On Market Designs for the Transition of Power Systems towards Climate Neutrality

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Jonas Zinke — Düsseldorf, January 2024

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1. Introduction

1.1. Motivation

The strive for climate neutrality requires a fundamental overhaul of the capital stock as fossil-fueled assets have to be replaced by low-carbon technologies. At the heart of this transformation lies the electricity sector, which assumes a pivotal role in realizing climate neutrality across the energy consumption sectors. Here, new electricity-based, low-carbon technologies, such as heat pumps, electric vehicles, or industrial electric appliances (e.g., electric arc furnaces), are driving up the electricity demand. In order to supply the required clean electricity, smaller, decentralized, and weather-dependent renewable power plants like wind and solar farms must replace the existing fleet of large fossil-fueled power plants. Concurrently, the grid structure and transport capacity must also adapt to accommodate these changes.

The International Energy Agency estimates that global investment in clean-energy technologies has to increase from about 1.8 trillion USD in 2023 to 4.5 trillion USD a year by the early 2030s (IEA, 2023). To mitigate these investment costs and their societal distributional impact, effective coordination of existing resources and new capital spending is key.

Theoretically, electricity prices could provide all the information needed to coordinate the transformation process, as they result from transactions between market participants and thus reveal their respective value for electricity. High electricity prices during certain periods or locations indicate a high value for additional generation or transport capacities, incentivizing market participants to dispatch existing assets and guide new investments accordingly. However, in reality, market prices do not reflect all relevant information due to the intricate requirements associated with pricing electricity as a commodity. These complexities include, in particular, the consideration of physical transport restrictions resulting from the grid-bound nature of electricity and the negative externality of greenhouse gas (GHG) emissions in the case of fossil-fired power generation. As a result, coordination issues arise, and efficient regulation is required.

The European Union (EU) organizes power systems with a regulated monopolistic grid infrastructure on the one hand and competitive wholesale markets within regional bidding zones on the other. Transmission scarcities manifest as price differences only between bidding zones, i.e., the market neglects innerzonal grid restrictions. While this structure fosters highly competitive and liquid electricity wholesale markets, it hinders the provision of local investment and dispatch signals. Consequently, additional market design elements and regulations are required to coordinate between the grid and the market.

To address the negative externality of GHG emissions, the EU employs the emission trading system (EU ETS). This system mandates emitters to acquire allowances for their GHG emissions. Thus, the total allowance supply limits total emissions. Firms trade these allowances on markets, with the resulting prices theoretically reflecting the scarcity of allowance supply and firms' marginal abatement costs. Thereby, emissions trading discloses the firms' private information on abatement costs and handles this information so that the emission target is met at the least cost. This system serves as an inter-temporal coordination mechanism, signaling to GHG emitters when to invest in new low-carbon technologies and when to decommission existing fossil-fueled assets. However, important parameters like the future marginal abatement costs are subject to uncertainty.

Against this backdrop, the regulatory challenge is to create a framework that efficiently coordinates investment and dispatch decisions both spatially and temporally. Simultaneously, it must mitigate distributional effects perceived as socially unjust and maintain liquid and competitive markets without increasing uncertainty. As these challenges have proven non-trivial, the current regulatory system is the subject of debate in science and politics. This dissertation aims to provide new insights into this debate by analyzing different aspects of the coordination task and the impact of potential market design elements. The focus is particularly on the European and German context. The thesis consists of four chapters, each based on a single paper to which the authors contributed equally:

1. One Price Fits All? On Inefficient Siting Incentives for Wind Power Expansion in Germany under Uniform Pricing. Joint work with Lukas Schmidt, *EWI Working Paper 20/06* and published in *The Energy Journal.* (Schmidt and Zinke, 2023)
2. The Place beyond the Lines - Efficient Storage Allocation in a Spatially Unbalanced Power System with a High Share of Renewables. Joint work with Berit Czock and Amelie Sitzmann, *EWI Working Paper 23/01* and under review at *Energy Policy.* (Czock et al., 2023)
3. Two Prices Fix All? On the Robustness of a German Bidding Zone Split. *EWI Working Paper 23/07.* (Zinke, 2023)
4. On the Time-Dependency of MAC Curves and its Implications for the EU ETS. Joint work with Martin Hintermayer and Lukas Schmidt, *EWI Working Paper 20/08.* (Hintermayer et al., 2020)

The remainder of the introduction provides an outline of the following chapters (section 1.2), discusses the methodological approaches and hints at opportunities for future research (section 1.3).

1.2. Outline

1.2.1. One Price Fits All? On Inefficient Siting Incentives for Wind Power Expansion in Germany under Uniform Pricing

With wind power capacities expected to play a central role in reducing greenhouse gas emissions, the decision as to where to install these systems becomes increasingly important. Chapter 2 evaluates investment incentives for wind power under two market designs: uniform and nodal pricing. To this end, an electricity system model is developed that allows for investments in wind power capacities while carefully accounting for static transmission grid constraints. Wind power capacities are assumed to reach the same expansion target by 2030 under both market designs. The results show that under nodal pricing, investments in wind power plants shift to locations with lower wind yields. The amount of electricity fed into the grid from wind power plants, however, is higher under nodal pricing as curtailment is reduced by two-thirds. Furthermore, grid-optimal wind locations are shown to require higher direct subsidy payments but decrease yearly variable supply costs by 1.5% in 2030. Yet distributional effects present an obstacle to the introduction of a nodal pricing regime, with about 75% of German demand facing an increase in electricity costs of about 5%. To mitigate the distorted investment signals arising from uniform pricing regimes, restricting investments within grid expansion areas proves more promising than including latitude-dependent generator-component in the grid tariff design.

1.2.2. The place beyond the lines - efficient storage allocation in a spatially unbalanced power system with a high share of renewables

Increasing shares of wind and solar generation serve to decarbonize electricity generation; however, their temporal and spatial variability poses challenges in grid operation. While grid expansion is restricted in the medium term, storage technologies can potentially increase the power system's efficiency by temporally aligning generation and demand and increasing network utilization. Chapter 3 uses a theoretical and a numerical model to evaluate the optimal allocation of battery storage. In a case study for Germany, the results show that batteries can reduce system costs when placed behind the north-south grid bottleneck and near solar power. The supply costs in a setting with uniform prices and a random battery distribution are 9.3% higher than in the theoretical first-best benchmark with nodal prices. An optimal allocation of batteries can reduce this efficiency gap by 0.7 percentage points to 8.6%. This corresponds to almost a doubling of supply cost savings per euro spent on battery installation. Due to the lack of spatially differentiated investment incentives under the German uniform pricing scheme, batteries must be allocated by additional policies. Simple allocation rules such as tying battery siting to solar capacity or explicitly identifying a limited number of suitable sites and auctioning capacity can approximate an optimal allocation.

1.2.3. Two Prices fix all? On the Robustness of a German Bidding Zone Split

As redispatch costs and their associated distributional impacts continue to rise, the discussion on reconfiguring bidding zones in European power markets persists. However, determining an appropriate bidding zone configuration is a non-trivial task, as it must prove beneficial under varying weather conditions, load situations, and an uncertain future – in other words, it must be robust.Chapter 4 uses the German-Luxembourg market area as an example to investigate the impact of uncertain factors, such as short-term weather patterns and long-term system changes, on the potential reduction of redispatch costs resulting from a two-zone split. Employing hierarchical clustering on hourly time series of Locational Marginal Prices for multiple historical weather and future scenario years, the paper derives bidding zone splits and assesses their robustness regarding redispatch cost reduction. Sensitivities to uncertain factors such as grid and renewable expansion, demand development, and fuel prices are investigated. The results indicate that a north-south split of the German-Luxembourg market area can robustly reduce redispatch costs. The impact of yearly weather fluctuations on the reduction potential is limited, owing to the structural nature of grid bottlenecks. However, the long-term transformations within the power system, coupled with their associated uncertainties, can significantly diminish the potential for cost reduction through a bidding zone split.

1.2.4. On the Time-Dependency of MAC Curves and its Implications for the EU ETS

Several articles have analyzed the coordination function of the EU ETS, mostly relying on marginal abatement cost (MAC) curves. While the assumptions on MAC curves drive the results, the prevailing literature on the EU ETS does not take the shape of MAC curves into account. Chapter 5 discusses the implications of MAC curve properties for the EU ETS. Using a partial equilibrium model of the European power sector, this chapter derives two essential properties of MAC curves: Firstly, the shape of MAC curves is convex and depends on economic developments such as fuel prices and interest rates. Secondly, MAC curves flatten over time, mainly due to enlarging investment opportunities. With convex MAC curves, marginal abatement costs in the EU ETS increase over time, which triggers higher banking of firms. On the contrary, flattening MAC curves over time lead to lower incentives for banking. In particular, short-term MAC curves are steep and, thus, raise the price path.

1.3. Methodological Approaches

The thesis uses numerical fundamental models of real-world markets. All of them are partial equilibrium optimization models, which isolate individual markets and take assumptions on other markets as given. The models rely on the assumption of competitive, efficient markets and rational market participants with perfect foresight. Further, the models assume electricity demand to be inelastic.

Each chapter of this thesis highlights a specific aspect of coordination in European power markets. Thus, a model configuration specifically tailored to the research question of each chapter was developed. Chapters 2 through 4 address their respective research questions by modeling spatially high-resolved electricity markets. To analyze the efficient allocation of new investments into decentralized generation capacity (chapter 2 and 3) or to determine suitable splits of the German bidding zone (chapter 4), they apply the concept of nodal pricing. While the assumption of perfect competition seems reasonable for existing large European day-ahead markets, market power issues are more likely to arise in the much smaller nodal markets. Similarly, the assumption of perfect foresight, i.e., the absence of uncertainty, is more critical under nodal pricing. Future nodal prices are sensitive to other firms' actions or grid expansion decisions, while uniform prices are comparatively robust due to the market size. Consequently, the project profitability experiences higher uncertainty under nodal pricing, prompting investors to adjust their risk premia. The results of the nodal pricing model runs must, therefore, be regarded as hypothetical benchmarks rather than realistically achievable results.

In order to maintain linearity, non-linear alternating current (AC) power flow restrictions are approximated via direct current (DC) power flow constraints. Although this means that the model neglects grid losses and reactive power, the general findings remain undistorted. Moreover, the model results depend on the quality of the input data. Where feasible, the models apply real-world data. Nevertheless, some approximations are necessary, for example, regarding the distribution of demand and power plants among the German grid nodes. Neighboring countries are depicted as singular nodes to keep the computational effort manageable. Chapter 4 extends the detailed network representation to Germany's neighbors, which enables assessing interactions of cross-border electricity trading and network congestion issues in more detail. Further, the chapter applies the model as a pure dispatch model in hourly resolution, making all investment decisions exogenous assumptions.

To derive candidates for a bidding zone reconfiguration, chapter 4 applies hierarchical agglomerative clustering. Even though this is an established method, it should be noted that it does not guarantee optimality. Therefore, the development of new methods for the delineation of bidding zones offers further scope for research.

Finally, chapter 5 applies an investment and dispatch model of the European power market to derive stylized facts on the shape of MAC curves. To this end, the model allows for endogenous investments in more technologies and covers a larger area than the models employed in the previous chapters but uses a simplified representation of transmission constraints. The general drivers of the MAC curve's shape should hold for all sectors. Nevertheless, further research is warranted, considering that the EU ETS covers not only the electricity but also the industrial sector and may be extended to the mobility and heating sectors in the future.

In addition to this discussion, each respective chapter provides comprehensive descriptions of the methodological approaches employed.

2. One Price Fits All? On Inefficient Siting Incentives for Wind Power Expansion in Germany under Uniform Pricing

2.1. Introduction

2.1.1. Motivation

With wind power capacities expected to play a central role in reducing greenhouse gas emissions, the decision as to where to install these systems becomes increasingly important. First, spatially distributed locations can flatten the variable nature of their electricity feed-in (balancing effects) and hence reduce the need for dispatchable generation capacities. Second, sites with high wind yield usually do not coincide with main load centers (cf. Borenstein, 2012). A large concentration of wind power plants at attractive but remote sites imposes challenges to the grid. Selecting the location of wind power plants is thus often a trade-off between high wind yield and grid congestion. This trade-off becomes more critical with increasing market shares of renewable energy sources (RES).

The paper analyzes this problem by considering the example of Germany. About 25% of the electricity demand in Germany was covered by wind energy in 2019 (cf. AGEB, 2021), and further expansion is a clear political goal (cf. EEG, 2021). The typical pattern of remote locations offering better wind conditions also applies to Germany: Wind yield peaks in Northern Germany close to both the North Sea and the Baltic Sea. Demand for electricity, however, is highest in the densely populated, industry-rich areas of Southern and Western Germany. As a direct consequence, integrating RES generation into the grid has posed a challenge in recent years.[1] The current country-wide market design, which imposes a uniform electricity price, does not take grid bottlenecks into account. As a result, scheduled generation may be adjusted after market-clearing to align with grid restrictions, often referred to as redispatch.[2] Both redispatch volumes and costs have risen over recent years. Coordinating wind power expansion with grid bottlenecks is crucial to minimize electricity supply costs.

In liberalized electricity systems, grid expansion - in terms of increasing transmission capacity - is subject to regulatory decisions, whereas wind power plants

[1] Government decisions on phasing-out coal and nuclear power plants exacerbate the problem further, since these plants are usually located close to load centers.

[2] With redispatch, remote intermittent RES are usually curtailed and replaced by ramping-up conventional power plants close to load centers to overcome congestion.

are built by private investors. Due to long approval and construction periods, grid expansion projects are fixed for the long term, usually before the decision to invest in new generation capacity is made.[3] German and European regulatory authorities usually review and approve grid expansion projects at least 10 years in advance (cf. Bundesnetzagentur, 2019). Since this analysis covers the time horizon up to 2030, grid expansion is considered to be a given, even though the optimal grid expansion may differ between the nodal and the uniform market design. The expansion of wind power, on the other hand, is subsidized by the German government, as is the case in many other European countries. In addition to the revenue generated via the electricity market, wind turbines also receive a market premium for electricity fed into the grid. The value of the market premium is determined in capacity-based pay-as-bid auctions: new wind power projects bid according to their expected revenue, which is calculated based on the expected electricity prices, expected wind yield at the respective location and the correlation between wind availability and electricity price. Incentives for spatial diversification only arise due to the variations in wind feed-in[4] patterns across regions and the resulting balancing effects (cf. Schmidt et al., 2013). However, wind yield often prevails over balancing effects under uniform pricing due to high correlation of feed-in patterns (cf. Eising et al., 2020). As a result, wind power investors seek to maximize wind feed-in. In order to reduce the concentration of wind power investments in regions with high wind yields, the German government introduced a wind bonus-malus component into the auctions that is determined based on the expected wind yield (cf. EEG, 2021). The component aims to create incentives for constructing wind power plants in locations with lower wind yield. Nevertheless, wind power has continued to be primarily deployed at high wind-yield sites in Northern Germany.

The expansion of intermittent electricity generation exerts negative externalities on the electricity grid. Pricing of externalities is the economically desirable instrument to overcome their detrimental effects (cf. e.g., Borenstein, 2012, Hogan, 1999, Wagner, 2019). While uniform prices fail to reflect grid externalities, nodal pricing regimes internalize these in market prices, to reflect the cost of both generation and grid constraints (cf. Weibelzahl, 2017). If, e.g., wind power feed-in in Northern Germany is too high to be integrated into the grid, low electricity prices arise there. If such situations occur frequently, the electricity price level drops and investments in wind power become unprofitable. This mechanism creates dynamic incentives in nodal price regimes for an efficient coordination of investments in wind energy with the existing grid (cf. Green, 2007). This also applies to investments in demand-side or flexibility assets: building energy-

[3] Höffler and Wambach (2013) argue that an early commitment to grid extension is also welfare-optimal as long as the investment costs of the companies are not private information. The investment costs for wind power plants are transparent so that an early commitment to grid expansion is economically desirable.

[4] Within this paper, the term *(maximum) wind feed-in refers to the electricity generation potential of wind power plants given under the* the wind conditions. Actual generation may deviate due to curtailment, in the event of grid bottlenecks.

intensive industries becomes more attractive in regions with lower electricity prices, flexibility is added to regions with large fluctuations in the electricity price.

In order to counteract problems with the grid integration of wind energy under uniform pricing, the amendment to the Renewable Support Scheme in 2017 (*Erneuerbaren-Energien-Gesetz 2017*) introduced the so-called "grid expansion area" (*Netzausbaugebiet*). Within this designated area, investments are restricted to prevent excessive expansion of wind turbines at windy but grid-critical locations. Furthermore, spatially-differentiated grid tariffs for generators (cf. e.g., Grimm et al., 2019, Haucap and Pagel, 2014) can penalize wind power generation at grid-critical sites and hence positively affect social welfare (cf. e.g., ACER, 2015, Daxhelet and Smeers, 2007). Several European countries have introduced spatially-differentiated generator-components (g-components) in their grid tariff schemes, including e.g., Sweden, the UK and Norway (cf. ENTSO-E, 2019). While node-specific g-components can replicate the efficient investment signals of nodal pricing, the simplefied g-component approach eases information gathering for investors and tariff setting for regulators. Since distorted signals of uniform prices develop mainly along the North-South axis (cf. Obermüller, 2017), this paper follows the Swedish grid tariff design and assess latitude-dependent g-components (THEMA, 2019).

This paper quantifies the effects of nodal and uniform prices on the spatial distribution of wind power expansion. Welfare losses stemming from distorted incentives set by uniform prices as well as distributional effects resulting from the introduction of nodal prices are also examined. Furthermore, this paper evaluates to what extent welfare losses resulting from inefficient wind power siting can be mitigated by complementing uniform pricing with latitude-dependent g-components in grid tariffs or defining grid expansion areas.

2.1.2. Related Literature

This paper builds on two strands of literature: The first strand uses the concept of market values to evaluate the financial worth of power generation facilities. In recent years, several articles have used market values to analyze efficient RES expansion pathways. Joskow (2011), for example, introduces market values to evaluate intermittent power generators. Among others, Grubb (1991), Jägemann (2014) and Hirth (2013) discuss how RES market penetration affects market value. Some studies find that higher penetration of RES undermines their market value due to cannibalization effects (see e.g., Prol et al., 2020). In the case of increasing wind capacities, high intermittent feed-in, especially when there is a high degree of simultaneity, may result in a drop in the electricity price and thus lower the market revenue of wind power plants. Grothe and Müsgens (2013), Elberg and Hagspiel (2015) and most recently Eising et al. (2020) use market values to shed light on the optimal distribution of wind power plants in Germany. However, these papers only consider uniform pricing. Accordingly, the market values only reflect the correlation of local wind feed-in with the uniform price signal and do not address grid restrictions. Consequently, the problem of coordination between RES deployment and grid bottlenecks is not examined.

The second strand includes papers that either examine the trade-off between grid expansion and investment or analyze nodal market designs as a theoretically efficient instrument to solve this coordination problem. Lamy et al. (2016) examine the trade-off between grid expansion and investments in wind power plants at less attractive locations and find that wind power plants close to load centers are economically desirable. Opportunity costs of choosing sites with lower wind yields are lower than the avoided grid expansion costs. However, in a scenario comparison for Germany Böing et al. (2017) find the opposite. Grid expansion imposes fewer costs than an increased deployment of wind power plants in the low-wind area of Southern Germany. In an early work on nodal prices, Green (2007) investigates the welfare effects of switching from uniform to nodal prices in England/Wales. He finds that, in a static setting, the introduction of nodal prices avoids welfare losses of 1.5% with regards to the spot market revenues of electricity producers. He suggests that the efficient, dynamic incentive effects of nodal prices should significantly increase welfare gains. Leuthold et al. (2008) conduct a similar, static investigation of uniform and nodal market designs for Germany and find comparable welfare effects. They also emphasize the advantages of nodal prices in a dynamic context. Most recently, Triolo and Wolak (2021) estimate that switching from uniform to nodal pricing in Texas reduced supply costs of thermal power plants statically by 3.9%. Pechan (2017) sheds light on the dynamic incentives of nodal pricing. Using a simplified six-node model, she investigates the effects of uniform and nodal pricing on the location of wind turbines. The spatial distribution of wind turbines changes significantly if negative grid externalities are taken into account. Similar to the paper at hand, Lamp and Samano (2020) investigate inefficient incentives for building photovoltaics under the German uniform pricing market design. Karhinen and Huuki (2020) examine locational prices for Finland, a country that also has high wind capacities far from load centres. The authors find that prices differ between regions only temporarily until grid expansion is completed.

Closest to this article, Obermüller (2017) combines the two strands of literature. He uses a static dispatch model to examine the market values of wind power plants under uniform and nodal pricing in Germany for 2014. He derives diverging market values and concludes that uniform prices set inefficient investment incentives for wind power plants. Yet, a dynamic evaluation to quantify the resulting inefficiencies is not included.

The prevailing literature on evaluating spatially-differentiated grid tariffs or grid expansion areas to mitigate inefficient investment signals of uniform pricing is scarce. Lück and Moser (2019) assess the German grid expansion area and its impact on redispatch volumes but do not evaluate its benefits from an economic perspective. Numerically evaluating spatially-differentiated g-components, Bertsch et al. (2016b) and Grimm et al. (2019) find only minor positive effects of their implementation on congestion costs and welfare.

2.1.3. Contribution and Structure

The work presented sheds light on the dynamic coordination of wind power investments for given grid expansion under nodal and uniform pricing. Our contribution is fourfold: First, an electricity system model is developed that allows for investments in power plants while considering a detailed representation of transmission grid constraints. To isolate the effects of the spatial distribution of wind power plants, this paper considers only endogenous siting of an exogenously defined target capacity of wind power, while conventional power plants follow an exogenous path.

Existing dynamic modelling approaches either (i) decouple investment decisions and grid modelling to approximate an equilibrium solution using iterative model runs (e.g., Bertsch et al., 2016b; Fürsch et al., 2013; Hagspiel et al., 2014 or most recently Fraunholz et al., 2020) or (ii) use highly aggregated grid representation with only few nodes or zones (e.g. Grimm et al., 2016b). In order to accurately address the spatial distribution of wind power plants and the impact on grid congestion, the model developed considers 380 nodes to represent the German transmission grid. To the best of the author's knowledge, existing models with high spatial resolution are static and neglect investments in power plant capacities (e.g., Obermüller, 2017 or Breuer and Moser, 2014). Second, the efficient expansion of wind power plants in Germany is derived using nodal pricing. Third, inefficiencies implied by the current uniform pricing market design are quantified. To this end, market values of wind power plants are compared under nodal and uniform pricing, and necessary direct subsidies, as well as the resulting welfare losses and distributional effects, are derived. Fourth, this paper investigates the introduction of latitude-dependent g-components as well as grid expansion areas to counteract welfare losses due to inefficient siting of wind power plants under uniform pricing.

Our main findings are as follows:

First, building the same amount of wind capacities at grid-friendly sites rather than at sites with maximal wind yield increases the amount of wind energy fed into the grid. The reduced need for curtailment overcompensates losses in wind yield.

Second, sites that require low (or even no) subsidies have low system values and hence increase redispatch and curtailment. In general, uniform prices lower subsidies for wind power but lead to yearly welfare losses amounting to 1.5% of variable supply costs in 2030 due to inefficient wind power expansion.

Third, latitude-dependent g-components fall short in adequately reflecting distortions in uniform pricing regimes. A single grid expansion area, which is currently the case in Germany, outperforms latitude-dependent g-components. Yet, further differentiation into multiple grid expansion areas can significantly enhance these positive effects.

Fourth, spatially-differentiated signals of nodal prices for wind power investments lead to distributional effects. Consumers in Northern Germany, representing about 25% of German demand, would benefit from up to 30% lower nodal electricity prices compared to uniform prices in 2030. In contrast, electricity prices in Western and Southern Germany would increase by about 5% under nodal prices. As a result, electricity consumers in the load centers in Western and South-Western Germany would bear higher costs, while electricity generators in Northern Germany would face declining revenue and vice versa.

The remainder of this paper is structured as follows: Section 2.2 introduces the model, the input data and central assumptions. The differences in investment locations, electricity generation, market values as well as welfare and distributional implications triggered by switching from a uniform to nodal pricing regime are explained in Section 2.3. Latitude-dependent g-components and grid expansion areas as complementary measures to mitigate distorted investment signals of uniform pricing are analyzed in Section 2.4. Section 2.5 offers a critical discussion of the applied methodology, and Section 2.6 forms the conclusion.

2.2. Methodology, Input Data and Scenario Design

This paper uses the notation presented in Table A.1. To distinguish exogenous parameters and endogenous optimization variables, the latter are written in capital letters.

2.2.1. Power Market Model

This paper develops an investment and dispatch model, which considers a detailed representation of the German transmission grid. It is based on the power market model DIMENSION[5]. SPIDER is a partial equilibrium model of the European power sector. The model invests into new power plants and dispatches generation capacities such that the net present value of variable and fixed costs is minimized. Within this paper, network investments are considered exogenous, i.e., the transmission system operator has already defined its grid expansion for the timeframe considered. Electricity demand, which is defined by the load structure, spatial distribution and consumption level, assumed to be inelastic, i.e., demand does not adjust to prices. By assuming perfect markets and no transaction costs, the market rationale of profit maximizing power generation

[5]DIMENSION was used in numerous analyses, e.g., in Bertsch et al. (2016b) and Peter (2019). For a thorough introduction to DIMENSION and its characteristics, the reader is referred to Richter (2011).

firms corresponds to a cost minimization of a central planner. The competition of profit-maximizing symmetric firms constitutes the dual optimization problem to a central planners' cost minimization. The technical details of the cost minimization problem are given in Appendix A.2.

The inner-German transmission grid infrastructure is considered within a linear optimal power flow problem (LOPF). Non-linear AC power flow restrictions are approximated via linear DC power flow constraints. Thereby, it neglects grid losses (cf. Van den Bergh et al., 2014). To implement DC power flow, the cycle-based Kirchhoff formulation is used, which presents an efficient formulation (cf. Hörsch et al., 2018). Appendix A.2 presents the corresponding constraints in detail.

Incorporating a detailed representation of grid constraints as well as endogenous investments in generation is computationally challenging. Thus, the model underlies several limitations to keep it tractable: Investments in transmission grid lines are exogenous assumptions. To avoid mixed-integer optimization, ramping and minimum load constraints are approximated. The model does not depict combined heat and power plants. Further, the model abstracts from uncertainty and assumes perfect foresight. The model also uses representative days to reduce the temporal dimension of the optimization problem.

2.2.2. Assumptions and Data

Scope and Transmission Grid

The regional focus of the model is Germany with a spatial resolution at transmission grid node level, i.e., 220 kV to 380 kV voltage levels. For the representation of the transmission grid, grid information from multiple sources is combined, e.g., Matke et al. (2016) and 50Hertz et al. (2019). Grid extensions follow the latest version of the German grid development plan (cf. Bundesnetzagentur, 2019). The model covers Germany and its neighboring countries, depicted as one node without inner-country grid restrictions. Interconnectors both to and between neighboring countries are approximated via Net Transfer Capacities based on ENTSO-E (2018b). Overall, the model incorporates 380 nodes and 606 connecting lines within Germany. The regional scope and the representation of the German transmission network is visualized in A.2.

The temporal scope covers the years 2019, 2020, 2025 and 2030, represented by 12 representative days in an hourly resolution. The representative days are derived using k-medoids clustering concerning residual load (cf. Kotzur et al., 2018).

The technological scope comprises the most common conventional and renewable power plant types, as well as pumped storage. Table A.3 provides an overview of the considered technologies, including their techno-economic parameters. Endogenous investments are only allowed for onshore wind power plants and gas turbines in Germany. The capacity development of all other technologies is exogenous. It follows the *National Trends* scenario in ENTSO-E (2018b) and *Scenario B* in 50Hertz et al. (2019). The development of power plant capacities follows political announcements. For instance, the phase-out of German lignite and coal power plants is implemented according to the latest public information. The exogenous development of conventional generation capacities is sufficient to meet demand at any time, i.e., it is assumed that the electricity market design triggers sufficient investments in backup power plants such as open-cycle gas turbines. Their location is determined efficiently in the nodal run and fixed for the uniform run. A.3 discloses further assumptions on demand development per country, investment costs as well as fuel prices.

Input data: Time-series and Regionalization

Demand time-series are based on hourly national demand in 2014, according to ENTSO-E (2020b). The German demand is distributed to the nodes similar to the approach in 50Hertz et al. (2019). Based on sectoral demand shares on federal state level (cf. Länderarbeitskreis Energiebilanzen, 2020), household demand is broken down to nodes via population shares. For regionalizing industry and commercial demand, regional data on gross value added is used for the respective sectors (cf. EUROSTAT, 2020).

