference [–]
Δp^{sorted}	sorted day-ahead price difference [EUR/MWh_{el}]
λ	locational marginal price [EUR/MWh_{el}]
$\overline{p}$	average day-ahead price [EUR/MWh_{el}]
b	bid price [EUR/MWh_{el}]
b^{min}	bid price for minimal load [EUR/MWh_{el}]
b^{rest}	bid price for rest load [EUR/MWh_{el}]
C^{cong}	total costs of congestion management [EUR]
C^{curt}	total costs of curtailment [EUR]
C^{inf}	total infeasibility costs [EUR]
C^{redisp}	total costs of redispatching [EUR]
c^{start}	specific start up costs [EUR/MW_{el}]
f^{AC}	net flow AC [MWh_{el}]
f^{DC}	net flow DC [MWh_{el}]
g	electricity generation [MWh_{el}]
g^{market}	market-dispatched electricity generation [MWh_{el}]
l^{add}	artificially added load [MWh_{el}]
l^{charge}	storage charging demand [MWh_{el}]
l^{dump}	dumped load [MWh_{el}]
t^{off}	offline time [h]
t^{on}	online time [h]

power. Moreover, the German *Kommission für Wachstum, Strukturwandel und Beschäftigung* (commonly called *Kohlekommission*) has recently agreed on a phase-out of coal-fired generation until 2038, which will particularly affect regions in the West (Rhineland) and East (Lusatia, Central German district) of the country (Bundesministerium für Wirtschaft und Energie, 2019).

- Electricity generation from wind power has increased significantly over the past years and is expected to continue to do so. However, these generation capacities are to a large extent located in Northern Germany.
- Low wholesale electricity prices provide poor incentives for investments in additional conventional generation capacity or utility-scale storage units.
- While these developments result in a shift of generation capacity to Northern Germany, the industrial load centers with a rather inflexible demand structure are mainly located in Western and Southern Germany. In the past years, this locational mismatch between generation and consumption has already led to an increasing number of hours where the market result had to be corrected by redispatching and curtailment of RES (Bundesnetzagentur and Bundeskartellamt, 2019). Moreover, Poland and the Czech Republic have already installed phase shifters to reduce loop flows from Northern Germany to Southern Germany through their domestic grid.
- Although new high-voltage direct current (HVDC) lines are supposed to solve these issues to a large extent, their completion is likely to be delayed by a few years.

Apart from resulting in additional costs for congestion management, these trends might also endanger security of supply in (Southern) Germany in the upcoming years. Regional price signals could help to counteract these risks by incentivizing investments in generation capacity or avoiding decommissioning of further power plants by adequately indicating regional scarcity.

In this context, nodal pricing is often considered to be the theoretically first best solution as prices in this market design directly reflect not only marginal generation costs but also bottleneck costs (Stoft, 1997). This concept is currently for instance used in the PJM market area of the USA and in New Zealand (Pettersen et al., 2011). However, a short-term implementation of nodal pricing in Germany or even Europe is unlikely (Trepper et al., 2015).

Alternatively, country price zones can be split up into multiple zones, such as those in the Nordic electricity market (Norway, Sweden, Finland, Denmark) (THEMA Consulting Group, 2013), resulting in diverging electricity prices and therefore regional investment incentives. With regard to Germany, this solution might be quicker and easier to implement than a nodal pricing approach. However, the current German government is strongly in favor of staying with a single German price zone and has recently even changed the legislation (*Stromnetzzugangsverordnung – StromNZV*) accordingly (Bundesministerium für Wirtschaft und Energie, 2017). Nevertheless, the topic remains highly relevant not only from an academic and political perspective, but also for generation companies and grid operators.

While the short-term impacts of dividing the German price zone have already been extensively analyzed by different authors (Burstedde, 2012; Breuer et al., 2013; Breuer and Moser, 2014; Trepper et al., 2015; Egerer et al., 2016; Plancke et al., 2016), the only investigations of the long-term impacts to date have been carried out by Grimm et al. (2016a,b, 2017, 2018) and Ambrosius et al. (2019). Yet, as Grimm et al. (2016b) point out, the consideration of these long-term effects is an essential aspect for the political discussion on concrete splitting of zones.

Against this background, we use an innovative modeling framework consisting of an agent-based electricity market simulation model (PowerACE) and an optimal power flow model (ELMOD) to investigate the long-term impacts of splitting the German price zone. Contrary to the method used in Ambrosius et al. (2019), this new approach allows to consider multiple time periods with regard to generation and storage expansion planning and is therefore able to capture the real-world long-term dynamics appropriately.

Our results focus on the German day-ahead market, required congestion management measures as well as associated system costs and distributional effects under a zonal split as compared to the status quo of a single German price zone. Despite the explicit focus on Germany, the obtained results are also relevant for other regions using multiple price zones within a country, such as the Nordic electricity market or Italy.

The remainder of the paper is structured as follows. In Section D.2, we briefly review the relevant literature and derive the research gap our paper aims to fill. Section D.3 introduces the proposed modeling framework and explains important methodological aspects in details. We then describe the most relevant input data as well as the scenario definition in Section D.4. In Section D.5, we present possible long-term impacts of splitting the German price zone. Ultimately, Section D.6 provides a summary and an outlook on future work.

D.2 Literature Review and Research Gap

In the following, an overview of the previous literature relevant for this article is provided. Firstly, we briefly review existing methods for bidding zone delimination. Secondly, the focus is set on the short-term impacts of reconfiguring the European price zones and splitting the German price zone in particular. Thirdly, we summarize literature on the long-term impacts of such market design changes. Ultimately, we outline the research gap that this paper aims to fill.

Regarding the bidding zone configuration method, four main approaches can be distinguished. Firstly, the zonal delimination is based on historical real-world grid congestion (Egerer et al., 2016; Plancke et al., 2016). Secondly, splitting a price zone can be conducted along the main bottlenecks of the transmission grid for a future reference year (Trepper et al., 2015). Thirdly, nodal electricity prices are clustered, e.g., by using genetic algorithms (Breuer et al., 2013; Breuer and Moser, 2014). Fourthly, a new bidding zone configuration is determined model-endogenously (Grimm et al., 2017; Ambrosius et al., 2019). In the paper at hand, we assume the regulator to base his decision on the division of the German price zone on knowledge available to him at the time of decision-making. For this reason, nodal prices of the year 2020 are clustered using a fuzzy c-means algorithm, rather than applying a model-endogenous approach (see Section D.3).

Reconfiguring European bidding zones brings along a number of short-term impacts, which have already been extensively analyzed in several studies to date. The relevant contributions are shortly presented in the next paragraphs.

Burstedde (2012) compares a nodal pricing approach and a zonal configuration based on the clustering of nodal prices on a European level for the scenario years 2015 and 2020. Both variants are then contrasted with the current situation of nationwide price zones in terms of generation and redispatching costs. While the costs of redispatching are significantly reduced when the current zones are reconfigured and even more so under the nodal pricing approach, the rise of generation costs almost entirely compensates this effect.

Breuer et al. (2013) and Breuer and Moser (2014) apply genetic algorithms for the scenario years 2016 and 2018 in order to deduce an optimal zonal configuration on a European level from nodal prices. They investigate different numbers of zones and ultimately conclude that reconfiguring the European price zones into 10 to 15 new zones, the costs of redispatching would decrease more than the costs of generation would rise as compared to the reference case. However, also in these studies, the savings are very low in relation to the total traded electricity volume.

Trepper et al. (2015) investigate a splitting of the German price zone based on the most heavily congested lines for the scenario year 2020. With trading capacities of 10.2–15.3 GW, the redispatching volumes decrease significantly and average price differences of 1.55–3.56 EUR/MWh_{el} between the two new zones occur. Moreover, the authors find decreasing producer rents and increasing consumer rents in Northern Germany, while the opposite is true for Southern Germany.

Egerer et al. (2016) analyze a splitting of the German price zone for the years 2012 and 2015 without taking into account the German neighboring countries. With a trading capacity of 8 GW, only small average price differences of 0.40 EUR/MWh_{el} (2012) and 1.70 EUR/MWh_{el} (2015) between the two German zones arise. Redispatching volumes decrease slightly in 2012 and more significantly in 2015.

Plancke et al. (2016) apply a European spot market model to a scenario for the year 2020 and examine the European impact of a splitting of the German price zone. Assuming a trading capacity of 8 GW, the average price differences between the two zones amount to 5.16 EUR/MWh_{el}. While the greatest changes in consumer rents and producer rents can be observed in Germany, to a lesser extent, many neighboring countries are also affected. Since the authors don't use an additional grid model, no analyses on the changes in redispatching volumes and costs are carried out.

All of the studies mentioned so far focus on the static short-term perspective without taking into account dynamic long-term aspects, such as the impact on investments in new generation capacity. The literature tackling these particular issues, as presented in the following, is substantially less extensive to date.

Applying an integrated generation investment, spot market and redispatching model to a small-scale test network, Grimm et al. (2016b) provide a theoretical analysis of potential long-term welfare effects of splitting up price zones under consideration of investment behavior. In their work, they explicitly point out that for the political discussion regarding concrete splitting of zones, the consideration of such long-term impacts is essential for decision making.

This aspect is further investigated in a number of additional contributions (Grimm et al., 2016a, 2017, 2018; Ambrosius et al., 2019), all of which apply multilevel equilibrium models considering both the electricity market and the electrical grid.

In Grimm et al. (2016a), a model with decision levels for line expansion, generation capacity expansion and spot market including redispatching is introduced, formally analyzed and applied to a small-scale case study. Grimm et al. (2018) then extend this model and investigate different market design changes including market splitting for a strongly simplified representation of the German electricity system and a single future year (2035). The division of the German price zone is conducted in a simplified fashion along the borders of some German federal states. The authors find that the locational price signals occurring under market splitting induce a more efficient allocation of conventional power plants. This, in turn, reduces the need for grid expansion. Moreover, the choice of appropriate transfer capacities between the two German zones proves to be crucial.

The first decision level of Grimm et al. (2016a) is modified in Grimm et al. (2017) in order to model-endogenously derive an optimal specification of price zones instead of deciding on line investments. While Grimm et al. (2017) focus on solution algorithms and highly-aggregated test cases, Ambrosius et al. (2019) use an again slightly modified version of this model to derive an optimal delimination of the German price zone under consideration of anticipated generation capacity expansion as well as spot market trading and redispatching. A novelty of this contribution is the model-endogenous determination of the transfer capacities between the different German price zones. The extended model is applied to a strongly simplified representation of the German electricity system in a single future year (2035). Ambrosius et al. (2019) find that under two or three price zones in Germany, the major part of the theoretically achievable welfare gains is already realized, while increasing the amount of zones further brings little additional benefit.

The above-mentioned contributions are the first in the literature to present important insights in potential long-term impacts of splitting the German price zone in two or multiple zones. Yet, despite modeling different decision levels, Ambrosius et al. (2019) assume perfect anticipation of the regulator in terms of generation expansion planning, spot market trading and redispatching. Moreover, the long-term effects of splitting the German price zones are only analyzed for a single future year and under strong simplifications, particularly in terms of grid resolution. We therefore propose an alternative modeling framework, which extends the work of Ambrosius et al. (2019) in three important aspects.

Firstly, in our approach, the regulator decides on an optimal delimination of the German price zone prior to the decisions of the companies on investments in new generation and storage units, i.e., under imperfect information. In a real-world setting, this is exactly the situation a regulator would be confronted with when deciding on a new price zone configuration. Not having any information on the reactions of the generation companies, he could only base his decision on information available to date.

Secondly, our proposed modeling framework includes an agent-based multi-period simulation covering 2020 through 2050 as well as Germany and all neighboring countries. This approach allows to capture long-term investment and short-term market behavior under imperfect information while adequately accounting for both intertemporal effects and cross-border effects.

Thirdly, the applied optimal power flow model considers the entire German transmission grid and auxiliary nodes in the neighboring countries rather than using a strongly simplified representation of the grid. Therefore, cross-border effects in terms of required congestion management measures and persistent intra-zonal congestion can also be considered.

For these reasons, the novel approach presented in the following is very well suited to capture dynamic long-term impacts of a zonal split in Germany in a closer-to-real-world fashion than any other publication available to date.

D.3 Methodology

Any approach that aims to investigate all relevant long-term aspects of a zonal split in Germany needs to cover the decisions of different actors. Firstly, a regulator deciding on the actual zonal split, secondly, the long-term investment and short-term market decisions of the different generation firms, and thirdly, the required

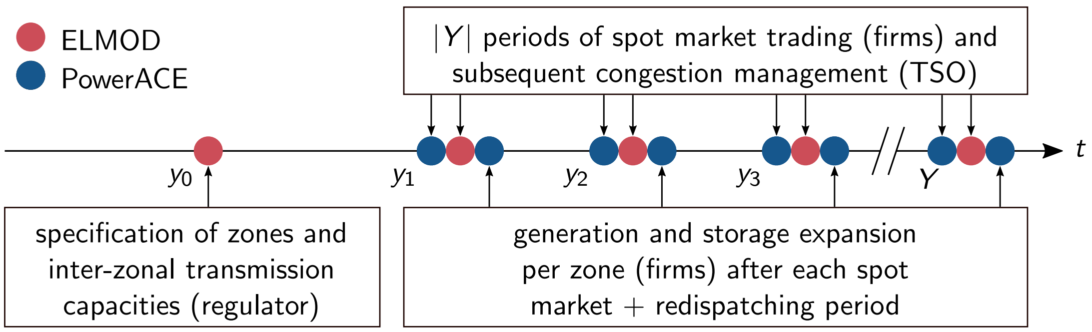


Figure D.1: Timeline of the combined application of the models ELMOD and PowerACE. *Source:* based on a similar illustration in Ambrosius et al. (2019).

congestion management measures carried out by the transmission system operator (TSO).

We tackle this challenge by jointly applying two established energy-related models, namely the optimal power flow model ELMOD and the electricity market simulation model PowerACE. In Section D.3.1, we describe the interaction of the two models and outline the advantages of our modeling framework. Sections D.3.2–D.3.5 then explain in detail, how the different decision levels are modeled in ELMOD and PowerACE.

D.3.1 Overview of the Modeling Framework

The timeline of the different decision levels in the combined application of ELMOD and PowerACE is presented in Fig. D.1. In order to outline the differences between our modeling approach and that of Ambrosius et al. (2019), we use the same style for our illustration as they do.

In a first step (bottom-left box), the regulator decides on an optimal splitting of the German price zone and corresponding transfer capacities. For this purpose, hourly nodal prices that are simulated with ELMOD for the base year 2020 are clustered in two zones (see Section D.3.2 for details). Contrary to Ambrosius et al. (2019), the zonal delimitation is independent of the subsequent decisions on expansion planning and (re)dispatch, since a regulator wouldn't have a priori knowledge on these decisions in a real-world setting.

Next, $|Y|$ periods are simulated, each denoting one year at hourly resolution. For each period, the simulation covers three steps. Firstly, using the information on the new zonal delimination, the day-ahead market is simulated with PowerACE (for details see Section D.3.3). Secondly, the hourly dispatch originating from the market simulation serves as input to determine required congestion management measures with ELMOD (for details see Section D.3.4). These two steps correspond to the top-right box in Fig. D.1. Thirdly, the different companies create their individual generation and storage expansion plan for the subsequent periods (bottom-right box). Contrary to Ambrosius et al. (2019), these decisions are not directly related to the (re)dispatch of the following periods, but the companies rather prepare future price forecasts and generate their expansion plans accordingly. This approach is again closer to a real-world setting, since real companies only have limited knowledge on the future developments of the day-ahead markets. Moreover, multiple years are simulated and therefore also multiple investment decisions are taken, which makes it possible to better grasp the long-term dynamics of a zonal split. For details on the investment planning, see Section D.3.5.

In the subsequent Sections D.3.2–D.3.5, we describe the different decision levels in more detail. Additionally, Appendix D.7.1 provides a brief general introduction to the models.

D.3.2 Zonal Configuration and Transfer Capacities

As a first step when investigating the impacts of market splitting in Germany, we need to carry out an adequate reconfiguration of the bidding zone which is both stable and has low intra-zonal congestion. Stable in this context means that considering all hours of a base year, the final zonal configuration is predominant to other configurations.

In electricity systems, the nodal price or locational marginal price (LMP) of a given grid node represents the marginal cost of delivering an additional unit of electricity to this specific node. The LMP includes information on both marginal generation costs and the physical aspects of the transmission grid. Using the standard objective function of minimizing total generation costs, we apply ELMOD to calculate the LMP λ_n at every node $n \in \boldsymbol{N}$ which corresponds to the dual variable of the energy balance as shown later in Eq. (D.2).

If the grid is congested between two nodes, the LMPs of these nodes diverge. In contrast, nodes with identical or similar LMPs are typically not affected by congestion between each other. These properties of LMPs imply that clustering nodes with similar LMPs is a promising approach in order to determine stable zones with low intra-zonal congestion. Therefore, in order to split the German market area into two bidding zones, we apply a fuzzy c-means clustering algorithm (Dunn, 1973; Bezdek, 1981; Hong et al., 2002) to the LMPs of all German grid nodes over 8760 hours of the base year 2020.

The major challenge when clustering the LMPs is to avoid fragmented zones, meaning that some nodes are clustered in the same zone but are not physically connected. A proven solution for similar scientific network questions is the application of spatial clustering which is based on graph theory (e.g., von Luxburg, 2007). Spatial clustering of an electricity network uses a Laplacian matrix L which considers the relation between two nodes $n_i, n_j \in \boldsymbol{N}$ as well as lines/edges $e \in \boldsymbol{E}$ within graph $G = (\boldsymbol{N}, \boldsymbol{E})$. This procedure has previously been applied by Metzdorf (2016).

After determining the new bidding zone configuration for Germany, we calculate the trading capacities between the two bidding zones based on the transmission capacities on the border lines of the zones for 2020. Thereby, DC-lines are counted at full and AC-lines at one third of their capacity to account for uncertainties regarding the state of the grid at a given point in time. For the subsequent years, we take into account additional capacities on the basis of the network development plans.

D.3.3 Day-Ahead Market Simulation

Splitting the German market area into two price zones has a direct impact on the outcomes of the day-ahead markets, both in the short-term and the long-term. Using the zonal split determined with ELMOD, we can now apply PowerACE to quantify these effects as explained hereafter.

The PowerACE model is structured into different market areas $m \in \boldsymbol{M}$, in each of which multiple supply traders, i.e., utility companies, are active on the day-ahead market. The simulation of the day-ahead market consists of four steps, which are briefly outlined in the following.

Price forecast According to the economic theory, market participants are willing to sell electricity at their marginal generation costs. However, starting up a power plant leads to additional costs due to higher fuel consumption and a reduced lifetime caused by material stress. In order to account for these costs and prepare bids accordingly, it is important for the supply traders to estimate, if and how long a specific power plant will be in the market on the following simulation day. Thus, in a first step, all supply traders prepare a price forecast for all hours $h \in \boldsymbol{H}$ of the following day. The basic approach for this price forecast is an extended merit-order model, i.e., a cost-minimal power plant dispatch serving the expected hourly residual loads in the respective market area is determined under consideration of both variable and start-up costs[41]. The major output of the price forecast are the expected running hours for all power plants on the following simulation day.