For modeling intermittent renewable feed-in of photovoltaics and wind power, data provided by Pfenninger and Staffell (2016a) and Pfenninger and Staffell (2016b) is used for Germany and its neighbors. Since this paper investigates wind power expansion, regional feed-in within Germany is used based on Henckes et al. (2017), which applies a novel meteorological reanalysis model to derive wind speeds in high spatial resolution (6kmx6km). The derived wind speeds were transformed into feed-in time-series and calibrated to historical feed-in of wind parks.

Existing power plant capacities, as well as their distribution across Germany are derived from data of the German regulator *Bundesnetzagentur*.[6] Power plants are distributed via their postcodes to the nearest transmission grid node. The future distribution of offshore wind farms and solar power plants is in line with 50Hertz et al. (2019).

Figure 2.1 displays the regionally differentiated capacity factors for onshore wind power plants as well as the initial distribution of wind power plants across Germany in 2019.

[6] Conventional power plants are based on the power plant list (Bundesnetzagentur, 2020a), Renewables on *Marktstammdatenregister* (Bundesnetzagentur, 2020b).

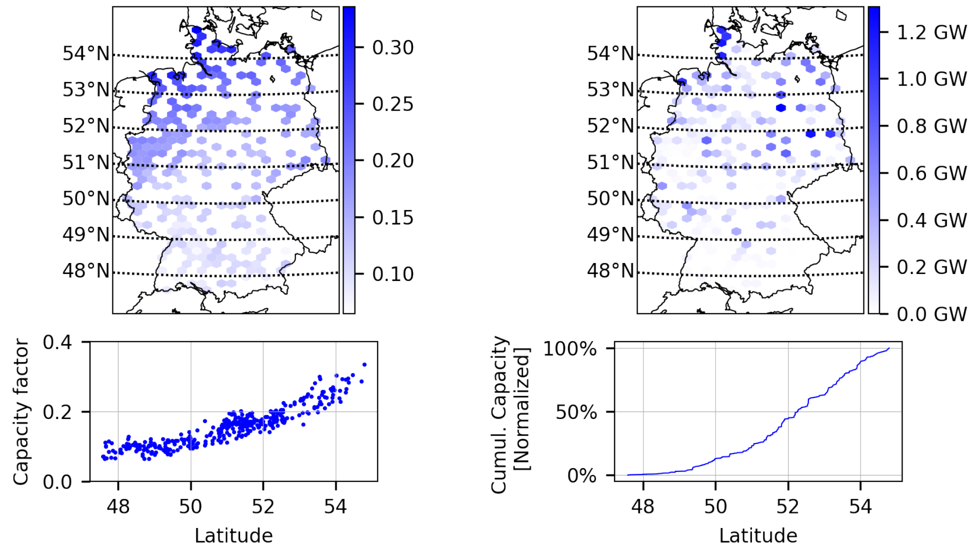


Figure 2.1.: Regional capacity factors of wind power plants (left) and spatial distribution of wind power plants in 2019 (right)

Capacity factors of wind power plants in Northern Germany range from 25% up to 35%. Towards the south, capacity factors decrease gradually. In Western Germany, wind yield stays above a capacity factor of 20% until the 51st parallel, followed by a sharp decrease towards the south. In Southern Germany, most sites offer only around 10% to 15%. As a result, about 75% of existing capacity are located above the 51st parallel. Yet, wind power capacities are low in densely populated Western Germany despite the above average wind conditions. This is mainly due to politically driven space restrictions which deviate among German federal states.

2.2.3. Scenario Setup

This paper analyzes investment decisions into wind power plants under different market designs. Apart from the uniform price market design, a nodal pricing regime is set up to derive efficient locations for new wind power plants. Under nodal pricing, each transmission grid node constitutes a market, and grid constraints are considered within the price formation. Uniform pricing considers only nationwide electricity markets where prices do not reflect inner-German grid bottlenecks. Like Germany, several European countries use uniform pricing.[7] While the transmission grid constraints are modeled via DC power flow (cf. Section A.2) for the nodal pricing regime, these constraints are turned off under uniform pricing. Inner-German power flows, hence, are not restricted under uniform pricing. Two scenarios are considered:

[7]Exemptions are, e.g., Norway, Sweden, and Italy, where the electricity market is split into bidding zones.

- *Nodal*, where invest and dispatch are derived under nodal pricing.
- *Uniform*, where invest and dispatch are derived under uniform pricing. The scheduled dispatch after market clearing, however, might violate physical grid restrictions and hence necessitates curative redispatch measures. The subsequent redispatch is assumed to derive the cost-efficient dispatch decision under the given power plant fleet.[8]

Additionally, Section 2.4 evaluates the effects of complementing uniform pricing with either latitude-dependent g-components or grid expansion areas. Both instruments are proposed to mitigate inefficient investment signals of uniform pricing.

For both nodal and uniform pricing, a homogeneous RES expansion target is assumed. The overarching target of Germany is to reach a 65% share of RES generation with regard to gross electricity demand, according to the government coalition agreement in 2018. For meeting this target, RES capacities are extended linearly according to announced capacity targets - i.e., 20 GW of Wind Offshore in 2030 - or capacities stated in the Grid Extension Plan (cf. scenario B in 50Hertz et al., 2019). Table 2.1 shows the assumed RES expansion in Germany.

Table 2.1.: Assumed development of installed RES capacities in Germany, based on 50Hertz et al. (2019)

[GW]	2019	2020	2025	2030
Wind Onshore	53.4	55.9	68.7	81.5
Wind Offshore	7.5	8.7	14.3	20.0
Photovoltaics	49.2	53.0	72.1	91.3

The expansion of photovoltaics as well as offshore wind power plants is exogenous, the spatial distribution of new capacities follows the development in the latest grid extension plan (cf. 50Hertz et al., 2019). For the expansion of onshore wind power plants, the model is required to expand capacities by 2.56 GW per year. The assumptions on RES expansion are in line with the goal of the German government to provide 65% of gross electricity demand via RES power plants.

In order to avoid an unrealistic concentration of new wind power plants, upper bounds for yearly expansion at each transmission node based on area-corrected historical expansion rates (data retrieved from Bundesnetzagentur, 2020b) are implemented. There are two reasons for defining the wind onshore target with regard to capacity instead of energy feed-in: First, the current auction design in Germany is capacity-based. The government auctions off a pre-defined amount of capacity to be built. Second, a capacity target ensures that investment costs

[8]Within this run, the cost-efficient dispatch decision is derived, including optimal trade flows. In reality, market clearing under uniform pricing pre-determines trade flows, which renders system-optimal trade in redispatch impossible. Cross-border redispatch is only viable based on bilateral contracts.

are the same under uniform and nodal pricing. Resulting changes in total costs are only due to different incentives to coordinate wind power investments and the grid topology.

2.3. Implications of Wind Power Expansion under Uniform and Nodal Pricing

2.3.1. Siting of Wind Power and Implications for Wind Feed-In

The gross wind capacity expansion is assumed to equal 2.56 GW per year in both market designs, regardless of nodal or uniform pricing. Whereas the regional investment bounds, from e.g., limited social acceptance and space potential, are identical, the market-based incentives for the spatial distribution differ between both market designs: under uniform pricing, only a difference in feed-in patterns and the resulting balancing effects trigger a spatial differentiation. Under nodal pricing, market revenue reflects costs resulting from grid congestion. Hence, nodal pricing incentivizes investments at grid-friendly locations. Figure 2.2 visualizes the impact of market design on the siting of wind power plants up to 2030.

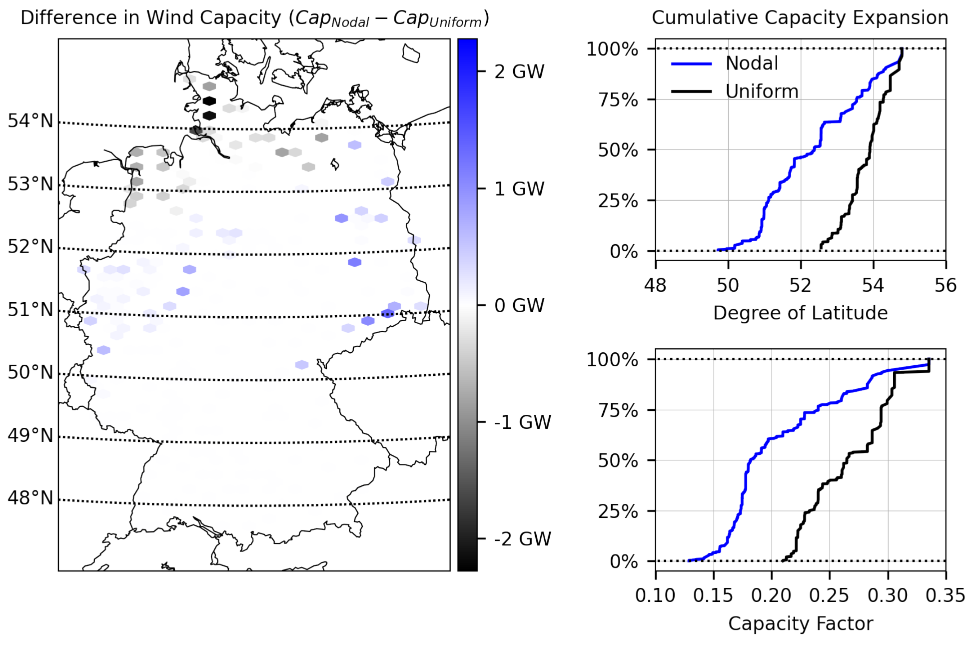


Figure 2.2.: Difference in spatial distribution of wind capacities in 2030 (left) and cumulative wind expansion by latitude and capacity factor (right)

Under uniform pricing, wind power expansion is concentrated in Northern Germany. Sites above the 53rd parallel cover approximately 90% of wind power expansion. Under nodal pricing, the investment pattern differs in two aspects: First, wind energy investments spread over more nodes than under uniform pricing and second, the locations chosen for new wind power plants move southwards. Furthermore, nodal pricing leads to a decrease in the capacity additions at windy sites above the 53rd parallel, with sites at latitudes between 51 and 53 attracting about 75% of new wind power plants instead. As a result, capacity factors of newly installed wind power plants decrease: Whereas wind power investments are found exclusively at sites with a capacity factor of at least 20% under uniform pricing, only about 40% of new wind power plants reach an equally high capacity factor under nodal pricing. Uniform pricing appears to set rather low incentives for spatial diversification, as wind yield and wind power investments are strongly correlated. Nodal pricing, on the other hand, triggers spatial diversification. Wind power expansion spreads to mediocre wind yield sites in Western and Eastern Germany. These sites are either close to load centers or own comparatively low existing wind capacities (cf. Figure 2.1). Both aspects ease the grid integration of wind power. Yet nodal pricing does not appear to trigger additional investments in Southern Germany: on the one hand, benefits from easing grid congestion do not compensate for the lower capacity factors in Southern Germany, since the main grid bottlenecks are between Northern and Central Germany.[9] On the other hand, high shares of photovoltaic and hydropower plants both locally as well as in the neighboring countries of Austria and Switzerland further decrease the profitability of wind power plants in Southern Germany.

As a consequence of different investment patterns, feed-in from wind power plants as well as curtailment volumes vary between market designs. Figure 2.3 depicts the spatial generation pattern of wind power plants and the development of actual feed-in as well as curtailment volumes. As discussed in Section 2.2.3, this analysis assumes capacity-based RES expansion targets. Therefore, installed wind capacities are equal under both nodal and uniform pricing.

The model results reveals two key findings: first, the southward shift of capacity additions naturally shifts generation in the same direction. Second, the internalization of grid costs under nodal pricing reduces grid congestion significantly, which allows for both existing and newly installed wind power plants to feed-in a higher proportion of potential generation into the grid. Consequently, overall wind power curtailment in 2030 is cut to a third under nodal pricing compared to uniform pricing.[10] All in all, the introduction of nodal pricing leads to a decrease in the curtailment of wind generation, overcompensating for lower wind yield and achieving greater volumes than under uniform pricing.

[9] The high wind capacities of Germany's Northern neighbor exacerbates these bottleneck.

[10] It is assumed, that investors get a compensation for curtailed energy and thus, do anticipate the curtailment. The compensation is subject to regulation. In the case of Germany the compensation amounts to at least 95% (cf. EEG, 2021).

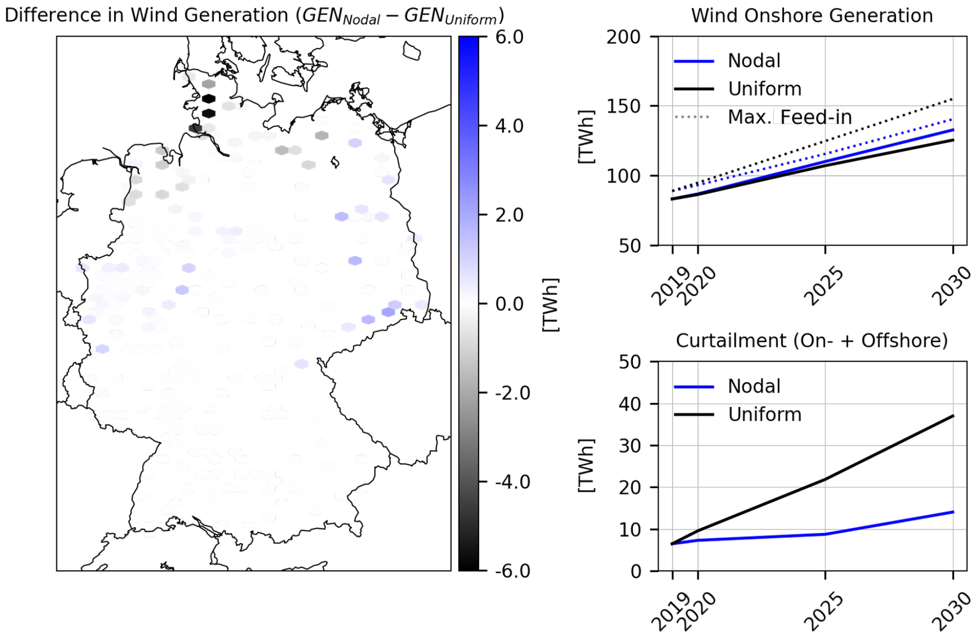


Figure 2.3.: Difference in spatial distribution of wind generation in 2030 (left) and development of wind generation and curtailment (right)

2.3.2. Regional Electricity Prices

Wind power investments strongly interact with electricity prices under nodal pricing. Nodal prices, combined with total wind yield and temporal pattern, set spatially-differentiated signals for wind power expansion. However, wind power investments depress nodal prices locally if the grid is congested (cannibalization). Figure 2.4 illustrates the results for uniform and nodal electricity prices in 2030.[11]

Given the assumptions on power plant phase-outs, fuel and carbon prices, the weighted average of Germany-wide uniform electricity prices rises to slightly above 61 EUR/MWh in 2030 compared to about 38 EUR/MWh in 2019. Nodal electricity prices differ between regions. Average nodal electricity prices in Northern Germany are found to be significantly lower than the uniform price, falling as low as 43 EUR/MWh at single nodes. About 25% of German electricity consumption would benefit from lower prices, whereas the remaining share of demand would face an price increase of about 5%[12] However, electricity prices at single nodes increase up to 75 EUR/MWh. These price peaks occur mostly in Western Germany where demand is high, RES capacities are low and conventional capacity is scarce due to phase-outs of lignite power plants. Furthermore,

[11]The prices shown are the demand-weighted average of the power price time-series reflecting the marginal costs of power generation.

[12]In contrast to uniform prices, nodal prices already internalize grid congestion costs. Hence, redispatch costs of 1.5 EUR/MWh (see Section 2.3.4) are add to the uniform electricity prices.

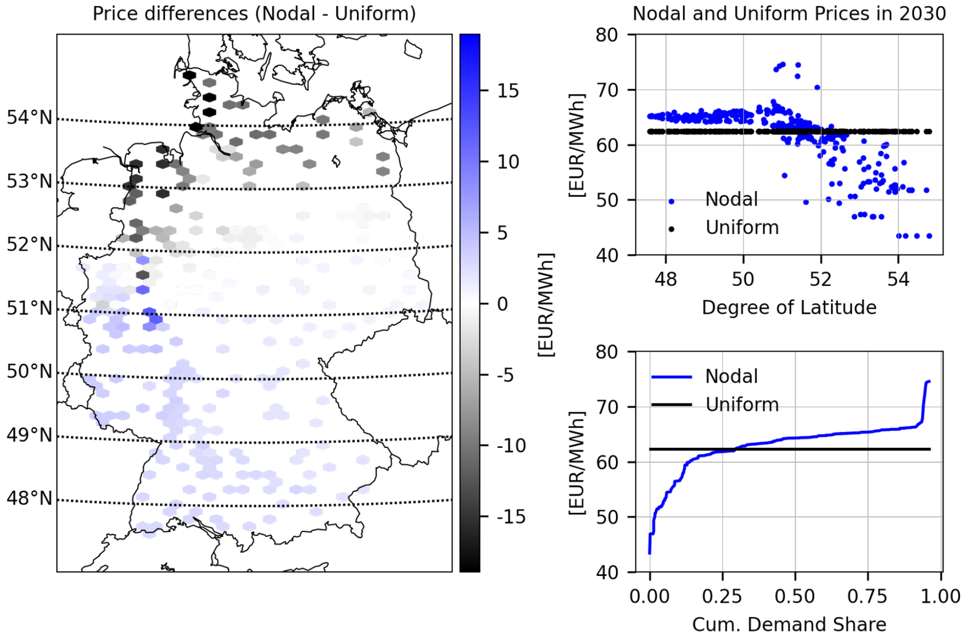


Figure 2.4.: Difference between weighted-average nodal and uniform prices (left) as well as nodal and uniform prices over latitude and cumulative demand (right)

Western Germany is not as well connected to wind-rich Northern Germany as Southern Germany, whose interconnection enhances due to three new DC lines installed after 2025. Nodal prices in Southern Germany also profit from high shares of PV and hydro, including flexible pumped hydro. Additionally, imports from nuclear- or hydropower-dominated neighbors in the South, namely France, Switzerland and Austria, reduce price peaks in Southern Germany.

Nodal prices cause a change in the trade flows between Germany and its neighbors. Grid bottlenecks are not visible under uniform pricing. Consequently, high wind feed-in in Northern Germany leads to a low electricity price throughout Germany, which triggers exports to all neighboring countries, even to the south. If the wind feed-in in Northern Germany does not comply with grid constraints, power plants in Southern Germany would have to ramp up to deliver the scheduled exports. In such situations, however, electricity imports from neighboring countries in the south would be favorable. Nodal prices reveal information on grid congestion issues and hence prevent inefficient incentives for cross-border trade. Net trade indicates that inefficient trade flow incentives of uniform prices will become more problematic as the RES shares in the German electricity generation mix increase (see A.4).

2.3.3. Market Values and Subsidies

This paper uses the concept of market values to reflect the market revenue of power plants.[13] In contrast to nodal pricing, market values under uniform pricing fail to reflect the actual value of power plants. To evaluate whether market values under uniform pricing set distorted incentives, system values of wind power plants are derived in the uniform market design from an optimal nodal dispatch given invest decisions made under uniform pricing. Under nodal pricing, market and system values are equal. Figure 2.5 depicts the market and system values of wind power plants in 2030 under uniform and nodal pricing.

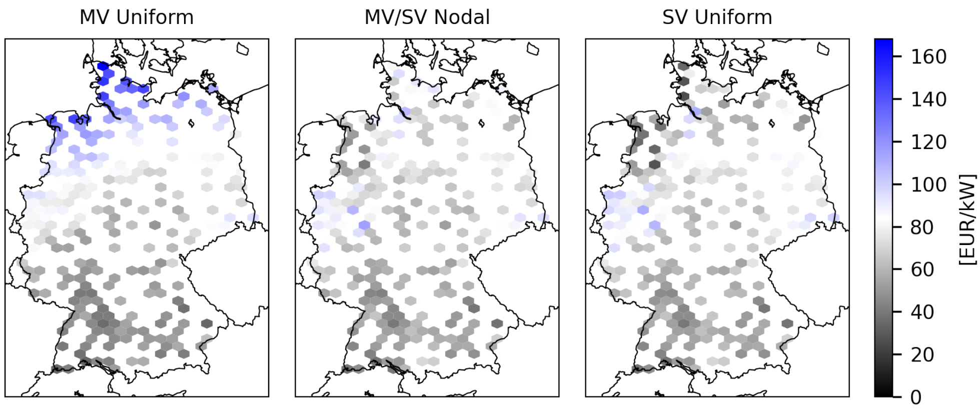


Figure 2.5.: Market (MV) and system values (SV) under uniform and nodal pricing in 2030

Market values under uniform pricing strongly correlate with wind conditions. Market values peak in Northern Germany close to the sea, where the best wind conditions prevail although there is already a lot of wind power installed. Since the market area is large and grid restrictions are not visible in uniform prices, a large amount of local wind power investments would be possible before market prices would drop due to cannibalization effects. However, the actual system values are low in Northern Germany. The difference between market and system values indicates that uniform prices send distorted signals for the site selection of wind power plants. Market revenue triggers high investments in Northern Germany, although the system values are low due to grid bottlenecks. Under nodal prices, though, market values at Northern Germany's shores are significantly lower than under uniform pricing. Wind power plants in Western Germany close to load with mediocre wind yield become relatively more valuable than under uniform pricing. As a result, wind power expansion is spatially widespread.

To further assess the incentives set by uniform and nodal pricing, the subsequent paragraph compares the distribution of market values and the system values of wind power investments. Furthermore, the required direct subsidies are

[13]Within this study, market values reflect revenue under the respective market design per capacity.

derived from the difference between fixed costs of wind power plants and market values divided by the actual feed-in.[14] [15] Figure 2.6 depicts the distribution of market and system values of newly built wind power plants and the required subsidies with boxplots.[16]

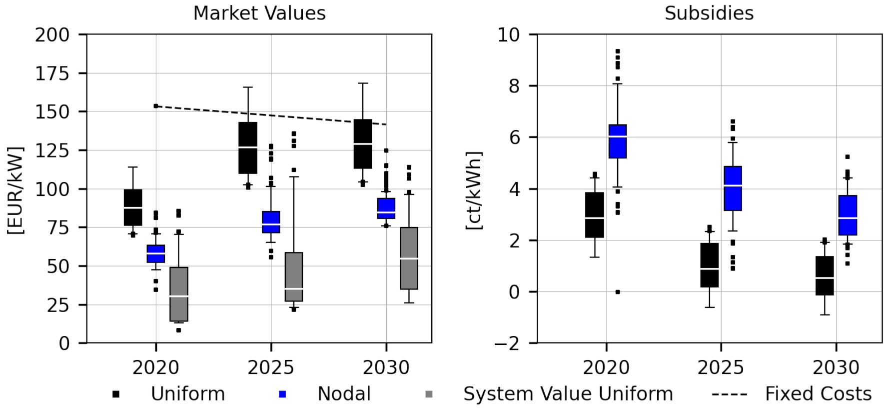


Figure 2.6.: Boxplots of market and system values as well as required subsidies for wind power investments

Under uniform pricing, market values of wind power investments exceed 75 EUR/MW and even the best sites are not profitable without subsidies. Required subsidies range from about 1.5 up to just below 5 ct/kWh.[17] Until 2025, market values increase due to rising electricity market prices as a result of higher fuel and carbon prices as well as the Nuclear phase-out until the end of 2022. At the same time, fixed costs decrease due to the assumed learning rates in investment costs (cf. A.3). Consequently, almost 25% of wind power capacity additions become economically feasible without direct subsidies, while most of the residual sites require subsidies 0 to 2 ct/kWh.[18] Between 2025 and 2030, market values and subsidies remain relatively constant under uniform pricing.

Market values under nodal pricing are significantly lower than under uniform pricing. Wind power cannibalizes itself and lowers market revenue at sites with high wind power installations due to grid bottlenecks. As a result of soaring

[14]Beside "direct" subsidies there are "indirect" subsidies, since uniform prices do not not reflect negative grid externalities of wind power investments. Wind power plant investments are cross-subsidized by electricity consumers, which have to bear these externalities, i.e., redispatch costs, via higher grid tariffs.

[15]In line with real auctions, subsidies are indicated in terms of electricity production (ct/kWh).

[16]Boxplots visualize the range of values. The boxes represent the 25 and 75% percentiles, the whiskers the 5 and 95% percentiles. The line within the boxes represents the median, outliers are scattered.

[17]Historical auction tenders in 2017 are in the same range. At the moment, auctions are not competitive due to issues in approval processes and subsidies are close to the regulated maximum bid of 6.2 ct/kWh.

[18]Uniform prices do not not reflect negative grid externalities of wind power investments. Wind power plant investments are cross-subsidized by electricity consumers, which have to bear these externalities, i.e., redispatch costs, via higher grid tariffs.

electricity market prices as well as grid expansion, nodal market values increase steadily from 2020 to 2030. Subsidies under nodal pricing are about twice as high as under uniform pricing. However, the higher subsidies under nodal pricing include grid integration costs. If negative externalities of wind power plants on the grid are considered for wind power plant additions under uniform pricing, their system value is significantly lower than the respective market value.

To evaluate whether market prices set efficient signals for the site selection of new wind power plants, Figure 2.7 visualizes the required subsidies over system values under uniform and nodal pricing.

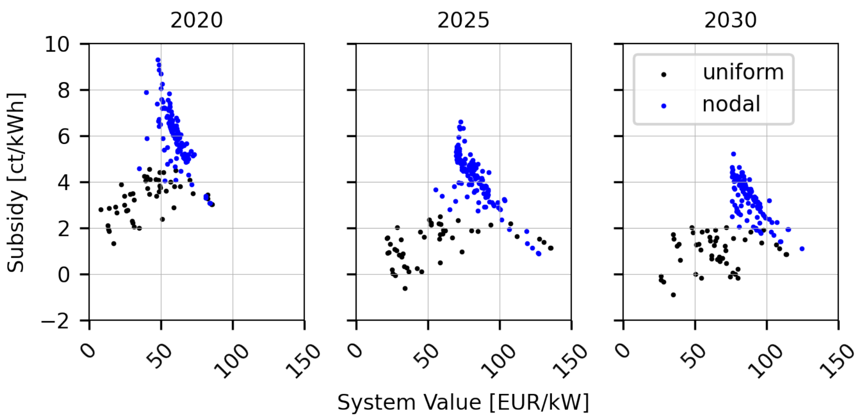


Figure 2.7.: Required subsidies vs. system values of newly built wind power plants under nodal and uniform pricing

Under nodal pricing, subsidies naturally reflect system values and stimulate an efficient site selection of wind power. Under uniform pricing, though, particularly sites, where little subsidies are needed, have low system values. Hence, uniform prices set inefficient incentives: productive but grid-hostile sites are tendered first in auctions under uniform pricing.

Summing up, uniform prices do not reflect negative externalities of wind power plants, grid congestion costs are not reflected in market revenue. Hence, investments in wind power are close to profitability and require only comparatively low direct subsidies. Wind power plants though receive indirect subsidies as their integration is non-transparently borne by consumers via grid charges. Auctions that minimize subsidy costs under uniform pricing lead to inefficient wind power expansion. Nodal pricing internalizes negative grid externalities. As a result, subsidies double compared to uniform pricing, but wind power expansion shifts to system-optimal sites.

2.3.4. System Costs

Comparing the system costs provides insights into welfare losses due to inefficient siting of wind power plants. Note that fixed costs are equal across scenarios since the capacity expansion of wind power and conventional power plants is held constant (compare Section 2.2.3). Average electricity supply costs reflect the total variable costs of electricity supply divided by aggregate electricity demand. Table 2.2 compares variable supply costs for the two scenarios.

Table 2.2.: Average variable electricity supply costs

[EUR/MWh]	2019	2020	2025	2030
Uniform	17.5	18.3	23.8	22.8
- incl. redispatch costs	0.6	0.9	1.3	1.5
Nodal	17.5	18.3	23.6	22.4
Delta Uniform - Nodal	0.0	0.04	0.24	0.34

The average variable supply costs increase until 2025 for both scenarios driven by increasing fuel and carbon prices as well as the phase-out of nuclear power plants in Germany. After 2025, costs decrease since the expansion of intermittent RES with low variable costs overcompensates the slight increase in fuel prices after 2025.

Supply costs in *Uniform* reflect the costs after redispatch. The development of redispatch costs is given separately. Despite grid expansion, redispatch costs increase from 0.6 EUR/MWh in 2019 to 1.5 EUR/MWh until 2030 due to distorted investment signals of uniform pricing. Elasticity of demand, i.e. load curtailment, could decrease redispatch costs under both market designs.

The difference between *Nodal* and *Uniform* reflects the lower bound of welfare losses implied by distorted wind power investment signals under uniform pricing.[19] Consequently, there is no cost difference in 2019. Until 2025, the additional costs per year due to sub-optimal siting of new wind power plants increase to about 0.24 EUR/MWh. Due to grid expansion, particularly the installation of DC lines between Northern and Southern Germany in 2026, the increase in electricity supply costs slows down afterward. It reaches 0.34 EUR/MWh in 2030, which corresponds to an annual cost increase of 1.5% compared to the least-cost electricity supply under nodal pricing. If only the direct costs of wind power generation are considered, an efficient siting of wind power plants and thus higher wind feed-in, the average levelized costs of electricity generation of new wind power plants decreases to 79.8 EUR/MWh in 2030, which is about 15% lower than the average cost of 93.3 EUR/MWh under uniform pricing. Lower

[19] Withing this paper, cost-optimal redispatch with optimal trade flows between countries is assumed. Therefore, the neighbouring countries partly bear the costs caused by inner-German bottlenecks. In reality, though, market clearing under uniform pricing predetermines cross-border trade. Hence, optimal trade flows are usually not feasible since cross-border redispatch is limited to bilateral contracts.

supply costs under nodal pricing imply a welfare gain. Yet, this paper does not consider how consumers and producers share the additional welfare. The change in consumer and producer surplus depends on the electricity system, i.e., which power plants are price-setting in both market designs.[20] In general, however, a welfare gain means both a higher consumer and a higher producer surplus.

Moreover, nodal pricing makes congestion - and thus the necessary network investments to alleviate congestion - more transparent. As such, nodal pricing may spark additional welfare benefits, for example, by incentivizing efficient investments in transmission grids as well as the efficient siting of wind power plants. As shown in the results, this would enable the same wind power feed-in to be realized with lower wind power capacities.

2.4. Evaluation of G-Components and Grid Expansion Areas

This section analyzes two instruments to reduce the distorting investment incentives of uniform prices: first, spatially-differentiated grid tariffs, i.e., latitude-dependent generation components and second, grid expansion areas. Both instruments are already implemented in European power market designs: For instance, Sweden charges energy-based g-components, which linearly increase with the latitude. Germany restricts wind power expansion within a grid expansion area, which is dynamically adjusted and usually covers Germany's most Northern federal states.

2.4.1. Configuration

G-Components

This paper considers capacity based g-components. These spatially-differentiated grid charges can be considered a grid connection fee, which depicts grid externalities of wind power at the respective sites. Optimally, the g-component reflects the distorting signals of uniform prices. In the setting presented the distorting signals are given by the difference in market values between uniform and nodal pricing. Optimal g-components are highly correlated to the latitude of the specific node. To develop an easy-to-implement heuristic, g-components are derived by regressing this difference on the latitude and consider two designs: G-components, which either linearly (*Lin. g-comp.*) or cubically (*Cub. g-comp.*)

[20] The distributional effects between nodal and uniform pricing are particularly interesting because redispatch under uniform pricing is cost-based while nodal pricing is entirely market-based. Thus, even if the same power plants are dispatched after redispatch, power prices are different. This leads to changes between consumer and producer surplus between both market designs.

depend on the latitude. Figure 2.8 visualizes the development of the derived g-components.

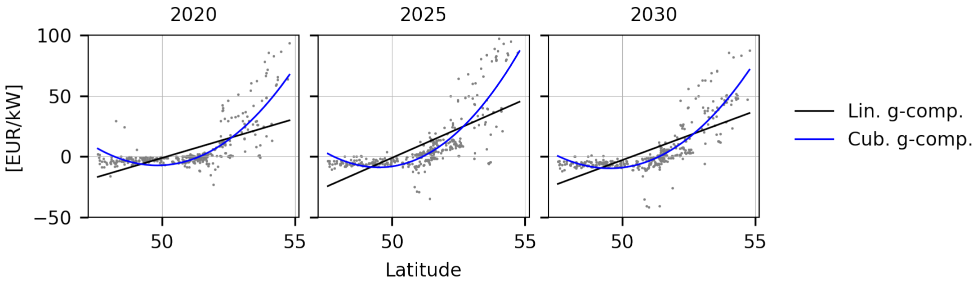


Figure 2.8.: Derivation of latitude-dependent g-components from the differences in market values between *Uniform* and *Nodal*

The difference in market values is (slightly) negative in Southern Germany (below the 50th parallel). Uniform prices underestimate the system value of Southern Wind power plants. In contrast, sites in Northern Germany largely exhibit strong distortions (above the 52nd parallel). The market revenue of wind power plants at these sites is higher than their system value. The distorting signals of uniform pricing do not develop linearly with the latitude but increase convexly. Thus, linear g-components are particularly far off for sites with high wind yields in Northern Germany. Cubical g-components reflect the non-linear correlation of market value distortions and latitude better, in particular above the 52nd parallel.

Grid Expansion Areas

Furthermore, this paper considers two designs of grid expansion areas, in which an annual investment limit restricts the wind power expansion. First - close to the currently implemented design[21] - this paper evaluates a single grid expansion area (*GEA1*), which covers the three coastal states of Mecklenburg-Western Pomerania (MP), Schleswig-Holstein (SH) and Lower Saxony (LS) as well as the city-states of Hamburg and Bremen). A.5 visualizes their geographical situation. Second, this region is subdivided into three grid expansion areas (*GEA3*) to assess whether further differentiation would be beneficial. The three grid expansion areas are in line with the three aforementioned federal states. The investment limit for wind power expansion within the defined grid expansion areas equals the efficient investments under nodal pricing and is given in table 2.3.

[21] The specific configuration is subject to bi-annual reviews. From 2017 to 2020, the grid expansion area limited wind power expansion within MP, SH and the Northern part of LS including the city-states of Hamburg and Bremen to 902 MW per year (cf. Lück and Moser, 2019). From 2020 on, the annual limit decreases to 786 MW and changes the spatial configuration by including also the Southern part of LS while excluding MP.

Table 2.3.: Yearly investments limit [MW/a] for the two designs of grid expansion areas

Variation name	2020	2025	2030
GEA1	646	889	1289
GEA3	LS: 436 SH: 33 MP: 177	LS: 457 SH: 220 MP: 212	LS: 441 SH: 670 MP: 178

The investment limit in *GEA1* equals the sum of the three limits in *GEA3*. Until 2030, the investment limit rises, in particular for the most Northern state of SH, due to grid investments, which improve the connection between Northern and Southern Germany. The subsequent section discusses the impact of complementing uniform prices with the described additional instruments.

2.4.2. Effects on Siting, Feed-in and System Costs

Siting of Wind Power Plants

For understanding the effects on the siting of wind power plants, Figure 2.9 depicts the spatial distribution of wind power plants if uniform pricing is complemented with the four aforementioned instruments compared to the two pure market designs *Nodal* and *Uniform*.

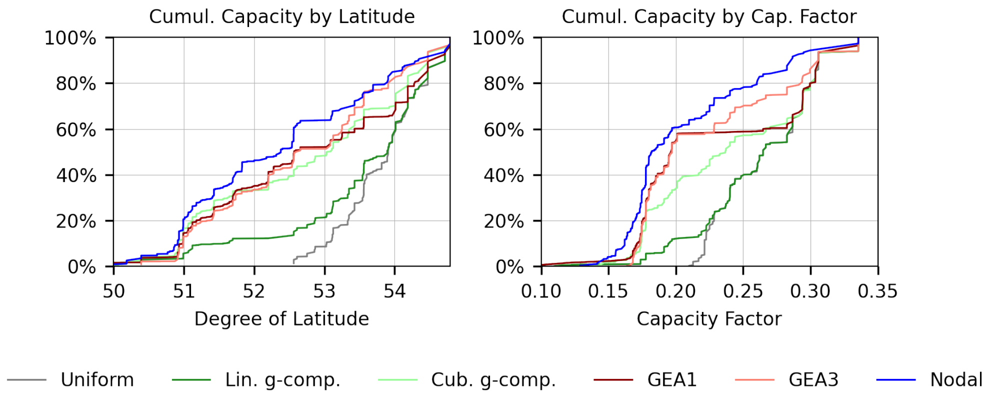


Figure 2.9.: Cumulative wind power expansion by latitude (left) and capacity factor (right) until 2030

The investment pattern with linear g-components is similar to *Uniform*. The high distortions for very productive sites are not sufficiently internalized so that expansion in the very North of Germany hardly changes. About 50% of the installed capacity is still allocated above the 54th degree of latitude. The location of the remaining half of investments shifts a bit southward. Cubical g-components address the distorting signals more accurately and shift the investment pattern with regard to latitude closer to the *Nodal* pattern. Looking at the investments concerning the capacity factors reveals that still very productive sites are preferred. But below the few very windy sites, cubical g-components significantly trigger investments at sites with lower capacity factors.

Under a single grid expansion area (*GEA1*), the sites with the highest capacity factors are still utilized, while the expansion stagnates between capacity factors of 20% and roughly 27%. This is intuitive: The best sites are still exploited while the investment limit prohibits the development of less attractive sites within the grid expansion area. Splitting the single grid expansion into three parts (*GEA3*) prevents such a clear drop. However, the very best wind conditions, which are also subject to the highest distortions, are still exploited. Yet, the investment pattern under *GEA3* comes close to the outcomes of nodal pricing.

Feed-in and Curtailment

Figure 2.10 depicts the impact on potential and realized feed-in as well as curtailment resulting from the changed investment pattern, i.e., it shows the difference to *Nodal*.

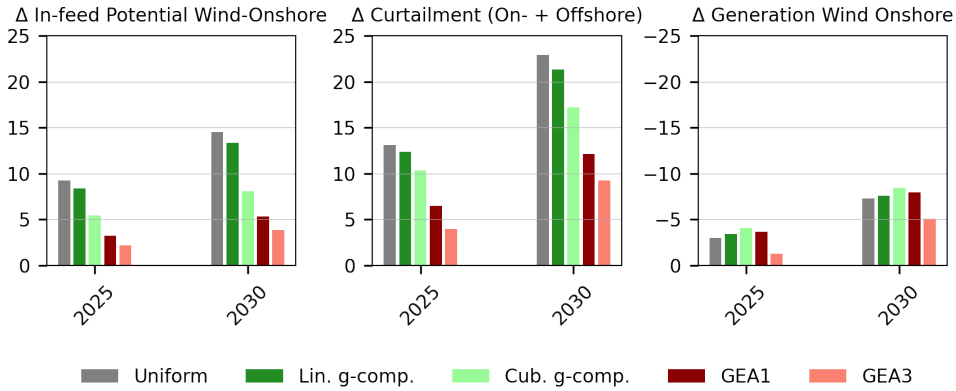


Figure 2.10.: Change in feed-in potential, curtailment and realized generation compared to *Nodal*

Under all considered market designs, the feed-in potential is higher than under nodal pricing since wind power plants are built at sites with higher capacity factors. All of the instruments also decrease curtailment compared to *Uniform*. The actual wind power feed-in is the difference between generation potential and curtailment. Compared to *Uniform*, only *GEA3* performs better and allows for higher wind power feed-in, while all other instruments slightly lower the realized compared to *Uniform*. For evaluating the efficiency of the instruments, though, wind power feed-in is not decisive. Lower grid congestion could improve the overall working of the electricity system, e.g., by allowing an efficient dispatch of conventional power plants. In particular, grid expansion areas significantly lower curtailment by prohibiting excessive wind power expansion at very productive but grid-critical sites. For evaluating whether the considered instruments avoid welfare losses through inefficient siting of wind power plants, the next section analyzes system costs.

System Costs

Figure 2.11 depicts the annualized discounted increase of variable supply costs compared to the efficient benchmark (*Nodal*) for the considered market designs.

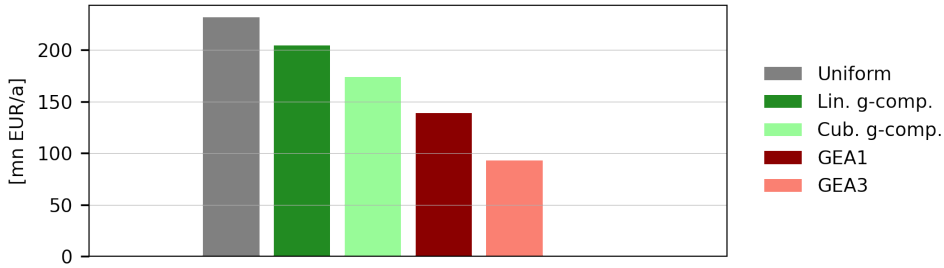


Figure 2.11.: Annualized increase of discounted additional supply costs compared to *Nodal*

Linear g-components reduce the annualized costs increase due to uniform pricing from 231 to about 204 mn EUR/a. Cubical g-components better reflect high distorting signals for productive sites in Northern Germany and hence drive the additional costs down by about 25% compared to (*Uniform*). Both designs of grid expansion areas perform better than latitude-dependent g-components. A single grid expansion area (*GEA1*) cuts the welfare losses implied by uniform pricing to about 60%. Yet, a further differentiation into multiple grid expansion areas (*GEA3*) leads to a significant additional welfare gain, reducing additional costs to 93 mn EUR/a.

Summing up, this paper evaluates selected designs of g-components and grid expansion areas. In general, the bandwidth of design options for these instruments is broad. Nonetheless, this paper finds that latitude-dependent g-components do not adequately reflect the distortions of uniform prices in Germany. Hence, such grid charges struggle to mitigate adverse effects from inefficient investment signals under uniform pricing. In particular, linearly dependent g-components are hardly beneficial. Grid expansion areas are superior in addressing these inefficiencies. In particular, a well-considered differentiation into several areas, which account for inter-dependencies of wind power expansion and grid congestion, can significantly lower welfare losses.

2.5. Discussion of the Methodology

This paper relies on several strong assumptions, e.g., perfect foresight, no transaction costs, exogenous distribution of new conventional power plants and inelastic exogenous demand.

First, future nodal prices are sensitive to other firms' actions or grid expansion decisions, while uniform prices are robust due to the market size. Consequently, long-term profitability of wind power plants are subject to higher uncertainty under nodal pricing. Ceteris paribus, investors would adjust their risk premia according to the higher risk. Second, nodal prices increase transaction costs (e.g., Breuer and Moser, 2014), particularly for setting up a new market environment and the necessary regulations. Third, demand reacts to power prices, particularly in the long term, e.g., via the siting of new industrial plants or investments in energy efficiency. The siting of conventional plants also depends on expected revenue under different market designs. All of the aspects mentioned above affect welfare gains or distributional effects imposed by the introduction of nodal markets.

Furthermore, the analysis relies on real-world data; however, some assumptions have to be made regarding the regionalization due to the lack of data. For example, the distribution of industrial load within a federal state is derived based on the regional distribution of value added. This is a common approximation for load at single network nodes, which certainly deviates from the real distribution due to inhomogeneous industrial structures within federal states. However, this simplification should not affect the overall findings of this paper, which rather depend on the inbalance of demand and RES generation in larger spatial areas. Furthermore, assumptions on capacity factors of future wind turbines rely on the rather conservative assumptions of Henckes et al. (2017). Assuming higher capacity due to technical advances (e.g., increasing hub heights), would exacerbate the inefficient siting incentives uniform prices.

This paper quantifies the distorting effects of uniform pricing for the isolated problem of coordinating wind power investments with (given) grid restrictions. The derived welfare loss is rather a conservative estimation since lock-in effects in redispatch, e.g., due to scheduled trades or ramping constraints of power plants, are neglected. Widening the scope, allocating flexibility options on the demand side and incentivizing optimal grid expansion is crucial for an efficient integration of RES into electricity systems. This paper neglects interactions between regulated grid expansion and investments of firms in competitive electricity generation markets. While today's market design and network regulation overlooks this important coordination task, nodal pricing incentivizes efficient investments and indicates the need for network expansion via price spreads between nodes.

Whether nodal prices raise market power issues (cf. Weibelzahl, 2017), or market power stems from physical realities, i.e., grid bottlenecks, and market design only determines where it unfolds (cf. Hogan, 1999 or Bertsch, 2015) is beyond the scope of this paper. Zonal prices, i.e., splitting the uniform pricing market into several bidding zones, are an alternative for spatially-differentiated prices (cf. Grimm et al., 2016a). Apart from spatially-differentiated investment incentives, zonal pricing mitigates the inherent weakness of uniform prices to set distorted incentives for cross-border trade due to the single price signal for all neighboring markets. The results presented suggest that a division into a Northern, Southern and Western zone may appropriately internalizes grid congestion issues. Yet, zone configuration based on nodal prices should be interpreted with caution, requiring a more sophisticated approach (see e.g., Ambrosius et al., 2020).

While the quantification of inefficiencies crucially depends on the country-specific network infrastructure the overall findings can be generalized for other countries beyond Germany. Uniform prices lead to inefficient incentives for siting of RES generators if locations with the best conditions are far from load centers. This pattern is typical for most European countries like the UK or France.

2.6. Conclusion

Within this research work, a power system model is developed that allows for investments in wind power plants and incorporates a detailed DC power flow representation of the German transmission grid. In applying the model, this paper investigates the siting of wind power plants in Germany under nodal and uniform pricing up to 2030, as well as the implications for the electricity system, including welfare and distributional effects.

The findings confirm that uniform prices fail to incentivize spatial diversification of wind power plants as investments tend to be made concentrated at locations with high wind yield. Since uniform prices do not reflect negative externalities on the grid, wind power expansion only requires low direct subsidies, if any. The large market size prevents significant cannibalization effects. Hence, wind capacities at productive but grid-hostile sites are found to have a competitive edge in subsidy-minimizing auctions. In other words, low subsidy requirements correlate strongly to low system values under uniform pricing.

Nodal pricing as the efficient benchmark shifts investments closer to load centers at the expense of lower potential wind yield. However, curtailment is cut to a third such that more wind energy is actually fed into the grid under nodal pricing when holding installed capacities equal in both market designs. By harmonizing wind power expansion with grid restrictions, variable generation costs in 2030 under nodal pricing are shown to be 1.5% lower than under uniform prices only due to system-optimal wind power expansion. However, distributional effects may pose political challenges to introducing spatially-differentiated electricity prices. Only about 25% of German electricity demand would profit from lower wholesale electricity prices, while wholesale electricity prices would increase by about 5% for densely-populated and industry-rich regions such as Western Germany. Additionally, the quantitative analysis reveals that nodal prices require higher direct RES subsidies because they disclose the costs for RES integration, which are typically hidden in grid charges used in uniform pricing. Whether such a transparent price indicator is in line with targets concerning political economy aspects is unclear. Subsidies also have distributional effects, which makes political feasibility even more difficult (cf. Liski and Vehviläinen, 2020).

If introducing nodal or zonal pricing is deemed politically impossible, additional instruments such as spatially-differentiated, i.e., latitude-dependent, g-components in grid tariffs or grid expansion areas to incentivize grid-friendly siting of wind power are worth considering. Both instruments partly mitigate the inefficient investment signals of uniform prices - but their design matters. G-components, which increase linearly with the latitude, are not able to adequately reveal the distortions of uniform prices at the very productive Northern sites. Cubical g-components address these distortions more accurately. Grid expansion areas, on the other hand, are more effective in mitigating distortion of uniform price signals for wind power investments. Differentiating a large grid expansion area, as is the case in the current German market design, into several areas could significantly enhance the efficiency gains. Grid expansion areas, however, are technology-specific investment restrictions, while g-components could be generalized to include other generators such as gas power plants. Beyond generation, nodal pricing incentivizes an efficient allocation of demand and discloses information on grid bottlenecks.

Future research could extend the model to shed light on the efficient integration of flexibility options, such as power-to-heat or electrolyzers. Implementing the grid topology of neighboring states would allow investigating inefficiencies stemming from limited possibilities for cross-border redispatch. Another extension could investigate the optimal layout of price zones by clustering nodes to bidding zones. Finally, including endogenous grid investments in the model would allow the analysis of efficient incentives for coordinating power plant and grid investments.

3. The Place beyond the Lines - Efficient Storage Allocation in a Spatially Unbalanced Power System with a High Share of Renewables

3.1. Introduction

As countries strive for climate neutrality, they aim for high wind and solar power penetration rates. Wind and solar are intermittent, so temporal congruence with demand is not guaranteed. Additionally, resource quality varies across regions, which may lead to a spatial imbalance between supply and demand or extensive transmission requirements that exceed the capacity of existing grid infrastructure. Efficient coordination of investments in wind and solar, as well as in transmission grid expansion and power system flexibility, can mitigate these challenges and decrease system costs. Storage technologies, such as electric batteries, provide such power system flexibility. They can address temporal imbalances by shifting generation and load and reduce spatial imbalances by improving network utilization if allocated accordingly. Whether such an allocation is achieved ultimately depends on the market design. Under nodal pricing, allocation incentives are set by market prices. Such incentives do not exist in uniform pricing systems.

This paper analyzes investment in storage technologies in both a nodal and a uniform setting. We focus on a rapidly changing, spatially unbalanced power system, i.e., where solar and wind capacity expansion is fast, but grid expansion is slow. By applying a stylized, theoretical, and a numerical investment and dispatch model, we answer the following three research questions: Firstly, where in the transmission grid should batteries be allocated? Secondly, how important is storage allocation for the system's efficiency and, thirdly, how could policy instruments be designed to approximate an optimal allocation under uniform pricing?

The importance of storage allocation is first illustrated using a theoretical two-node, two-time-step model that stylizes the characteristics of a spatially unbalanced power system. This model enables us to show fundamentally that storage capacity can increase line utilization depending on its location. We show that both an allocation before or behind a grid bottleneck can be efficient. Which allocation rule dominates crucially depends on the temporal relationship between the volatility pattern of renewable generation, the demand structure, and available transmission capacity. Naturally, the complexity of the allocation question increases as soon as more than two nodes and time steps are considered. Therefore, we provide a comprehensive numerical model to investigate optimal storage allocation in a system with multiple technologies and a detailed grid representation. We use the German electricity system as a case study.

Already today, Germany exhibits characteristics of a spatially unbalanced electricity system. Under the single bidding zone, i.e., uniform pricing, wind generation is dominantly allocated in northern Germany on the shore of the North and Baltic Seas, while electricity demand is historically centered in the south and west of Germany, which is more densely populated and industrialized. As a result of this spatial mismatch, the volume and costs of network congestion measures have risen and are likely to increase further, given Germany's latest renewable capacity targets.

To investigate the optimal allocation of storage and identify policy design options for coordinating investments, we use a linear optimization market and grid model that endogenously determines the allocation of storage and renewable generation technologies. The storage technology is calibrated as short-term battery storage. The model computes a closed-form solution to the investment and dispatch optimization problem while considering a high spatial resolution. We use the results from modeling a nodal setup with consideration of transmission constraints as a theoretical first-best benchmark. This allows benchmarking battery allocation under a uniform setup without consideration of transmission constraints in the investment problem, similar to the current German market design.

The numeric simulation results confirm the significance of local demand, renewable feed-in volatility, and grid infrastructure availability for optimal battery allocation. Especially solar generation, which has a daily generation pattern that matches the batteries' short-term shifting abilities, is a key driver for an efficient allocation. Compared to the nodal first-best benchmark, we see that the uniform setting with randomly distributed batteries increases supply costs by 9.3%. An optimal allocation of batteries can reduce this efficiency gap by 0.7 percentage points to 8.6%. In relation to the cost of battery investments, this corresponds to almost a doubling of the supply cost savings per euro spent. The supply cost savings are realized in redispatch, where the location of batteries is crucial.

In the current system in Germany, such an optimal allocation is not achieved because spatially differentiated investment signals are not available under uniform pricing. However, with the help of an additional policy instrument, location-specific information could be made transparent to provide a reference point for allocating batteries in a system-beneficial way. To get insights on how to design this policy instrument, we model different allocation rules. We find that simple heuristics, such as tying battery allocation to solar generation or explicitly defining a limited number of nodes for capacity auctions, can closely approximate the optimal battery allocation.

3.2. Literature review

Only a limited amount of publications have fundamentally examined the role storage could play in unbalanced power systems. Newbery (2018) argues fundamentally that storage can increase grid utilization, thus decreasing system imbalances. Using theoretical models, Neetzow et al. (2018) analyze whether grid expansion and storage are complements or substitutes, and Weibelzahl and Märtz (2018) examine the effect of storage on the optimal definition of price zones, highlighting the additional complexity storage brings into the system. Predominantly, the current literature is based on more complex, numerical studies considering specific countries or regions. Many of the studies focus on the short-term deployment of storage in uniform price systems (e.g. Abrell et al., 2019, Bertsch et al., 2016a, Schill and Zerrahn, 2018, Zerrahn and Schill, 2017). These papers analyze the possibilities of using storage to balance the temporal volatility of renewables but do not include a grid representation. To model spatial allocation and derive market design implications, a representation of grid constraints is crucial. Such an analysis is, for example, carried out by Schmidt and Zinke (2023) for the case of wind generation allocation in Germany in 2030 and similarly, vom Scheidt et al. (2022) investigate differences between a nodal and a uniform pricing system in Germany, focusing on the integration of hydrogen and system-optimal locations of electrolyzers in 2030. Lindner et al. (2023) analyze the impact of batteries used as grid boosters or virtual power lines and place them at two exemplary nodes in the north and south of Germany.

Closest to our analysis is literature on efficient incentives for flexibility assets. Ambrosius et al. (2018) investigate the effects of different market designs on investment incentives for flexible demand in the German industry in various scenarios under nodal and uniform pricing. However, the paper uses a simplified transmission grid representation with just 16 zones. Babrowski et al. (2016) apply a more detailed model but focus on the optimal amount of storage.

Some further publications focus on the longer term and analyze efficient power system configurations with (nearly) 100% renewable power generation in the European power system, e.g., Brancucci Martínez-Anido and de Vries (2013), Bussar et al. (2014), Schlachtberger et al. (2017), and Göke et al. (2021).

Research gap and contribution

Reviewing current literature reveals a lack of systematic analysis of optimal storage allocation and market design implications. Consequently, our paper seeks to bridge the gap between existing publications that address storage, grid issues, or market design as individual issues in power systems with high shares of wind and solar. We contribute a fundamental analysis of storage allocation in a simplified model and verify and expand our findings by employing a numerical electricity market and detailed grid model with endogenous storage allocation in light of the current conditions in Germany. Analyzing storage allocation in a uniform setting and a first-best nodal benchmark allows us to translate the insights from our integrated analysis into policy suggestions.

3.3. The economic rationale for storage allocation

This section introduces a model with two nodes and two time steps to analyze determinants of cost-optimal spatial allocation of storage in a spatially unbalanced transmission network. Generally, electrical storage technologies can shift electricity supply between different points in time.

Depending on their allocation in the grid, storage can use its temporal shifting potential to increase network utilization and thus reduce spatial imbalances. For illustration, consider the following:

Assume a weather-dependent, renewable generation technology in node R, for example, a wind or a solar generator g_{res}, with constant zero marginal costs $c_{res} = 0$. Renewable generation is stochastic and can take two possible states, res_{low} and res_{high}. Demand d is allocated in node D and can also take two possible states d_{low} and d_{high}. For simplicity, demand and renewable availability are assumed not to be correlated, and renewable generation meets demand when both are in the same state, i.e., $res_{low} = d_{low}$ and $res_{high} = d_{high}$. Further, we consider a peak-load technology g_{peak} at node D, with constant marginal costs $c_{peak} > 0$ and enough capacity to serve the demand in each time, i.e., $\overline{g}_{peak} >= d_{high}$.

Both nodes are connected by a transmission line l with line capacity $d_{low} < \bar{l} < d_{high}$. Hence, if both demand and generation in node R are high, node D could still not be fully supplied by the renewable generation technology due to a grid bottleneck. The model is illustrated in Figure 3.1.

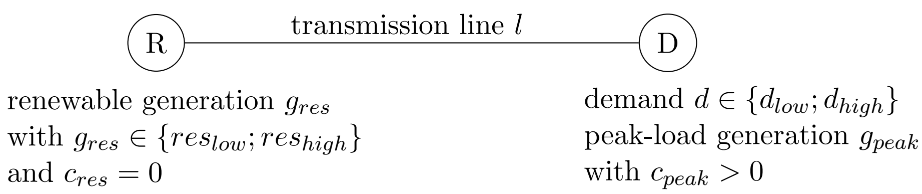


Figure 3.1.: Two-node example

We consider two time steps t_1 and t_2. Combining renewable generation and demand in all its possible states yields eight different cases, shown in table 3.1.[22]

Storage s can either be built in node R or D and comes without any investment costs. We further assume no storage losses or other variable costs in addition

[22] We do not consider combinations in which renewable generation is low in t_1 as storage is per se useless in these cases.