Bidding Using the information from the price forecast, the different supply traders now prepare bids for all of their own power plants and each hour h of the following day. These bids consist of volume (MWh), price (EUR/MWh) and type (buy or sell). While the bid volume for each power plant is determined considering an exogenously given availability factor and a potential obligation to provide balancing power, the bid price depends both on the type of the power plant and whether the power plant is expected to run in the respective hour or not. An overview of the bidding strategies is provided in Appendix D.7.2.

Market clearing All bids prepared in the previous step are then submitted to the market coupling operator. In the market clearing process, supply and demand bids are matched across all market areas, such that welfare is maximized subject to the limited interconnector capacities between the different market areas. For a formal description and details of the market coupling and clearing, see Ringler et al. (2017). As a result, the information, which bids have been partly or fully accepted is returned to the different supply traders.

Dispatch All supply traders now calculate their individual hourly load curve, which is the sum of their hourly bids that have been accepted. In the final step of

[41] Formally, this step requires to solve a mixed-integer optimization problem. However, to save computational resources, a heuristic approach is applied, such that only close-to-optimal solutions can be guaranteed.

the day-ahead market simulation, the different traders determine a cost-minimal dispatch of their individual power plant fleet, which serves their hourly load curve under consideration of both variable and start-up costs[41].

D.3.4 Congestion Management

Using the hourly dispatch of all power plants as obtained from the day-ahead market simulation with PowerACE, we can now determine the impact of splitting the German market area on the required congestion management measures using ELMOD. In the ELMOD version applied in this contribution, the congestion management comprises redispatching of conventional power plants and curtailment of renewable energy production. The integration of these instruments into ELMOD is briefly described in the following.

As shown in Eq. (D.1), ELMOD has a linear objective function in which the total costs of congestion management $C_{\text{total}}^{\text{cong}}$ across all market areas $m \in \boldsymbol{M}$ are minimized.

$$\text{minimize} \quad C_{\text{total}}^{\text{cong}} = \sum_{m \in \boldsymbol{M}} \left(C_m^{\text{redisp}} + C_m^{\text{curt}} \right) \tag{D.1}$$

where

C_m^{redisp} = total redispatching costs in market area m
C_m^{curt} = total curtailment costs in market area m

The main restriction of ELMOD is the energy balance presented in Eq. (D.2), which needs to be fulfilled at every transmission grid node n and in every hour h. Please note:

- The power plant set $\boldsymbol{P}_n$ at node n comprises subsets for conventional power plants $\boldsymbol{P}_n^{\text{con}}$, storage plants $\boldsymbol{P}_n^{\text{stor}}$ and renewable power plants $\boldsymbol{P}_n^{\text{ren}}$.
- The gross load $l_{n,h}^{\text{gross}}$ is exogenously set and assumed fully price-inelastic.
- The neighboring countries of Germany are represented with one aggregated grid node and additional auxiliary nodes to capture interconnector behavior.

$$l_{n,h}^{\text{gross}} + \sum_{p \in \boldsymbol{P}_n^{\text{stor}}} l_{p,h}^{\text{charge}} = \sum_{p \in \boldsymbol{P}_n} g_{p,h} + f_{n,h}^{\text{AC}} + f_{n,h}^{\text{DC}} \quad \forall n \in \boldsymbol{N}, h \in \boldsymbol{H} \tag{D.2}$$

where

$l_{n,h}^{\text{gross}}$ = gross load at node n in hour h
$l_{p,h}^{\text{charge}}$ = storage charging of unit p in hour h (decision variable)
$g_{p,h}$ = electricity generation of power plant p in hour h (decision variable)
$f_{n,h}^{\text{AC}}$ = net input of the AC lines at node n in hour h
$f_{n,h}^{\text{DC}}$ = net input of the DC lines at node n in hour h

The redispatching costs C_m^{redisp} of all market areas $m \in \boldsymbol{M}$ are determined based on the deviations between the hourly market-dispatched power plant generation $g_{p,h}^{\text{market}}$ with $p \in \boldsymbol{P}_m^{\text{con}}$ and the endogenous generation variables $g_{p,h}$ of ELMOD, which are multiplied by the marginal costs of the respective power plant c_p^{var} as shown in Eq. (D.3).

$$C_m^{\text{redisp}} = \sum_{p \in \boldsymbol{P}_m^{\text{con}}} \sum_{h \in \boldsymbol{H}} \left(g_{p,h} - g_{p,h}^{\text{market}} \right) \cdot c_p^{\text{var}} \quad \forall m \in \boldsymbol{M} \tag{D.3}$$

It is important to note that for computational performance reasons start-up costs are considered in the market simulation with PowerACE, but not in the grid model ELMOD. Consequently, $g_{p,h}^{\text{market}}$ could be re-optimized without an actual grid congestion need. In order to avoid this, Eq. (D.3) needs to be reformulated such that both positive and negative redispatching of conventional power plants are penalized. For details on the reformulation, please refer to Appendix D.7.3.

If the redispatching capacities of the conventional power plants are not sufficient to find a feasible solution, curtailment of the market-dispatched renewable generation $g_{p,h}^{\text{market}}$ with $p \in \boldsymbol{P}_{\boldsymbol{m}}^{\textbf{ren}}$ is deployed by the model, i.e., $g_{p,h}^{\text{market}}$ is reduced to $g_{p,h}$. The differences between $g_{p,h}^{\text{market}}$ and $g_{p,h}$ lead to curtailment costs C_m^{curt}, which are integrated into ELMOD as shown in Eqs. (D.4) and (D.5)[42].

[42]The curtailment costs for renewable generation are an artificial penalty, because generation costs are already included in the market dispatch and additional costs for the system will only occur for the positive redispatching which is needed to balance the system. Nevertheless, these penalty costs can be explained by the Renewable Energy Directive (2009/28/EC) which claims

$$C_m^{\text{curt}} = \sum_{p \in \boldsymbol{P}_m^{\text{ren}}} \sum_{h \in \boldsymbol{H}} \left(g_{p,h}^{\text{market}} - g_{p,h} \right) \cdot c^{\text{curt}} \quad \forall m \in \boldsymbol{M} \tag{D.4}$$

$$g_{p,h} \leq g_{p,h}^{\text{market}} \quad \forall p \in \boldsymbol{P}^{\text{ren}}, h \in \boldsymbol{H} \tag{D.5}$$

Although most of the grid congestion events can be relieved by redispatching and curtailment measures, it is reasonable to use additional auxiliary variables for dumped load $l_{n,h}^{\text{dump}}$ and artificially added load $l_{n,h}^{\text{add}}$ to guarantee a feasible solution. For details on the integration of these variables, please refer to Appendix D.7.3.

Finally, it is important to mention that the neighboring countries of Germany are only represented in a simplified fashion. Therefore, the focus of the congestion management measures is on Germany with the neighboring countries being used for redispatching only if the German power plant capacities are not sufficient (see also Appendix D.7.3).

D.3.5 Investment Planning

The potential impact on investment incentives is an essential aspect when evaluating the long-term efficiency of splitting the German market area. For this purpose, the different utility companies modeled as agents in PowerACE can perform long-term decisions on investments in new conventional power plant and storage capacities at the end of each simulation year. Contrary to the common approach of expansion planning with the objective of minimizing total future system costs, an actor's perspective is taken. Consequently, investments are only carried out if expected to be profitable by the investor agents. The applied investment planning algorithm is introduced and described in detail in Fraunholz et al. (2019). A brief overview of the basic principles is given in the following.

The decisions of the different investors are primarily based on their expectations regarding future electricity prices. As these, vice versa, are influenced by the investment decisions of all investors in all interconnected market areas, a complex

priority access to the grid for renewable generation in real time. Furthermore, renewable generation is often subsidized by feed-in tariffs or premiums which add to the generation costs of the market (Bjørndal et al., 2018). Therefore, the curtailment costs of renewable generation c^{curt} are orientated at the maximum penalty costs for negative redispatching in Germany in the respective year. Using this approach, curtailment is only carried out if the available redispatching capacities are not sufficient to relieve the grid congestion – similarly to the real-world process.

game with multiple possible strategies opens up. To find a stable outcome for this game, a Nash-equilibrium needs to be determined.

Therefore, the investment planning algorithm terminates when all planned investments are profitable and at the same time none of the investors is able to improve his expected payoff by carrying out further or less investments, i.e., there is no incentive for any investor to unilaterally deviate from the equilibrium outcome. The eleven different market areas[43] are defined as the players interacting with each other and the planned investments are then distributed among the investors within each market area. This is achieved by first randomizing and then iterating over the different investors after each investment being carried out[44]. Following this approach, it is possible to consider the mutual impact of investments in one market area on the electricity prices and consequently investments in the interconnected market areas.

After the investment planning in PowerACE has been carried out, the grid nodes of ELMOD are sorted per market area in descending order beginning with the node where most old power plant capacity has been decommissioned. The new investments in the respective market area are then allocated to the sorted list of grid nodes. Please note that it may also occur that more capacity is newly built than decommissioned in a given market area. In this case, the ratio between total newly installed capacity and total decommissioned capacity in the given zone is computed. The installed capacity at each node is then increased by this factor.

D.4 Data and Scenario Setup

As cross-border effects have a strong impact on the splitting of market areas, we model Germany and all neighboring countries plus Italy in our analysis. The time horizon covers 2020 through 2050 at hourly resolution. While we carry out a continuous simulation over the whole time period in PowerACE, we only investigate selected years in terms of required congestion management with ELMOD. An overview of the model resolutions is provided in Table D.1 and further details

[43]Germany in two price zones and all of its neighboring countries plus Italy.

[44]If the investors within each market area are differently parameterized, it would also be possible to have the single investors instead of the market areas play against each other. However, since the focus of our paper is not on market power issues, we choose the more basic approach of defining the market areas as players.

Table D.1: Model resolution of PowerACE and ELMOD.

Type	PowerACE	ELMOD	
	All countries	Germany	Other countries
Temporal resolution	2020–2050 (yearly), 8760 h/a	2025/2035, 8760 h/a	
Transmission grid	interconnectors	full representation	aggregated grid nodes
Conventional power plants	unit level	unit level	technology aggregated
Electricity demand	market area, hourly	grid node, hourly	aggregated grid node, hourly
Renewable feed-in	market area, hourly	grid node, hourly	aggregated grid node, hourly

are described in the following. Please note that all (future) prices and costs are calculated in real values to exclude the effect of inflation.

Both models – PowerACE and ELMOD – use consistent data on the power plant fleets in the year 2020 which has been compiled using information from Bundesnetzagentur (2017) for Germany and S&P Global Platts (2015) for the other countries. In PowerACE, this data is used on unit level for all countries, while ELMOD applies technology aggregated data for the neighboring countries. Based on their individual commissioning year, the existing power plants are gradually decommissioned over the time horizon until 2050 after reaching the end of their technical lifetime. This is exemplary shown on a technology aggregated level for the German market area in Fig. D.2. In Germany, the phase-out of all nuclear power plants until 2022 as well as of all coal-fired power plants until 2038 is implemented, following the suggestions of the German *Kohlekommission* (Bundesministerium für Wirtschaft und Energie, 2019).

Fossil fuel prices are based on the EU Reference Scenario (de Vita et al., 2016), while the CO_2 price development path is taken from the same source, yet scaled to reach 150 EUR/t_{CO_2} in 2050. Historical electricity demand profiles of 2015 obtained from ENTSO-E (2017) are used and scaled to the yearly demand according to de Vita et al. (2016). Electricity generation from renewables is based on historical profiles of 2015 (ENTSO-E, 2017), which are scaled such that an overall renewable share in relation to electricity demand of 80 % in 2050 is reached. Fig. D.3 illustrates the assumed composition of the renewable electricity generation in

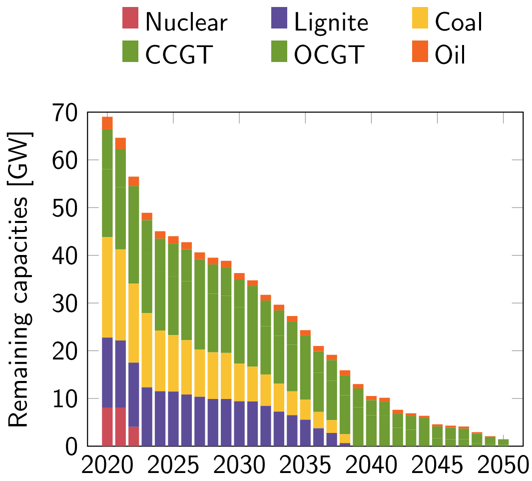


Figure D.2: Assumed conventional power plant capacities in Germany without additional new investments. *Source:* Bundesnetzagentur (2017), and own assumptions. *Abbreviations:* CCGT—combined cycle gas turbine, OCGT—open cycle gas turbine.

Germany as well as the total yearly gross electricity demand[45]. Despite the potential impact of market splitting on regional incentives to flexibilize load, demand side management is out of the scope of this paper and not taken into account.

In ELMOD, the transmission grid is modeled on a nodal level for Germany while aggregated artificial grid nodes are defined for the neighboring countries (see Fig. D.4). Future grid extension is based on the Ten-Year Network Development Plan (ENTSO-E, 2016). However, given the current status of the different HVDC projects in Germany, we assume a delay of five years compared to the official plans.

For the German market area, the power plant fleet, hourly renewable feed-in and hourly electricity demand are regionalized and then assigned to the respective grid nodes in ELMOD. The regionalization of renewable power plants is based on data from Bundesnetzagentur (2019). For the electricity demand, a load share for each node is calculated based on gross domestic product and population per NUTS-3 area. Please note that the shares of renewable feed-in by technology and

[45]In reality, driven by sector coupling, the electricity demand may increase much stronger than we assumed. This is particularly true in the period after 2040. However, the grid would then likely also be further extended. Since no data on grid extension after 2035 is currently publicly available, we use relatively conservative assumptions regarding demand growth and renewable expansion. In future research, more ambitious scenarios should therefore also be investigated.

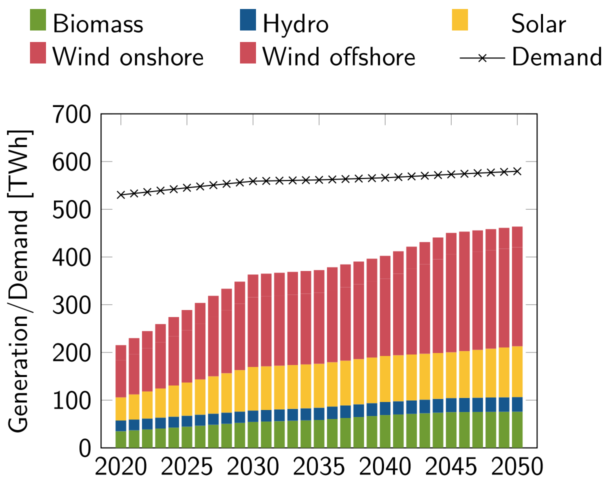


Figure D.3: Assumed annual renewable electricity generation and gross electricity demand in Germany. *Source:* de Vita et al. (2016), and own assumptions.

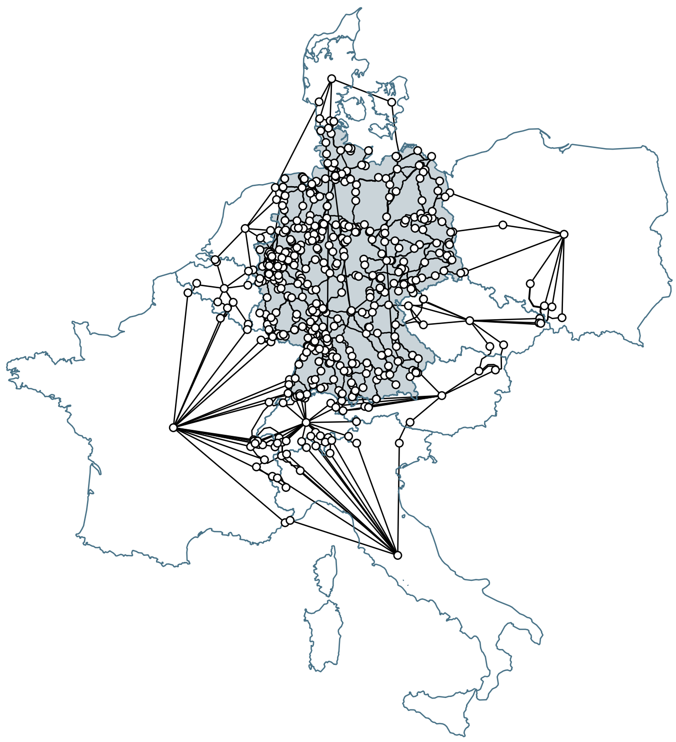


Figure D.4: Simulated market areas and corresponding level of detail of the grid model.

electricity demand at each node are assumed constant over the whole simulation period, i.e., today's yearly generation and demand are scaled to the respective future values.

For the day-ahead market simulation in PowerACE, the exchange of electricity between Germany and its neighboring countries is limited by fixed maximum transfer capacities obtained from ENTSO-E (2016), while – similarly to the real-world market clearing process – intra-zonal grid constraints are not considered.

The agents in PowerACE can invest in different conventional power plants as well as utility-scale storage technologies. An overview of these investment options with their respective techno-economic characteristics is provided in Appendix D.7.4. Accounting for the political situation in the different market areas, investments in lignite- or coal-fired power plants are only eligible in the Czech Republic and Poland.

In order to analyze the long-term impacts of splitting the German price zone, two different scenarios need to be investigated. Table D.2 summarizes the main characteristics of these scenarios. In scenario *REF*, which serves as a benchmark, the German market area consists of only one countrywide price zone (*DE*). Consequently, no intra-zonal transmission grid constraints are considered in the day-ahead market simulation with PowerACE. However, these constraints become relevant in the subsequent step, when calculating the required congestion management measures in ELMOD based on the market outcome of PowerACE. Contrary, in scenario *SPLIT*, a division of the German market area in a Northern price zone (*DEN*) and a Southern price zone (*DES*) is investigated.

The splitting of the German market area is assumed to take place in 2020. In order to implement the market splitting, we apply a limited static transfer capacity between the two German price zones for the day-ahead market simulation in PowerACE. This transmission limit is adjusted over time to account for grid extension within Germany (see Section D.5.1). For the calculation of required congestion management in ELMOD, we consider the full German transmission grid in the same way as for the scenario REF.

Table D.2: Overview of the investigated scenarios.

Scenario	German market area	Day-ahead market clearing	Congestion management
REF	one countrywide price zone (DE)	no consideration of any intra-zonal transmission grid constraints	consideration of intra-zonal transmission grid constraints
SPLIT	two price zones (DEN/DES)	limited static transfer capacity between German price zones	consideration of intra-zonal transmission grid constraints

D.5 Results and Discussion

D.5.1 Zonal Configuration and Transfer Capacities

Before delving into the long-term impacts of splitting the German market area, let us start with a brief look at the zonal delimination resulting from the clustering of nodal prices (Fig. D.5). While the regionalized electricity demand (cf. Section D.4) is split roughly evenly between DEN and DES, we can see that the majority of conventional power plants, in particular lignite-fired capacities with low variable costs, is located in DEN. Regarding renewable electricity generation, we can state that solar is split evenly, whereas wind power is predominantly located in DEN and hydro power in DES. For details, please refer to Table D.3.