Table 3.1.: Possible combinations of renewable generation and demand in both time steps

	Volatility	t_1	t_2	Allocation rationale
case 1	none	res_{high}, d_{low}	res_{high}, d_{low}	no storage
case 2	none	res_{high}, d_{high}	res_{high}, d_{high}	no storage
case 3	in generation	res_{high}, d_{high}	res_{low}, d_{high}	storage in R
case 4	in both	res_{high}, d_{low}	res_{low}, d_{high}	indifferent (R or D)
case 5	in generation	res_{high}, d_{low}	res_{low}, d_{low}	no storage
case 6	in demand	res_{high}, d_{low}	res_{high}, d_{high}	storage in D
case 7	in demand	res_{high}, d_{high}	res_{high}, d_{low}	no storage
case 8	in both	res_{high}, d_{high}	res_{low}, d_{low}	no storage

to charging costs, such that $c_s < c_{peak}$ when storage is charged with renewable energy. For simplicity, we assume that storage power (charge and discharge) capacity equals supply and demand states res_{high} and d_{high}. Furthermore, storage volume capacity $\overline{s}_{power}$ is sufficient to store at least one period of full charging, i.e., $\overline{s}_{volume} \geq \overline{s}_{power}$.

By definition, storage is only useful if there are fluctuations in the system, either in renewable generation or demand. If renewable generation is high in both time steps and demand does not fluctuate either, the transmission line l is already used at capacity and peak generation is minimized. Hence, storage has no benefit to the system as a whole, which holds for cases 1 and 2.

If demand fluctuates and transmission line l is not utilized in t_1 or t_2, temporal shifting becomes useful. Consider the case that renewable supply is high in t_1 and low in t_2 and demand in node D is high in both time steps (case 3). Because there is a transmission bottleneck in t_1, storage could be used to store excess renewable generation $res_{high} - \overline{l}$. In t_2, the stored energy can be released and transmitted to node D, as transmission line l is not utilized because generation is otherwise low. Storage has to be allocated at the generation node R to do so, as l is fully utilized in t_1 when the storage is charged. A similar effect occurs, if demand is low in t_1 and high in t_2 (case 4). In this case, however, the location does not matter. Without storage, line l is not utilized at capacity in either time step. Thus, storage can charge regardless of whether it is allocated at node R or node D. In case 5, where demand is low at both times, no storage is needed because both renewable generation and grid capacity are sufficient to meet demand at both times.

If the renewable generation is high at both times, the benefit of storage depends solely on the demand profile. In case 6, where demand is low in t_1 and high in t_2, storage capacity equal to $\overline{s}_{power} = \overline{l} - d_{low}$ is built in node D to use renewable generation in t_2 instead of the more expensive conventional generation. In cases 7 and 8, where res_{high} and d_{high} coincide, again, temporal shifting has no benefit.

Main findings and generalization

The model demonstrates that storage can decrease supply costs by increasing line utilization and that storage location is crucial to unlock said system benefits. The results suggest that storage can be optimal either before or behind a grid bottleneck. In the simple setup, the optimal location depends on the volatility of the underlying demand and generation profiles. Thus, storage is allocated where volatility is higher. In practice, however, the underlying profiles are stochastic and exhibit more time steps, i.e., a sequence of the individual cases discussed above. When combining the cases into a sequence, the strict dominance of an allocation case ceases to exist, meaning that one of the cases could prevail or storage capacity could be split between the two nodes.[23]

Furthermore, the complexity of the model and the underlying relationships increases as soon as more than two nodes and technologies with different characteristics are considered. Even in the very simple model setup with only two nodes and two time steps, the storage allocation depends on the parametrization of generation and demand volatility. To decide where storage is allocated optimally, it is thus necessary to use a well-parametrized and numerical real-world model.

3.4. Methodology and input data

3.4.1. Model framework

We employ an extended version of the investment and dispatch model SPIDER initially developed in Schmidt and Zinke (2023). SPIDER is a model of the European power sector that considers a detailed depiction of the German transmission grid.[24] The model invests in new power plants and dispatches generation capacities such that the net present value of the variable and fixed costs is minimized.

Demand, which means the structure, spatial distribution, and level, is assumed to be inelastic, i.e., not adjusting to prices. The model relies on the assumption of perfect markets and no transaction costs. Thus, the competition of profit-maximizing symmetric firms corresponds to the model's cost minimization of a central planner.

[23] With a longer sequence of time steps, also the assumption regarding the volume factor of storage $\frac{\bar{s}_{volume}}{\bar{s}_{power}}$ becomes more relevant than it is in the two-time-step example. The volume factor determines the maximum duration of temporal shifting. Different volume factors mean that different parts of a stochastic demand and supply pattern can be exploited, thus also potentially affecting efficient allocation.

[24] For a thorough description of the underlying model and its characteristics, the reader is referred to Schmidt and Zinke (2023).

We set up a linear optimal power flow problem (LOPF) to approximate the inner-German transmission grid infrastructure. To keep the problem linear, DC power flow constraints approximate non-linear AC power flow restrictions. Thereby, the model neglects grid losses and reactive power (c.f. Van den Bergh et al., 2014). The implementation of DC power flows is based on the cycle-based Kirchhoff formulation, which has been proven to be an efficient formulation (c.f. Hörsch et al., 2018). Network investments are assumed to be exogenous, which is valid for the 2030 time horizon due to the long approval and construction times. European regulatory authorities usually review and approve grid expansion projects 10 to 15 years in advance (c.f. Bundesnetzagentur, 2019).

In addition to the initial model of Schmidt and Zinke (2023), in this paper, SPIDER is extended to allow for endogenous investments in storage as well as solar power capacities. The model optimizes the allocation of storage, but the ratio of maximal charging power (hereafter referred to as capacity) and stored energy (hereafter referred to as storage volume) is set exogenously. The key formulation of the cost minimization problem and the storage constraints are given in B.2.

Modeling a detailed representation of grid constraints and endogenous investments in generation and storage is a computational challenge. As in Schmidt and Zinke (2023), the model is subject to several limitations: As mentioned above, investments in transmission grid lines are exogenous assumptions. Ramping and minimum load constraints are approximated to avoid a mixed-integer optimization and the model does not include combined heat and power plants. Further, the model abstracts from uncertainty and assumes perfect foresight.

3.4.2. Assumptions and data

The regional focus of the model is Germany, with a spatial resolution at transmission grid node level, i.e., 220 kV to 380 kV voltage levels. The depiction of the transmission grid is based on grid information from multiple sources, including Matke et al. (2016) and 50Hertz et al. (2019). Grid extensions follow the German 2030 grid development plan, which was reviewed and approved by the German grid regulator (c.f. Bundesnetzagentur, 2019).

While the German transmission grid is modeled for 2019 with 380 nodes and 606 lines, Germany's neighboring countries are depicted as singular nodes without intra-country grid restrictions. The model includes interconnectors to as well as between neighboring countries, which are approximated via net transfer capacities (NTC) based on ENTSO-E (2020a).

The regional scope and the depiction of the German transmission grid are visualized in Figure 3.2.

Our analysis covers the years 2019, 2025, and 2030. Each year is represented by 12 representative days at hourly resolution. We derive the representative days by using k-medoids clustering with respect to residual load (c.f. Kotzur et al., 2018).

For our case study, we parameterize the storage technology as large-scale electric batteries. Therefore, these batteries participate in the wholesale market and may be subject to redispatch measures (in the uniform setting).[25] B.3 discloses further assumptions on technology parameters, demand development per country as well as fuel prices.

Existing power plant capacities and their distribution across Germany are derived from data provided by the German regulator Bundesnetzagentur.[26] Power plants are distributed via their postcodes to the nearest transmission grid node. The future distribution of offshore wind farms is based on 50Hertz et al. (2019).

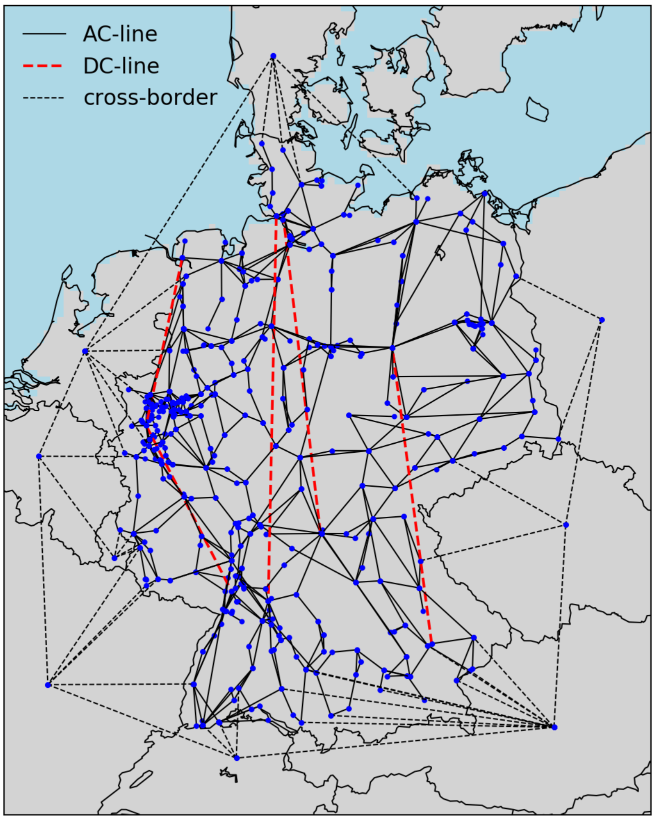


Figure 3.2.: German transmission grid and NTC connections to neighboring countries

[25]In practice, this does not apply to small storage systems such as photovoltaic systems or storage for electric vehicles designed to increase self-sufficiency.

[26]Conventional power plants are based on the power plant list (Bundesnetzagentur, 2020a) and renewables on data from the *Marktstammdatenregister* (Bundesnetzagentur, 2020b).

Capacity development at the national level is exogenous and follows the *National Trends* scenario in ENTSO-E (2020a) for all countries except Germany. For Germany, the assumed capacity development reflects the legal and political situation. Wind and solar expansion follow the current legal targets (EEG, 2023, WindSeeG, 2023). The legislation does not include a specific capacity target for batteries in 2030. Instead, aggregated battery capacity is an assumption based on *Scenario B* from the 2037/2045 grid development plan (50Hertz et al. (2022)).[27] Table 3.2 shows the assumed expansion of wind, solar, and battery capacities in Germany.

Table 3.2.: Assumed development of installed wind, solar and battery capacities in Germany

[GW]	2019	2025	2030
Wind Onshore	53.4	65.4	115.0
Wind Offshore	7.5	14.3	30.0
Solar	49.2	105.2	215.0
Batteries	0.0	5	15.0

The phase-out of German nuclear, lignite, and coal power plants is implemented according to the path defined in the Act to Reduce and End Coal-Fired Power Generation (KAG, 2020). In addition, the announced phase-out of lignite-fired power generation by 2030 is considered for the state of North Rhine-Westphalia (BMWK, 2022b). We assume that the electricity market triggers sufficient investments into backup power plants to meet demand at all times. The location of the required gas capacities is efficiently determined in the nodal setting and fixed for all model runs.

The regional allocation of onshore wind, solar, and battery storage capacity is determined endogenously. Therefore, their regional allocation follows the economic rationale of the considered model setup (see 3.4.3) while considering distributions of determining factors such as demand and resource quality. Since the total installed capacities are the same in all settings examined, the efficiency of regional allocation alone determines the differences in electricity supply costs.

Demand time-series for neighboring countries are based on hourly national demand in 2014, according to ENTSO-E (2020b). The German demand is distributed to the nodes similar to the approach in 50Hertz et al. (2019): Based on sectoral demand shares on the federal state level (c.f. Länderarbeitskreis Energiebilanzen, 2020), household demand is distributed onto nodes proportionally to population shares. The distribution of industry and commercial demand reflects the regional distribution of gross value added for the respective sectors (c.f. EUROSTAT, 2020)). The demand time series are synthesized in a bottom-

[27]In a sensitivity analysis, our results prove robust for deviating total battery capacities of 5, 10, and 20 GW, respectively B.4.

up approach using sector and application-specific standard load profiles, which reflect 2014 as a calendar and weather year.

The intermittency of renewable feed-in is modeled via weather-dependent hourly regional feed-in potential. The time series for onshore wind in Germany and solar generation are based on high-resolution reanalysis meteorological data from the COSMO-REA6 model. For onshore wind, the conversion of wind speeds to regional feed-in data is based on Henckes et al. (2017). For solar generation, solar radiation was converted to regional feed-in potential as described by Pfenninger and Staffell (2016a). Data for Germany's neighboring countries and German offshore wind power is provided by Pfenninger and Staffell (2016a) and Pfenninger and Staffell (2016b).

3.4.3. Nodal and uniform setting, allocation rules, and benchmarking

The model framework is applied to simulate investment and dispatch decisions under two different settings: nodal and uniform. Each transmission grid node constitutes a market in the nodal setting, and grid constraints are considered within the price formation. When grid constraints are binding, prices differ between nodes. In the case of new investments, these spatially differentiated price signals and hence, transmission bottlenecks are considered in siting decisions. Without any friction, the nodal setting represents the first-best configuration for efficient coordination of power generation investments, dispatch, and the grid.

Germany employs a uniform pricing approach. Uniform pricing relies on larger market areas or zones, usually defined by a country's national borders. Under uniform pricing, physical constraints concerning power flows within a market area are not considered in the market clearing. As a result, the scheduled dispatch after market clearing may violate physical grid restrictions and require curative redispatch measures carried out by grid operators. As grid restrictions are not reflected in the market, prices within a market area are the same. We model a uniform setting where transmission bottlenecks are neglected; As a result, coordination between generation investment, dispatch, and the grid is missing. This setup represents the uniform pricing market design currently in place in Germany in a simplified way.[28]

Consequently, the two setups differ regarding the amount of information available or, more specifically, in terms of the consideration of transmission constraints. In the uniform setting, a subsequent dispatch run considering the DC power flow reveals whether the scheduled dispatch with given investment deci-

[28] We neglect additional factors that might impact siting decisions, such as additional policies or locational factors that relate to the preference of individual investors. Consequently, in the uniform setup, siting decisions for wind and solar are guided by resource quality so that new facilities are primarily built in areas where meteorological conditions allow a maximum yield. Other generators, including batteries, are indifferent to siting in the uniform setup.

sions violates grid constraints, i.e., whether a redispatch is required. The difference in supply costs between the initial dispatch and the subsequent redispatch run is considered the resulting redispatch cost.[29] We quantify efficiency losses of the uniform setting by comparing total supply costs with the nodal first-best benchmark. Capital costs can be neglected since the total installed capacity is the same in each setting.

Assuming that the uniform pricing system is politically desired and will be maintained in Germany, location-specific information could be made transparent with the help of an additional policy instrument that provides a reference point for a system-beneficial allocation of storage capacities. To get insights on how to design this policy instrument, we use the numerical model to analyze different allocation rules for storage investment in an otherwise uniform setting. Thereby, we focus on allocation rules that coordinate the storage allocation isolated from other technologies. Specifically, we test for *heuristic* approaches and *explicit* allocation rules.

Heuristic approaches, on the one hand, allocate storage capacity based on a reference distribution. We select the heuristics based on an analysis of drivers for optimal storage allocation. A similar instrument to such a heuristic is used in the capacity auction for wind power generation. To achieve a broader capacity distribution over Germany, the merit order of capacity bids is altered to compensate for yield losses at sites with lower resource quality. The correction follows a non-linear heuristic based on the deviation from a reference wind generator. Another example of a heuristic allocation approach can be found in Sweden, where generation network tariffs depend on latitude. The differentiation of network tariffs incentivizes generation investment at lower resource quality sites close to demand.

On the other hand, we test *explicit* approaches which allow storage investment at a limited number of candidate nodes identified as suitable in the optimal case. The capacity is then optimized across the candidate nodes. Hence, this approach requires detailed information about load flows. A similar policy is already implemented within the capacity auctions for wind generation, where a certain percentage of capacity is reserved for bids from the so-called south zone, a predefined area below the structural grid bottleneck. A different kind of location-specific capacity mechanism is used to procure the so-called grid reserve. The German grid regulator monitors the capacity demand for redispatchable power plants in the south of Germany. If available capacity is lower than capacity demand, grid operators can procure specific mothballed power plants or power plants scheduled for phaseout for grid reserve.

[29] We model a perfectly efficient redispatch that includes all generation units in all modeled countries. Thus, the resulting total supply costs, i.e., dispatch plus redispatch costs, would be equal if capacity allocations in the nodal and uniform setting were the same. However, the allocation of new capacity is sub-optimal in the uniform case, resulting in higher total supply costs than in the nodal setup.

To rank the different instruments and their efficiency gains, we derive the optimal allocation of batteries for the uniform setup and use it for comparison. To obtain the optimal allocation, we perform a first model run calculating the distribution of wind and solar capacity without considering transmission constraints. Subsequently, in a second model run, we optimize the battery allocation considering transmission constraints and the given distribution of wind and solar. While the optimal allocation represents the upper bound for the efficiency achieved with a storage allocation mechanism, determining a lower bound is somewhat more complicated. In the uniform setting, there is no clear decision rule for storage because resource quality does not vary. Different factors such as demand typology, innovation drive or existing infrastructure could potentially influence storage allocation in the real world without spatially differentiated investment incentives. It is, however, unclear whether and how such factors influence the allocation and we, therefore, cannot include them in our model. Instead of a lower bound, we compute a demand-weighted random distribution of storage across Germany as a benchmark for the lack of coordination incentives. The random distribution is sampled 100 times and averaged to reflect an expected value.

3.5. Numerical model results

3.5.1. Battery allocation

In both settings, placing 15 GW battery capacity reduces supply cost, i.e., dispatch (and redispatch) costs.[30] In the nodal setting, supply costs decrease by 1.1% compared to a case without batteries in the system. In the uniform setting, batteries can reduce supply costs by 1.5%. The drivers for the efficiency gains differ between the two settings. Under the nodal setup, wind, solar, and batteries are allocated in an integrated optimization and under the consideration of grid constraints. This allows wind and solar generation to be shifted to locations with higher full-load hours that were subject to grid constraints without batteries.[31] Thus, renewable power generation increases and higher-cost fossil generation is avoided compared to a case without batteries. In the uniform setting, supply cost reductions are split between cost savings in the initial market clearing and in redispatch. In the market clearing, batteries shift excess renewable energy to peak residual load periods, avoiding high-cost peak generation. The supply cost reductions are realized independent of the location and are equal in both battery allocation cases under the uniform setup. In redispatch, batteries create additional efficiency by avoiding high-cost generation behind grid bottlenecks.

[30] Note that the amount of battery capacity is imposed exogenously in our setting. Thus, we do not investigate whether the savings in supply cost cover the capital cost of the batteries and hence do not infer conclusions about the economic efficiency of the chosen amount of batteries installed. We discuss some rough estimates at the end of section 3.5.3.

[31] For a more detailed understanding of the different allocations of wind and solar under nodal and uniform setting without batteries, see Appendix B.4.

To achieve efficiency gains in redispatch, the allocation of batteries is relevant. This is illustrated by comparing a case of optimal battery allocation to a case of random battery allocation. On average, when allocated randomly, batteries can only decrease supply costs by 0.8% in comparison to a case without batteries. An optimal allocation sets the upper bound for supply cost reduction at 1.5%. Figure 3.3 compares the efficiency gains of placing 15 GW of battery capacity in the grid for the three cases.

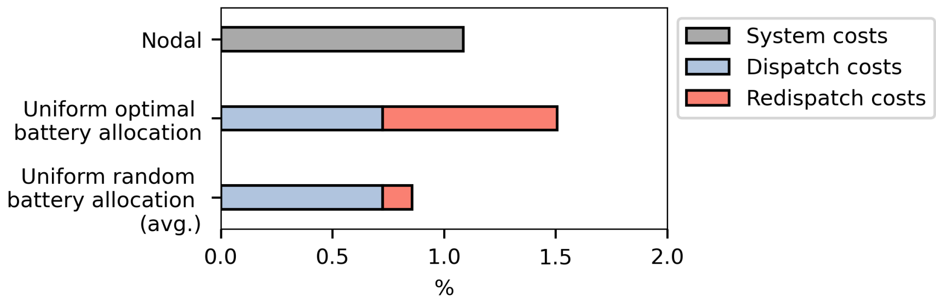
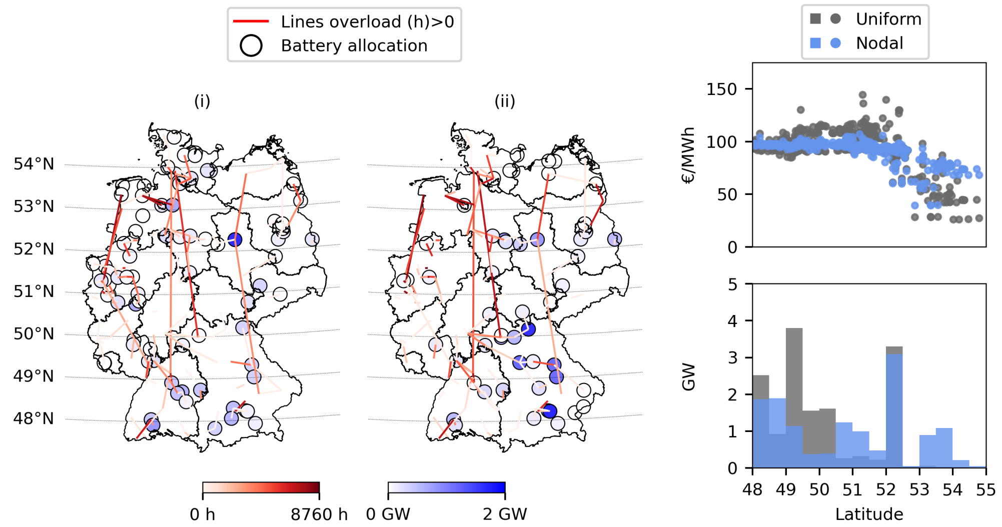


Figure 3.3.: Relative reduction of supply costs due to batteries in the nodal and uniform setting compared to the case without batteries

When comparing the two settings, we find that the total supply costs are 8.6% higher in the uniform than in the nodal setting, even for optimal battery allocation. This cost difference is attributed solely to the sub-optimal distribution of renewable generation capacity.

In both settings, nodal and uniform, the optimal battery allocation follows the allocation of wind and especially solar generation capacity. Thus, in the nodal case, batteries are allocated broadly across Germany, while in the uniform case, batteries concentrate in the south of Germany and especially below the 51st latitude. Moreover, under both settings, batteries are allocated close to congested transmission lines, i.e., lines that are frequently utilized at full capacity (depicted in red).



(a) Spatial distribution of battery capacity expansion and line utilization in the (i) nodal and (ii) uniform setting

(b) Nodal marginal supply costs and battery allocation by latitude

Figure 3.4.: Spatial distribution of 15 GW battery capacity and marginal supply costs in 2030

Grid congestion is illustrated in the upper graph of Figure 3.4b, which shows marginal supply costs at each node over latitudes. In the nodal setting, marginal supply costs equal the nodal prices. In the uniform case, they reflect the supply costs in redispatch. Prices differ between nodes if transmission constraints are binding, i.e., if a bottleneck exists. This is especially the case between the 52nd and 53rd parallel, where price differences of up to 44 EUR/MWh in the nodal case and 70 EUR/MWh in the uniform case occur. The price difference in the uniform setting is higher because the grid bottleneck is more prevalent here. This can be attributed to the sub-optimal renewable allocation in this case. In both settings, placing most of the battery capacity below the grid bottleneck is optimal. It follows the distribution of solar generation capacity. Thus, it is distributed more uniformly across the west and east in the nodal setting, while it is concentrated in the southeast (the federal state of Bavaria) in the uniform setting. Close to solar generation, batteries can flatten the daily solar generation profile, mitigate local grid congestion, and thus reduce local residual demand peaks. Doing so, batteries help to avoid the high-cost (re-)dispatch of conventional power plants in this area.

Furthermore, in both settings, a significant battery capacity of about 3 GW is allocated right above the structural north-south transmission bottleneck. Under the nodal setup, this capacity is shifted closer to western demand centers, where substantial wind and solar generation capacity is allocated. Through temporal shifting, these batteries increase the utilization of connections to the north and the usage of local wind and solar generation. In the uniform setting, the battery capacity allocated at the structural grid bottleneck is concentrated in the middle and the east of Germany, making use of solar capacity allocated there while at the same time increasing utilization of the easternmost HVDC connection.

The north of Germany, i.e., above the 53rd parallel, attracts a battery capacity of 1.4 GW under the nodal setup. The allocation of this capacity is the result of the simultaneous optimization of battery and renewable capacity allocation. Batteries allocated in the far north increase the north-south transmission utilization at locations where HVDC lines are connected. Thus, they enable wind generation to increase its full load hours by moving further northwards. This rationale does not hold under the uniform setup, where the optimization of renewables and batteries is decoupled. Additionally, the structural north-south bottleneck is too prevalent to achieve a similar transmission. As a result, there are no batteries allocated in the far north.

The numerical model results confirm for the case study of the 2030 scenario of Germany what the two-node model revealed: Storage can reduce supply costs in transmission constraint power systems with high volatility, but allocation matters to unlock the efficiency gains. For the case of batteries, we show that efficiency gains can be made, especially in conjunction with solar generation, as batteries flatten the daily generation pattern. By locating them near solar generation and grid congestion, the batteries avoid high residual demand peaks, i.e., costly generation during dispatch and redispatch.

3.5.2. Policy instruments for battery allocation

The uniform pricing setting sets no spatial coordination incentives for batteries; thus, achieving optimal allocation is unlikely. Therefore, we investigate the supply costs of potential allocations that could be realized by regulatory mechanisms that impose additional price signals under uniform pricing. We test for two types of capacity distribution mechanisms: *heuristic* allocation rules that allocate battery capacities over all nodes according to a predefined distribution and *explicit* mechanisms that allow battery allocation only at specific candidate nodes.

Heuristic allocation rules

As shown in the two-node model and the numerical example, optimal storage allocation is driven by the volatility induced by renewable feed-in, demand, and transmission grid constraints. Therefore, the first two heuristics distribute battery capacity proportionally to solar generation capacity and demand, respectively. Even though wind generation allocation is not a driver for optimal battery allocation in the uniform setting, we test whether batteries could exploit the volatility of wind generation and decrease supply costs when distributed according to wind generation capacity in a third heuristic. Heuristic four reflects the allocation of both wind and solar, thus taking a combined approach to renewable volatility. Capturing the dynamic influence of transmission grid constraints in a heuristic approach is more difficult. We investigate whether heuristic five can address grid congestion, which distributes storage capacity proportionally to phased-out power plants. Phased-out plants were historically allocated close to demand and may thus address the north-south bottleneck.

To discuss the suitability of these heuristics, we assess them against the optimal battery allocation given the distribution of wind and solar in the uniform setting discussed in the previous section. The relative increase in total supply costs resulting from the heuristics compared to the hypothetical, optimal allocation of batteries lies between close to 0 and 1.1% (see table 3.3).

Table 3.3.: Summary of relative cost increases and battery capacity factors for *heuristic* battery allocations

	opt. benchmark	random benchmark	solar	wind & solar	demand	phased-out power plants	wind
Supply cost delta [%]	-	0.66	0.27	0.38	0.61	0.90	1.07
Redispatch cost delta [%]	-	3.84	1.58	2.19	3.58	5.25	6.24
Battery capacity factor	0.15	0.15	0.16	0.15	0.16	0.13	0.08

As market efficiency gains are independent of the allocation, the differences in supply costs between the benchmark and the heuristic allocations correspond to the difference in redispatch costs, which are determined by the total redispatch volume and the power plants used in redispatch. The total redispatch volumes are similar in the benchmark case and for all heuristics. Redispatch is mainly caused by high wind power curtailment in the north of Germany. Situations of high wind feed-in and north-south transmission bottlenecks continue for long periods, and therefore the ability of batteries to reduce curtailment volumes is limited.

Hence, redispatch costs differ mainly due to the different types of power plants used for redispatch. Redispatch costs are lowest if batteries frequently shift low-cost electricity in time to avoid costly fossil-fired generation. In our scenario results, this is especially the case in the south and east of Germany, where high solar generation leads to high volatility in local marginal generation costs. Batteries can utilize this volatility by charging when solar power generation is high. They then use this energy to displace lignite power plants and gas turbines, which replace south German nuclear capacities, in redispatch. Conclusively, a heuristic, which distributes capacity according to solar generation capacity, is the most efficient, followed by a heuristic, which considers both wind and solar.

A demand-based heuristic is the third most efficient. Here, more battery capacity is located in the west of Germany, while solar power generation is concentrated in the east and south. Since marginal generation costs are higher in the west, battery charging is more expensive and replacement of fossil power plants in redispatch is less frequent. A similar effect occurs if the batteries are allocated accordingly to phased-out power plants since they are located near demand centers, too.