In Table D.4 we show the corresponding assumed total net transfer capacities, which are an important driver for the day-ahead market simulation and generation expansion planning. We calculate the capacities based on the transmission capacities on the border lines of the zones in the respective year as described in Section D.3.2. As previously mentioned, we assume a delay of five years for the different HVDC projects compared to the official plans.

D.5.2 Day-Ahead Market Impacts

Let us now move on to the short-term and long-term day-ahead market impacts of splitting the German market area.

We can see that in both scenarios REF and SPLIT, the average day-ahead prices $\overline{p}$ in Germany increase significantly throughout the simulation period despite the high shares of renewable electricity generation (Fig. D.6a). This trend can mainly be attributed to the assumed strong increase in CO_2 prices, more frequent

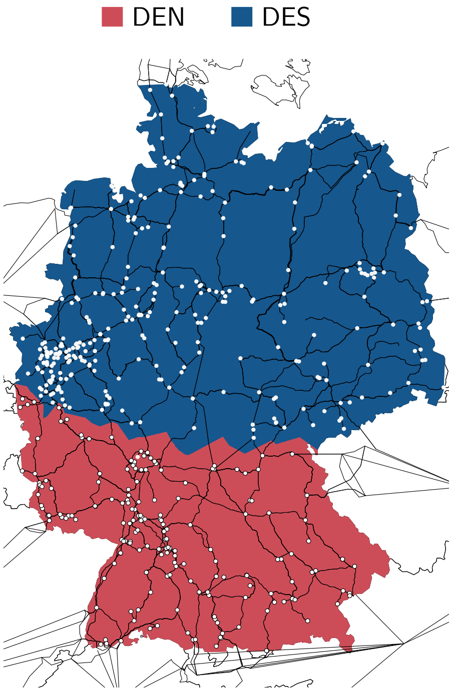


Figure D.5: Optimal delimination of the German bidding zone resulting from the clustering of nodal prices.

Table D.3: Conventional power plant capacity, renewable feed-in and electricity demand in Germany for the base year 2020 and the respective shares in DEN and DES as resulting from the bidding zone delimination. *Source:* Bundesnetzagentur and Bundeskartellamt (2017); de Vita et al. (2016), and own assumptions/calculations. *Abbreviations:* CCGT—combined cycle gas turbine, OCGT—open cycle gas turbine.

Technology type	Capacity/Generation/Demand	Share in DEN	Share in DES
Nuclear	8.1 GW	51 %	49 %
Lignite	14.7 GW	98 %	2 %
Coal	21.0 GW	63 %	37 %
CCGT	14.2 GW	71 %	29 %
OCGT	8.3 GW	72 %	28 %
Oil	2.7 GW	82 %	18 %
Pumped storage	6.4 GW	38 %	62 %
Biomass	33.9 TWh	64 %	36 %
Hydro	22.5 TWh	20 %	80 %
Solar	48.5 TWh	49 %	51 %
Wind onshore	78.2 TWh	87 %	13 %
Wind offshore	31.3 TWh	100 %	0 %
Electricity demand	530.3 TWh	58 %	42 %

Table D.4: New high-voltage direct current (HVDC) lines and assumed total net transfer capacity (NTC) of all lines between DEN and DES (both directions) in scenario SPLIT. *Source:* ENTSO-E (2016), and own assumptions.

Years	New HVDC lines	Total NTC
2020–2026	Ultranet	8 GW
2027–2028	Suedlink	12 GW
2029	SuedOstLink	14 GW
2030–2034	A-North	16 GW
2035–2050	DC21/DC23	18 GW

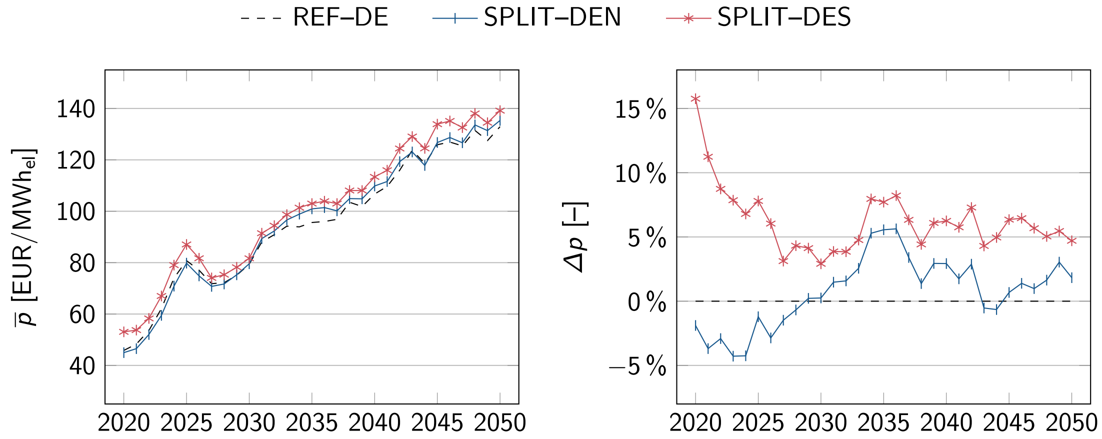
and costly start-ups of conventional power plants as well as some scarcity hours with prices of 3000 EUR/MWh_{el}.

In order to isolate the price impact resulting from the split of the German market area, we transform the mean prices $\overline{p}$ to relative price differences for further analysis (Fig. D.6b). For this purpose, we define the German mean day-ahead price in scenario REF as a reference and then compute the relative price differences $\Delta p_{s,m}$ in scenario s and market area m as $\Delta p_{s,m} = \overline{p}_{s,m} / \overline{p}_{\text{REF,DE}} - 100\,\%$. Consequently, by definition, the relative price differences of REF–DE are always at 0 % throughout the simulation period.

We can see from Fig. D.6b that initially, in 2020, the average prices in DEN are only around 2 % (corresponds to 0.87 EUR/MWh_{el}) lower, but those in DES almost 16 % (7.23 EUR/MWh_{el}) higher than in the single German price zone[46]. Between 2020 and 2035, the relative price differences between DEN and DES continuously decline, which is mainly driven by the grid extension and the resulting increase in transfer capacities between the two German price zones (cf. Table D.4). However, due to the ongoing strong expansion of renewables (cf. Fig. D.3) and no additional grid extension after 2035, the relative price differences rise again slightly in the second part of the simulation period (2035–2050).

This result is also reflected in Fig. D.7 showing the sorted hourly price differences between DES and DEN. While the share of hours with positive price differences (i.e., higher prices in DES than in DEN) declines strongly from around 40 % to less than 10 % between 2020 and 2035, their absolute magnitude increases sharply between 2035 and 2050. The reasons for this finding are twofold. Firstly, towards 2050, renewables are increasingly often price-setting in DEN with their marginal cost of 0 EUR/MWh_{el}, while conventional capacity is still needed in DES due to a lack of transmission capacity between the two German price zones. Secondly, the general level of the day-ahead prices rises strongly over the course of the simulation as previously explained. Situations with higher prices in DEN than

[46] These price differences between the two German price zones are higher than those found in the literature (cf. Section D.2). However, previous studies are difficult to compare to ours due to varying scenario years and substantially different assumptions, e.g., regarding the power plant fleets. In additional sensitivities with higher (lower) net transfer capacities of 10 GW (6 GW), we find the price differences to decrease (increase) to 4.96 EUR/MWh_{el} (12.37 EUR/MWh_{el}). These results stand well in line with those of Plancke et al. (2016). Splitting the German market area already in 2015 instead of 2020, we obtain an average price difference of 2.35 EUR/MWh_{el}, which is comparable to that found by Egerer et al. (2016) for 2015 (1.70 EUR/MWh_{el}).



(a) Volume-weighted average day-ahead prices

(b) Relative price differences

Figure D.6: Simulated development of the day-ahead prices (real values) in absolute (a) and relative (b) terms for both scenarios REF and SPLIT.

in DES occur in well below 1 % of the hours throughout the simulation period and are therefore not further discussed.

Fig. D.6b also illustrates that in the medium to long term, the price level in both DEN and DES is slightly higher than in REF–DE. Given the completely different setup regarding location of (new) power plants (discussed below, cf. Fig. D.8), grid extension (cf. Table D.4) and renewable expansion (cf. Fig. D.3) as compared to the base year 2020, the assumed zonal configuration has become outdated by 2035. Moreover, the limited transfer capacity between the two German price zones leads to a less efficient market outcome than under a single German price zone. The major reason for this finding is that the additional restrictions at the market clearing stage lead to more electricity generation by peak load units with high variable costs, while at the same time the market-based curtailment of renewables with zero variable costs increases under a zonal split (discussed in Section D.5.3, cf. Fig. D.9c).

The bidding zone delimination and the related price divergence between DEN and DES also has an impact on the respective investment incentives for conven-

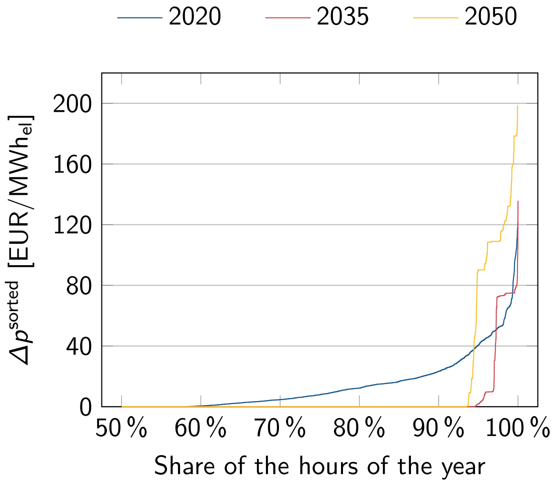


Figure D.7: Simulated sorted day-ahead price differences (real values) between DES and DEN in scenario SPLIT.

tional power plants and utility-scale storage units[47]. In Fig. D.8, the simulated development of the conventional power plant and utility-scale storage capacities in the two prices zones DEN and DES is depicted for both scenarios REF and SPLIT[48].

As compared to scenario REF, significantly more investments are carried out in the price zone DES in scenario SPLIT, while the opposite is true for the price zone DEN. This is a direct outcome of the investment planning module presented in Section D.3.5. Due to the higher electricity price forecasts in DES, investments in DES are often preferred over DEN in scenario SPLIT. Contrary, in scenario REF, new power plants are distributed equally between DEN and DES.

The generally slightly higher price level in scenario SPLIT also leads to the cumulated new capacity across both price zones being a bit higher than in scenario REF. Moreover, while storage investments are not profitable in scenario REF, some investments in these technologies are carried out in scenario SPLIT and price zone DEN. Given the high amount of renewable electricity generation in DEN as well

[47]The expansion of renewable generation capacities is not modeled endogenously, instead the renewable feed-in is based on exogenously defined hourly profiles (see Section D.4).

[48]In scenario REF, new capacities in Germany are distributed evenly between the two zones DEN and DES to allow for a comparison with scenario SPLIT.

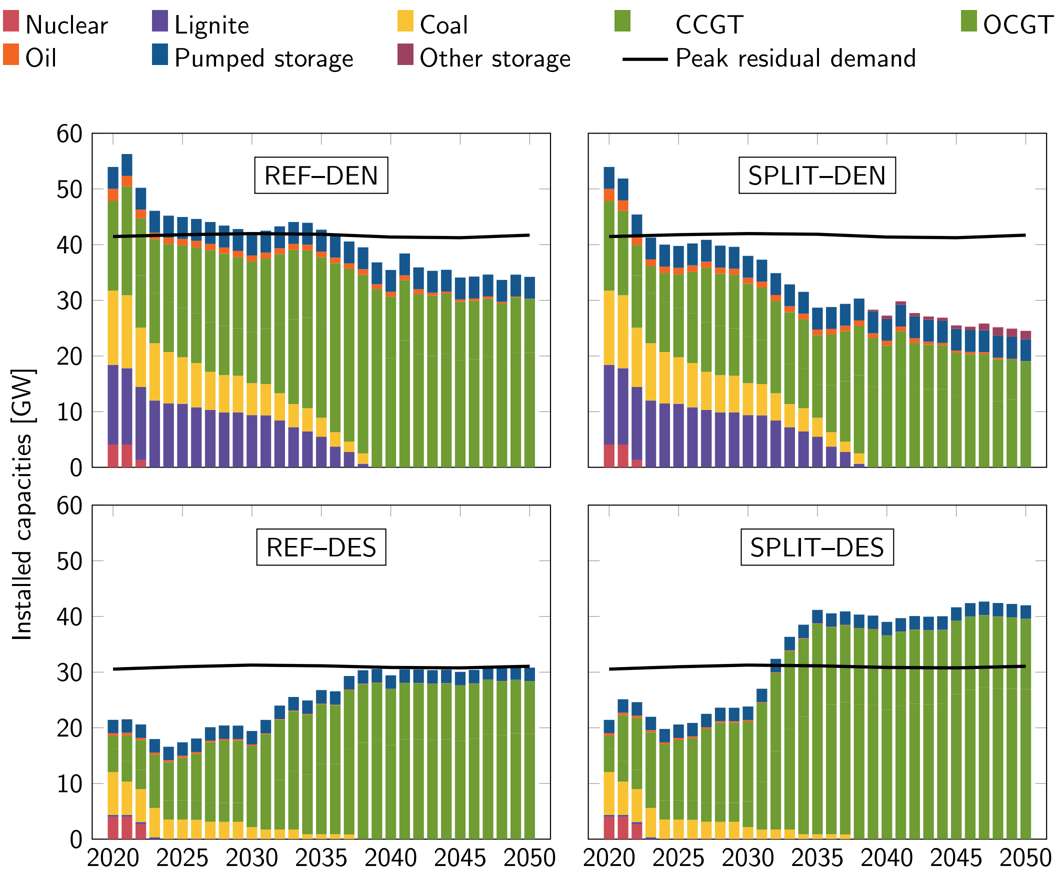


Figure D.8: Simulated development of the conventional power plant and utility-scale storage capacities in Germany for both scenarios REF and SPLIT. *Abbreviations:* CCGT—combined cycle gas turbine, OCGT—open cycle gas turbine.

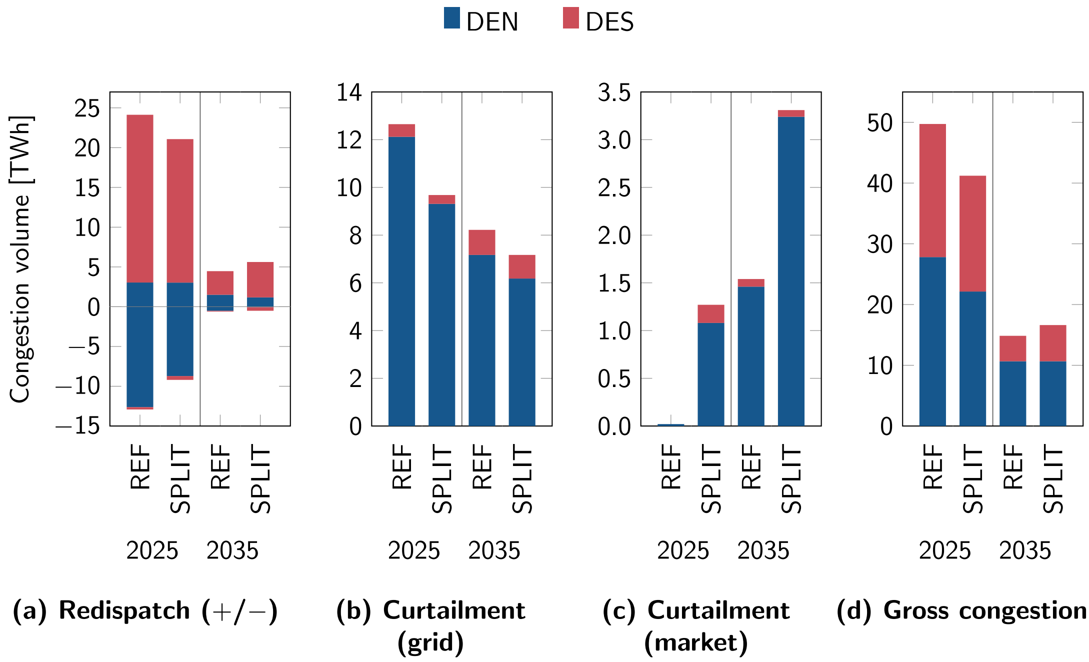


Figure D.9: Required congestion management measures by category for both scenarios REF and SPLIT. As is common practice, the gross congestion volume (d) is calculated as the absolute sum of categories (a)–(c).

as the limited transfer capacities to DES in scenario SPLIT, this finding is quite straightforward.

D.5.3 Congestion Management

The day-ahead market results described in the previous section have an immediate impact on the required congestion management measures. The volumes of these measures are presented by category and for both scenarios REF and SPLIT in Fig. D.9.

We can see that in 2025 the redispatching volumes decrease as a result of the zonal split (Fig. D.9a). More specifically, by considering potential grid congestion between DEN and DES already at the market clearing stage, negative redispatching in DEN and positive redispatching in DES can be reduced. However, as discussed before, the different setup as compared to the base year 2020 leads to the assumed zonal configuration becoming outdated by 2035, which ultimately causes an increase of positive redispatching volumes in DES.

As expected, splitting the German market area leads to a reduction of grid-related curtailment in both 2025 and 2035 (Fig. D.9b). This is particularly relevant for DEN due to the large amount of wind power installed. However, the positive effect is overcompensated in 2035 by additional market-related curtailment (Fig. D.9c), which results from the strong increase in renewable electricity generation and the limited net transfer capacities between DEN and DES. In consequence, we can observe a negative total effect of the market splitting on required curtailment of renewables in 2035.

Summing up redispatching and curtailment measures, we end up with the gross congestion volume[49] (Fig. D.9d), which decreases under a zonal split in 2025, yet increases in 2035 due to the outdated and therefore inadequate zonal configuration. These finding shows that policymakers and regulators should regularly re-assess and potentially adjust bidding zone configurations.

D.5.4 System Costs and Distributional Effects

Using the results from Sections D.5.2 and D.5.3, we can now derive a number of economic indicators, which are summarized in Table D.5. A brief description of our major findings is provided in the following.

The price differences between DEN and DES (cf. Fig. D.6b) lead to a decrease of the wholesale costs of electricity generation in DEN and an increase in DES (2025) under a zonal split, before increasing in both DEN and DES (2035). In contrast, volumes and costs of redispatching are lower for scenario SPLIT in 2025, but then rise in 2035 since the previously optimal zonal configuration has become outdated for several reasons, as mentioned before. In consequence, we find the total system costs to be higher in both 2025 and 2035 if the German market area is split into two zones.

Since we have assumed the electricity demand to be completely static, the increase in system costs is identical with the reduction of the consumer rents. In scenario SPLIT, producers in DES benefit from higher prices as compared to

[49] Please note that it is common practice to count all congestion management measures in positive terms, i.e., also negative redispatching contributes to an increase of the gross congestion volume.

Table D.5: Effects of the market splitting on economic indicators in Germany in million EUR (real values). All values show the respective deltas between the scenarios SPLIT and REF.