In contrast, if batteries are deployed close to wind generation, their contribution in redispatch is more limited. Even though batteries prevent more wind curtailment than in the other heuristics, they can only participate in redispatch above the structural grid bottleneck. There, marginal generation costs in redispatch are low, and so is volatility, making this allocation the least efficient. In fact, redispatch costs are even higher than in a case without batteries. This is because batteries increase the share of wind generation in the initial market outcome, which then has to be curtailed in redispatch due to grid constraints. However, market gains outweigh redispatch losses, resulting in lower total supply costs than without batteries. Moreover, the allocations according to wind or phased-out power plants are even less efficient than a random allocation of batteries. The random allocation leads to a broad distribution of batteries across Germany, meaning that at least some batteries are close to solar generation and demand.

The heuristics' supply cost differences are also reflected in battery utilization. In the wind-based heuristic, the battery capacity factor is less than half of the capacity factor of the solar-based heuristic, where a capacity factor of 0.16 is achieved. This corresponds to 345 battery cycles per year or an average of almost one charge cycle per day, i.e., a steady reduction of residual loads. The reason is the assumed capacity-to-volume ratio of 4h, which makes batteries better suited to buffer daily solar generation than wind generation profiles with their coarser volatility.

Explicit allocation rules

Secondly, we investigate *explicit* approaches that allow for an optimal battery allocation at predefined candidate nodes. We test the following variations: Starting from the 40 nodes with the highest capacity in the hypothetical benchmark case, we iteratively reduce the number of candidate nodes to 1. The resulting supply costs of these explicit allocation rules are between 0.00 and 0.85% higher than the optimal benchmark. The higher the number of candidate nodes, the lower the supply costs. At 40 or more candidate nodes, supply costs are almost the same as in the optimal benchmark case. Even reducing the allocation to just two nodes leads to a cost increase of 0.37%, which is between the supply costs of the solar heuristic (0.27%) and the heuristic allocation according to solar and wind capacity (0.38%). If the number of candidate nodes is reduced to one, the supply cost delta more than doubles compared to the case with two nodes. With one endogenously chosen candidate node, all capacity is placed at a node in southern Germany. In this case, the battery cannot have its full effect because the installed battery capacity is higher than the sum of renewable and transmission capacity at that node. Consequently, the resulting capacity factor is much lower, and the total supply cost is higher than in the case of random distribution. Nevertheless, it is noteworthy that the single-node allocation is still more efficient than an allocation by wind capacity or phased-out power plants.

The *explicit* approaches that distribute battery capacity to five or more nodes outperform all *heuristic* approaches.[32]

Table 3.4 compares resulting capacity factors and supply costs relative to the hypothetical benchmark for each of the *explicit* options.

Table 3.4.: Summary of relative cost increases and battery capacity factors for *explicit* battery allocations

	opt. benchmark	random benchmark	40	20	10	5	3	2	1
Supply cost delta [%]	-	0.66	0.00	0.02	0.10	0.16	0.29	0.37	0.85
Redispatch cost delta [%]	-	3.84	0.00	0.12	0.57	0.94	1.70	2.14	4.97
Battery capacity factor	0.15	0.15	0.15	0.15	0.15	0.15	0.14	0.13	0.10

3.5.3. Summary

We quantify the efficiency gains of placing 15 GW of batteries in the German transmission grid by comparing supply costs for two settings, nodal and uniform, to equivalent cases without batteries. The results show that batteries reduce supply costs in both cases. In the uniform setting, the efficiency gains are composed of supply costs reduction in the electricity market, which are independent of battery allocation, and in redispatch, which depend on battery location. To compare different allocation rules under the uniform setup, a hypothetical, optimal allocation for a given distribution of renewable capacity is used as an upper benchmark. Furthermore, a random distribution of batteries is used as a benchmark for missing local investment incentives. The analysis shows for our scenario that *explicit* approaches with endogenous battery investment allowed at a limited number of pre-determined nodes can approximate the optimal distribution well, and already from five nodes, it outperforms all *heuristic* approaches with a fixed distribution. Among the fixed *heuristic* approaches, an allocation that mimics the distribution of solar generation capacity performs best. Solar generation is a crucial driver for optimal allocation since batteries can exploit the daily solar generation pattern to reduce gas-fired redispatch. Other *heuristic* approaches prove to be less suitable. An allocation proportional to phased-out power plants or wind generation capacity is less efficient than a random distribution. The wind-based heuristic leads to even higher redispatch costs than the case without any batteries.

The performance of the different allocation rules is compared to the theoretical first-best nodal benchmark. Figure 3.5 shows the relative increase in supply costs

[32] When comparing the results, however, it has to be noted that the installed capacity per node is optimized endogenously in the *explicit* cases. In contrast, capacity distribution is determined exogenously in the *heuristic* cases.

compared to this benchmark for the allocation variations ordered by efficiency. It highlights the efficiency gains that can be made by introducing and coordinating batteries. The most efficient allocation rule is the *explicit* allocation to 40 nodes, leading to 8.6% higher supply costs than the nodal benchmark. Least efficient is the *heuristic* allocation by wind capacity (+9.7%). Hence, the range of total supply costs between the best and the worst performing allocation amounts to 1.1% of the nodal supply costs.

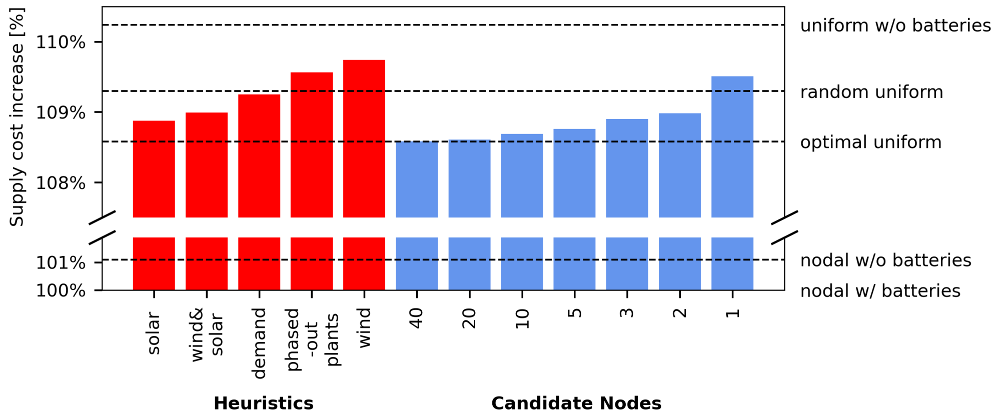


Figure 3.5.: Supply cost differences between allocation rules and the first-best nodal benchmark in 2030

The relevance of appropriate coordination can be further illustrated by relating the supply cost savings achieved by batteries to the capital cost incurred. The supply cost saving of each battery allocation is the difference in total supply costs compared to the uniform setting without any batteries. To calculate the capital costs of batteries, we assume investment costs of 600 EUR/kW, a lifetime of 16 years, and an interest rate of 8% (c.f. EWI, 2021). The ratio of savings to annualized capital cost depends strongly on battery allocation. Batteries can yield 1.08 EUR in savings per euro spent if allocated optimally in the uniform setting. A random allocation reduces the savings by 47 ct per euro spent. With an explicit allocation at five or more candidate nodes, the battery-induced savings come close to the savings under an optimal allocation (0.96 - 1.08 EUR saved per euro spent, depending on the number of nodes). In the best heuristic allocation (solar), the ratio of savings to expenditures is 19 ct lower than with an optimal allocation. In the worst case (wind) examined, the savings drop to just 33 ct per euro spent. Under the assumed capital costs, 15 GW of battery capacity is in the money if allocated optimally. With the help of the allocation rules, savings are higher than the annualized capital costs for explicit approaches at 10 or more nodes. With all other rules, savings are below expenditures. However, batteries can generate additional value not considered in the present analysis through system services, e.g., balancing power provision or avoiding grid expansion in the long run and thus savings can be higher. Further, these results highly depend on the (assumed) capital costs.

3.6. Discussion

3.6.1. Generalization

Although the numerical model results are specific to the chosen setting, they can be generalized for several aspects. First, the finding of the two-node model that optimal storage allocation is driven mainly by volatility is valid and applicable for all time horizons and countries. In our case study, solar power is the dominating renewable capacity driving volatility and, thus, battery allocation. Divergent renewable energy shares may lead to different optimal battery allocations, e.g., previous analyses assuming higher shares of wind power conclude that higher shares of battery capacity should be allocated near wind energy.

Secondly, the numerical analysis at hand focuses on batteries, i.e., a storage technology with a relatively small storage volume compared to installed charging capacity, which complements the daily fluctuations of solar power generation. Therefore, we perform a sensitivity analysis regarding the storage type and show that the optimal allocation depends on the specific technology. In particular, storage with a larger power-volume ratio is favorable at locations with high shares of wind power (see B.4).

Thirdly, we show that storage can generate value in a uniform setting in both the initial market clearing and in redispatch. The latter can only be exploited if the market design allows for the participation of storage in redispatch. If this is not the case, a substantial part of the potential benefits of storage technologies - in our numerical analysis, about 50% - cannot materialize.

Fourthly, the findings for the transmission level can be used to get insights for the distribution grid. Distribution grid operators could use the batteries' flexibility to lower curtailment volumes and required grid expansion if the batteries' allocation matches flexibility demands and technical and regulatory properties allow. However, on the distribution grid level, storage is usually used to increase the self-consumption of solar generation, e.g., home-storage systems. Therefore, these systems are neither dispatched by market signals nor used in redispatch.

3.6.2. Limitations

Several limitations should be noted when considering the results and analysis presented. First, the numeric modeling results are based on several strong assumptions, e.g., perfect foresight, no transaction costs, perfect markets, and the exogenous distribution of inelastic exogenous demand. The mathematical duality between a central planer and a profit-maximization of symmetric firms holds only if these assumptions are all met. In practice, this is rather not to be expected. In particular, the first-best nodal benchmark is a rather theoretical benchmark as in reality frictional losses can distort optimality, e.g., reduced liquidity, lack of transparency, market power issues, and increased transaction costs (c.f. Antonopoulos et al., 2020).

Furthermore, modeling the market setup of uniform pricing, as it is currently in place in Germany, comes along with some simplifying assumptions. We abstract from additional policy instruments for the expansion of wind and solar power. In particular, the reference yield model should affect wind power expansion compared to our modeled distribution. The cost-based redispatch mechanisms applied in practice are less efficient than those modeled in our numerical analyses. In our model, power plants outside Germany and all technologies including storage can be used for redispatch without any restrictions, which is not necessarily the case in practice. In particular, redispatch of hydro-pumped storage in the Alps can be fully exploited in the model which might cannibalize the value of batteries in Southern Germany. Additionally, further efficiency gains of storage deployment are possible, which were not part of the numerical analyses, e.g., avoided grid expansion or increased security of supply.

In addition to these model properties, the results have to be interpreted in light of the specific scenario chosen for the analysis. To demonstrate the robustness of our results, we perform a sensitivity analysis regarding the total installed battery capacity in B.4. Additionally, the scenario-specific renewable energy allocation largely determines the magnitude of the identified efficiency gap between the first best nodal and the uniform setting. Besides resource quality, further aspects, such as land availability and residents' opposition, play into renewable investors' decision process. Hence, the resulting renewable energy distribution for 2030 is likely to be less concentrated in reality, which also impacts the optimal storage allocation and system efficiency.

3.7. Conclusion and policy implications

This paper investigates the allocation of battery storage in spatially unbalanced power systems in the transition to climate neutrality, i.e., with rapidly increasing shares of wind and solar power generation. Specifically, we seek to answer three questions: Firstly, where in the transmission grid should batteries be allocated, secondly, how important is storage allocation for the system's efficiency, and thirdly how could policy instruments be designed to approximate an optimal allocation?

To investigate the drivers of optimal storage allocation, we develop a theoretical two-node, two-time-step model that simplifies the dynamics of spatially unbalanced power systems. We show that an allocation close to volatile renewables or close to demand can be optimal. We find that optimal allocation depends on the volatility and location of demand and generation relative to grid bottlenecks.

These results are verified and expanded in a numerical case study using the example of a spatially unbalanced power system in Germany. The largest efficiency difference occurs between the nodal and uniform setting. Supply costs are at least 8.6% higher in the uniform case than under the nodal setup. This is primarily because in the nodal setting wind and solar generators are allocated optimally and shows that the leverage of a simultaneous allocation and coordination of wind and solar expansion exceeds the leverage of allocating batteries. However, the results in the nodal setting rely on several assumptions that tend not to hold in practice, and switching from uniform to nodal pricing may not be politically feasible.

In practice, there is no allocation coordination under uniform pricing; thus, the optimal battery allocation that minimizes the efficiency gap to the nodal benchmark is not achieved. Our analysis reveals that with a random battery allocation, the efficiency gap relative to the first-best nodal case lies 0.7 percentage points higher than with an optimal allocation. The least efficient allocation that was tested even increases the efficiency gap by 1.1 percentage points. [33] It is, therefore, worth discussing how coordination can be achieved and local incentives can be set even in a system with uniform pricing. In Germany, this question is currently being asked as part of the government initiative *Climate Neutral Electricity System Platform* - a dialogue platform that aims to prepare for an upcoming electricity market reform.

Our model results show that several allocation rules are conceivable to approximate an optimal allocation of batteries in the uniform setting. For example, a heuristic approach that allocates batteries close to solar capacity or explicit approaches that rely on grid analyses to determine a limited number of locations for a capacity auction can reduce supply costs in the uniform setting. In addition, implementing such an allocation rule would ensure that inefficient distributions, like an allocation close to installed wind power capacity, are not realized.

Policymakers designing regulatory instruments based on these findings should weigh the reduction in supply costs resulting from improved allocation against the implementation costs. In the case of the heuristic approaches, the difficulty lies in identifying a mechanism that yields the desired distribution of batteries. Costs could also be incurred if the chosen mechanism leads to a high number of transactions, e.g., if batteries were subsidized via feed-in tariffs. For the explicit approaches that allow the installation of batteries at limited locations in the grid, the allocation could be managed via a limited number of auctions. Here, transaction costs arise from the information asymmetries of the regulator in determining optimal locations and capacities. Further, our results benefit from

[33] However, the benefits of optimal battery allocation in the uniform setup are split roughly half-half between market-based dispatch and subsequent redispatch, underlining the importance of including flexibility assets in redispatch.

the assumption of perfect foresight. In practice, it may be more complicated to determine optimal candidate notes ex-ante, in particular, if only a few nodes are chosen and in a dynamic setting the optimality of nodes may change over time. Choosing a heuristic approach directly connected to the distribution of solar power may be more robust to the deviations from a modeled scenario.

Policies that coordinate wind, solar, and storage capacity in an integrated way could come even closer to the first-best benchmark. The analysis of such an integrated approach could be part of further research. It would likely lead to additional efficiency gains but would be a more complex endeavor with higher implementation costs.

We conclude that it is possible to design a policy instrument suitable to approximate an optimal storage allocation under uniform pricing. Any potential policy should either be simple and low-cost to implement or be part of a comprehensive mechanism that coordinates all types of generation and flexibility with the grid.

4. Two Prices Fix All? On the Robustness of a German Bidding Zone Split

4.1. Introduction

The liberalization of electricity markets resulted in the unbundling of former vertically integrated utilities into separate companies for power generation and grid operation. Nevertheless, to ensure grid stability, there is a need for coordination between the dispatch decisions of power generators and given grid constraints. Different approaches exist, such as the nodal pricing approach used in markets like PJM in the United States, where Locational Marginal Prices (LMPs) are assigned to each grid node. Differences in LMPs are explicit scarcity signals for transmission. In contrast, markets in Europe use a zonal pricing approach, in which intra-zonal constraints, i.e., grid constraints within zones, are neglected in the market clearing. With a few exceptions, e.g., the Nordics and Italy, these zones largely correspond to national borders. Violations of transmission constraints within zones are administratively handled via remedial actions by a Transmission System Operator (TSO), e.g., by adjusting the dispatch schedule of power plants (a so-called redispatch) or the trade balance (so-called countertrading) post-market clearing.

With increasing capacities of volatile renewable power generation, the German nuclear phase-out, decreasing fossil generation capacities, closer integration of European power markets, and slow grid expansion, the need for remedial actions rose significantly: in Germany, nominal costs for redispatch, countertrading, and compensation payments for renewable curtailment, increased from 200 million Euros in 2014 to 3.7 billion euros in 2022 (Bundesnetzagentur, 2023). It is important to note that these costs do not necessarily imply static inefficiency. In theory, assuming full participation in redispatch and no additional readjustment costs, zonal pricing and subsequent redispatch can lead to optimal power plant dispatch and maximize social surplus (c.f. Bjørndal et al., 2013).[34] However, the zonal pricing leads to distributional effects if structural bottlenecks are not considered in the zonal market clearing. For instance, if high demand in one region requires costly power generation adjustments through redispatch, the associated costs are socialized by being passed on to consumers via the grid tariffs. Essentially, regions with favorable energy conditions may cross-subsidize

[34] However, these theoretical assumptions do not hold in practice, resulting in inefficiencies. Conversely, in reality, the nodal pricing approach also has disadvantages, such as increased complexity, price volatility, and uncertainty. Therefore, it remains a matter of active discussion on which option is the more favorable one.

those with higher power generation costs. As redispatch costs continue to rise, so do these distributional effects. Besides issues of fairness, this system obscures the true local electricity supply costs and lacks efficient allocation signals for investors of generation and demand capacities and could thus lead to dynamic inefficiency (c.f. Jeddi and Sitzmann, 2021). Consequently, there is a growing call to revise the current bidding zone configuration to better reflect structural grid bottlenecks within Europe and, thereby, reduce redispatch costs (e.g., Höffler, 2009).

In line with Article 34 of the EU capacity allocation and congestion management (CACM) guideline (European Union, 2015), the efficiency of the bidding zone (BZ) configuration has to be assessed every three years by the Agency for the Cooperation of Energy Regulators (ACER), an umbrella organization of European regulators. As part of this process, in 2016, ACER requested the European Network of Transmission System Operators (ENTSO-E) to draft a first bidding zone review, which was published in 2018 (ENTSO-E, 2018a) but did not include quantitative analyses. ACER then required the TSOs to submit proposals on a methodology, assumptions, and the alternative BZ configurations to be considered (ACER, 2020). As the TSOs could not agree on alternative configurations, ACER decided on the bidding zone configurations to be reviewed based on a Locational Marginal Price analysis provided by the TSOs (ACER, 2022, ENTSO-E, 2022).

The bidding zone review process highlights the complexity of finding an appropriate bidding zone configuration. First of all, there is no optimal number of bidding zones, as any reconfiguration requires a trade-off between, e.g., complexity and correctness of prices. Increasing the number of zones substantially and, thus, moving towards nodal pricing increases the informational transparency in the market. Therefore, prices reflect actual grid constraints more properly and set incentives for system-friendly investments. Yet, larger bidding zones might be beneficial in practice. In particular, in forward markets, nodal pricing lacks efficiency if the market participants have inadequate expectations about the prices, transaction costs are high, or the limited number of participants leads to low liquidity (e.g., Adamson et al., 2010, Bartholomew et al., 2003, Deng et al., 2010, Kristiansen, 2004, Siddiqui et al., 2005).

ACER's proposal does not aim to drastically increase the number of zones. For Germany, which received most configurations for review, a division into two to a maximum of four zones is being considered (c.f. ACER, 2022).[35]

Even with a given number of bidding zones, it is difficult to determine a suitable bidding zone split. Grid bottlenecks and, hence, the most effective bidding zone configuration might change frequently as volatile renewable generation and demand alter the grid load. In the long run, the commissioning and decom-

[35] If TSOs cannot allocate generation and load units to a single bidding zone for any of the initially proposed BZ configurations, they may consider fallback options with up to five zones instead.

missioning of new generators, consumers, and transmission capacities as well as changing fuel prices, might affect the optimal bidding zone configuration. However, bidding zones should not be adjusted frequently because the reconfiguration increases uncertainty and involves high transaction costs. For example, it requires the transformation of existing forward and long-term contracts. Thus, if a new bidding zone configuration must be stable over time, it should be beneficial under different weather conditions, load situations, and future scenarios – in other words, it must be robust.

This paper addresses the robustness of a bidding zone reconfiguration under stochastic weather patterns and structural changes in the power system over time, e.g., demand and capacity development. It uses a two-zone split of the current German-Luxembourg bidding zone as a case study. To determine suitable BZ split configurations of the German-Luxembourg bidding zone, hourly LMPs are calculated within a linear market and grid model for 24 weather years and the scenario years 2021, 2025, 2030, and 2035. The hourly LMPs are then clustered hierarchically based on Ward's criterion. For the resulting bidding zone splits, the effect on redispatch costs is analyzed. Furthermore, this paper sheds light on how uncertain factors impact the efficiency of a bidding zone reconfiguration by investigating sensitivities regarding grid and renewable expansion as well as fuel prices.

The results show that a north-south division of the German-Luxembourg market area is beneficial in terms of reduced redispatch costs largely independent of weather conditions. However, the cost reduction depends highly on the period for which the bidding zone split is held stable and the future scenario. The sensitivities show that uncertain factors greatly affect the bidding zone split's effectiveness in reducing redispatch costs. If the system properties change strongly, e.g., if a substantial part of grid congestion is driven by solar power generation, the redispatch costs reduction from splitting the bidding zone decreases significantly.

The paper is organized as follows. Section 4.2 presents relevant literature on determining suitable bidding zone reconfigurations. Section 4.3 introduces the numerical model, relevant input data, and scenario assumptions. Section 4.4 presents and discusses the results, by comparing redispatch costs for different bidding zone configurations, weather conditions, and scenarios. Section 4.5 summarizes the main findings and draws conclusions.

4.2. Related Literature

This research builds on extensive literature applying mathematical models to find suitable bidding zone configurations. The bulk of existing research uses LMPs as an indicator for determining bidding zones, following Stoft (1997), who states that the definition of bidding zones should be based on price differences between nodes, as these contain all relevant information on network-related costs. Exceptions are, e.g., Kang et al. (2013), Kumar et al. (2004), Kłos et al. (2014), who cluster power transfer distribution factors (PTDFs) due to a lack of information available to calculate LMPs or to reduce complexity. ENTSOE-E applies both PTDF and LMP clustering in its first bidding zone review but does not use the results of clustering PTDFs due to the high sensitivity regarding some input assumptions (c.f. ENTSO-E, 2018a, p. 30). Most research on LMP clustering focuses on a specific load situation, e.g., Imran and Bialek (2008), who test geographical, fuzzy-c-means, and price differential clustering. Bovo et al. (2019) provide a comprehensive review of this kind of work.

A smaller sub-strand of literature considers multiple time steps in clustering LMPs to analyze the impact of stochastic factors such as weather and/or exogenous factors such as capacity and demand development. Burstedde (2012) uses a simplified 72-node model of the European transmission grid to calculate LMPs for the scenario years 2015 and 2020 and applies a hierarchical algorithm based on Ward's criterion to evaluate suitable amounts and shapes of bidding zones. Her results suggest that redefining bidding zones can increase the static efficiency of the system, even without increasing the number of bidding zones. Furthermore, the results show that the clustered bidding zones vary in time. This result is confirmed by Breuer et al. (2013), who apply a more detailed model of the European electricity grid to calculate LMPs for 2016 and 2018. Yet, the authors do not evaluate redispatch costs or volumes. Wawrzyniak et al. (2013) investigate the impact of different wind conditions on optimal bidding zone splits of the Polish market. The authors propose a two-step methodology: first, they apply hierarchical clustering based on Ward's criterion for every load situation (i.e., time step) individually and then use consensus clustering to determine a suitable bidding zone split for all modeled load situations. Although the authors include comparatively little installed wind capacity (1.4 GW) in their analysis, they find that wind conditions affect the clustering results. Breuer and Moser (2014) examine the appropriate amount of bidding zones, taking into account the level of competition and network security. Furthermore, they analyze the cost savings for various reconfiguration frequencies and find that a bidding zone reconfiguration after three years almost halves the benefits compared to a yearly reconfiguration. Felling and Weber (2018) determine bidding zone configurations that are robust to six scenarios for the future development of the electricity system in Central Western Europe. In a follow-up paper, Felling et al. (2019) expand the analysis by calculating redispatch costs and welfare effects. The authors find that an optimized bidding zone configuration can reduce total system costs by 1.8%. This cost reduction is confirmed by the authors in a recent publication for the year 2020 (Felling et al., 2023). In addition, the authors emphasize the distributional effects resulting from the reconfiguration of bidding zones. In another recent publication, Brouhard et al. (2023) cluster bidding zone configurations based on 600 grid load situations for the scenario year 2025. The authors find that the resulting BZ configuration can reduce the need for redispatch significantly in

2025 but leads to increased redispatch volumes in 2030 and 2040 compared to the status quo configuration. They conclude that multiple time horizons have to be considered when creating a robust market design.

Research gap and contribution

Reviewing current literature reveals a lack of systematic analysis of the fundamental drivers that determine the impact of a bidding zone split. This paper seeks to close the gap between existing publications focusing on stochastic factors such as wind power generation (e.g., Wawrzyniak et al., 2013) and publications investigating suitable BZ configurations for specific scenarios (e.g., Burstedde, 2012, Felling and Weber, 2018). For this purpose, the present study analyzes splitting the German-Luxembourg market area into two separate bidding zones. This bidding zone split is done by clustering LMPs obtained from running simulations over 24 weather years for the scenario years 2021, 2025, 2030, and 2035. The resulting bidding zone splits are then analyzed with regard to redispatch costs. Subsequent sensitivity analyses investigate the robustness of the determined bidding zone configuration to uncertain scenario-related factors.

4.3. Methodology, input data and scenario design

This paper applies a three-step methodology to find and evaluate bidding zone splits. First, SPIDER (Spatial Investment of Distributed Energy Resources, c.f. Czock et al., 2023, Schmidt and Zinke, 2023), a detailed electricity system model of the Central European transmission grid, is applied to derive Locational Marginal Prices for one reference scenario under 24 different weather years. Secondly, these LMPs are clustered to determine bidding zones. In the third step, SPIDER is used to model the market results and redispatch costs for the obtained bidding zone configuration for the reference scenario and sensitivities. The following presents the applied model, the underlying assumptions, the clustering algorithm, and the reference scenario. Throughout this work, the notation presented in table B.1 is used. To distinguish (exogenous) parameters and optimization variables, the latter are written in capital letters.

4.3.1. Spot market and grid modeling

SPIDER is a model of the European power sector that considers a detailed depiction of the central European transmission grid. In the present work, the commissioning and decommissioning of transmission, generation, and demand capacities are exogenous. Hence, SPIDER is applied as a pure dispatch model, minimizing the variable costs of electricity generation. Variable costs are the product of electricity generation GEN in each market zone z, timestep t and per technology i and the technology-specific variable operating costs γ:

$$min!\ VC = \sum_{z \in Z, i \in I, t \in T} GEN(t, z, i) \cdot \gamma(t, i). \tag{4.1}$$

Nodal modeling

For calculating LMPs and when modeling redispatch, each grid node constitutes a market zone z, and all transmission grid constraints are considered within a linear optimal power flow problem (LOPF). To keep the problem linear, DC power flow constraints are used to approximate non-linear AC power flow restrictions. Thereby, the model neglects grid losses and reactive power (c.f. Van den Bergh et al., 2014). The implementation of DC power flows is based on the cycle-based Kirchhoff formulation, which has been proven to be an efficient formulation (c.f. Hörsch et al., 2018). For a thorough description of the LOPF implementation, the underlying model, and its characteristics, the reader is referred to Schmidt and Zinke (2023) and Czock et al. (2023).

Zonal modeling

In addition to the initial model of Schmidt and Zinke (2023), the model formulation is extended to consider different bidding zone configurations in the European spot market by applying the so-called flow-based market coupling (FBMC). Flow-based market coupling was introduced in Central Western Europe (CWE) in 2015 and has since been extended to neighboring markets. In contrast to the Net Transfer Capacity (NTC) approach used before, TSOs determine flow-based parameters, and the actual use of cross-zonal capacities is decided within the market clearing algorithm. A short, general introduction to FBMC modeling is given in the following. For a more detailed description, the reader is referred to Van den Bergh et al. (e.g., 2014), Müller et al. (2018), or Felten et al. (2019).

In every timestep t, the system-wide electricity load and supply must be in equilibrium (4.2). A market's net position ($SALDO$) is the delta of supply (GEN) and consumption ($CONS$) (4.3) and, consequently, equals the sum of flows ($FLOW$) from one market to its neighbors (4.4). The coefficient $\kappa_{z,l}$ depicts the flow direction (1 if line l starts in zone z, -1 if line l ends in zone z, 0 else).

$$\sum_{z \in Z} SALDO(t,z) = 0 \qquad \forall t \in T \tag{4.2}$$

$$SALDO(t,z) = \sum_{i \in I} GEN(t,z,i) - \sum_{j \in J} CONS(t,z,j) \qquad \forall t \in T, \forall z \in Z \tag{4.3}$$

$$SALDO(t,z) = \sum_{l \in L} \kappa(z,l) \cdot FLOW(t,l) \qquad \forall t \in T, \forall z \in Z \tag{4.4}$$

The FBMC approach accounts for the fact that AC-flows between two zones are influenced by the trades between other zones via the zonal Power Transfer Distribution Factors ($zPTDF$) (4.5). The zonal PTDF is a linear sensitivity between the net position of each zone and the power flows on each AC line. The flows on lines identified as critical lines L are restricted by the tradeable line capacity, the Remaining Available Margin (ram^-/ram^+), in positive and negative flow direction (4.6):

$$FLOW(t,l) = \sum_{z \in Z} zPTDF(t,z,l) \cdot SALDO(t,z) \qquad \forall t \in T, \forall l \in L \tag{4.5}$$

$$ram^-(t,l) \leq FLOW(t,l) \leq ram^+(t,l) \qquad \forall t \in T, \forall l \in L \tag{4.6}$$

The parameters ram and $zPTDF$ are called FBMC parameters and have to be defined prior to the market clearing. The zonal PTDF is defined as the sum of the nodal PTDF, which can be calculated from the line reactances (see, e.g., Van den Bergh et al., 2014), weighted with Generation Shift Keys (gsk).

$$zPTDF(t,l,z) = \sum_{n \in N} nPTDF(n,l) \cdot gsk(t,n,z) \qquad \forall t \in T, \forall l \in L, \forall z \in Z \tag{4.7}$$

The GSKs are an assumption on how the changes in the net position of a market zone are distributed among the nodes. So far, there is no standardized approach how to calculate GSKs for future scenarios and different calculation approaches exist (c.f. Felten et al., 2019, Wyrwoll et al., 2018). The simplest method involves using static GSKs per year, based on parameters such as installed capacities or marginal generation costs. However, this approach neglects the temporal changes in the spatial distribution of demand and supply. More sophisticated approaches calculate GSK on an hourly basis, requiring a preceding model run with all trade set to zero (the *base case*) to determine the distribution of generation and demand. These methods mainly differ in the technologies considered. A common approach is to base GSK calculations on the generation of dispatchable capacities, i.e., thermal power plants, batteries, etc. However, this approach faces limitation in scenarios with 100% renewable power generation during many hours. To avoid this problem, this study, calculates GSKs for each hour as the proportion of a node's total generation of the total zone's generation.

The ram parameter is the remaining line capacity available for commercial exchange without endangering grid security. It is defined as follows:

$$ram(t,l) = f^{max}(t,l) - f^{ref}(t,l) - frm(l) - fav(l) \qquad \forall t \in T, \forall l \in L \quad (4.8)$$

f^{max} is the maximal power flow per line, determined by the line's physical thermal limit. f^{ref} is the reference flow representing loop and transit flows. In addition, safety margins (the Flow Reliability Margin (frm) and Final Adjustment Value (fav)) are subtracted from the line capacity. In contrast to AC lines, DC lines allow controlling power flows. In this paper, DC lines are modeled via the so-called "Advanced Hybrid Market Coupling" such that the impact of DC flows on AC flows is considered. For an in-depth introduction to the coupling of DC and AC modeling, see, e.g., Müller et al. (2018).

In this study, the frm is set to 10% of the line capacity and the fav is set to zero (c.f. Müller et al., 2018). Reference flows are determined in the *base case*. Furthermore, only cross-border lines are considered critical lines in this study. Thus, all other intra-zonal transmission restrictions are not taken into account. However, in reality, TSOs designate critical network elements based on their experience (cf. 50Hertz et al. (2018) and intra-zonal lines can also be classified as critical. Since TSOs' experience is not available when modelling future scenarios, critical intra-zonal lines must be determined through calculation. This is typically done by analyzing the impact of changes in zonal positions on intra-zonal flows (see Schönheit et al. (2021)). However, the present study identifies structural bottlenecks and examines the impact of splitting the bidding zone based on these bottlenecks. If intra-zonal lines are considered critical, these bottlenecks are factored into the uniform market clearing, which complicates the comparison of different bidding zone configurations as it distorts the resulting redispatch costs.

Redispatch modeling

The scheduled dispatch after zonal market clearing might violate intra-zonal physical grid restrictions and require remedial redispatch measures. The costs for increasing and decreasing the dispatch of power plants are calculated in a subsequent simplified redispatch run. Within this run, a LOPF is calculated while holding the zonal net trade positions fixed. Therefore, only adjustments in the generation distribution within each zone are possible. Additionally, it is assumed that wind, solar, battery, and electrolysis dispatch determined in the zonal market-clearing can only be curtailed in redispatch, not increased. Differences in generation costs between the zonal and redispatch runs are interpreted as redispatch costs.

The resulting redispatch costs tend to be higher than in reality because of model simplifications: Countertrading, which is not considered in the modeling, can be advantageous over intra-zonal redispatch. Furthermore, the flow-based, zonal results can be more efficient in reality, as TSOs draw on many years of experience when setting flow-based parameters such as the ram and frm or choosing critical lines.

Modeling a detailed representation of grid constraints is computationally challenging.[36] The model is, therefore, subject to several limitations: As mentioned above, investments in transmission, generation, and demand capacities are exogenous assumptions. Ramping and minimum load constraints are approximated to avoid a mixed-integer optimization and the model does not include combined heat and power plants.

4.3.2. Clustering algorithm

The SPIDER model is applied to calculate LMPs for all nodes, time steps, and scenarios. Subsequently, nodes are grouped into zones using hierarchical agglomerative clustering based on the LMP time series. The clustering process is initiated by considering each node as an individual zone. Then, following a bottom-up approach, pairs of zones are systematically merged by adhering to Ward's minimum variance criterion (c.f. Ward, 1963). This criterion aims to minimize the sum of squared differences among all LMP time series within the zones during the merging process. This iterative procedure continues until all nodes are grouped into zones, resulting in a hierarchical structure representing the relationships between the LMP time series across the power system. The penultimate iteration holds particular significance in this study, as it represents the definition of two German bidding zones.

In the context of this paper, agglomerative clustering has some advantages. Foremost, existing connections between nodes can easily be considered within the clustering procedure as a prerequisite for merging two zones. This ensures that every node is electrically connected to any of the other nodes within a bidding zone. Second, the cluster method is deterministic, i.e., unlike the commonly used heuristic k-means algorithm, the result does not depend on the starting point. Thirdly, the results of agglomerative clustering based on Ward's criterion tend to form clusters of similar size, which is beneficial for defining sufficiently large

[36]The model run time depends on the specific weather and scenario year. On a Windows Azure cloud machine with eight AMD EPYC 7763 cores @2.44GHz each and 128 GB RAM, nodal model runs take about 2:05 hours on average. A full zonal model run, including base case and redispatch, takes about 2.1 hours. For this work, 96 nodal and 118 zonal model runs were evaluated, which add up to a runtime of more than 18 days.

markets. Hierarchical agglomerative clustering of LMPs is applied and described in more detail, e.g., by Burstedde (2012) and Wawrzyniak et al. (2013).

4.3.3. Assumptions and data

Scope and Transmission Grid

The regional focus of the model is central Europe with a spatial resolution at transmission grid node level, i.e., 220 kV to 380 kV voltage levels. The transmission grid model includes 13 European countries that are part of the "Core Flow-Based Market Coupling project" and is based on the published grid information of the Joint Allocation Office (JAO, 2022). Grid extensions follow the German grid development plan (c.f. 50Hertz et al., 2023), and ENTSO-E's Ten-Year Network Development Plan (c.f. ENTSO-E and ENTSOG, 2022). To reduce complexity, a grid reduction algorithm proposed by Biener and Garcia Rosas (2020) is applied to reduce the initial grid from 1063 nodes to 533 nodes and 859 lines in 2021. Important neighboring countries outside the core FBMC region, i.e., Italy, Switzerland, Denmark, Norway, and Sweden, are depicted as singular nodes without intra-country grid restrictions. Interconnectors to these markets are approximated via net transfer capacities (NTC).

The regional scope and the depiction of the reduced transmission grid are visualized in Figure 4.1.

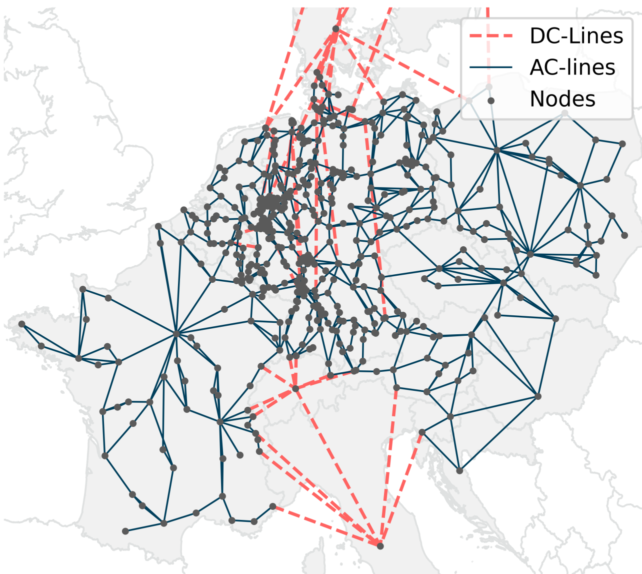


Figure 4.1.: Modeled transmission grid after grid reduction

Input data: Regionalization and Time-series

Existing power plant capacities and their distribution across Europe are based on Bocin et al. (2019) and updated by own research. Data on German conventional power plants is derived from the power plant list of the German grid regulator (Bundesnetzagentur, 2022a), and data on renewables is the *Marktstammdatenregister* (Bundesnetzagentur, 2022b). Power plants are allocated to the geographically nearest transmission grid node.

The analysis covers the years 2021, 2025, 2030, and 2035, each in hourly resolution. The country-specific demand time series are taken from ENTSO-E and ENTSOG (2022). The German demand is distributed by sectoral demand shares on the federal state level (c.f. Länderarbeitskreis Energiebilanzen, 2020). For residential demand, the distribution is assumed to follow population shares, while industrial and commercial electricity demand is distributed in proportion to the regional gross value added (c.f. EUROSTAT, 2020). This approach is similar to the one used by 50Hertz et al. (2022). For all other countries, the assumed demand distribution follows the population per local administrative unit (EUROSTAT, 2023).

The hourly onshore wind and solar generation potential dataset comprises 24 climate years (1995 to 2018). These time series are computed based on a reanalysis of meteorological data from the COSMO-REA6 model in a regional resolution of 48x48 km. To match the data to the nearest nodes, Voronoi cells were employed. The generation potential of offshore wind regions (hourly) and hydropower (weekly) is provided by Copernicus Climate Change Service (2020).

4.3.4. Scenario

For Germany, the assumed capacity development reflects the legal and political situation. The expansion of Wind and solar follows the legal targets of the EEG (2023) and WindSeeG (2023), while the capacities of hydrogen (H2) electrolyzers follow the political targets of BMWK (2023). The phase-out of German nuclear, lignite, and coal power plants is implemented according to the path defined in the Act to Reduce and End Coal-Fired Power Generation (KAG, 2020). In addition, the announced phase-out of lignite-fired power generation by 2030 is considered for the state of North Rhine-Westphalia (BMWK, 2022b). New onshore wind, solar, and gas capacities are distributed across the federal states, according to 50Hertz et al. (2023). Within the federal states, wind and solar capacities are assigned to nodes based on existing capacities, while the distribution of new gas power plants aligns with the decommissioning of coal-fired and nuclear power plants until 2035. The future distribution of offshore wind farms is given by 50Hertz et al. (2023). To reduce computational costs, new batteries are exclusively positioned at the 30 nodes with the highest demand. Electrolyzers are allocated according to existing German hydrogen projects. The demand development, the capacity development for all other countries, and the expansion

Table 4.1.: Assumptions on installed capacities [GW] and electricity demand development [TWh] in Germany

Technology [GW]	2021	2025	2030	2035
Wind Onshore	54.5	76.0	115.0	157.0
Wind Offshore	7.8	10.9	29.6	35.6
Solar	53.3	108	215.0	309.0
Hard Coal	23.5	14.0	8.4	0.6
Lignite	20.5	14.9	8.9	7.9
Gas	31.9	36.2	47.0	48.0
Nuclear	8.1	-	-	-
Batteries	-	2.8	14.6	22.0
Others	27.5	27.5	27.5	27.5
H2 Electrolyzer	-	0.9	10.0	17.5
Demand [TWh]	532	595	652	686

of batteries in Germany follow the *Global Ambition* scenario in ENTSO-E and ENTSOG (2022). Table 4.1 shows Germany's assumed capacity and demand development.

Additional flexible demand exists from hydrogen electrolyzers, which are assumed to consume electricity when electricity prices are below a certain threshold. The threshold price is assumed to be 70 EUR/MWh.[37] Fuel price assumptions are based on IEA (2022). C.2 discloses fuel and carbon prices as well as further assumptions on technology parameters and demand development per country.

4.4. Results and Discussion

4.4.1. Short-term robustness to weather conditions

Locational Marginal Prices depend on transmission constraints and the distribution of generation and demand. In Germany, electricity demand is concentrated in the densely populated and industrialized regions of Western and Southern Germany, while wind power generation is abundant in the north. If grid bottlenecks occur in high wind power generation situations, LMPs are lower in Northern than Western and Southern Germany. As wind speeds and solar radiation fluctuate, potential bottlenecks can change from hour to hour. A bidding zone split needs to be robust to such variations in weather conditions. Therefore, LMPs are calculated for many weather years (1995 to 2018) in hourly resolution (210,240 load situations per scenario year) and used as input to the clustering algorithm.

[37]This threshold leads to about 3500 full-load hours in 2030, which is in line with the assumptions of the German hydrogen strategy BMWI (2020)

Figure 4.2 shows the resulting LMPs for the reference year 2021 averaged across all weather years and the bidding zone split obtained from the clustering.

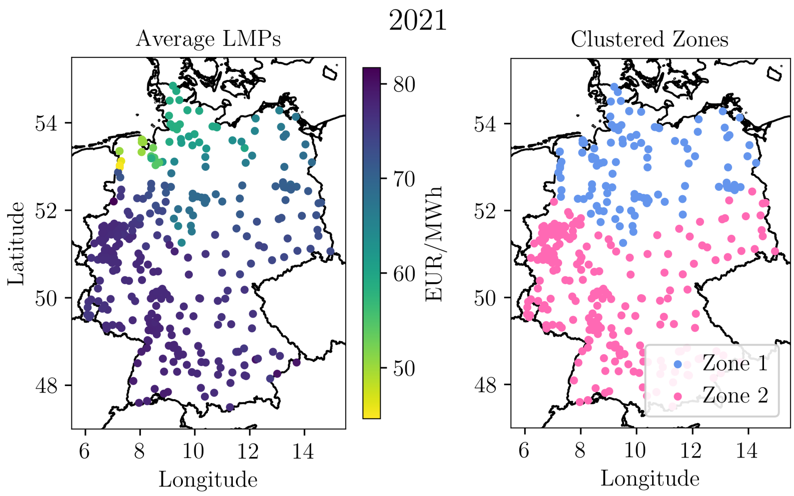


Figure 4.2.: Spatial distribution of LMPs averaged across all weather years (left) and resulting bidding zone split (right) in 2021

In 2021, the annual average LMPs in Northwest Germany are up to 30 EUR/MWh lower than LMPs in Southwest Germany, indicating a structural bottleneck between the North and the South. The LMP clustering results in a bidding zone split approximately along the 53 latitude. Average LMPs in the northern price zone are about 18.5 EUR/MWh lower than in the larger, southern high price zone.

The robustness to weather conditions is evaluated by comparing the resulting redispatch costs for the presented bidding zone split (*all weather year split*) to bidding zone splits, clustered for each individual weather year (*weather year-specific split*), as an upper bound, and to a single bidding zone, i.e., without split (*single BZ*), as a lower bound. Note that the *weather year-specific splits* are rather hypothetical benchmarks since weather conditions are uncertain and unpredictable in the long term. Table 4.2 depicts the resulting redispatch costs for Germany.

Table 4.2.: Resulting redispatch costs in Mio. EUR per weather year. The relative reduction [%] relates to the *single BZ* case.

weather year	single BZ	all weather year split	[%]	weather year-specific split	[%]
2018	2061.7	877.8	-57.4%	626.2	-69.6%
2017	1854.4	284.8	-84.6%	99.5	-94.6%
2016	1536.4	220.9	-85.6%	58.9	-96.2%
2015	2768.3	811.6	-70.7%	621.6	-77.5%
2014	1886.8	333.0	-82.4%	153.1	-91.9%
2013	1681.5	287.3	-82.9%	105.0	-93.8%
2012	1772.1	278.6	-84.3%	112.4	-93.7%
2011	2351.2	567.9	-75.8%	427.5	-81.8%
2010	1406.0	266.1	-81.1%	88.6	-93.7%
2009	1687.8	431.0	-74.5%	200.9	-88.1%
2008	2096.8	373.6	-82.2%	112.6	-94.6%
2007	2130.9	287.8	-86.5%	99.0	-95.4%
2006	1859.1	549.5	-70.4%	319.9	-82.8%
2005	1851.8	437.0	-76.4%	150.6	-91.9%
2004	1875.6	391.6	-79.1%	188.0	-90.0%
2003	1602.1	332.0	-79.3%	185.3	-88.4%
2002	1786.4	233.8	-86.9%	147.0	-91.8%
2001	1597.2	346.3	-78.3%	208.1	-87.0%
2000	2003.0	267.6	-86.6%	85.9	-95.7%
1999	1643.6	255.7	-84.4%	61.1	-96.3%
1998	2058.1	273.2	-86.7%	100.2	-95.1%
1997	1756.9	351.1	-80.0%	202.8	-88.5%
1996	1450.3	282.2	-80.5%	107.1	-92.6%
1995	1975.9	311.7	-84.2%	206.6	-89.5%
Average	1862.2	377.2	-79.7%	194.5	-89.6%

Without a bidding zone split, the derived redispatch costs for 2021 amount to 1.4 to 2.8 billion EUR depending on the weather year.[38] In the benchmark case of weather year-specific bidding zone configurations, average redispatch costs are about 90% lower than with a single bidding zone, indicating that without weather uncertainty, a yearly two-zone split captures almost all congestion. The *all weather year split* reduces the redispatch costs by about 80% on average. However, redispatch costs are almost twice as high compared to the *weather year-specific split*. For individual weather years, the cost reduction ranges from -57.4% for 2018 to -86.5% for 2007. For 23 out of 24 weather years, the reduction

[38] In reality, costs for redispatch, countertrading, and the dispatch of grid reserves amounted to about 1.2 billion EUR in 2021 (Bundesnetzagentur, 2022c). See section 4.3.1 for a brief discussion of the underlying drivers of the higher modeled redispatch costs.

is higher than 70%, and for 14 weather years, it is even higher than 80%. As the redispatch cost reductions are significant for all weather years, it can be concluded that the obtained bidding zone split is robust to weather conditions. However, the deviations in total redispatch costs between weather years are high. Therefore, it seems important to consider different weather years when assessing the impact of a bidding zone split.

This analysis assumes a risk-neutral central planner treating all weather years and events equally in the clustering process. However, a risk-averse central planner might weigh redispatch-intensive weather years higher when determining a bidding zone split. This could potentially reduce the maximum and increase the minimum redispatch costs across all weather years. The result would be a lower weather-related variance in redispatch costs. Moreover, it would be conceivable to adjust the bidding zone within a year to account for structural differences in weather patterns. For instance, applying distinct bidding zone configurations in summer and winter could be beneficial if the structural bottleneck shifts due to different renewable power generation and load patterns. An illustration of such a season-specific split is presented in C.3; however, assessing the impact on redispatch costs falls beyond the scope of this paper.

4.4.2. Robustness to system changes

Besides short-term uncertainty, the suitability of a bidding zone split is subject to changes in the electricity system, e.g., new generation capacity, changing electricity demand, and grid extension. Analogous to 2021, LMPs are calculated for 2025, 2030, and 2035 based on the scenario defined in section 4.3.4. Figure 4.3 shows the resulting LMP distribution and the clustered bidding zone split per scenario year.

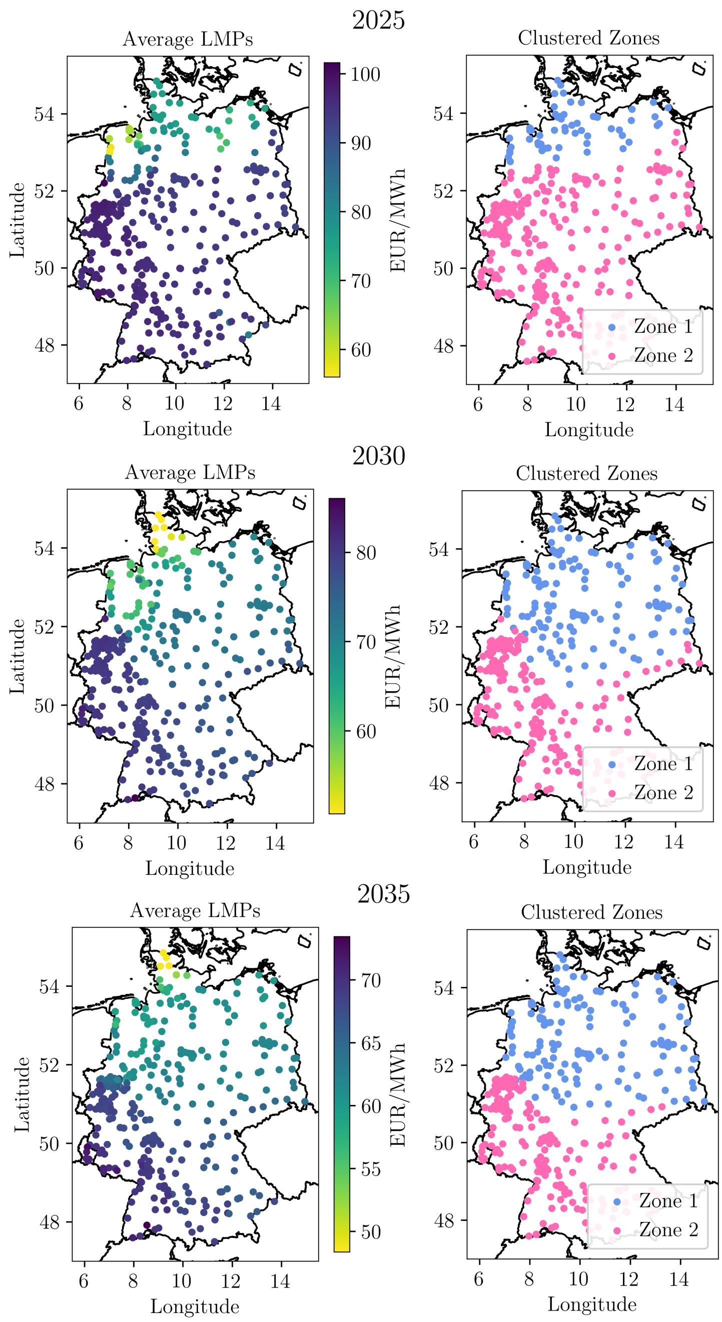


Figure 4.3.: Spatial distribution of LMPs (left) and clustering results (right) for 2025, 2030, and 2035

Several overlapping effects influence the development of the LMP level and distribution. The main drivers of the electricity price level are fuel prices, renewable investments, and electricity demand development. Under the given assumptions, the LMP level increases compared to 2021 due to rising carbon prices and electricity demand. Towards 2030 and 2035, the LMP level declines as large amounts of renewable capacity come into operation. The LMP distribution, in turn, is determined mainly by the distribution of renewable capacity additions and the grid extension (or missing grid extension, i.e., new bottlenecks). Given the assumptions of the reference scenario, new wind power plants in the North, particularly new offshore wind farms, increase the demand for power transmission year by year. Few new AC lines are commissioned by 2025, which hardly changes the resulting bidding zone split. Conversely, substantial grid expansion is planned until 2030, including six new DC projects with a capacity of 2 GW each. As a result, the bottleneck and the boundary between the two clustered bidding zones shift from around the 53rd parallel in 2021 and 2025 southwards towards the 51st parallel in 2030 and 2035.

In practice, frequent adjustments of the bidding zone split would lead to transformation costs and increase complexity and uncertainty for investors and market participants. Determining the future bidding zone configuration well in advance is therefore advantageous. In the following, a *stable* bidding zone configuration until 2035 is examined. To determine such a split, the calculated German-Luxembourg LMPs for all 840,960 time steps (24 weather and four scenario years in hourly resolution) are used as input for the clustering algorithm. The clustering does not incorporate an additional discount factor. Thus, the central planner is assumed to have no time preference.[39] Figure 4.4 shows the average LMPs across all scenario years and the obtained bidding zone split.

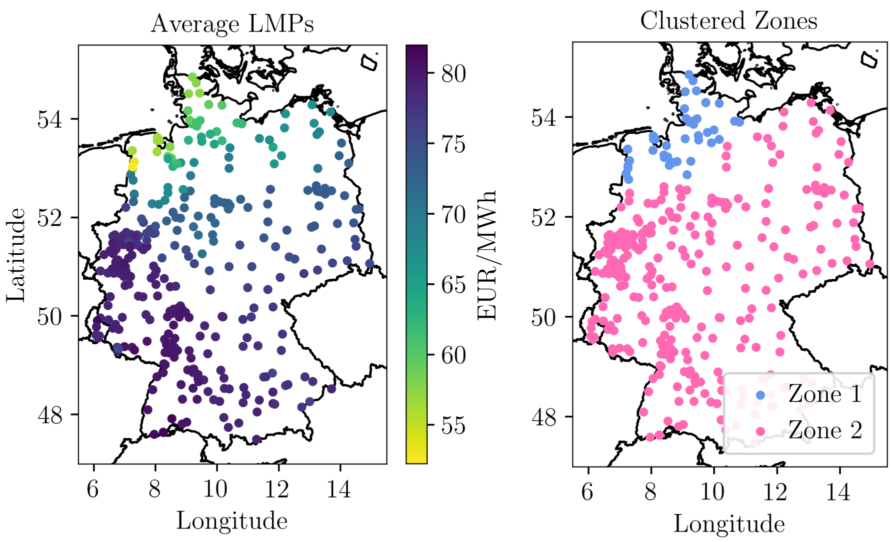


Figure 4.4.: Spatial distribution of average LMPs across all scenario years (left) and resulting bidding zone split (right)

[39]Introducing a discount factor greater than zero would assign a higher weight to the earlier years, potentially changing the clustering result. For example, with a discount rate of 3%, about 4.6% (16 nodes) of the Luxembourg-German nodes are in a different cluster. See Appendix C.3 for an illustration.

The resulting northern, low-price bidding zone comprises only the Northwest of Germany along the North Sea coast. It is notably smaller in size compared to those derived from scenario year-specific LMPs. This is due to Ward's criterion, which minimizes the in-cluster variance. High wind power generation on- and offshore leads to transmission bottlenecks towards the south and causes low LMPs along the coast in all scenario years. For individual scenario years, other bottlenecks are more prevalent and dominate in the clustering process. Yet, these bottlenecks shift over the scenario years while the bottleneck along the coast remains stable. In addition, the LMPs of the different scenario years are not weighted equally in the clustering. The year 2025 is characterized by the highest LMP levels, resulting in larger Euclidean distances and consequently exerting a stronger influence on the clustering process.[40]

Holding the bidding zone split stable over multiple years decreases the information quality on transmission restrictions in the market. Consequently, the need for redispatch increases in all scenario years compared to a yearly split. Table 4.3 presents the changes in redispatch costs per scenario year compared to the benchmarks of a single bidding zone and the annually changing bidding zone splits presented above. The results are based on 2009 weather conditions as ENTSO-E and ENTSOG (2022) considers these to be the most representative.

Table 4.3.: Resulting redispatch costs in Mio. EUR per scenario year under the weather conditions of 2009. The relative reduction [%] relates to the *single BZ* case.

scenario year	single BZ	stable split	[%]	Year-specific split	[%]
2021	1687.8	548.2	-67.5%	431.0	-74.5%
2025	2595.7	1128.0	-56.5%	315.4	-87.8%
2030	4784.0	1651.0	-65.5%	470.0	-90.2%
2035	7884.8	3773.6	-52.1%	1226.5	-84.4%
Average	4238.1	1775.2	-58.1%	610.7	-85.6%

Without a bidding zone split, the total redispatch costs increase strongly until 2035. This is due to the chosen scenario: a strong increase in renewable generation capacity, growing electricity demand, and comparably slow grid expansion lead to increased redispatch demand, while rising carbon prices increase the costs for (re-)dispatching fossil-fueled power plants. If redispatch costs were equally distributed among all consumers, grid fees to cover the congestion management on the transmission level increase from 0.32 ct/kWh in 2021 to 1.15 ct/kWh in 2035, more than tripling the associated distributional effect.