ID/Calculation	Indicator	Year 2025 [10^6 EUR]			Year 2035 [10^6 EUR]		
		DEN	DES	DEN+DES	DEN	DES	DEN+DES
A	Δ Wholesale costs	−308	+1440	+1132	+1732	+1735	+3467
B	Δ Redispatching costs	+243	−360	−117	+10	+88	+98
$C = A + B$	Δ System costs	−65	+1080	+1015	+1742	+1824	+3566
$D = -C$	Δ Consumer rents	+65	−1080	−1015	−1742	−1824	−3566
E	Δ Producer rents	−1207	+1115	−92	−280	+2093	+1813
F	Δ Congestion rents	+298	+380	+677	+198	+180	+378
$G = D + E + F$	Δ Total welfare	−844	+414	−430	−1824	+450	−1374

scenario REF. Thus, the producer rents in DES increase in 2025, while the opposite is true for DEN, in total leading to a reduction of the producer rents. In 2035, a substantial increase of the producer rents in DES can be observed due to the preferred allocation of new generation capacity in DES as well as higher prices as compared to scenario REF. In DEN, a lot less generation capacity is installed in scenario SPLIT, leading to a decrease of the producer rents. Since the effect in DES is much stronger than in DEN, we find an overall increase of the producer rents in Germany in 2035.

Apart from affecting the system costs, the price differences between DEN and DES also lead to higher congestion rents under a zonal split. Since the prices in both zones converge to a certain extent (cf. Fig. D.6b), this effect is less pronounced in 2035 than 2025.

We can ultimately conclude that splitting the German market area in two zones has strong distributional effects. DES benefits from a significant increase of the producer rents, which overcompensates the corresponding reduction of the consumer rents, resulting in a positive welfare effect. Yet, the opposite effect occurs in DEN. Overall, we find a negative welfare effect for Germany. Finally, it is important to mention that we take a purely German perspective in our analysis, while other neighboring countries may benefit from a German market splitting. However, given our simplified representation of the neighboring countries, we are unable to derive profound results in this regard.

D.6 Conclusion and Policy Implications

Using an innovative modeling framework consisting of an agent-based electricity market simulation model (PowerACE) and an optimal power flow model (ELMOD) we investigated the long-term impacts of splitting the German price zone in a multi-period setting with different decision levels. We found strong impacts of a market splitting on day-ahead electricity prices, investment planning of generation companies, required congestion management and, ultimately, system costs and social welfare.

After splitting the German market area into a Northern price zone (DEN) and a Southern price zone (DES) in 2020, the day-ahead prices in both zones initially diverge significantly with higher prices in DES and lower prices in DEN. The price differences then decline between 2020 and 2035, which is mainly driven by grid extension, and rise again slightly between 2035 and 2050 due to the ongoing strong expansion of renewables without additional grid extension. Since the limited transfer capacity between the two German price zones leads to a less efficient market outcome, we found the price level in both DEN and DES to be slightly higher than under a single German price zone in the medium to long term.

The higher electricity prices in DES than DEN also have an immediate impact on investment incentives, leading to much more new power plants being built in DES than DEN as compared to the reference case of a single German price zone.

The required congestion management decreases in 2025 under a zonal split, however, we found it to be higher in 2035, since the bidding zone delimination has become outdated given the completely different setup regarding location of (new) power plants, grid extension and renewable expansion as compared to the base year 2020.

These results are also reflected in system costs, which rise under a zonal split in both 2025 and 2035, mainly due to significantly higher wholesale prices for electricity. In terms of social welfare, the generation companies in DES benefit from substantial increases in producer rents, which overcompensate the reduction of consumer rents. In contrast, the generation companies in DEN suffer from lower producer rents (mainly 2025), which are then supplemented by a strong decrease in consumer rents in 2035. Overall, we found a negative welfare effect in Germany under a zonal split. However, it is important to mention that we took a purely German perspective in our analysis, while other neighboring countries may benefit from the German market splitting.

Our findings are particularly crucial for policymakers and regulators in the field of electricity market design, but also for generation companies and grid operators. Optimization approaches with perfect anticipation of future decisions by different players as previously applied in the literature typically lead to positive welfare effects of market splitting. This is rather straightforward, given the perfect foresight and single-period character of these models. In contrast, our multi-period approach with imperfect information of the different players showed that a zonal delimination optimal from today's perspective may become outdated over time in a dynamic environment with grid extension, renewable expansion and investments in new power plants.

Therefore, we recommend that policymakers and regulators should regularly re-assess and potentially adjust bidding zone configurations. However, one major objective of price zones is to provide locational investment incentives. These would be reduced, if investors could not rely on stable price zones. In consequence, adequately setting up stable bidding zones remains a major challenge, which is reflected by most of the European electricity market still being organized in countrywide price zones. Importantly, our results are not only valid for Germany, but also highly relevant for any other region using multiple price zones within a country, such as the Nordic electricity market or Italy.

We are well aware that despite providing important insights on the long-term impacts of splitting price zones, our work could be substantially extended to get a more complete picture on this issue. Regarding the day-ahead market simulation, much depends on the appropriate choice of the transfer capacities between the different zones, which is a difficult task. In reality, flow-based market coupling is already in place in Central Western Europe, which automatically accounts for and at least partly solves this issue. Our day-ahead market simulation could therefore be extended to a flow-based market coupling approach.

Moreover, we have assumed exogenous expansion of renewables. However, the different electricity price levels in DES and DEN might not only affect investments in conventional power plants, but also lead to more renewables being placed in Southern Germany despite better wind locations in Northern Germany. Our approach could therefore also be extended in this direction and account for model-endogenous renewable expansion. The same applies for the electricity demand, which we have assumed to be exogenously given and fully static. Yet, market splitting and the related price differences might create regional incentives to flexibilize load.

In future research, it would also be possible to use a more detailed representation of the grid in the German neighboring countries than we did in our paper. Like this, the welfare effects in all these countries could be investigated rather than only in Germany. Such an analysis would likely bring interesting insights on why Germany is reluctant to split its market area, while some neighboring countries are rather in favor of this measure.

Lastly, we have assumed the regulator to decide on the zonal delimination based purely on information available to him at the time of decision-making. Alternatively, some kind of iterative procedure could be implemented, in which the regulator tries to anticipate the future status of the electricity system and the behavior of the market participants as a result of his zonal split. The regulator could then adjust the initial zonal delimination accordingly. Carrying out this iteration multiple times, we would then likely end up with similar results as in the literature, where perfect anticipation of future decisions is often assumed. However, given the high degree of uncertainty that a regulator deciding on a zonal delimination is confronted with, we expect our results to be closer to the real-world setting than models with perfect anticipation of all players' decisions.

D.7 Appendix

D.7.1 Model Descriptions

Optimal Power Flow Model ELMOD

ELMOD is a linear optimization model for the analysis of interactions between electricity generation and transmission grid. Originally developed at TU Dresden (Leuthold et al., 2008), ELMOD has already been used for numerous system analyses (e.g., Kunz et al., 2011; Kunz, 2013). In ELMOD, the European transmission grid as well as power plants and electricity demand are regionally modeled on a grid node level. The load flow is approximated by a direct current (DC) approach. The objective of the standard model version is to minimize total generation costs. In this contribution, however, costs for congestion management are minimized instead, since the electricity generation of the different power plants results from the market simulation with PowerACE and is an exogenous input for ELMOD. The constraints of ELMOD include maintaining the energy balance for each point in time and grid node as well as further equations regarding restrictions of the load flow and the dispatch of generation and storage units. An overview of the detailed mathematical formulations can be found in Leuthold et al. (2012). ELMOD is formulated in the General Algebraic Modeling System (GAMS) and solved with the commercial CPLEX solver.

Table D.6: Overview of power plants' hourly bidding prices $b_{p,h}$ depending on the type of the power plant and the expected online hours.

Case (1):	Power plant p (base-/medium-/peak-load) is in the market in all hours h	
	$b_{p,h} = c_p^{\text{var}}$	$\forall h \in H_p^{\text{on}} = H$
Case (2):	Power plant p (base-load) is in the market in some hours h	
	$b_{p,h} = c_p^{\text{var}}$	$\forall h \in H_p^{\text{on}} \subseteq H$
	$b_{p,h}^{\text{min}} = c_p^{\text{var}} - c_p^{\text{start}}/t_p^{\text{off}}$	$\forall h \in H_p^{\text{off}} \subseteq H$
	$b_{p,h}^{\text{rest}} = c_p^{\text{var}}$	$\forall h \in H_p^{\text{off}} \subseteq H$
Case (3):	Power plant p (medium-/peak-load) is in the market in some hours h	
	$b_{p,h} = c_p^{\text{var}} + c_p^{\text{start}}/t_p^{\text{on}}$	$\forall h \in H_p^{\text{on}} \subseteq H$
	$b_{p,h} = c_p^{\text{var}} + c_p^{\text{start}}/\Delta t$	$\forall h \in H_p^{\text{off}} \subseteq H$

Electricity Market Simulation Model PowerACE

The agent-based simulation model PowerACE has been developed at Karlsruhe Institute of Technology and has already been applied for various energy system analyses (e.g., Bublitz et al., 2017; Genoese, 2010; Keles et al., 2016; Ringler et al., 2017). In PowerACE, major wholesale electricity markets and the associated market participants such as utility companies, regulators and consumers are modeled. The agents representing electricity suppliers can decide on the daily scheduling of their power plants and storage units as well as on the construction of new power plants and utility-scale storages. Thus, the short-term and long-term decision levels are considered jointly and their interactions can be investigated. Ultimately, the development of the markets emerges from the simulated behavior of all agents.

D.7.2 Day-Ahead Market Simulation

The different supply traders prepare bids $b_{p,h}$ for all of their own power plants p and each hour h of the following simulation day. The respective bid price depends both on the type of the power plant and whether the power plant is expected to run in the respective hour (i.e., $h \in \boldsymbol{H}_p^{\text{on}} \subseteq \boldsymbol{H}$) or expected not to run (i.e., $h \in \boldsymbol{H}_p^{\text{off}} \subseteq \boldsymbol{H}$). All bidding prices for the different cases are briefly described in the following and formally summarized in Table D.6.

Case (1): If a power plant of any type (base-, medium- or peak-load) is expected to be in the market in all hours, i.e., $\boldsymbol{H}_p^{\text{on}} = \boldsymbol{H}$, the hourly bids $b_{p,h}$ only consist of the variable costs c_p^{var}, which are determined by the fuel price p_p^{fuel}, the power plant's net electrical efficiency η_p, the price of CO_2 emission allowances p^{CO_2}, the CO_2 emission factor of the fuel e^{fuel} and the costs for operation and maintenance $c_p^{\text{O\&M}}$ as shown in Eq. (D.6).

$$c_p^{\text{var}} = \frac{p_p^{\text{fuel}} + p^{CO_2} \cdot e^{\text{fuel}}}{\eta_p} + c_p^{\text{O\&M}} \tag{D.6}$$

Case (2): If a base-load power plant is expected to be in the market only in some hours or never, i.e., $\boldsymbol{H}_p^{\text{off}} \neq \emptyset$, variable costs are bid for the expected running hours $\boldsymbol{H}_p^{\text{on}}$ and two different bids are created for each hour $h \in \boldsymbol{H}_p^{\text{off}}$ – the minimum running load of the power plant is bid at variable costs minus avoided start-up costs c_p^{start}, while the remaining load is bid at variable costs. The avoided start-up costs are evenly distributed among the expected offline time t_p^{off}. The economic reasoning behind this strategy is, that base-load power plants are expected to temporarily accept market prices below their marginal generation costs in order to avoid start-up costs in subsequent hours.

Case (3): If a medium- or peak-load power plant is expected to be in the market only in some hours or never, the hourly bids consist of variable costs and start-up costs. If the online time t_p^{on} is longer than one hour, start-up costs are distributed evenly.

Further price-inelastic bids for demand, renewable feed-in and pumped storage units are prepared by a single trader per market area, respectively. For details on the determination of the bid volumes for pumped storage plants, please refer to Fraunholz et al. (2017).

D.7.3 Congestion Management

For computational performance reasons start-up costs are considered in the market simulation with PowerACE, but not in the grid model ELMOD. Consequently, redispatching might be carried out without an actual grid congestion need. In the following, we describe how this issue can be avoided by reformulating Eq. (D.3). Thereby, the following crucial conditions need to be satisfied:

- Both, positive and negative redispatching have to be penalized to avoid redispatching without a grid congestion need.

- Positive redispatching should be carried out with the lowest-variable-cost power plants able to resolve the grid congestion.
- Negative redispatching should be carried out with the highest-variable-cost power plants running according to the day-ahead market outcome.
- Redispatching measures should preferably be carried out within Germany rather than in neighboring countries.

As a first step, we define the reverted variable costs $c_p^{\text{var,rev}}$ of a German conventional power plant $p \in \boldsymbol{P}_{\text{DE}}^{\text{con}}$ as shown in Eq. (D.7), where $\overline{c}_{\text{DE}}^{\text{var}}$ denotes the average variable costs of the German conventional power plant fleet.

$$c_p^{\text{var,rev}} = \left(\frac{\overline{c}_{\text{DE}}^{\text{var}}}{c_p^{\text{var}}} \right) \cdot \overline{c}_{\text{DE}}^{\text{var}} \quad \forall p \in \boldsymbol{P}_{\text{DE}}^{\text{con}} \tag{D.7}$$

We can now calculate the total costs for redispatching in Germany $C_{\text{DE}}^{\text{redisp}}$ according to Eq. (D.8). In this formulation, positive redispatching is penalized with the respective variable costs, whereas negative redispatching is penalized with the respective reverted variable costs. Like this, cost-minimal redispatching is carried out, yet only if required for grid congestion reasons.

$$C_{\text{DE}}^{\text{redisp}} = \sum_{p \in \boldsymbol{P}_{\text{DE}}^{\text{con}}} \sum_{h \in \boldsymbol{H}} \left(\max\left(g_{p,h} - g_{p,h}^{\text{market}}, 0\right) \cdot c_p^{\text{var}} - \min\left(g_{p,h} - g_{p,h}^{\text{market}}, 0\right) \cdot c_p^{\text{var,rev}} \right) \tag{D.8}$$

As previously mentioned, the neighboring countries of Germany are considered via interconnectors and aggregated auxiliary grid nodes. Moreover, the focus of this analysis is on the congestion management capabilities of Germany. For these reasons, contrary to redispatching in Germany, both positive and negative redispatching in neighboring countries are penalized at the maximum variable costs of the German conventional power plants $c_{\text{DE}}^{\text{var,max}} = \max_{p \in \boldsymbol{P}_{\text{DE}}^{\text{con}}} c_p^{\text{var}}$ as shown in Eq. (D.9). Using this approach, redispatching is always preferably carried out in Germany.

$$C_m^{\text{redisp}} = \sum_{p \in \boldsymbol{P}_m^{\text{con}}} \sum_{h \in \boldsymbol{H}} |g_{p,h} - g_{p,h}^{\text{market}}| \cdot c_{\text{DE}}^{\text{var,max}} \quad \forall m \in \boldsymbol{M} \setminus \{\text{DE}\} \tag{D.9}$$

In reality, if a power plant has to conduct negative redispatching, the saved marginal costs have to be payed back to the TSO. To account for this practice, the final redispatching costs are determined by subtracting the artificial negative redispatching costs from the positive redispatching costs subsequently to the cost minimization with ELMOD.

Although most of the grid congestion events can be relieved by redispatching and curtailment measures, situations in which the load cannot be served by the available generation units under grid restrictions may occur. In these cases, part of the load can be dumped through $l^{\text{dump}}_{n,h}$ at a high penalty of $c^{\text{voll}} = 10\,000\,\text{EUR/MWh}_{\text{el}}$[50]. Contrary, the artificially added load $l^{\text{add}}_{n,h}$ is implemented for modelling reasons only in order to ensure a feasible solution and is also strongly penalized with specific costs of $c^{\text{add}} = 10\,000\,\text{EUR/MWh}_{\text{el}}$. If $l^{\text{add}}_{n,h}$ volumes arise, it may reveal model failures. Both penalty costs sum up to C^{inf}_m as shown in Eq. (D.10). The objective function of ELMOD as introduced in Eq. (D.1) now needs to be extended to the version shown in Eq. (D.11). Moreover, the energy balance shown in Eq. (D.2) has to account for the introduced auxiliary variables, leading us to Eq. (D.12).

$$C^{\text{inf}}_m = \sum_{n \in \boldsymbol{N}_m} \sum_{h \in \boldsymbol{H}} \left(c^{\text{add}} \cdot l^{\text{add}}_{n,h} + c^{\text{voll}} \cdot l^{\text{dump}}_{n,h} \right) \quad \forall m \in \boldsymbol{M} \tag{D.10}$$

$$\text{minimize} \quad C^{\text{cong}}_{\text{total}} = \sum_{m \in \boldsymbol{M}} \left(C^{\text{redisp}}_m + C^{\text{curt}}_m + C^{\text{inf}}_m \right) \tag{D.11}$$

$$l^{\text{gross}}_{n,h} + \sum_{p \in \boldsymbol{P}^{\text{stor}}_n} l^{\text{charge}}_{p,h} + l^{\text{add}}_{n,h} - l^{\text{dump}}_{n,h} = \sum_{p \in \boldsymbol{P}_n} g_{p,h} + f^{\text{AC}}_{n,h} + f^{\text{DC}}_{n,h} \quad \forall n \in \boldsymbol{N}, h \in \boldsymbol{H} \tag{D.12}$$

D.7.4 Input Data

An overview of the techno-economic characteristics of the different investment options modeled in PowerACE is provided in Tables D.7 and D.8.

[50]The Value of Lost Load (VoLL) is defined as the willingness to pay of electricity consumers to avoid a disruption of their electricity supply. The determination of the VoLL is non-trivial and depends on several customer-specific factors as well as the respective point in time. Therefore, we assume an average value, which is chosen high enough to only consider load shedding as a last resort when carrying out congestion management.

Table D.7: Conventional power plant investment options modeled in PowerACE with their respective techno-economic characteristics. *Source:* Schröder et al. (2013); Louwen et al. (2018), and own assumptions.

Technology	Block size [MW_{el}]	CCS	Net efficiency[1] [%]	Lifetime [a]	Building time [a]	Specific investment (2015–2050)[1] [$\frac{EUR}{kW_{el}}$]	O&M costs fixed [$\frac{EUR}{kW_{el}\,a}$]	O&M costs var.[2] [$\frac{EUR}{MWh_{el}}$]
Coal	600	no	45–48	40	4	1800	60	6
		yes	36–41			3143–2677		30
Lignite	800	no	43–47	40	4	1500	30	7
		yes	30–33			3840–3324		34
CCGT	400	no	60–62	30	4	800	20	5
		yes	49–52			1216–1078		18
OCGT	400	no	40–42	30	2	400	15	3

Abbreviations: CCGT—combined cycle gas turbine, CCS—carbon capture and storage, OCGT—open cycle gas turbine, O&M—operation and maintenance

[1] Resulting from technological learning, the net efficiency is assumed to increase over time. Since conventional power plants can generally be regarded as mature technologies, it is further assumed that only the specific investments of the CCS-technologies are declining.