[40] This effect could be prevented by normalized time series. However, higher LMPs represent higher system costs, so a higher weighting in the clustering process may make sense. An analysis of different weightings is beyond the scope of this study.

Splitting the bidding zone once and holding it stable from 2021 to 2035 decreases the yearly redispatch costs by about 58% on average. However, the relative reduction ranges from -56.5% to -67.5% because the *stable split* cannot adequately depict the shifting inner-German bottleneck. In contrast, an annually changing bidding zone configuration (based on LMPs of all weather years) leads to significantly lower redispatch costs. Particularly noteworthy is the decrease in redispatch costs from 2021 to 2025. While redispatch costs in case of a *stable split* are just 27.2% (+127 Mio EUR) higher than with the *year-specific split* in 2021, this ratio increases to factor 3.1 (+2547 Mio EUR) by 2030. Overall, the results show how changing system properties complicate the delimitation of an efficient bidding zone configuration. These findings align with the research by Breuer et al. (2013), who found, for a different scenario setting, that the benefits of a bidding zone split halves if it is held stable over three years instead of an annual reconfiguration.[41] However, dividing the existing bidding zone into two stable market areas is nevertheless beneficial in terms of reducing the distributional effects of redispatch for the assumed reference scenario in each scenario year.

4.4.3. Sensitivity analysis

The future is uncertain, and the identified bidding zone split might be less efficient or even detrimental if the scenario changes. In the following, a sensitivity analysis is performed to investigate and identify critical parameters that drive the effectiveness of a bidding zone split. To reduce complexity, the sensitivity analysis is done only for the representative weather conditions of 2009 (c.f. ENTSO-E and ENTSOG, 2022). In the following, the *stable* split determined in the previous chapter for the period 2021 to 2035 is considered as the reference case.

System development

The observed grid bottlenecks are largely driven by the assumed substantial development of the electricity system: the renewable generation capacities, particularly wind power, the growth in electricity demand, and the expansion of the transmission capacity.

Delayed wind power expansion: The German expansion targets for renewable energies have been regularly missed in recent years. Therefore, it appears uncer-

[41] Similar to a season-specific split discussed in section 4.4.1, the bidding zone split could theoretically be regularly reconfigured without significantly increasing uncertainty. This would require the reconfigurations to be determined well in advance and made transparent, e.g., by publication when implementing the initial split. Potentially, this could lead to the redispatch cost reductions of *year-specific splits*. However, the complexity and transformation costs would be higher than in the case of an *stable split*. Quantifying and weighing both is beyond the scope of this paper.

tain whether the 2030 targets will be achieved. Within a sensitivity, the effects of splitting the German bidding zone are examined for a scenario with only half the speed of wind power expansion.

Delayed wind power expansion and stable demand: Recent studies on the transition of the German and European energy systems towards climate neutrality show the need for electrification and, hence, growth in electricity demand, as assumed in the reference case. However, the current progress in electrifying the industry, mobility, and heating sectors lags behind those scenarios. Moreover, comparably high electricity prices and limited availability of renewable electricity set incentives for industries to move production overseas. A case with delayed wind power expansion and stable demand is analyzed as a second sensitivity.

Delayed grid expansion: To relieve grid congestion and counteract the increasing redispatch costs, TSOs invest in new transmission capacities. However, several of Germany's grid expansion projects are currently delayed (c.f. 50Hertz et al., 2019, 2021, 2023). Further delays in grid expansion would amplify congestion and redispatch costs. To analyze the impact of further setbacks, this sensitivity considers a scenario where projects in Germany set to be operational before 2030 face a one-year delay, while those with later commissioning dates encounter a delay of two years.

The resulting redispatch costs without a bidding zone split in the reference case and the three sensitivities regarding the system development are depicted in figure 4.5 and described in the following.

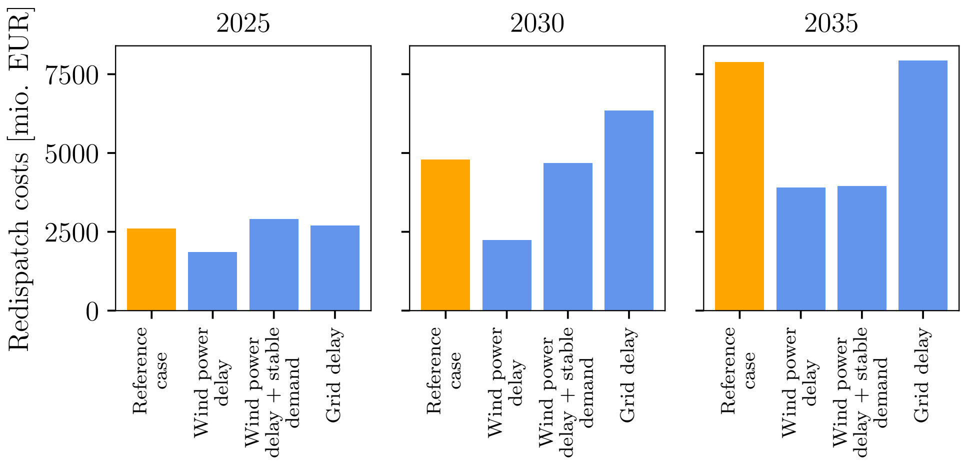


Figure 4.5.: Redispatch costs without a bidding zone split in the system development sensitivities.

Slower wind power expansion reduces grid congestion. As a result, the redispatch costs increase much slower than in the reference case: in 2030 and 2035, these costs are nearly halved compared to the reference case.

If, in addition, the demand remains stable at the level of 2021, the regional surplus generation and, thus, the need for transmission increases. In 2025 and 2030, the level of redispatch costs is similar to the reference case. In 2035, however, the redispatch costs decline due to higher market-driven curtailment: The lower electricity demand leads to more hours of negative residual load, i.e., if wind power generation in Germany exceeds the total demand, renewable power is curtailed already in the market clearing. These market-driven renewable curtailment volumes can be shifted cost-neutral within Germany in redispatch.

Any delay in expanding the transmission capacity increases the need for redispatch and, consequently, redispatch costs. In 2030, redispatch costs are almost 33% higher than in the reference case. By 2035, the difference in redispatch costs diminishes, as all high-capacity DC-lines come into operation, even with the two-year delay.

The absolute redispatch costs and the relative cost reduction in the case of the *stable* bidding zone split is presented in figure 4.6.

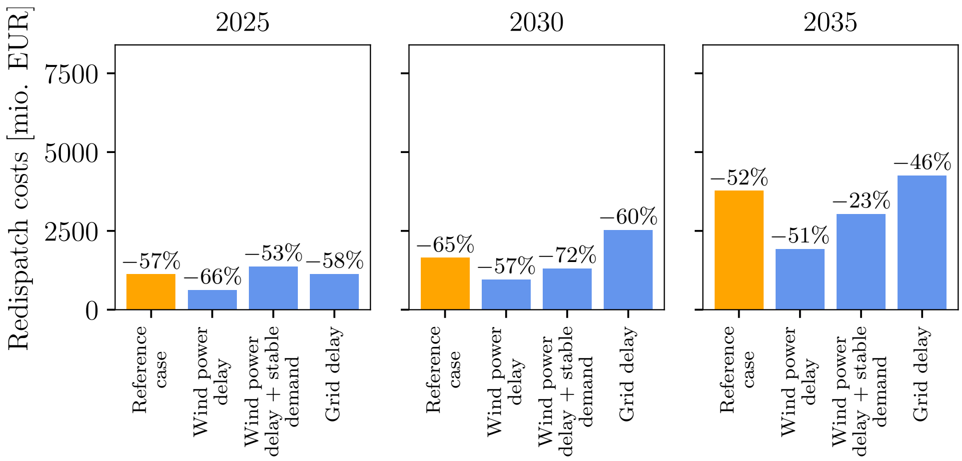


Figure 4.6.: Redispatch costs with a bidding zone split in the system development sensitivities.

The bidding zone split reduces the redispatch costs in all sensitivities substantially, but the effect varies between the sensitivities and scenario years. In case of delayed wind power expansion, the relative reduction amounts to 58% on average, marginally less than in the reference case. The absolute reduction is about 1 billion EUR less on average than in the reference case, indicating that the bottleneck is less severe, but the structure remains similar to the reference case.

If the wind power expansion is delayed and the demand does not increase, the redispatch cost reduction varies much more between years: In 2030, a market split reduces the redispatch costs by about 72%, the highest reduction across all sensitivities and scenario years. This is mainly because cross-zonal trade flows are managed better in the market clearing. Since the power systems of neighboring countries correspond to the reference case, the German electricity system is comparably smaller than in the reference case. The relative importance of cross-country trade increases. In contrast, the cost reduction in 2035 amounts to just 23%, which is the lowest observed across all years and sensitivities. Substantial grid expansion, including new DC lines in the North-South direction, and the higher market-driven wind power curtailment reduce redispatch costs even without a bidding zone split. Instead, high solar power generation leads to local bottlenecks in Southern Germany more often. This is reflected by the additional solar power curtailment of 26 TWh. These local bottlenecks are not captured by the bidding zone split, and hence, redispatch costs are comparably high.

In case of a delayed grid expansion, a bidding zone split reduces the redispatch costs by about 55% on average, with a peak of -60% (3.9 billion EUR) in 2030. Even though the absolute reduction is higher than in the base case, the relative reduction is lower. This is due to a higher absolute level of redispatch costs but a different structure of the grid bottlenecks, which are less well reflected in the studied bidding zone split.

Overall, the sensitivities regarding the system development show that the bidding zone split leads to a robust reduction of redispatch costs as long as the structure of the bottlenecks remains similar. If the system's properties change fundamentally, as in the case of lower wind power expansion and demand in 2035, the effectiveness of a bidding zone split decreases.

Fuel price changes

Assumed fuel prices are based on long-term trends identified by the International Energy Agency (c.f. IEA, 2022, p.110). However, these price trajectories are subject to uncertainty and - as stated by the authors - "do not attempt to track the fluctuations and price cycles that characterize commodity markets in practice." In reality, fuel prices can, and most likely will, deviate from these projections. Fuel prices affect the distribution of electricity generation and, hence, grid bottlenecks if the merit order of power plants changes. The German merit order primarily depends on the gas-coal spread, determined by coal, gas, and carbon prices. Besides the "normal" volatility of global gas market prices, blending low-carbon gases (e.g., hydrogen) could increase the fuel costs of gas-fired power plants. Carbon prices, in turn, depend on regulatory decisions. To achieve its climate goals, the European Union could reduce the number of emission certificates auctioned and increase the carbon price. This would disproportionately increase the electricity generation costs of hard coal and lignite-fired power plants. The effect of doubling gas and carbon prices is calculated in two sensitivities.[42] The resulting redispatch costs for the case of a single German-Luxembourg bidding zone are depicted in figure 4.7.

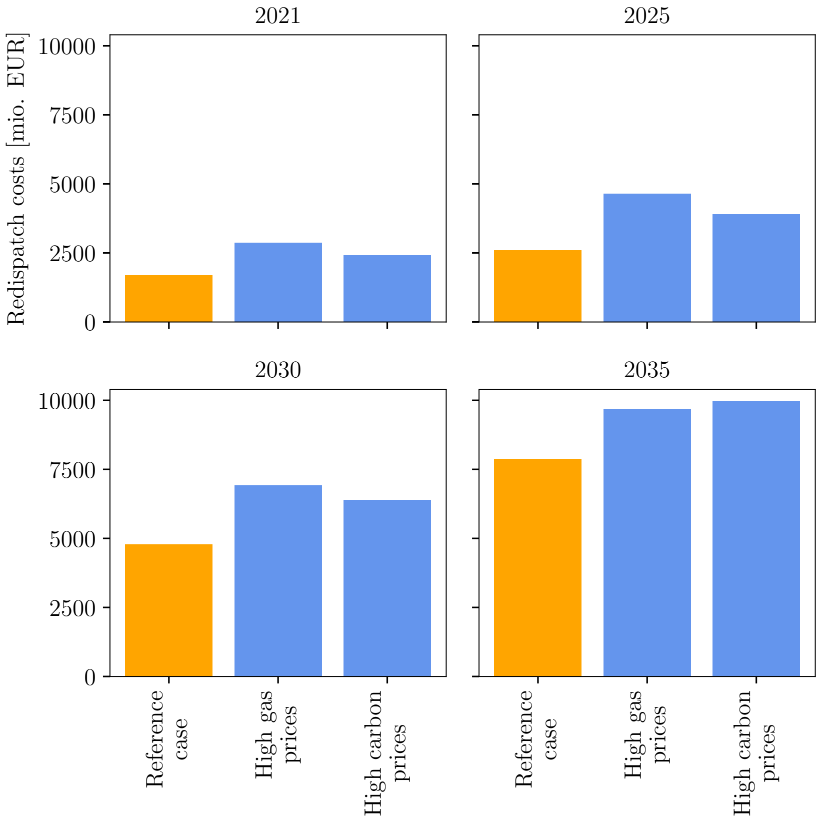


Figure 4.7.: Redispatch costs without a bidding zone split in case of doubled gas and carbon prices.

Elevated gas and carbon prices increase overall redispatch costs due to higher (re-)dispatchable power generation costs. This, in turn, impacts European trade balances. Higher gas prices lead countries like Italy and the Netherlands, with more gas-fired power generation, to import more electricity. Conversely, countries with significant coal capacities, such as Germany and Poland, export more electricity. This effect diminishes by 2035 as the merit order becomes similar in both sensitivities due to the exogenously assumed coal phase-out.

In contrast, high carbon prices make gas cheaper than coal and lignite for power generation. Consequently, lignite and coal power plants are already priced out in the counterfactual case of 2021, resulting in an overall reduction of Ger-

[42]The fuel price sensitivities focus on changes in the merit order. In fact, rising gas prices might imply higher carbon prices due to increasing emission-intensive coal-fired power generation, and vice versa. Neglecting this potential endogeneity allows for a more isolated examination of changes in the merit order.

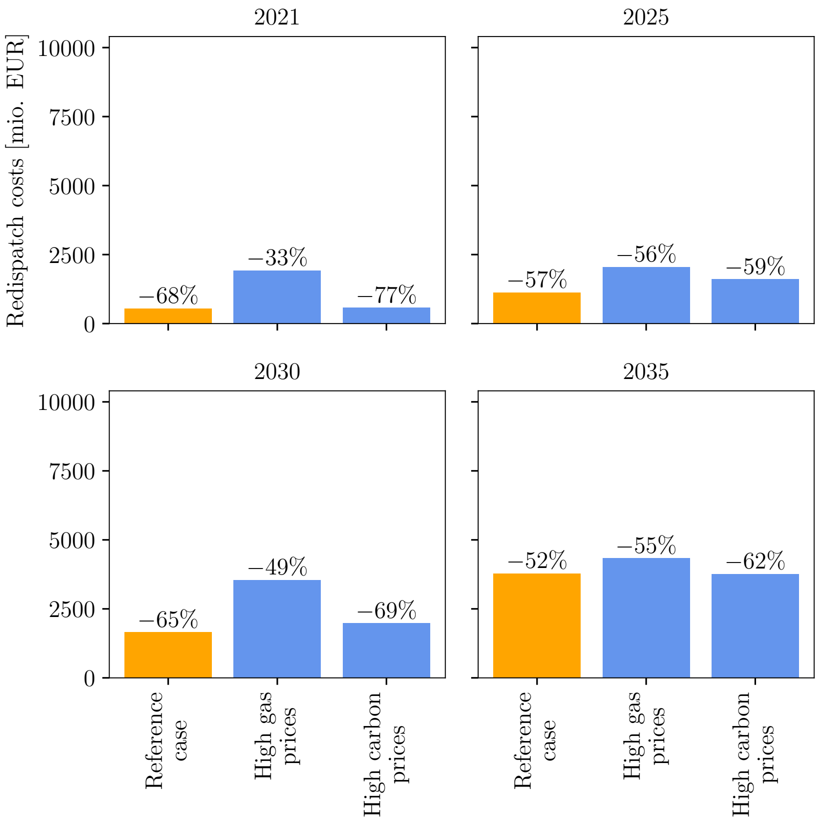


Figure 4.8.: Redispatch costs with a bidding zone split in case of doubled gas and carbon prices.

man exports, increased flows to the East, and reduced flows to the South. By 2025, however, carbon pricing also renders combined-cycle gas turbines cost-competitive to coal-fired power plants in the reference scenario. Therefore, in later years, higher carbon prices have only minimal additional effects on the merit order of power plants and grid congestion. Elevated redispatch costs, compared to the reference case, stem mostly from increased fuel costs. The effects on the merit order and changed trade flows also determine the impact of the bidding zone split on redispatch costs, depicted in figure 4.8.

The high imports from Poland and southbound exports, e.g., to Switzerland and Austria, triggered by high gas prices, increase the inner-German grid congestion. However, the bidding zone split studied has a comparably small impact on these trade flows because the countries mentioned all border the Southern zone (see figure 4.3). This effect decreases over time as the congestion caused by the wind power expansion dominates and coal- and lignite-fired capacities decrease. High gas prices, in turn, increase the German bottleneck due to higher imports to Germany and higher exports to Poland. Splitting the German market reduces imports from the Netherlands and Denmark in particular, resulting in a redispatch cost reduction of 77%. The effect decreases from 2025 as the effect on the merit order disappears.

All in all, fuel prices primarily affect the overall redispatch cost level. To a lesser extent, they influence the effectiveness of a bidding zone split in the short term via the merit order. In the longer term, however, the merit order effect decreases with the decline in coal-fired power plant capacities.

4.5. Conclusion

This paper addresses a bidding zone reconfiguration's long- and short-term robustness. Specifically, it analyzes the effects of stochastic weather patterns and, second, structural changes in the power system over time on the redispatch cost reduction due to a two-zone split of the German-Luxembourg market area. For this purpose, Locational Marginal Prices are calculated for 24 weather years and the scenario years 2021, 2025, 2030, and 2035 and used as input for hierarchical clustering based on Ward's criterion to derive a bidding zone split. The robustness of the resulting bidding zone configuration is then analyzed in terms of corresponding redispatch costs. Furthermore, additional sensitivity analyses are performed to investigate the impact of uncertain parameters, such as grid and wind power expansion, as well as fuel prices.

The key findings are threefold: First, the impact of changing weather conditions on the exact bidding zone split is limited if there is a structural bottleneck, such as in Germany. A bidding zone split derived from clustering LMPs of 24 weather years for the reference year 2021 results in a redispatch cost reduction of about 80% on average - 10 percentage points less than the hypothetical benchmark of individual bidding zone splits for each weather year. Second, looking at several scenario years, the structural grid bottleneck shifts southwards over time as the system changes, i.e., transmission, generation capacity, and demand. Annually adjusted bidding zone splits, i.e., obtained from clustering LMPs for each scenario year individually, lead to reductions in redispatch costs of -75 to -90%. If the bidding zone split is stable from 2021 to 2035, the redispatch cost reduction is significantly lower (-52 to -68% per year) for the assumed scenario. Third, deviations in uncertain scenario parameters like the expansion of wind power, transmission capacity, or fuel prices impact the effectiveness of a bidding zone split. If grid expansion projects are delayed, the existing grid bottleneck becomes more structural and severe, increasing the effectiveness of a bidding zone split in reducing redispatch costs. On the other hand, delays in wind power expansion lead to less congestion than in the reference case. Hence, the absolute reduction in redispatch costs is lower. If the congestion is less structural but replaced by local, solar power-driven negative residual loads and associated congestion, the two-zone split studied is less effective. Increases in gas and carbon prices primarily drive up the absolute redispatch costs. To a lesser extent, they impact the bidding zone split's effectiveness due to the altered distribution of fossil power generation within Germany and among neighboring countries. Notably, the impact of fuel prices decreases over time, especially by 2035, as coal and lignite capacities decline.

The results suggest that dividing the German-Luxembourg market area into two stable bidding zones would yield a robust reduction in redispatch costs, mitigating distributional effects. Nonetheless, the sensitivities show that the advantage of a bidding zone split diminishes when the underlying system characteristics change. Considering this dependence on uncertain parameters, the development of novel methods to robustly determine suitable zones is both a relevant and fruitful direction for further research. For instance, the shifting boundaries of the clustered zones over the years could indicate that a third zone may be beneficial. If the northern boundary of this third zone aligns with the existing structural bottleneck, and the southern boundary corresponds to the identified future structural bottleneck, a three-zone setup could significantly enhance the robustness to system developments. Another approach to increase the bidding zone split's effectiveness could involve periodic transitions between configurations, such as switching between summer and winter or day and night. This dynamic adaptation could better reflect the seasonal or daily patterns of renewable power generation and corresponding grid bottlenecks. Furthermore, it may be worthwhile to investigate methods to reduce the weather-induced volatility of redispatch costs. One potential approach could involve assigning higher weights to weather events or years that trigger exceptionally high redispatch costs during the clustering process. Last but not least, this paper uses the German-Luxembourg market area as a case study. In Europe, however, bidding zone splits are discussed for multiple market areas marked by structural bottlenecks, e.g., Great Britain, the Netherlands, or France. The key findings of this study should hold in general for all these market areas, too. However, it should be analyzed in more detail how splitting one bidding zone affects the benefits of splitting another (neighboring) zone.

5. On the Time-Dependency of MAC Curves and its Implications for the EU ETS

5.1. Introduction

The mitigation of greenhouse gas emissions requires a fundamental overhaul of the capital stock, i.e., investments in low-carbon technologies. The efficient coordination of investment capital is essential to minimize overall abatement costs. Economists agree that the pricing of emissions is a suitable instrument for allocating capital efficiently (e.g., Coase (1960) and Borenstein (2012)). By introducing the European emissions trading system (EU ETS), the EU has implemented a quantity control system with an endogenous price on emissions. The EU ETS requires that firms in the power sector, energy-intensive industries, and inner-European aviation submit allowances to cover their emissions. Overall, the EU ETS regulates about 40 % of total European emissions.

The latest reform of the EU ETS has introduced the Market Stability Reserve (MSR) and the Cancellation Mechanism (CM), which have fundamentally changed the EU ETS to a system with restricted banking and responsive allowance supply (cf. Bocklet et al. (2019)). A comprehensive literature strand evaluates the reforms' impact via partial equilibrium models of the EU ETS (e.g., Perino and Willner (2016) and Bocklet et al. (2019)). Most of these articles do not model allowance demand endogenously.[43] They assume allowance demand exogenously based on marginal abatement cost (MAC) curves. MAC curves match emission mitigation with abatement costs and have been crucial tools to evaluate environmental policies for decades (e.g., Jackson (1991) or Aaheim et al. (2006)).

In the EU ETS related literature, the assumptions on MAC curves are heterogeneous. While some articles assume linear MAC curves (e.g., Perino and Willner (2016) or Bocklet et al. (2019)), others use convex MAC curves (e.g., Beck and Kruse-Andersen (2018) or Schmidt (2020)). Without evidence from the literature, papers usually presume a time-independent shape of MAC curves. Nevertheless, both the shape as well as its development over time drives results. In particular, these assumptions affect total emissions in the EU ETS due to the responsive allowance supply of the EU ETS.

[43] To the best of our knowledge, Bruninx et al. (2018) present the only approach that combines power market modeling with a depiction of the EU ETS regulation.

This paper assesses the fundamental properties of MAC curves and their implications for the EU ETS. To this end, we carry out a case study to derive stylized MAC curves for the European power sector. Multiple runs of a partial equilibrium model map carbon price paths onto emission abatement. We find that MAC curves are convex. The curvature is subject to economic developments, such as fuel prices and interest rates. Further, MAC curves are time-dependent. In the short term, they are steep since coal-to-gas fuel switching is the only abatement measure. With enlarging investment opportunities and technological learning, MAC curves flatten over time.

Assuming convex instead of linear MAC curves increases banking since future abatement becomes relatively more expensive. On the contrary, flattening lowers incentives for banking. Under idealized assumptions, steep short-term MAC curves shift the equilibrium price path upward while also reducing short-term banking. This effect could cause strong price reactions in the short term when market frictions such as myopia are considered. For a numerical evaluation of these effects, we propose methodological approaches to account for the time-dependency of MAC curves.

The remainder of the paper is organized as follows: Section 5.2 reviews the prevailing literature on MAC curves. Section 5.3 derives stylized MAC curves for the European power sector. Section 5.4 discusses the implications of the identified properties of MAC curves for the EU ETS. Section 5.5 concludes.

5.2. Prevailing Literature on MAC Curves

This section sheds light on the properties of MAC curves discovered in the existing literature. We consider quantitative evaluations as well as qualitative discussions of MAC curves.

The prevailing literature uses four methodological approaches to quantitatively evaluate MAC (compare Huang et al. (2016)): (1) Estimations based on distance functions, (2) expert-based evaluations, (3) top-down models, and (4) bottom-up models.

MAC evaluation via distance functions estimates past and present marginal abatement costs based on historical data (Ma et al. (2019)). For example, Du et al. (2015) find that the marginal abatement costs in the Chinese energy system increase over time in a convex shape. However, these historical observations do not allow statements about future MAC or the construction of MAC curves.[44]

Expert-based evaluations, e.g., performed by McKinsey & Company (2013), derive MAC curves by gathering expert knowledge on abatement costs and po-

[44]In particular, observed marginal abatement costs reflect rather the part of the MAC curve with low mitigation efforts, which likely do not represent MAC for extensive emission mitigation. For a comprehensive and critical review of MAC evaluation by distance functions, the reader is referred to Ma et al. (2019).

tentials. While revealing abatement potential even at negative abatement costs, the derived MAC curve for 2030 is convex-shaped in its positive part.

The use of top-down models, mostly integrated assessment models, covers economy-wide activities, their interactions, and the consequences on the natural environment at a global level.[45] For the EU ETS sectors, Landis (2015) finds that MAC curves are convex in abatement.

In contrast to top-down models, bottom-up partial equilibrium models abstract from global interactions between different economic sectors but allow for more technical details. Kesicki (2013) finds that the MAC curve of the UK energy system in 2030 is convex-shaped and robust to changes in fossil fuel prices, but depends strongly on the underlying interest rate. Delarue et al. (2010) find that short-run abatement in the European power markets depends on the carbon price as well as on the price margin between coal and gas. Van den Bergh and Delarue (2015) compare two abatement options, namely fuel-switching from coal to gas and wind investments, with a model of the central-western European power sector. They point out that MAC of the different abatement options are not additive but impact each other.

Summing up, articles with different methodological approaches consent that MAC curves are convex. However, Kesicki and Ekins (2012) generally calls for caution when interpreting MAC curves. MAC curves depend on uncertain assumptions, which are often not transparent. Further, the concept of MAC curves takes the perspective of a perfectly informed central planner who decides cost-efficiently on abatement under perfect foresight. In reality, the decisions on abatement measures depend on individual preferences. If individuals decide solely based on abatement costs and their actions are coordinated in perfect markets, the cost-efficient MAC curve of the central planner coincides with the aggregation of individual decisions on abatement measures. However, individual decision-making is subject to non-financial costs and behavioral aspects. Consequently, MAC curves of a central planner often identify abatement measures with negative abatement costs, which are not realized yet. Moreover, MAC curves are always a static snapshot in time and do not reveal what abatement measures are taken before and after the reference year. Historic abatement and expectations about future abatement drive the shape of MAC curves.[46]

[45] Most integrated assessment models use a computable general equilibrium framework to depict economic interrelations via substitution elasticities. Kuik et al. (2009) provides a comprehensive meta-analysis on the derivation of MAC curves with integrated assessment models.

[46] At the same time, today's decisions on abatement also impact future's abatement costs, e.g., due to technological learning effects.

5.3. Case Study: MAC Curves of the European Power Sector

To illustrate the different properties of MAC curves, this section carries out a case study for the European power sector.

5.3.1. Methodological Approach

Power market model DIMENSION

We derive MAC curves with the partial equilibrium European power market model DIMENSION.[47] By assuming inelastic electricity demand in the short term and perfectly competitive markets without transaction costs, the decision making of individual, profit-maximizing firms under perfect foresight is equivalent to a central planner's cost minimization problem. The central planner minimizes the total discounted costs of investments in power plants and their dispatch to satisfy electricity demand. Appendix D.1 presents the most relevant equations of DIMENSION.

Approach for Deriving MAC Curves

To obtain MAC curves for the European power sector, we feed different carbon price paths $\boldsymbol{\tau}$ into the model and derive the corresponding level of emissions $emissions(y)_{|\boldsymbol{\tau}}$ for each considered year y. The emissions of the baseline scenario (baseline emissions) $u(y) := emissions(y)_{|\boldsymbol{\tau}=0}$ are used to define the abatement level of a carbon price path $\boldsymbol{\tau}$ as $abatement(y, \tau) = u(y) - emissions(y)_{|\boldsymbol{\tau}}$. Figure 5.1 sketches the methodology to derive MAC curves using the power market model DIMENSION.