[2] Including variable costs for carbon capture, transport and storage, where applicable.

Table D.8: Electricity storage investment options modeled in PowerACE with their respective techno-economic characteristics. *Source:* Louwen et al. (2018); Siemens Gamesa (2019), and own assumptions.

Technology	Block size [MW_{el}]	Storage capacity[1] [MWh_{el}]	Round-trip efficiency[2] [%]	Lifetime[2] [a]	Building time [a]	Specific investment (2015–2050)[2] [$\frac{EUR}{kW_{el}}$]	O&M costs fixed[2] [$\frac{EUR}{kW_{el}\,a}$]
Li-ion battery	300	1200 3000	85–95	20–30	2	3149–572 7643–1388	63–11 153–28
RF battery	300	3000	75–85	20–30	2	4206–892	84–18
A-CAES	300	3000	60–75	30	2	1095	22
ETES	300	1200 3000	50–60	40	2	600 672	12 13

Abbreviations: A-CAES—adiabatic compressed air energy storage, ETES—electric thermal energy storage, O&M—operation and maintenance, RF battery—redox-flow battery

[1] For RF batteries and A-CAES, a substantial share of the investment expenses is related to the converter units. Consequently, for economic reasons, only higher storage capacities of 3000 MWh_{el} are eligible as investment options for these technologies.

[2] Resulting from technological learning, round-trip efficiency and lifetime are assumed to increase over time for the emerging storage technologies. Analogously, specific investments and fixed costs for O&M are assumed to decline.

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Paper E

Diffusion and System Impact of Residential Battery Storage under Different Regulatory Settings

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Abstract

Cost reductions of rooftop photovoltaics and battery storage, increasing retail electricity prices as well as falling feed-in remuneration provide strong incentives for many German households to engage in self-consumption. These developments may also affect the electricity system as a whole. Against this background, we jointly apply a prosumer simulation and an agent-based electricity market simulation in order to investigate the long-term impacts of a residential battery storage diffusion on the electricity market. We analyze different regulatory frameworks and find significant effects on the household level, yet only moderate system impacts. In the long run, the diffusion of residential battery storage seems difficult to govern, even under a restrictive regulation. In contrast, the way the batteries are operated may be easier to regulate. Policymakers and regulators should focus on this aspect, since a system-friendly battery operation supports the system integration of residential photovoltaics while having little impact on the households' self-sufficiency.

E.1 Introduction

Since the introduction of the Renewable Energies Act in 2000, more than 1.8 million photovoltaic (PV) systems with a nominal capacity of 49 GW_p have been installed in Germany (Bundesverband Solarwirtschaft, 2020c), including more than 1 million small-scale rooftop systems with 6.4 GW_p (50Hertz et al., 2019a). These high installation rates have led to drastic cost decreases for electricity generated by rooftop PV systems (Kost et al., 2018). At the same time, the retail electricity prices faced by German households have followed an upward trend in the past years (Bundesverband der Energie- und Wasserwirtschaft, 2020). As a consequence, *grid parity* has been reached in Germany around 2012, meaning that the cost of self-produced electricity from PV systems has fallen below the retail electricity prices. The politically driven reduction of PV feed-in remuneration – as a reaction to the falling generation cost – further increases the attractiveness of self-consumption (Wirth, 2020).

Moreover, prices for lithium-ion batteries have decreased by more than 50 % since 2013 and continue to decline. Consequently, in the past years, about every second new small-scale PV system in Germany has been equipped with a battery storage in order to increase self-consumption. As of today, more than 180000 battery systems have already been installed (Bundesverband Solarwirtschaft, 2020b). In contrast, most PV systems installed before 2012 feed large shares of their electricity into the grid. However, feed-in tariffs under the Renewable Energies Act are only granted for 20 years after installation. Thus, starting from 2020, the first of these systems will not receive such remuneration anymore. Since retrofitting the existing PV systems with battery storage is often profitable, this will most likely lead to additional battery installations (Fett et al., 2018). However, despite the potentially significant impacts on the electricity market, literature investigating the long-term impacts of residential battery storage diffusion is still scarce.

Against this background, we propose a novel modeling framework consisting of a prosumer simulation and an agent-based electricity market simulation, which is applied to Germany and its neighboring countries. In contrast to most of the existing literature, the prosumer simulation includes a calibrated diffusion model in order to account for certain non-financial drivers of households' investment decisions. The developed methodology allows us to analyze transformation pathways in great detail while accounting for the respective actors' (households and utilities) perspectives and their mutual influence. A particular emphasis is put on the regulatory framework. We simulate the status quo of the German regulation for self-consumption, a more system-friendly operational strategy, and a restrictive regulation comprising fixed grid charges as well as a self-consumption charge. Following this procedure, we are able to quantify long-term impacts of residential battery storage in a realistic and complex real-world setting. This enables us to provide policy advice regarding an adequate regulatory framework for self-consumption.

The remainder of this paper is structured as follows. In Section E.2, we briefly review the relevant literature on residential battery storage and derive the research gap our paper aims to fill. Section E.3 introduces the proposed simulation framework including the required input data. In Section E.4, we provide an overview of the investigated scenarios and discuss the results of our simulations. Section E.5 discusses limitations of the study. Finally, we summarize our findings, draw conclusions and derive policy implications in Section E.6.

E.2 Literature Review and Research Gap

Given the scope of our work, the following literature review explicitly focuses on quantitative studies that investigate the system impact of residential battery storage. In contrast, we do not delve into the large body of literature taking a pure household perspective (e.g., Bertsch et al., 2017; Fluri, 2019; Kaschub et al., 2016; Klingler, 2017; Schopfer et al., 2018). Although the research interest in system impacts of residential battery storage has grown over the past years, literature that simultaneously considers the household and the utility perspective is still scarce and neglects certain important aspects.

Jägemann et al. (2013) analyze the impact of the current regulatory framework in Germany on investments in residential battery storage and ultimately, the system impact of these storage units. The authors use two different optimization models, which are iteratively applied until convergence has been reached. In the first model, several sample households minimize their electricity cost by carrying out investments in optimally sized photovoltaic and battery storage systems. The second model takes the households' decisions into account and minimizes the cost of the electricity system by deciding on investments in large-scale generation technologies and optimally operating these units. The resulting electricity prices are in turn an input to the household optimization model. Despite the proximity to our concept, two important aspects are not considered by Jägemann et al. (2013). Firstly, all households are assumed to invest as soon as a battery storage system becomes profitable. However, a lack of information and uncertainty about PV battery storage and its costs – as well as other non-financial drivers – have an essential impact on households' investment decisions. This needs to be considered, e.g., by applying a diffusion model. Secondly, different operational strategies of the battery storage systems are not taken into account, but a maximization of self-consumption is assumed as the sole goal of each household. These two aspects are likely to lead to a substantial overestimation of the amount of battery storage being installed and are therefore crucial.

Say et al. (2019) apply a bottom-up simulation model to estimate investments in residential battery storage and analyze their impact on the electricity system. Their case study relies on demand and photovoltaic electricity generation time series of 261 real households in Australia. Using different feed-in tariff schemes, Say et al. first determine optimally sized photovoltaic and battery storage system investments for the different households. The resulting changes in the residual demand of all households are then aggregated to estimate impacts on the network and the retailer revenues. In a subsequent study, the methodological approach is extended by coupling the household simulation model with an optimization model of the Western Australian electricity system (Say et al., 2020). Like this, the authors are able to analyze the system impacts of large amounts of residential battery storage. However, the system optimization model is only applied for a single future year (2030). Consequently, the transformation pathway of the system cannot be investigated and the residential electricity prices need to be defined exogenously rather than being derived from simulated wholesale prices. Moreover, also the work by Say et al. (2019, 2020) neither applies a diffusion model nor considers different operational strategies.

Klingler et al. (2019) investigate the diffusion of residential battery storage in the EU countries, Norway and Switzerland. For this purpose, they apply the electricity system optimization model ELTRAMOD to derive wholesale electricity prices and then determine optimally sized battery storages for an average household per country. Finally, the authors use a diffusion model to estimate the total installed battery capacities for all countries. Also in this study, the impact of different operational strategies for the batteries is not analyzed. Moreover, ELTRAMOD is only used to provide wholesale electricity prices, rather than to evaluate system effects of residential battery storages.

Schwarz et al. (2019) use an agent-based model to analyze the diffusion and system impacts of residential battery storages in California under different policy scenarios. Their approach consists of three modules. Firstly, future wholesale electricity prices are forecasted based on a simple linear regression model. Secondly, these prices are converted to retail electricity prices. Thirdly, several sample households decide on a potential adoption of a photovoltaic and battery storage system. Much like in the studies mentioned above, the authors do not account for non-financial drivers of the households' investment decisions. Moreover, the module depicting the Californian wholesale market is strongly simplified and is therefore not able to properly account for long-term market dynamics.

Yu (2018) investigates systemic effects of residential battery storages in France. For this purpose, levelized costs of electricity generation for a photovoltaic and battery storage system are estimated. Subsequently, changes in the French residual load duration curve are calculated if all detached houses in France were to use such a system. The study by Yu makes some strong simplifications. Firstly, only one generic household is considered, although the diversity of household load profiles and solar profiles plays a crucial role. Secondly, no diffusion model is used, but all households are assumed to invest directly. Thirdly, the impact of different operational strategies and changes in the regulatory framework are neglected. Fourthly, France is considered as an isolated system without electricity exchange and pumped storage units. This is a particularly critical assumption given the strongly interconnected European electricity system. In consequence, the system impacts of residential battery storages in France are likely to be heavily overestimated.

In summary, our article complements the existing literature in a number of important aspects. We propose a novel modeling framework consisting of a prosumer simulation and an agent-based electricity market simulation. As previously described, most of the related literature only includes rudimental (if any) representations of the wholesale electricity market. In contrast, our agent-based approach allows to investigate transformation pathways in great detail while accounting for the respective actors' (households and utilities) perspectives and their mutual influence. Apart from the work of Jägemann et al. (2013), the proposed approach is the only in the literature to consider bidirectional dependencies between the different decision parties involved. Moreover, existing studies typically neither apply diffusion models nor consider alternative operational strategies for the batteries. In consequence, the system impacts of residential battery storage are likely to be substantially overestimated. This is sometimes further intensified by the use of standard load profiles which neglects the crucial role of diversity in terms of household load profiles and solar profiles. Our paper addresses the risk of overestimation by using a diffusion model, considering different operational strategies, and relying on empirically measured household load profiles. For the described reasons, the novel approach presented in the following is very well suited to capture dynamic long-term impacts of residential battery storage diffusion in Germany under different regulatory settings.

E.3 Methodology and Data

E.3.1 Overview of the Simulation Framework

In order to capture both, the household and the utility perspective, we apply a novel modeling framework comprising a prosumer simulation and an agent-based electricity market simulation (Fig. E.1). In both models, an individual actor's perspective is taken. The decisions of the household agents affect those of the the utility agents (via changes in the residual load curves) and vice versa (via changes in the wholesale electricity prices). Thus, household agents and utility agents iteratively adjust their decisions until convergence has been reached[51]. In Section E.3.2, we present more details on the prosumer simulation, while Section E.3.3 introduces the agent-based electricity market model PowerACE.

E.3.2 Prosumer Simulation

Investment Decisions

Similarly as Say et al. (2020), we use empirically measured household load profiles and consider them as representative for the total household electricity consumption. This approach allows to account for the diversity of households' load curves and avoid biases that result from aggregated or synthesized data (Quoilin et al., 2016; Schopfer et al., 2018; Fett et al., 2019).

The prosumer investment module assumes economically rational behavior of the households and a fixed investment horizon of 20 years (the period of the guaranteed feed-in tariff for PV installations in Germany). Net present values (NPVs) are determined for every combination of PV system size[52] (0–10 $\mathrm{kW_p}$ with step size 0.5 $\mathrm{kW_p}$) and battery size (0–10 kWh with step size 0.5 kWh) as well as for each sample household. For this purpose, the total costs including investment, expenditures for electricity, and income from PV feed-in remuneration are calcu-

[51]In a similar fashion as Jägemann et al. (2013), we use the deviation of the cumulative yearly residential PV and battery storage capacities between two iterations as the criterion for convergence. For our simulations, we define convergence as a deviation below 2 %. In all scenarios under investigation, one iteration is sufficient to fulfill this criterion.

[52]The size limit is chosen because prosumers with PV systems above 10 $\mathrm{kW_p}$ receive a lower feed-in remuneration (Bundesverband Solarwirtschaft, 2020a) and have to pay the self-consumption charge of 40 % of the renewable energy levy (§ 61a EEG 2017).

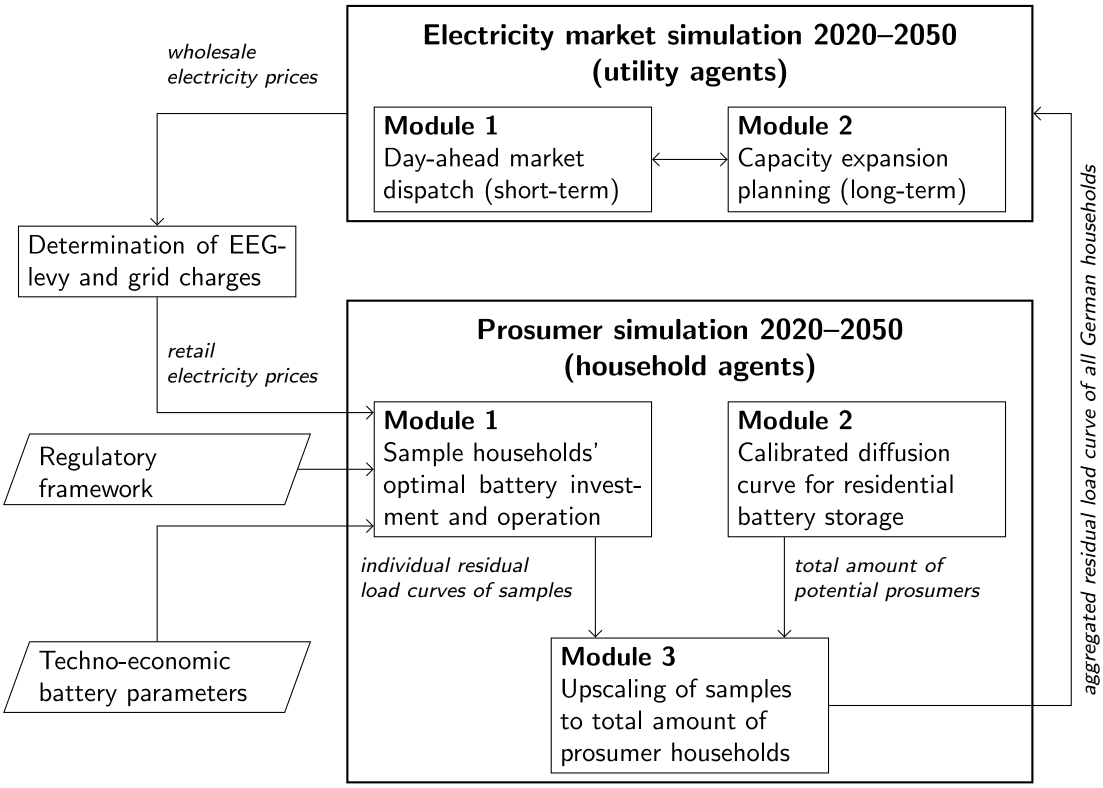


Figure E.1: Overview of the applied simulation framework. In the prosumer simulation, several agents representing sample households decide on optimal battery sizes and their operation. Using a calibrated diffusion model, the residual load curves of the individual households after battery operation are then scaled up to obtain an aggregated residual load curve of all German households. In the electricity market simulation, the utility agents react on the changes of the residential load curves and adjust their capacity expansion planning and day-ahead market dispatch accordingly. The resulting wholesale electricity prices serve as an input for the households' decisions to invest in battery storages. If required, the prosumer simulation and the electricity market simulation are run in multiple iterations until convergence has been reached.

lated and compared to the costs under the benchmark *no investment* case. These calculations require to simulate the battery operation for each system configuration and sample household (see Section E.3.2)[53]. Additional model inputs are wholesale electricity prices from the electricity market simulation (Section E.3.3), projections of the different components of the retail electricity price, and forecasts for PV and battery installation costs[54]. Households assume a constant PV feed-in remuneration and an electricity price that increases by 2 % per year, both based on their installation year. These model inputs are summarized in Table E.1. Finally, for each sample household, if profitable investments exist, the system configuration with the highest NPV is chosen. The described process is also performed for existing PV systems to consider the retrofit of battery storage systems after the expiry of the guaranteed 20-year feed-in tariffs. It is assumed that the PV system has a remaining lifetime of 15 years if the inverter is replaced.

Since we are interested in the transformation pathway, the investment module is run for each simulation year. In contrast to most of the related literature (see Section E.2), we also consider certain non-financial drivers of households' investment decisions by combining the results of the investment module with a diffusion model (Section E.3.2). Following this procedure, we finally obtain the additional PV feed-in and self-consumption, which are used to compute the self-reinforcing effect on the different charges and levies. This effect occurs because the increased feed-in has to be remunerated through the renewable energy levy, while at the same time, the grid consumption – to which the charges and levies are allocated – is reduced by the self-consumed electricity volume (for more details, see Fett et al., 2019).

Operational Strategies

Under the current regulatory framework and retail electricity tariffs, German households are neither exposed to dynamic prices nor to dynamic remuneration for

[53]Please note that since the household load profiles and the insolation profiles are assumed to remain unchanged throughout the simulation period, the battery operation only needs to be calculated once for each system configuration and sample household. Two matrices containing self-consumption and self-sufficiency rates can then be determined and re-used in each simulation year.

[54]Specific investments in PV and storage systems are assumed to be size-independent, which leads to a slight underestimation of system sizes (Dietrich and Weber, 2018).

Table E.1: Overview of the input data used for the prosumer simulation.

Model parameter	Unit	Value	Sources
Model characteristics			
Empirical household profiles	#	162	Tjaden et al. (2015); Kaschub (2017)
Simulation time step	h	0.25	Kaschub et al. (2016)
Investment horizon	a	20 (new) 15 (retrofit)	Fett et al. (2018)
Yearly discount rate	%	4	Fett et al. (2019)
Photovoltaics			
Evaluation range	kW_p	0–10	Own assumption
Specific investment[1]	EUR/kW_p	1169–537	Ram et al. (2019)
Lifetime	a	20 (new) 15 (retrofit)	Fett et al. (2018)
Operation & maintenance cost	EUR/(kW_p a)	24.26	Kaschub et al. (2016)
Specific annual yield	kWh/kW_p	1087	Kaschub (2017)
Battery storage			
Evaluation range	kWh	0–10	Own assumption
Energy-to-power ratio	kWh/kW	1	Kaschub et al. (2016)
Specific investment[1]	EUR/kWh	794–193	Ram et al. (2019)
Lifetime	a	20	Kaschub et al. (2016)
Round-trip efficiency	%	88	Fett et al. (2019)
Cost and remuneration of electricity			
Yearly increase of retail prices[2]	%	2	Fett et al. (2019)
Yearly decrease of feed-in tariff	%	1	Bundesverband Solarwirtschaft (2020a)
Renewable energy levy	EUR/kWh	time series	Öko-Institut and Agora Energiewende (2019)
Yearly increase of surcharges[3]	%	1	50Hertz et al. (2019b,c,d); Bundesverband der Energie- und Wasserwirtschaft (2020); Fluri (2019)

[1] Due to technological learning, the specific investments are assumed to decrease from 2020 to 2050.
[2] Expected by the household agents for the investment decision. The realized retail prices may differ.
[3] Only applicable for grid charges, CHP surcharge, §19 surcharge, and offshore wind surcharge. Other surcharges are assumed to remain constant.

excess electricity fed into the grid. Consequently, as of today, residential battery storage systems are most commonly operated with the sole objective of maximizing self-consumption (Klingler, 2017). This is reflected in our reference operational strategy (later referred to as *default*) that works as follows. The PV generation is first used to cover the household's electricity demand. Excess PV generation charges the battery or – if the battery is already fully charged – is fed into the grid. Contrary, if the household's electricity demand exceeds the current PV generation, the battery supplies electricity to the household until it is fully discharged. Demand not covered by PV generation and battery discharging is supplied by the electricity grid. No exchange between battery and the grid is allowed.

Alternatively, households could also use a forecast-based operational strategy and thereby potentially relieve the grid (Dehler et al., 2017; Deutsch and Graichen, 2015). We therefore additionally implement the so-called *dynamic feed-in limitation* (later referred to as *dynamic*) as proposed by Bergner et al. (2014). The aim of this operational strategy is to lower the peak PV feed-in as far as possible while keeping the impact on self-sufficiency at a minimum. This is achieved by shifting the battery charging to the hours with the highest PV generation around noon, rather than charging the battery directly as soon as a PV surplus occurs. Thus, in the dynamic strategy, the behavior for supplying the household's electricity demand stays the same, only the charging behavior of the battery is controlled differently. The battery is only charged if the excess PV generation is above a virtual feed-in limit. In contrast, PV generation below the virtual feed-in limit is self-consumed or – if the household load is not high enough – fed into the grid. The virtual limit is determined such that considering the current state of charge, the expected PV generation and household demand, the battery would be fully charged by the end of the day. For a formal description of the algorithm, please refer to the original article by Bergner et al. (2014). Since we assume perfect foresight for the PV and load forecast, households can maintain the same self-sufficiency rates under the *dynamic* strategy as compared to the *default* strategy. Thus, households can be considered indifferent with respect to the operational strategy. For this reason, the investment decisions (Section E.3.2) are always based on the *default* strategy.

Diffusion Model

Due to non-financial aspects, e.g., a lack of information and uncertainty about PV battery storage and its costs, only a small portion of the economic potential of residential battery storage is realized (Steinbach, 2015). This is often neglected in the literature, leading to an overestimation of the diffusion numbers and the impact of residential battery storage (see Section E.2). To address this shortcoming, we use a Bass diffusion model (Bass, 1969) to estimate the number of potential adopters for PV battery storage systems. The model formulation is shown in Eq. (E.1), where $N(t)$ denotes the cumulative number of (potential) adopters for PV battery storage systems up to time t. In a Bass model, the process of technology adaption is explained by innovation effects (represented by the coefficient of innovators p) and imitation effects (represented by the coefficient of imitators q). The total market size M is set to 11.15 million, which is the number of (semi-)detached houses that are inhabited by the owner[55] and have suitable roofs for PV systems (Prognos, 2016). In order to determine the parameters p and q, a nonlinear regression using the historical installations of small-scale PV systems ($<10\,\mathrm{kW_p}$) in Germany is carried out.

$$N(t) = M \frac{1 - \mathrm{e}^{-(p+q)(t-t_0)}}{1 + \frac{q}{p}\mathrm{e}^{-(p+q)(t-t_0)}} \tag{E.1}$$

The Bass model provides projections for the number of potential adopters of PV battery storage in each simulation year. Since we approximate the real household load by the load profiles of 162 measured households (see above), the results for these sample households are then scaled up to the numbers of potential adopters. Whether the sample households invest in PV battery storage systems is determined in the investment module described in Section E.3.2. In case that none of the investment options is profitable for a given load profile, the respective households are considered as potential adopters again in the subsequent simulation year.

In addition to potential adopters calculated using the Bass diffusion model, owners of existing PV systems (taken from 50Hertz et al., 2019a) whose feed-in tariffs ran out after 20 years are considered as potential adopters for battery

[55] Under German legislation, self-consumption is only possible if the consumer and the owner of the PV system are the same person.

storage systems. Moreover, households whose retrofitted systems reach the end of their lifetime, are also taken into account as additional potential adopters again.

E.3.3 Electricity Market Simulation

In order to investigate the system impacts of a large-scale diffusion of residential battery storage systems in Germany, we apply PowerACE, an established agent-based simulation model. Originally developed for long-term scenario analyses of the German electricity market, PowerACE has been substantially extended in the past years and now includes a representation of multiple interconnected market areas in Europe. The model has a long-term character with typical time horizons ranging from 2015 up to 2050. At the same time, the short-term perspective is modeled at a high temporal resolution of 8760 h/a.

In PowerACE, several agents represent the major market participants such as utility companies, consumers or regulators. As is typical for agent-based approaches, the different agents follow their own goals and the system behavior ultimately emerges from the individual actors' decisions. For example, the utility companies can decide on the daily operation of their conventional power plants and utility-scale storage units on the day-ahead market (short-term perspective) as well as on investments in new generation and utility-scale storage capacities (long-term perspective).

For the simulation of the day-ahead market, the utility companies in all market areas first create price forecasts in order to estimate the running hours of their generation fleet on the subsequent day (Fraunholz et al., 2020). The respective agents then prepare hourly bids including both variable and start-up costs for each of their power plants. Moreover, price-inelastic bids for renewable feed-in, electricity demand and utility-scale storage units are created by a single trading agent per market area. Please note that the bids for both the electricity demand and the renewable feed-in include the impact of the residential battery storage systems. A central market operator collects the supply and demand bids from all market areas and matches them with the objective of maximizing social welfare subject to the limited interconnector capacities (Ringler et al., 2017). This step is a simplified representation of EUPHEMIA (NEMO Committee, 2019), the algorithm used for the real-world day-ahead market clearing process across multiple interconnected market areas. Finally, all utility companies determine their individual power plant dispatch based on the outcome of the market clearing. Please note that the model-endogenous representation of utility-scale storage operation and electricity exchange across market areas allows to account for potential balancing effects of these flexibility options, which are likely to reduce the system impact of residential battery storages.

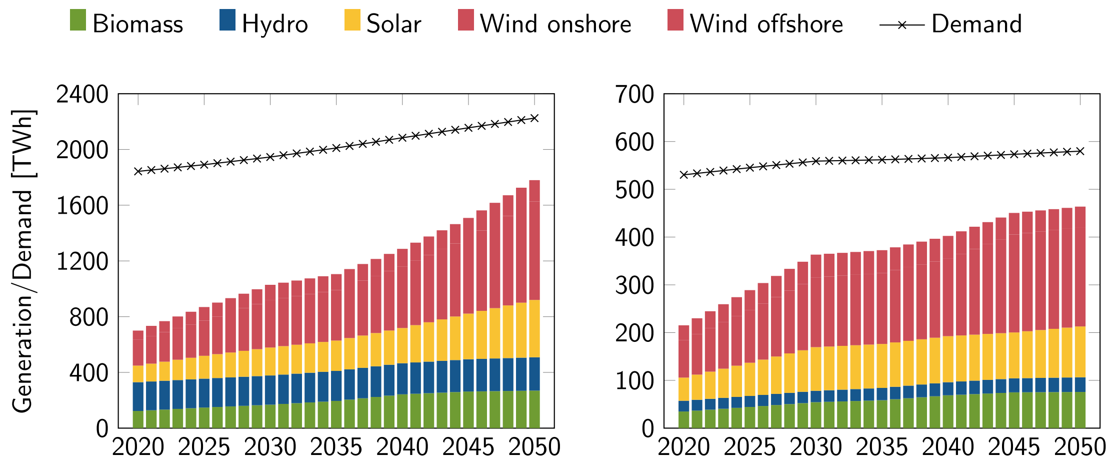
Additionally to the day-ahead market simulation, the utility companies have the opportunity to invest in new generation and utility-scale storage capacity once per simulation year. For this purpose, the respective agents estimate the profitability of different investment candidates based on long-term price forecasts. In an iterative procedure, a stable investment plan (more precisely, a Nash-equilibrium) across all considered market areas is then determined (Fraunholz et al., 2019).

As a detailed bottom-up simulation model, PowerACE relies on substantial amounts of input data. Table E.2 provides an overview of the data used in this study and the respective sources. In order to adequately account for cross-border effects, the applied version of PowerACE does not only cover Germany, but also all neighboring countries (Fig. E.2). Please note that the developments of electricity generation from renewables as well as electricity demand are exogenous inputs to PowerACE and remain unchanged for all scenarios to be investigated (Section E.4.1). Additional model-endogenous investments in renewable technologies are therefore not considered. Fig. E.3 shows the assumed composition of the renewable electricity generation as well as the total yearly electricity demand. The output data most relevant for this article comprises wholesale electricity prices up to 2050, the dispatch of conventional power plants and utility-scale storages, as well as electricity exchange flows between the different market areas. All these result data sets are determined at an hourly resolution over the time period from 2020 to 2050.

Table E.2: Overview of the input data used for the electricity market simulation with PowerACE. The table is based on a previous study (Fraunholz et al., 2021) since we mostly make use of the same data sets.

Input data type	Resolution	Sources and comments
Conventional power plants	unit level	Bundesnetzagentur (2017) for Germany, S&P Global Platts (2015) for all other countries, and own assumptions
Fuel prices	yearly	EU Reference Scenario (de Vita et al., 2016)
Carbon prices	yearly	EU Reference Scenario (de Vita et al., 2016), scaled to reach 150 EUR/t_{CO_2} in 2050
Investment options	yearly	Louwen et al. (2018); Schröder et al. (2013); Siemens Gamesa (2019), and own assumptions (cf. Tables E.6 and E.7)
Interconnector capacities	yearly	Ten-Year Network Development Plan (ENTSO-E, 2016)
Electricity demand	hourly, market area	historical time series of 2015 (ENTSO-E, 2017), scaled to the yearly demand given in the EU Reference Scenario (de Vita et al., 2016)
Renewable feed-in	hourly, market area	historical time series of 2015 (ENTSO-E, 2017), scaled to reach an overall renewable share in relation to electricity demand of 80 % in 2050

Figure E.2: Overview of the market areas covered by PowerACE. While the diffusion of residential battery storage is only considered in Germany (blue), the electricity market is also simulated for all neighboring countries (light gray) to account for cross-border effects.



(a) All countries **(b) Germany**

Figure E.3: Assumed annual renewable electricity generation and gross electricity demand (a) aggregated across all countries and (b) in Germany. In 2050, an overall renewable share of 80 % is reached. *Source:* de Vita et al. (2016), and own assumptions.

Table E.3: Overview of the investigated scenarios. Three settings with different regulatory frameworks are compared to a reference case without residential battery storage.

Scenario	Battery operation	Feed-in limit	Grid charges	Feed-in remuneration	Self-consumption charge
No Storage	–	–	–	–	–
Status Quo	default	70 %	volumetric	feed-in tariffs	none
Dynamic	dynamic	70 %	volumetric	feed-in tariffs	none
Restrictive	dynamic	50 %	fixed	market prices	40 % of renewable energy levy

E.4 Results and Discussion

E.4.1 Overview of the Investigated Scenarios

In order to analyze the effects of possible policy changes on the diffusion of battery storage systems and the resulting system impacts, we define four scenarios which are summarized in Table E.3 and briefly described in the following.

- The scenario *No Storage* is a reference electricity market simulation without any residential battery storage. This scenario serves as a benchmark to which the remaining scenarios are compared.
- In the *Status Quo* scenario, the grid charges are based on the households' power consumption. Surplus solar energy fed into the grid is remunerated with a guaranteed feed-in tariff for 20 years. The battery storage systems are operated using the *default* self-consumption maximizing operational strategy (cf. Section E.3.2). This scenario aims to represent the current German regulation for prosumers.
- In the scenario *Dynamic*, the cost structure for prosumers is identical to the Status Quo scenario. However, the operational strategy is changed to the forecast-based *dynamic* strategy (cf. Section E.3.2). This scenario is designed to analyze the impact of a more system-friendly operational strategy.
- The scenario *Restrictive* also relies on the dynamic operational strategy, but the maximum PV feed-in capacity is reduced to 50 % of the installed capacity. This was, e.g., a requirement in the recently expired subsidy scheme of the German *Kreditanstalt für Wiederaufbau* (Figgener et al., 2018). Additionally, the grid

charges are included in the basic charge of the electricity tariff[56]. Being independent from the actual consumption, the grid charges can then be considered as pure costs of grid access. In contrast to the two previous scenarios, the fed-in electricity is remunerated with the PV-weighted mean of the wholesale prices determined in the electricity market simulation (cf. Section E.3.3). Furthermore, it is assumed that the *de minimis* threshold is removed, meaning that also prosumer households have to pay the self-consumption charge of 40 % of the current renewable energy levy. The objective of this scenario is to analyze the impacts of a more restrictive regulation for self-consumption as compared to the rather favorable regulatory framework currently in place.

E.4.2 Investments Decisions of the Prosumer Households

Our simulations confirm that the regulatory framework has a substantial impact on the PV and battery investment decisions of the modeled sample households as well as the corresponding amounts of self-consumption. Table E.4 presents an overview of these results alongside a summary of the (partly model-endogenous) cost and remuneration of electricity under the different scenarios.

Due to the high levels of feed-in remuneration and retail electricity prices, only new residential PV systems with the maximum capacity of 10 kW_p are being built in the scenarios Status Quo and Dynamic in 2020. This does not change throughout the simulation period, since increasing cost of electricity as well as declining installation cost overcompensate the gradual decrease of the feed-in remuneration. Given the less favorable regulation for self-consumption in scenario Restrictive (cf. Section E.4.1), substantially smaller new systems are initially installed. However, from 2040 on, much like in the other scenarios, households only invest in new PV systems with the maximum size.

The situation is somewhat different for the retrofit of existing PV systems, i.e, the installation of a new inverter which comes along with a lifetime extension of 15 years. Until 2030, the results for retrofit systems are identical in all scenarios since only systems already existing today are retrofit and this is always profitable for the respective households. In 2040 and 2050, the retrofit systems corresponds

[56]For this purpose, the total electricity consumption of the household sector (128.6 TWh) is allocated to all 40.96 million households in Germany (Fett et al., 2019). Thus, the fixed grid charges are based on an average electricity consumption of 3140 kWh per household.

Table E.4: Aggregated results from household perspective for selected simulation years. The less favorable regulatory framework for self-consumption leads to substantially smaller installation sizes in scenario Restrictive. Due to decreasing investment costs and increasing retail electricity prices, the differences between the scenarios become smaller over time.

Model parameter/result	Unit	Status Quo/Dynamic[1]				Restrictive			
		2020	2030	2040	2050	2020	2030	2040	2050
Cost and remuneration of electricity[2]									
Retail electricity price[3]	EUR/kWh	0.30	0.32	0.34	0.39	0.21	0.22	0.23	0.26
Fixed grid charge	EUR/a	–	–	–	–	278.90	308.10	340.30	375.90
Self-consumption charge	EUR/kWh	–	–	–	–	0.03	0.02	0.01	0.01
Feed-in remuneration[4]	EUR/kWh	0.10	0.09	0.08	0.07	0.03	0.06	0.07	0.07
New systems (mean ± SD)									
PV capacity	kW_p	10.0 ± 0.0	10.0 ± 0.0	10.0 ± 0.0	10.0 ± 0.0	1.3 ± 0.7	5.9 ± 2.2	10.0 ± 0.0	10.0 ± 0.0
Storage volume	kWh	2.6 ± 1.2	6.5 ± 2.2	7.5 ± 2.3	8.1 ± 2.2	0.0 ± 0.1	4.6 ± 1.9	6.1 ± 2.1	6.9 ± 2.2
Self-consumption	MWh	2.5 ± 0.9	3.2 ± 1.1	3.3 ± 1.1	3.3 ± 1.1	0.8 ± 0.5	2.7 ± 1.1	3.2 ± 1.1	3.2 ± 1.1
NPV of installation[5]	kEUR	5.2 ± 1.9	10.7 ± 3.1	14.3 ± 4.1	17.4 ± 5.1	0.7 ± 0.5	3.1 ± 1.4	7.0 ± 2.2	10.1 ± 2.9
Retrofit systems (mean ± SD)									
PV capacity	kW_p	2.8 ± 1.6	6.4 ± 2.0	10.0 ± 0.0	10.0 ± 0.0	2.8 ± 1.6	6.4 ± 2.0	1.3 ± 0.7	5.9 ± 2.2
Storage volume	kWh	1.3 ± 0.9	6.0 ± 2.0	7.5 ± 2.3	8.1 ± 2.2	0.1 ± 0.2	4.3 ± 1.6	1.6 ± 0.9	6.4 ± 2.3
Self-consumption	MWh	1.4 ± 0.6	2.8 ± 1.0	3.3 ± 1.1	3.3 ± 1.1	1.1 ± 0.4	2.6 ± 0.9	1.1 ± 0.6	2.9 ± 1.2
NPV of installation[5]	kEUR	0.1 ± 0.2	2.2 ± 0.9	4.0 ± 1.4	5.2 ± 1.8	0.0 ± 0.0	0.5 ± 0.3	0.2 ± 0.2	2.2 ± 0.9

Abbreviations: NPV—net present value, PV—photovoltaics, SD—standard deviation

[1] Under perfect foresight, the operational strategy of the battery does not affect the profitability of an investment, but the resulting household load profiles and indirectly the wholesale electricity prices. However, since the results of the two scenarios Status Quo and Dynamic are almost identical, only the values for Status Quo are presented.
[2] If not stated otherwise, see Fett et al. (2019) for the calculation procedure of the different elements.
[3] Including model-endogenous wholesale electricity prices from PowerACE.
[4] Current yearly feed-in tariff (Status Quo/Dynamic) or PV-weighted mean of the wholesale electricity prices in the respective year (Restrictive).
[5] The values show the realized NPVs of the investments. Given the agent-based approach with only limited foresight about future electricity prices, some household agents may overestimate the profitability of an investment, leading to slightly lower realized NPVs.

to those model-endogenously built 20 years earlier. Consequently, the PV systems under the scenario Restrictive are once again much smaller than those in the other scenarios.

As regards residential battery storage, the more liberal regulation in the scenarios Status Quo and Dynamic leads to substantially larger storage volumes being installed than in scenario Restrictive. This holds for both, new systems and retrofit systems. The total storage capacities and volumes of all households are depicted in Fig. E.5. In scenario Restrictive, around one quarter less storage is installed in 2050.

The investment decisions of the households are a direct outcome of their profitability analyses. Consequently, alongside the larger systems also the realized NPVs of the systems being built increase substantially. This finding clearly shows how using batteries to increase self-consumption is becoming a more and more profitable business case for the majority of households over time.

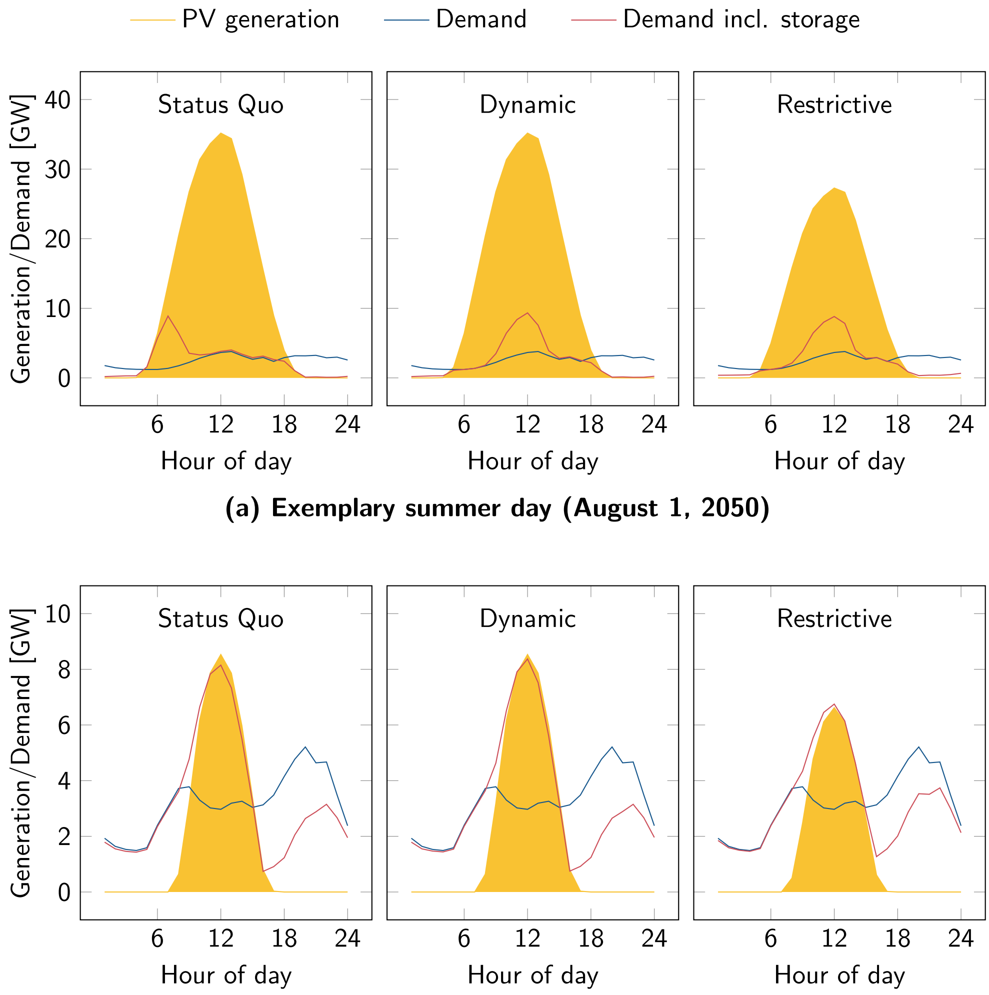
The generally smaller PV and storage systems in scenario Restrictive also lead to smaller amounts of self-consumption by the households. However, this is particularly true up to 2030, whereas later on, the self-consumption levels become more similar in all scenarios for the newly installed systems.

Overall, we can conclude that the ongoing cost reductions for PV and storage systems render investments in these technologies profitable for many households even under a far more restrictive regulation than in place today. Thus, while the impact of the regulatory framework may be significant in the medium term up to 2030, it gradually diminishes in the longer term.

E.4.3 Load Shifting of the Prosumer Households

Let us now move on to the impact of the regulatory framework and the prosumer households' investment decisions on their demand patterns. In Fig. E.4, the aggregated PV generation as well as the electricity demand of all prosumer households is shown for an exemplary summer and winter day in 2050.

In summer, a substantial PV overproduction can be observed across all scenarios. This is because investments in large PV systems are profitable for two reasons (cf. Section E.4.2). Firstly, prices for PV installation are assumed to decline further until 2050. Secondly, the feed-in remuneration remains relatively high – even



(a) Exemplary summer day (August 1, 2050)

(b) Exemplary winter day (February 1, 2050)

Figure E.4: Demand patterns of prosumer households under the different scenarios. The regulatory framework strongly affects the alignment of PV generation and electricity demand. While a high PV overproduction occurs in summer, substantial self-consumption rates can be achieved in winter.

in scenario Restrictive, where the remuneration is determined as the PV-weighted mean of the simulated wholesale electricity prices.

In scenario Status Quo, the residential batteries are directly charged as soon as a PV surplus exists. Consequently, by the time of peak PV production (around 12pm), the batteries are already fully charged and the high surplus PV generation is fed into the grid. Contrary, in scenario Dynamic, the battery charging is shifted by a few hours and therefore much better aligned with the PV production pattern. The discharging of the batteries is however not affected by the operational strategy and similar to the scenario Status Quo. In scenario Restrictive, an overall smaller amount of PV generation[57] can be observed due to the smaller system sizes. The general patterns of battery charging and discharging are however similar to scenario Dynamic.

The picture is completely different in winter. Due to the much lower PV generation, the prosumer households are able to self-consume almost their entire produced electricity either directly or by charging their batteries[58] This finding holds for all scenarios. Interestingly, since very little PV generation is fed into the grid, the battery charging and discharging patterns between the default operational strategy in scenario Status Quo and the dynamic strategy in scenarios Dynamic and Restrictive differ much less than in summer. Due to the smaller system sizes, we can again see a lower residential PV generation in scenario Restrictive.

[57] As previously indicated, the total renewable electricity generation is an exogenous input to the electricity market simulation and remains unchanged for all scenarios. Thus, if households invest in smaller PV systems, we assume this to be compensated by more utility-scale PV systems. This is because the expansion of renewables is typically driven by technology-specific political targets.

[58] The initial household demand is sometimes higher than the PV generation in the morning hours, but nevertheless battery charging is carried out. This effect is caused by the diversity of households' demand patterns. A simple numerical example with two prosumer households is useful to illustrate this. Let us assume that household 1 has a demand of 1.0 units and a PV generation of 0.5 units, while household 2 has no demand at all and generates 0.4 units of electricity. Since batteries are typically discharged in the morning hours, household 1 then directly self-consumes all produced electricity and covers the rest of its demand from the grid. Contrary, household 2 has a surplus generation of 0.4 units and uses this to charge its battery. Consequently, although the aggregated initial demand of both households (1.0 units) already exceeds the aggregated available PV generation (0.9 units), the aggregated demand is further increased by storage charging of household 2, leading to an overall aggregated demand of 1.4 units. Fig. E.6 in the Appendix shows the same setting for a sensitivity with a single standard load profile. Here, the described effect does not occur.

In summary, we find strong impacts of the regulatory framework on the load shifting carried out by the prosumer households. Moreover, significant seasonal differences between summer and winter exist in terms of PV production and consequently self-consumption as well as grid feed-in.

E.4.4 Utility-Scale Generation and Storage Capacities

As already described in Section E.4.2, substantially less residential storage is built in scenario Restrictive as compared to the scenarios Status Quo and Dynamic. We now change perspective and focus on the impact of the residential storage diffusion on the expansion planning of the utilities. For this purpose, Fig. E.5 shows the capacities of conventional power plants as well as utility and residential storage. Since the effects are rather small in magnitude, the middle and bottom part of the figure additionally shows the deltas with respect to the scenario No Storage.

Interestingly, despite more than 40 GW of residential battery storage capacity in the scenarios Status Quo and Dynamic – and still more than 30 GW in scenario Restrictive – these units only replace small amounts of conventional power plants and utility storage capacity. This is closely related to the residential storages' relatively small energy-to-power ratio[59] of 1 (cf. Table E.1). Consequently, while the households' batteries replace little utility storage *capacity* (in GW), they do indeed replace substantial amounts of utility storage *volume* (in GWh). This effect occurs because the profitability of utility storage investments is largely affected by the availability of cheap charging electricity due to a surplus of renewable generation. Residential storage, however, is a competing flexibility option in this regard, since it also relies on surplus PV generation for charging. Due to the more system-friendly storage operation, the described effect is more pronounced in scenario Dynamic. In terms of conventional power plants, we can observe a small shift from open cycle gas turbines (OCGT, typically used as peak load units) to combined cycle gas turbines (CCGT, medium load units). This is likely because the residential storages slightly increase the expected operating hours of conventional power plants, which renders CCGTs more profitable than OCGTs.

[59] While the energy-to-power ratio relates the storage volume (e.g., in GWh) to the storage capacity (e.g., in GW), the reciprocal of this is referred to as the *C-rate* of a battery.

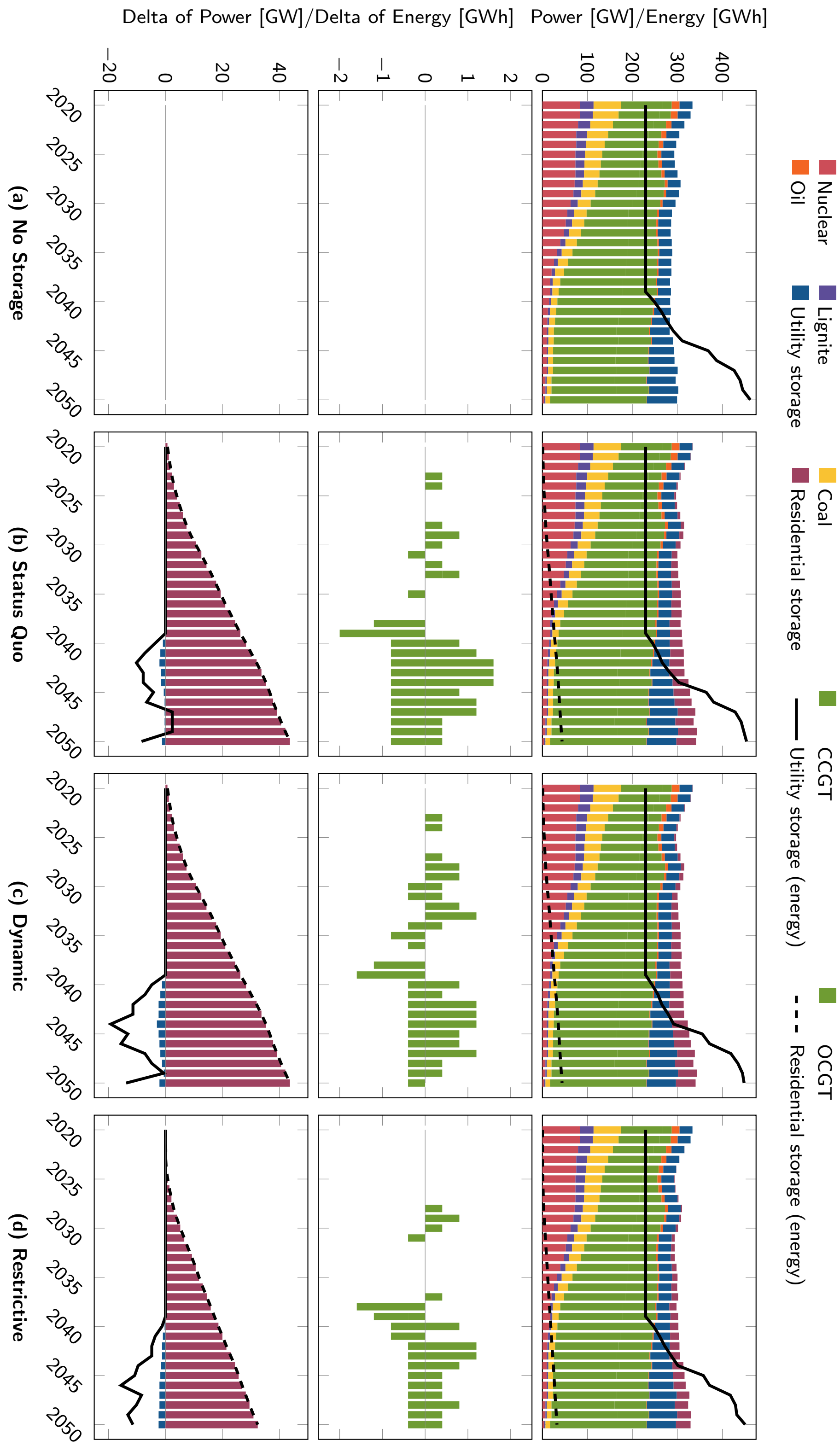


Figure E.5: Installed capacities of conventional power plants as well as utility and residential storage. The figure shows the absolute values (top) and the deltas with respect to the case without residential battery storage diffusion (middle/bottom). Across all scenarios, the residential battery storages replace rather small amounts of peak load and utility storage capacity. *Abbreviations:* CCGT—combined cycle gas turbine, OCGT—open cycle gas turbine.

Table E.5: Market-related curtailment of renewable electricity generation. The values show the arithmetic mean over the simulation years 2020–2050. Clearly, a dynamic feed-in limit incentivizes a more system-friendly operation of the residential battery storages. This leads to lower curtailment volumes, i.e., a better system integration of residential photovoltaics in the scenarios Dynamic and Restrictive.

Scenario	All countries [TWh/a]	thereof Germany [TWh/a]
No Storage	15.00	5.33
Status Quo	14.82 (−1.2 %)	5.13 (−3.6 %)
Dynamic	14.38 (−4.1 %)	4.76 (−10.7 %)
Restrictive	14.43 (−3.8 %)	4.77 (−10.5 %)

Overall, the impact of the residential battery diffusion on the utilities' expansion planning is rather small. This finding is largely attributable to balancing effects arising from utility storage dispatch and electricity exchange with the German neighboring countries.

E.4.5 System Integration of Residential Photovoltaics

Another relevant effect on system level is that by creating additional electricity demand at times of high PV generation, residential battery storage could support the system integration of renewables, or more specifically residential photovoltaics. Given our ambitious assumptions on the share of renewable electricity generation with respect to total electricity demand (80 % in 2050, cf. Table E.2), situations with surplus renewable generation would occur much more frequently in the future than today. Thus, an important indicator for the ability of a system to accommodate renewables is the amount of market-related curtailment[60]. Against this background, Table E.5 shows the mean yearly curtailment volumes for the different scenarios.

On the German level, the residential battery storages indeed contribute to a reduction of the renewable curtailment. Interestingly, the way the storages are operated seems more important than the installed storage volumes. While the curtailment is only reduced by less than 4 % under the default operational strategy

[60] Apart from market-based curtailment of renewables, insufficient grid capacities can lead to additional grid-related curtailment. Although this is currently an issue in Germany and intensively discussed (e.g., Hladik et al., 2020), our paper focuses on the market side while grid aspects are out of the scope.

(scenario Status Quo), the dynamic operational strategy (scenarios Dynamic and Restrictive) leads to more than 10 % decrease in curtailment. This is remarkable, since substantially less residential storage is installed in scenario Restrictive (cf. Fig. E.5).

Moving on to the overall system perspective comprising all modeled countries, the percentage decrease of curtailment is obviously lower since the total curtailment volumes are roughly three times as high as in Germany alone. The reductions of curtailment are again much higher in the scenarios Dynamic and Restrictive than in scenario Status Quo. Please recall that the diffusion of residential storage also affects the expansion of utility-scale storage. In this regard, it is interesting to see that the impact of the dynamic operational strategy even overcompensates the higher utility storage volumes of scenario Status Quo (cf. Section E.4.4).

In summary, we find the operational strategy of the residential battery storages to be an important driver for their ability to support the system integration of renewables. However, at the same time, it is crucial to consider interdependencies between different flexibility options, in this particular case, residential storage and utility storage.

E.4.6 Sensitivity Analyses

In order to investigate a higher diffusion rate as well as the impact of using a single household load profile rather than several empirically measures ones, we carry out two additional sensitivity runs.

In scenario *High Diffusion*, the number of potential prosumers in each year is increased by 50 %. Nevertheless, the overall system impacts remain small. Interestingly, the positive impact of the residential storages on the curtailment volumes is less pronounced in scenario High Diffusion than in the scenarios with the dynamic operational strategy (Dynamic, Restrictive). This confirms our previous finding that the operational strategy may be more crucial in this regard than the installed residential storage volumes.

In scenario *Standard Load Profile*, we find the prosumer households to invest in smaller battery storage systems than in scenario Status Quo, because the standard load profile is smoother than the empirical ones. Consequently, smaller batteries are sufficient to reach similar levels of self-consumption as in scenario Status Quo.

For more details on the results of the sensitivity runs, please see Appendix E.7.2.

E.5 Limitations

Despite substantial modeling effort, our work has certain important limitations, which we briefly address and qualitatively discuss in the following.

Firstly, while we consider the German neighboring countries in the electricity market simulation, we only model residential battery storage diffusion in Germany. This assumption is based on Germany's clear leadership regarding residential PV and battery storage systems. Currently, Germany is accountable for two of three battery units installed in Europe and this trend is expected to continue in the years to come (SolarPower Europe, 2020). At the same time, Germany has a high level of retail electricity prices. Consequently, residential storage is profitable for many German households already today, which is not the case in most other European countries. Unfortunately, since the regulatory framework for self-consumption differs substantially across Europe, the developed prosumer simulation model is currently only applicable for Germany. Nevertheless, in order to get a more complete picture, our approach should be extended to countries like Italy and Austria in future work.

Secondly, we assume the empirically measured household demand profiles to remain constant throughout the simulation period from 2020 to 2050. However, the shape of the electricity demand is likely to change in the future, e.g., driven by efficiency improvements as well as the electrification of heat and transport (Boßmann and Staffell, 2015). Depending on the flexibility of the new electric household applications, this could have different effects on investments in residential battery storages and their operation, which we are unable to quantify with our approach. Under the reasonable assumption that technologies like heat pumps and e-mobility offer additional demand flexibility for households, the installed battery storage systems would become smaller (Kaschub, 2017). Therefore our work is likely to provide an upper bound on the impact of residential battery storage.

Thirdly, the dynamic operational strategy for batteries is implemented with perfect foresight regarding PV generation and electricity demand. In reality, forecasting errors need to be considered, which slightly reduce the households' self-sufficiency (Bergner et al., 2014). However, additional adjustments to the regulatory framework, e.g., a reduction of the feed-in limit, could account for this aspect and create an incentive for households to apply a dynamic operational strategy nevertheless.

Finally, we have exogenously set technology-specific policy targets for renewable expansion. Consequently, even if households invest in less PV capacity due to the regulatory framework conditions, this is compensated by additional utility-scale PV generation. Thus, with our current modeling framework, we do not analyze the impact of prosumer households in general, but rather the impact of residential battery storage diffusion and operation. The assumption of a politically driven renewable expansion is reasonable for the current German setting. Nevertheless, dynamic model-endogenous investments in utility-scale renewable technologies could be considered in future work.

E.6 Conclusion and Policy Implications

In this article, we developed and applied a novel modeling framework to investigate the long-term impacts of residential battery storage diffusion in Germany. The proposed approach is the first in the literature to consider bidirectional dependencies between the decisions of households and utilities, the technology diffusion process, and alternative operational strategies for the residential batteries. In a simulation study, different regulatory settings for self-consumption were analyzed, leading to a number of relevant results which can be summarized as follows.

On the household level, a more restrictive regulation leads to investments in substantially smaller photovoltaic and storage systems in the medium term up to 2030. However, in the long run, this effect gradually diminishes and self-consumption becomes profitable for most households despite the unfavorable regulation. This effect is, amongst others, driven by decreasing cost of photovoltaics and battery storage as well as increasing retail electricity prices. In terms of battery operation, we find a forecast-based dynamic strategy to align photovoltaic generation and battery charging significantly better than a default strategy following the sole objective of maximizing self-consumption. Importantly, if reasonably accurate forecasts on photovoltaic generation and electricity demand are available, the self-sufficiency of households would only slightly suffer from this dynamic strategy. However, driven by relatively high feed-in remuneration, households are likely to invest in large photovoltaic systems, such that substantial amounts of photovoltaic generation are fed into the grid regardless of the operational strategy of the battery.

Despite the strong impacts of residential battery storage on an individual household level, we find moderate system impacts. There are three major reasons for this result, all of which are related to our innovative modeling approach. Firstly, we apply a diffusion model leading to a gradual battery expansion over time, such that even by 2050, only a fraction of the households invests in photovoltaic and storage systems. Secondly, the diffusion process of the residential batteries also affects the electricity market simulation. Since the utilities plan their investments in multiple decision periods, lock-in effects may occur: if a certain amount of power plants is built at a time with little residential storage, it will remain in the system even if the residential storage capacity increases later on. Thirdly, other flexibility options like utility-scale storage and electricity exchange with the German neighboring countries have a tremendous balancing effect. Nevertheless, the positive impact of a dynamic operational strategy for the residential battery storages is also visible on the system level. The more system-friendly operation strongly reduces the curtailment of renewables and therefore contributes to a better system integration of residential photovoltaics.

Our findings have important policy implications. Even if restrictive regulatory frameworks for self-consumption are set up, the diffusion of residential battery storage seems difficult to steer in the long term. However, on a system level, we find the way the residential batteries are operated to be more crucial than the amount of storage installed. Fortunately, relatively simple regulatory adjustments, such as a reduction of the maximum feed-in limit for residential photovoltaics, are suitable to incentivize a more system-friendly operation of the residential storages. Apart from the electricity market impact, the operational strategy of the residential batteries is also likely to have a substantial impact on the distribution grid level. This aspect should therefore be investigated in future research. Additionally, dynamic time-of-use tariffs could further incentivize a system-friendly operation of residential storage. However, in the German context, this would probably require substantial changes to the current tariff design. This is because a large portion of the residential electricity prices does not origin from the wholesale cost of generation, but rather from a number of taxes and levies. Since these are currently static, there is only a small margin between high-price periods and low-price periods. Consequently, taxes and levies might need to be designed dynamically in order to increase the lever.

E.7 Appendix

E.7.1 Input Data

An overview of the techno-economic characteristics of the different investment options modeled in PowerACE is provided in Tables E.6 and E.7.

E.7.2 Results of the Sensitivity Analyses

In the following, we present and briefly describe the results of the two additional sensitivity runs, which focus on the impact of a 50 % higher diffusion rate (scenario *High Diffusion*) and the role of using a single household load profile rather than several empirically measured ones (scenario *Standard Load Profile*). In order to put the results of the sensitivities into perspective, we mostly compare them to scenario Status Quo, sometimes also to the scenarios Dynamic and Restrictive, all of which are described in detail in Section E.4.

In terms of the prosumer households' PV and battery investment decisions (summarized in Table E.8), scenario High Diffusion is identical to scenario Status Quo for both, new and retrofit systems. This is because the same sample households are considered and only the diffusion rate is increased by scaling the yearly investments to 150 % of Status Quo. In scenario Standard Load Profile, the diversity of investments in new PV and storage systems is lost, since only a single load profile is considered for all prosumer households. As in scenario Status Quo, already in 2020, only PV systems with the maximum size are built. From 2030 onward, battery system sizes in scenario Standard Load Profile are somewhat smaller as compared to scenario Status Quo. Since the standard load profile is smoother than the empirical ones, smaller batteries are sufficient to reach an even slightly higher self-consumption than in scenario Status Quo. In terms of retrofit PV systems, the sizes are identical to scenario Status Quo in 2020 and 2030, since the

Table E.6: Conventional power plant investment options modelled in PowerACE with their respective techno-economic characteristics. *Source:* Schröder et al. (2013); Louwen et al. (2018), own assumptions.

Technology	Block size [MW_{el}]	CCS	Net efficiency[1] [%]	Lifetime [a]	Building time [a]	Specific investment (2015–2050)[1] [$\frac{EUR}{kW_{el}}$]	O&M costs fixed [$\frac{EUR}{kW_{el}\,a}$]	O&M costs var.[2] [$\frac{EUR}{MWh_{el}}$]
Coal	600	no	45–48	40	4	1800	60	6
		yes	36–41			3143–2677		30
Lignite	800	no	43–47	40	4	1500	30	7
		yes	30–33			3840–3324		34
CCGT	400	no	60–62	30	4	800	20	5
		yes	49–52			1216–1078		18
OCGT	400	no	40–42	30	2	400	15	3

Abbreviations: CCGT—combined cycle gas turbine, CCS—carbon capture and storage, OCGT—open cycle gas turbine, O&M—operation and maintenance

[1] Resulting from technological learning, the net efficiency is assumed to increase over time. Since conventional power plants can generally be regarded as mature technologies, it is further assumed that only the specific investments of the CCS-technologies are declining.
[2] Including variable costs for carbon capture, transport and storage, where applicable.

Table E.7: Electricity storage investment options modelled in PowerACE with their respective techno-economic characteristics. *Source:* Louwen et al. (2018); Siemens Gamesa (2019), own assumptions.

Technology	Block size [MW_{el}]	Storage capacity[1] [MWh_{el}]	Round-trip efficiency[2] [%]	Life-time[2] [a]	Build-ing time [a]	Specific investment (2015–2050)[2] [$\frac{EUR}{kW_{el}}$]	O&M costs fixed[2] [$\frac{EUR}{kW_{el}\,a}$]
Li-ion battery	300	1200 3000	85–95	20–30	2	3149–572 7643–1388	63–11 153–28
RF battery	300	3000	75–85	20–30	2	4206–892	84–18
A-CAES	300	3000	60–75	30	2	1095	22
ETES	300	1200 3000	50–60	40	2	600 672	12 13

Abbreviations: A-CAES—adiabatic compressed air energy storage, ETES—electric thermal energy storage, O&M—operation and maintenance, RF battery—redox-flow battery

[1] For RF batteries and A-CAES, a substantial share of the investment expenses is related to the converter units. Consequently, for economic reasons, only higher storage capacities of 3000 MWh_{el} are eligible as investment options for these technologies.
[2] Resulting from technological learning, round-trip efficiency and lifetime are assumed to increase over time for the emerging storage technologies. Analogously, specific investments and fixed costs for O&M are assumed to decline.

same systems already existing today are considered. However, storage sizes are smaller, since no diversity in household load profiles is considered. In 2040 and 2050, the new systems built model-endogenously in 2020 and 2030, respectively, are retrofit.

Fig. E.6 illustrates the load shifting of prosumer households by using their residential batteries. Again, the results of scenario High Diffusion are identical in shape to those of scenario Status Quo. However, due to the scaling, the values of generation and demand are 50 % higher. In scenario Standard Load Profile, steeper load gradients occur as compared to scenario Status Quo. This is because the lacking diversity in household load profiles does not allow for balancing effects, but all households operate their storages in the exact same way.

As regards the impact of the residential battery storages on utilities' expansion planning, the effects of the sensitivity scenarios High Diffusion and Standard Load Profile are qualitatively similar to those of the scenarios Status Quo, Dynamic, and Restrictive. Interestingly, in scenario Standard Load Profile, the lack of diversity in household load profiles reduces the effect described in Section E.4.4. The residential storages increase the expected operating hours of conventional power plants to a lesser extent than in scenarios Status Quo, Dynamic, and Restrictive, thus reducing the incentive to invest in CCGTs. Instead, more utility storage is built in the last years of the simulation period. Overall, the impact of the residential battery storages on the utilities' investments remains small, even under a higher diffusion rate.

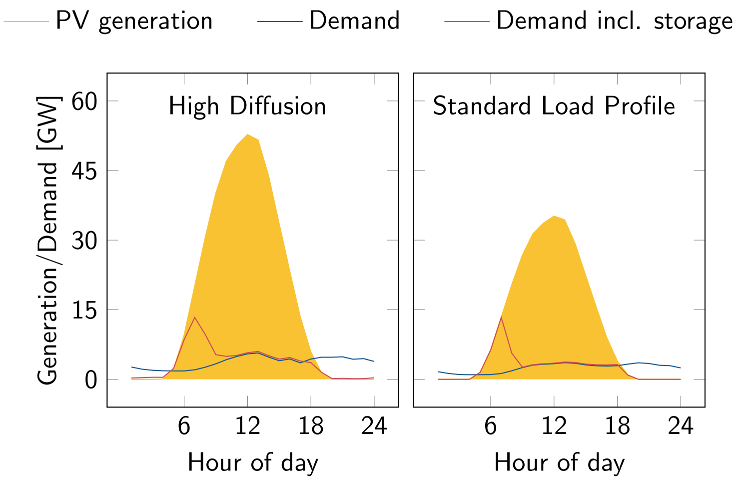
Finally, Table E.9 presents the curtailment volumes under the two sensitivity scenarios. In scenario High Diffusion, much less curtailment needs to be carried out than in scenario Status Quo. This is caused by the 50 % higher residential battery storage volumes. However, curtailment can still be reduced even more in scenarios Dynamic and Restrictive, despite the much lower amount of residential storage. This confirms our previous finding that the operational strategy may be more crucial in this regard than the installed residential storage volumes. The results of scenario Standard Load Profile are similar to those of scenario Status Quo.

Table E.8: Aggregated results from household perspective for selected simulation years (sensitivity analyses). In scenario High Diffusion, the outcomes are identical to scenario Status Quo, yet a faster diffusion process takes place. Since the diversity of households' load profiles is not considered in scenario Standard Load Profile, all newly built systems have an identical PV and storage size.

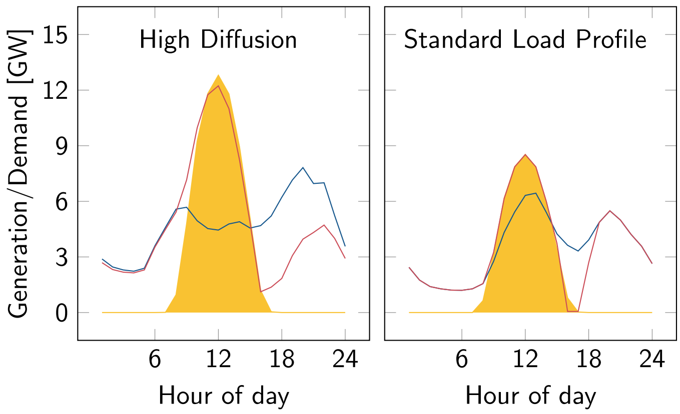
Model parameter/result	Unit	High Diffusion				Standard Load Profile			
		2020	2030	2040	2050	2020	2030	2040	2050
Cost and remuneration of electricity[1]									
Retail electricity price[2]	EUR/kWh	0.30	0.32	0.34	0.39	0.30	0.32	0.34	0.39
Fixed grid charge	EUR/a	–	–	–	–	–	–	–	–
Self-consumption charge	EUR/kWh	–	–	–	–	–	–	–	–
Feed-in remuneration[3]	EUR/kWh	0.10	0.09	0.08	0.07	0.10	0.09	0.08	0.07
New systems (mean ± SD)									
PV capacity	kW_p	10.0 ± 0.0	10.0 ± 0.0	10.0 ± 0.0	10.0 ± 0.0	10.0 ± 0.0	10.0 ± 0.0	10.0 ± 0.0	10.0 ± 0.0
Storage volume	kWh	2.6 ± 1.2	6.5 ± 2.2	7.5 ± 2.3	8.1 ± 2.2	3.5 ± 0.0	5.5 ± 0.0	6.5 ± 0.0	7.0 ± 0.0
Self-consumption	MWh	2.5 ± 0.9	3.2 ± 1.1	3.3 ± 1.1	3.3 ± 1.1	3.2 ± 0.0	3.5 ± 0.0	3.6 ± 0.0	3.7 ± 0.0
NPV of installation[4]	kEUR	5.2 ± 1.9	10.7 ± 3.1	14.3 ± 4.1	17.4 ± 5.1	5.6 ± 0.0	11.5 ± 0.0	15.1 ± 0.0	18.4 ± 0.0
Retrofit systems (mean ± SD)									
PV capacity	kW_p	2.8 ± 1.6	6.4 ± 2.0	10.0 ± 0.0	10.0 ± 0.0	2.8 ± 1.6	6.4 ± 2.0	10.0 ± 0.0	10.0 ± 0.0
Storage volume	kWh	1.3 ± 0.9	6.0 ± 2.0	7.5 ± 2.3	8.1 ± 2.2	0.8 ± 1.5	5.1 ± 0.3	6.5 ± 0.0	7.0 ± 0.0
Self-consumption	MWh	1.4 ± 0.6	2.8 ± 1.0	3.3 ± 1.1	3.3 ± 1.1	1.7 ± 0.6	3.1 ± 0.3	3.6 ± 0.0	3.7 ± 0.0
NPV of installation[4]	kEUR	0.1 ± 0.2	2.2 ± 0.9	4.0 ± 1.4	5.2 ± 1.8	0.0 ± 0.1	2.1 ± 0.4	3.8 ± 0.0	4.9 ± 0.0

Abbreviations: NPV—net present value, PV—photovoltaics, SD—standard deviation

[1] If not stated otherwise, see Fett et al. (2019) for the calculation procedure of the different elements.
[2] Including model-endogenous wholesale electricity prices from PowerACE.
[3] Current yearly feed-in tariff (exogenous assumption).
[4] The values show the realized NPVs of the investments. Given the agent-based approach with only limited foresight about future electricity prices, some household agents may overestimate the profitability of an investment, leading to slightly lower realized NPVs.

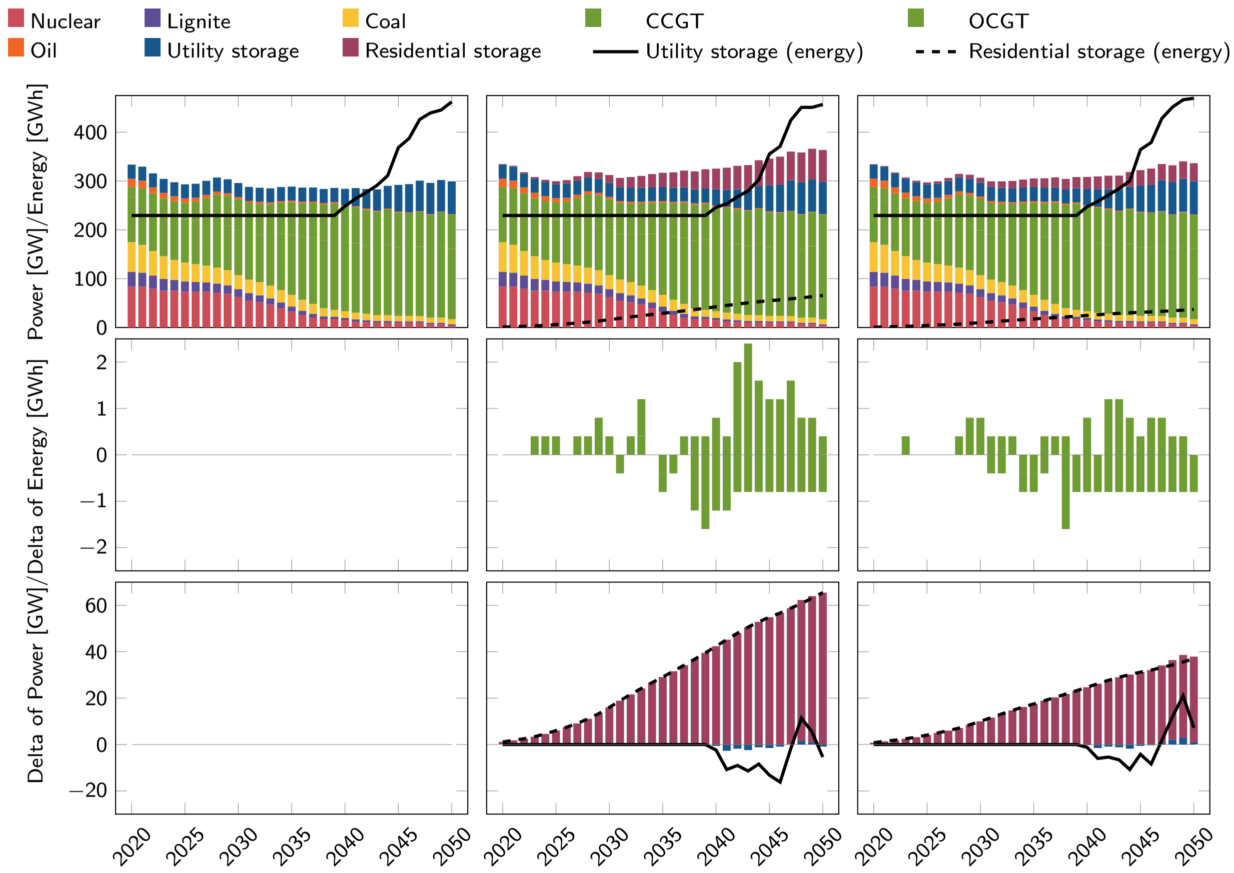


(a) Exemplary summer day (August 1, 2050)



(b) Exemplary winter day (February 1, 2050)

Figure E.6: Demand patterns of prosumer households under the different scenarios (sensitivity analyses). The curves of scenario High Diffusion have the same shape as those of scenario Status Quo, yet the absolute levels of generation and demand are 50 % higher. In scenario Standard Load Profile, steeper load gradients can be observed as compared to Status Quo.



(a) No Storage **(b) Triple Diffusion** **(c) Standard Load Profile**

Figure E.7: Installed capacities of conventional power plants as well as utility and residential storage (sensitivity analyses). The figure shows the absolute values (top) and the deltas with respect to the case without residential battery storage diffusion (middle/bottom). Both, in scenario High Diffusion and Standard Load Profile, the residential battery storages replace rather small amounts of peak load capacity, whereas some additional medium load power plants and utility storages are built. *Abbreviations:* CCGT—combined cycle gas turbine, OCGT—open cycle gas turbine.

Table E.9: Market-related curtailment of renewable electricity generation (sensitivity analyses). The values show the arithmetic mean over the simulation years 2020–2050. In scenario High Diffusion, the 50 % higher residential storage capacity reduces curtailment stronger than in scenario Status Quo, whereas the reduction in scenario Standard Load Profile is similar to scenario Status Quo.

Scenario	All countries [TWh/a]	thereof Germany [TWh/a]
No Storage	15.00	5.33
High Diffusion	14.64 (−2.4 %)	5.02 (−5.8 %)
Standard Load Profile	14.75 (−1.6 %)	5.16 (−3.1 %)

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