We assume that carbon prices develop according to the Hotelling rule (cf. Hotelling (1931)), i.e., they rise with the interest rate.[48] The model derives MAC curves in time period t anticipating this price development for a time horizon H of 15 years.

[47] The model DIMENSION has been developed by Richter (2011) and has been used in many analyses, e.g., Bertsch et al. (2016b), Peter and Wagner (2018) and Helgeson and Peter (2020).

[48] Emission allowances are a scarce resource. Rational firms with perfect foresight use allowances so that the corresponding carbon price increases with their private interest rate. Otherwise, arbitrageurs could take advantage of inter-temporal price differences. Ex-post, prices develop differently due to external shocks or new information on future costs or demand (cf. Bocklet and Hintermayer (2020)).

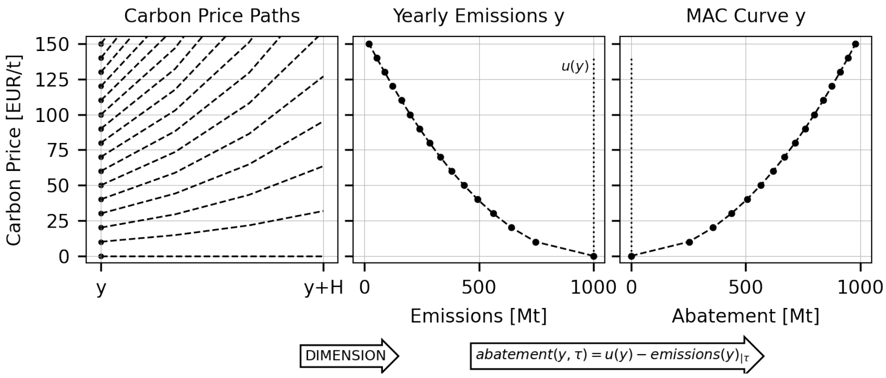


Figure 5.1.: Schematic illustration of the approach for deriving MAC curves

Parametrization

This case study derives stylized facts on MAC curves, using the European power sector as an example. To isolate the impact of single restrictions or input parameter changes, we keep the parametrization as plain as possible. We fix the status quo of European power plants, i.e., we abstract from decommissioning due to technical restraints or political goals. We assume the existing fleet of power plants in 2019 according to the database developed at the Institute of Energy Economics at the University of Cologne, which is continuously updated based on Platts (2016), Bundesnetzagentur (2020a) and ENTSO-E (2020b). Net transfer capacities develop according to the ENTSO-E Ten-Year Network Development Plan 2018 (ENTSO-E (2018b)). Fuel prices, investment costs, net trade capacities, and electricity demand are as of 2019. By default, we use an interest rate of 8%. Time-series rely on the historical weather year 2014. For keeping the model tractable, 16 representative days approximate the development for one year. Appendix D.2 gives an overview of the considered technologies and their techno-economic parameters.

5.3.2. The Change of MAC Curves Over Time

This section evaluates how different lead times for investment affect MAC curves. In the short term, the power plant fleet is fixed. Switching electricity generation from power plants with higher carbon intensity (e.g., hard coal or lignite) to power plants with lower carbon intensity is the only viable abatement measure (*Fuel Switching*). The existing capacity of the power plants with lower carbon intensity limits the abatement potential of fuel switching. With longer lead times, investment into generation capacities as a reaction to higher carbon prices is possible. Yet, installation capacities or necessary approval processes restrict the speed of changing the power plant fleet via investments. In the long term, freedom to invest is unrestricted. Additionally, demand can react to rising carbon prices, e.g., via investments into energy efficiency or carbon leakage.

For determining the development of MAC curves over time, we make the following stylized assumptions. In the short term, all capacities are fixed and only the dispatch of the generation portfolio can change with the carbon price. In the medium term, the expansion of RES capacities must not be higher than five times the average expansion between 2017 and 2019, reflecting investment lead times of five years. Investments into gas power plants are restricted to about 9 GW per year within the European electricity system. In the long term, investments are not restricted. Further, we assume that the development of long-term demand depends on the carbon price development.[49] Ceteris paribus, figure 5.2 depicts the resulting MAC curves for different time horizons and disaggregates the abatement into static fuel switching, (restricted) investment into power plants, and demand adjustment.[50]

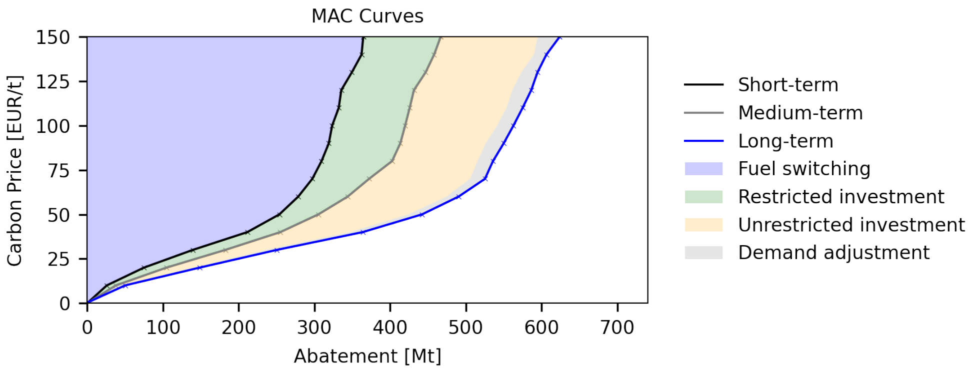


Figure 5.2.: Short-, medium- and long-term MAC curves and disaggregation of the abatement measures

In line with the literature, MAC curves are convex independent of the time horizon. They further flatten over time, primarily due to the increasing investment possibilities. In the short run, replacing coal generation with gas-fired power plants allows to reduce emissions. The short-term MAC curve is convex since modern gas power plants drive inefficient coal power plants out of the market already at low carbon prices. Later on, inefficient gas power plants replace modern coal generators at higher abatement costs.

Progressing in time, fuel switching is not the only abatement option but investments into modern gas power plants and particularly RES power plants are possible. As a result, the MAC curves flatten, i.e., the same carbon price results in higher abatement. While investment restrictions prevail in the medium term, unrestricted investment possibilities further flatten MAC curves in the long term.

[49]We approximate the impact of rising carbon prices on electricity prices via the difference in marginal costs of modern Combined Cycle Gas Turbine Power Plants (CCGT) and assume a demand elasticity of 5 % with regard to the electricity price.

[50]Throughout this paper, the end of the x-axis depicts maximum abatement, i.e., zero emissions.

Besides developments on the supply side, adjustments of the electricity demand further bend MAC curves downward.[51]

While the MAC curves above consider variations in investment freedom and demand adjustment, the following section analyzes how developments in markets beyond the power sector (i.e., fuel prices and interest rates) or technological progress affect long-term MAC curves.

5.3.3. Drivers of Long-term MAC Curves

This section analyzes three exogenous parameters, which influence long-term MAC curves: fuel prices, interest rates, and technological learning.

Fuel Prices

With regard to fuel prices, the power sector is mainly subject to the development of gas and hard coal prices. In particular, the margin between these fuels is considered a major driver. For a stylized illustration of the impact of fuel prices on the MAC curve, we compare three different levels of gas prices (10, 20, or 30 EUR/MWh$_{th}$, respectively), while the coal price is not varied. The variation of gas prices with constant coal prices alters the margin between coal and gas. Figure 5.3 depicts the corresponding MAC curves.

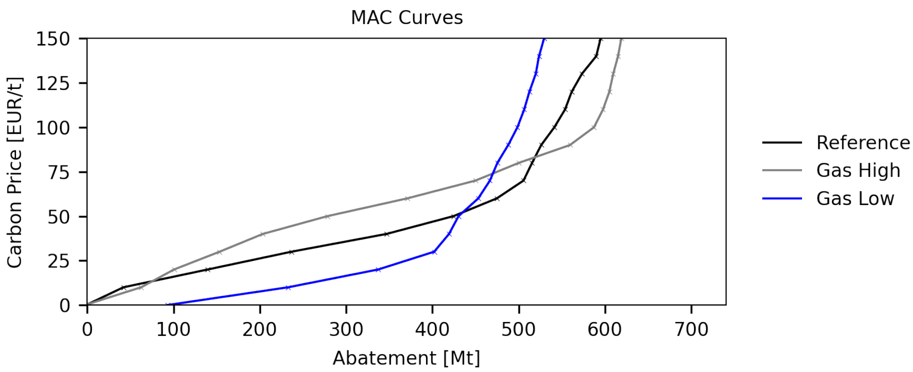


Figure 5.3.: Long-term MAC curves for different coal/gas price spreads

Lower gas prices affect MAC curves in two ways: First, gas power plants are more competitive against carbon-intensive coal generation. As a result, more abatement takes place at lower carbon prices, and the lower end of the MAC curve shifts downward. Second, investments into RES power plants are less competitive to gas power plants, since gas generation becomes cheaper. As a result, the MAC curve becomes steeper at the upper end. For higher gas prices, the same effects hold true vice versa.

[51] Based on our stylized assumptions, demand adjustment is only a minor abatement measure. Whether it is more relevant in reality depends on the assumed elasticity.

The same reasoning holds with a variation of fuel prices in the short term. As there is no investment in the short term, the only effect is the altered margin of fuel switching (see Appendix D.3).

Interest Rates

Apart from fuel markets, the development of financial markets affects the shape of MAC curves. The interest rate reflects the general development of financial markets, i.e., the risk-free interest rate, and the risk premium accounting for sector-specific uncertainty. Figure 5.4 depicts long-term MAC curves for different interest rates on long-term MAC curves.

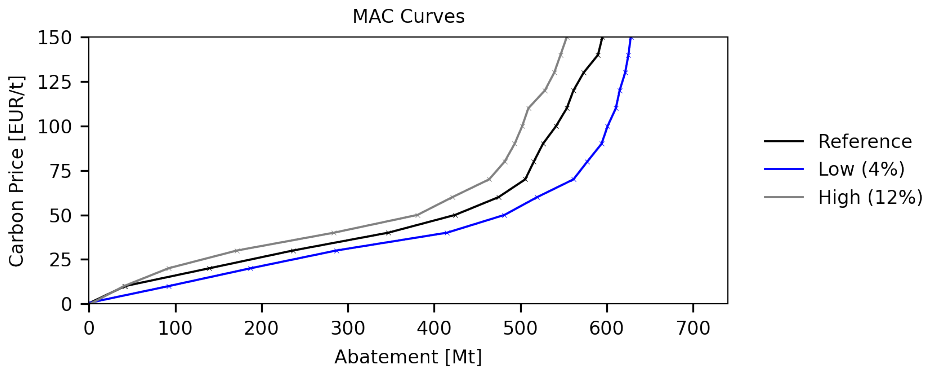


Figure 5.4.: Long-term MAC curves for different interest rates

Interest rates primarily affect the weighted costs of capital. The transformation of the power sector requires capital-intensive installations of RES power plants. With lower interest rates, RES becomes cheaper. As a result, the MAC curve is lower at all abatement levels. Since the lower part of the MAC is dominated by fuel-switching, the effect increases with abatement so that it mainly affects the end of MAC curves. A higher interest rate mirrors the effect of lower interest rates.

Technological Learning

Until now, we refrain from technological learning. However, new technologies exhibit possibilities to drive down investment costs or improve technological parameters such as efficiency. Figure 5.5 depicts the change in long-term MAC curves with projected technological learning of RES power plants. The respective cost assumptions can be found in Appendix D.2.

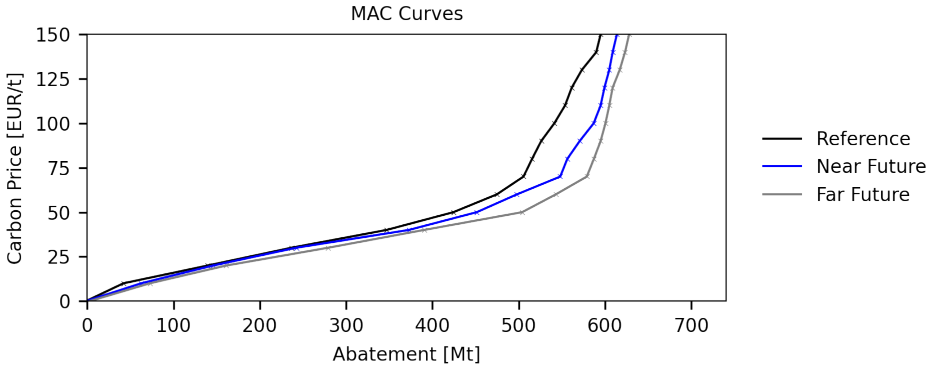


Figure 5.5.: Long-term MAC curves for different investment costs

The impact of technological learning is clear-cut: Lower investment costs drive down costs of RES generation. Hence, uncertainty about the future development of techno-economic properties mainly affects the upper part of MAC curves, i.e., beyond the potential of fuel-switching.

Beyond improvements of existing technologies, the cost development of so-called backstop technologies underlines this finding. These technologies are able to remove an arbitrarily large amount of emissions for a fixed price, the backstop price. In light of recent plans to establish a hydrogen economy, experts consider hydrogen-fueled gas turbines as a potential carbon-free and dispatch-able backstop technology in the power sector. In this case, the backstop price level is subject to future costs of hydrogen. The prevailing literature (e.g., Brändle et al. (2020)) projects costs of carbon-neutral hydrogen of roughly 1.5 to 3 EUR/kg. These prices equal about 45-90 EUR/MW_{th}, the marginal abatement costs to replace gas generation is thus approximately between 125 and 350 EUR/t compared to gas prices of 20 EUR/MW_{th}.[52]

Summing up, this case study of the European power sector reveals: first, MAC curves are convex. Their curvature depends on economic developments such as fuel prices and interest rates. Second, they flatten over time due to technological learning and investment restrictions.

5.4. Implications for the EU ETS

As pointed out in section 5.1, model-based analyses of the EU ETS typically assume static MAC curves. On the contrary, MAC curves are dynamic. They are only a snapshot in time so that they conceal dynamic interactions. Further, MAC curves flatten over time due to restrictions on investments and technological advancements. This section discusses the implications of these findings for the EU ETS.

[52]The (direct) marginal abatement costs reflect the difference in fuel prices between natural gas and hydrogen, divided by the emission factor of natural gas of about 0.2 t_{CO2}/MWt_{th}.

5.4.1. The Functioning of the EU ETS

The EU ETS is a cap-and-trade system, which requires firms to buy allowances to compensate for their emissions. By reducing the yearly supply of allowances to the market, the EU ETS enforces abatement. Firms are allowed to bank allowances for later use while borrowing allowances from future allocations is prohibited.

Firms choose their abatement so that they minimize abatement costs. In equilibrium, carbon prices equal MAC in a friction-less market. In line with the Hotelling rule (cf. Hotelling (1931)), the carbon price rises with the interest rate as long as firms hold a positive bank of allowances. If the aggregate private bank is empty, the price increases at a lower rate according to the yearly issued allowances. (cf. Bocklet et al. (2019))

In this idealized setting, the market determines an initial price, which reflects the discounted backstop costs and fully sets up a price path that sooner (lower initial price) or later (higher initial price) leads to an empty private bank. Market equilibrium paths, which consist of a sequence of price-emission tuples, solve the trade-off between low initial prices and a late point in time where allowances are scarce so that overall (discounted) abatement costs are minimal.

The implementation of the Market Stability Reserve and the Cancellation Mechanism poses additional restrictions on the banking of allowances. First, if banking volumes exceed a pre-defined level, the MSR absorbs allowances from the market. The allowances from the MSR enter the market when the bank falls below the reinjection threshold.[53] Second, the size of the MSR is limited. If the MSR exceeds the previous year's auction volume, the CM invalidates overhanging allowances. As a result of the MSR and the CM, banking decisions affect both the timing and the total volume of allowance supply. In particular, higher banking volumes increase cancellation volumes and thus reduce total emissions within the EU ETS.

5.4.2. Implications of Time-Dependent MAC Curves in the EU ETS

Section 5.3 reveals two properties of MAC curves, which should be considered in models of the EU ETS: MAC curves are convex and they flatten over time.

If the MAC curve is convex instead of linear, the MAC curve becomes steeper with higher abatement, which makes future abatement relatively more costly. Accordingly, firms bank more allowances to smooth the abatement in the steep upper part of the MAC curve. Due to the endogenous supply rules in the reformed EU ETS, a convex MAC curve causes higher banking volumes and more

[53] Allowances from the MSR enter the market in junks of 100 million allowances per year if the previous year's bank is below 400 million allowances.

cancellation compared to a linear MAC. Osorio et al. (2020) provides quantitative evidence by comparing the cancellation volumes of several articles. Modeling approaches that consider convex curvatures (e.g., Bruninx et al. (2018) and Beck and Kruse-Andersen (2018)), exhibit comparatively high cancellation volumes.

Along the same lines, models of the EU ETS usually assume the shape of the MAC curves to be time-independent, neglecting that short-term MAC curves are steeper due to investment restrictions and technological learning. As a result, abatement is more expensive in the short term and becomes cheaper over time. Figure 5.6 visualizes the stylized impact of a steeper short-term MAC curve on the price path in comparison to the assumption of the long-term MAC curve for all points in time.[54]

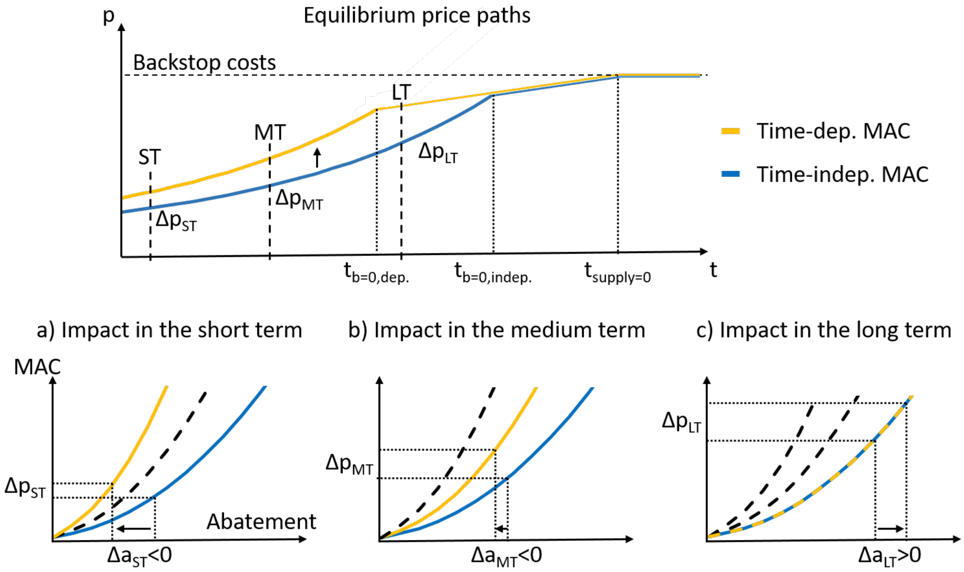


Figure 5.6.: Stylized impact of time-dependent MAC curves on the equilibrium price path and implications for abatement in the short (ST), medium (MT) and long term (LT)

Under perfect foresight, the whole price path is determined already in the first period. Backstop costs are obtained when the last allowance is issued ($t_{supply=0}$ in the upper part of Figure 5.6).[55] The quasi-linear price development after the bank is emptied ($t_{b=0,dep.}$ and $t_{b=0,indep.}$), depends on the allowance supply and the shape of long-term MAC curves.[56] Firms choose a sequence of price-emission

[54]This stylized analysis assumes that there is only one banking phase. If, for example, the flattening of MAC curves overcompensates the firms' interest rate, a second banking phase is economically rational.

[55]This holds true as long as backstop costs decrease slower than the firms' interest rate. In general, backstop costs only shift the price path as long as the rest of the MAC curve is kept constant (compare Bocklet et al. (2019)). Abatement and banking remain unaltered.

[56]After the private bank is empty, abatement decreases linearly with the allowance supply. Correspondingly, the price increases in accordance with the upper part of the MAC curve.

tuples that suffice the two fundamental rules, namely the price development with Hotelling until the bank is empty and the equivalence of MAC and carbon prices. Due to steeper short-term MAC curves (i.e., short-term abatement becomes more expensive), firms increase their short-term emissions, and thus, decrease banking volumes. At the same time, prices increase since the short-term MAC are higher even at the lower abatement level (see Figure 5.6a). In the medium term, the time-dependent MAC curve flattens and the difference in abatement decreases but abatement is still lower (see Figure 5.6b). As a result, the bank empties earlier ($t_{b=0,dep.} < t_{b=0,indep.}$). In the long term, firms need to increase their abatement with time-dependent MAC curves due to lower banking volumes (see Figure 5.6c). Summing up, with time-dependent MAC curves, the price level rises, and banking decreases in the short-term. Since cancellation volumes increase with short-term banking (see Herweg (2020)), the described effect increases total emissions due to lower cancellation volumes.

Beyond this theoretical analysis, myopia is considered important to understand the EU ETS market (compare Bocklet and Hintermayer (2020)). In a myopic setting, steep short-term MAC curves might be an additional driver of the price increase observed after the introduction of the MSR and the CM.

All in all, banking and cancellation volumes increase with convexity while flattening has the opposite effect. Accurate numerical models of the EU ETS should consider the shape and dynamic evolution of MAC curves to quantify the overall effects.

5.4.3. Approaches for Time-Dependent MAC Curves in EU ETS Models

In general, there are two approaches to account for the time-dependency of MAC curves: using exogenous but time-dependent MAC curves in EU ETS models or coupling of models for allowance demand and the EU ETS.

Exogenous dynamic MAC curves for the power sector can be derived via modeling, e.g., as described in Section 5.3. Deriving MAC curves for the energy-intensive industries - as the other large sector within the EU ETS - is more challenging, since industry processes are more heterogeneous and data availability is limited. Further, it is important to depict interactions between the sectors to account for the non-additivity of abatement measures. For example, the electrification of industry processes saves carbon in the industry sector but interacts with the MAC curves of the power sector. Feeding the derived time-dependent MAC curves into a model of the EU ETS improves the accuracy of the results. However, this approach neglects that MAC curves are interrelated, i.e., they are not a sequence of static curves but rather a family of curves, that depends on the carbon price path.

For considering interactions between the allowance demand and the EU ETS price path, it is worth to consider the coupling of an allowance demand-side model (covering the power sector and energy-intensive industries) and an EU ETS model. Via soft-coupling, the EU ETS model feeds the derived price paths to the allowance demand-side model, which then updates the MAC curves. By iterating these steps, a consistent model framework is set up if the model runs converge. Alternatively, the two models could be hard-coupled, i.e., a simultaneous equilibrium is calculated by an integrated approach. For example, the implementation as a mixed complementary problem (MCP) allows to derive a consistent solution with an endogenous depiction of allowance demand and the EU ETS market. Both variants of model-coupling open up possibilities to evaluate alternative EU ETS designs (e.g., the implementation of carbon price floors) or related environmental policies, such as electrification efforts.

5.5. Conclusion

Recent literature relies on MAC curves to analyze the design of the EU ETS as the key emission abatement instrument in Europe. While the assumptions on MAC curves drive the results, the literature on the shape of MAC curves within the scope of the EU ETS is scarce. Against this backdrop, this paper identifies implications of MAC curve properties for the EU ETS.

In a case study, we derive MAC curves for the European power sector. To this end, a partial equilibrium model is fed with carbon price paths to determine corresponding emission and abatement levels. We identify two fundamental properties of MAC curves of the European power sector: First, the shape of MAC curves is convex for all points in time. The curvature depends on economic developments, such as fuel prices and interest rates. Second, MAC curves flatten over time. In the short term, fuel-switching is the only abatement option and thus, the MAC curve is steep. With longer investment horizons, the degree of freedom for investment grows and enables the transformation of the capital stock. This additional abatement option flattens the MAC curve. Further, technological learning and demand adjustments lowers in particular the upper part of the MAC curve.

Idealized market equilibrium paths in the EU ETS consist of price-emission tuples that minimize overall abatement costs and comply with the allowance supply path. Emission decisions and thus market prices are a trade-off between emissions today and in the future. After introducing the Market Stability Reserve and the Cancellation Mechanism, the total allowance supply and thus total emissions decrease with banking volumes. With convex MAC curves, marginal abatement costs increase over time, which makes future abatement relatively more expensive compared to today's abatement. Thus, firms increase banking volumes compared to linear MAC curves. On the contrary, MAC curves flatten over time, which lowers the incentives for banking. Considering steeper MAC curves in the short term leads to a higher price path and an earlier depletion of the firms' bank. For quantifying these effects, the time-dependency of MAC curves should be depicted. A model of the allowance demand side could derive MAC curves, which are fed into a model of the EU ETS. Ideally, the allowance demand-side model is coupled with the EU ETS model to derive consistent equilibrium paths.

Beyond the power sector, MAC curves within energy-intensive industries should be analyzed to cover the whole scope of the EU ETS. Since MAC curves are only snapshots of a dynamic context, path dependencies and uncertainties are worth considering. In particular, the impact of global deep decarbonization and its implications for MAC curves are a subject of further research.

A. Supplementary Material for Chapter 2

A.1. Notation

Throughout the paper at hand, the notation presented in Table A.1 is used. To distinguish (exogenous) parameters and optimization variables, the latter are written in capital letters.

Table A.1.: Sets, parameters and variables

Sets		
$i \in I$		Electricity generation and storage technologies
$m, n \in M$		Markets
$l \in L$		Transmission Grid Lines
$c \in C$		Linear independent cycles of modelled grid
$y, y1 \in Y$		Years
$t \in T$		Representative timesteps
Parameters		
$d(y, t, m)$	[MWh]	Electricity demand
$avail(y, t, m, i)$	[-]	Availability of electricity generation technology
$linecap(y, m, n)$	[MW]	Available transmission capacity
$\beta(y)$	[-]	Discount factor
$\delta(y, i)$	[EUR/MW]	Annualized investment cost
$\sigma(i)$	[EUR/MW]	Fixed operation and maintenance cost
$\gamma(y, i)$	[EUR/MWh]	Variable generation cost
$cap_{add,min}(y, m, i)$	[MW]	Capacities under construction
$cap_{sub,min}(y, m, i)$	[MW]	Decommissioning of capacity due to lifetime or policy bans
$l(m, n)$	[-]	Relative transmission Losses
$\kappa(m, l)$	[-]	Incidence matrix
$\phi(l, c)$	[-]	Cycle matrix
Variables		
$CAP(y, m, i)$	[MW]	Electricity generation capacity
$GEN(y, t, m, i)$	[MWh]	Electricity generation
$CAP_{add}(y, m, i)$	[MW]	Investments in electricity generation capacity
$CAP_{sub}(y, m, i)$	[MW]	Decommissioning of electricity generation capacity
$TRADE(y, t, m, n)$	[MWh]	Electricity trade from m to n
$TRADE\_BAL(y, t, m)$	[MWh]	Net trade balance of m
$FLOW(y, t, l)$	[MWh]	Power flow along line l
TC	[EUR]	Total costs
$FC(y)$ / $VC(y)$	[EUR]	Yearly fixed or variable costs

A.2. Power Market Model

Basic Model

The central planner invests into new power plants and dispatches generation capacities such that the net present value of the variable (VC) and fixed costs (FC) is minimized, where β represents the discount factor.

The objective is hence:

$$min!\ TC = \sum_{y \in Y} \beta(y) \cdot [VC(y) + FC(y)]. \tag{A.1}$$

Installed electricity generation capacities (CAP) are modeled endogenously: The model invests in new generation capacities (CAP_{add}) and decommissions capacities (CAP_{sub}), which are not profitable. For a realistic depiction of European energy markets, existing as well as under construction capacities ($cap_{add,min}$) and decommissioning due to end-of-lifetime or technology bans ($cap_{sub,min}$) are given exogenously. These parameters serve as lower bounds for building or decommissioning capacities, respectively. The fixed costs per year comprise the annualized investment costs (δ) plus fixed operation and maintenance costs (σ) per installed capacity. The following equations describe these interrelations.

$$\begin{aligned}
CAP(y,m,i) &= CAP(y-1,m,i) + CAP_{add}(y,m,i) - CAP_{sub}(y,m,i) \\
CAP_{add}(y,m,i) &\geq cap_{add,min}(y,m,i) \\
CAP_{sub}(y,m,i) &\geq cap_{sub,min}(y,m,i) \\
&\forall y \in Y, \forall m \in M, \forall i \in I
\end{aligned}$$

$$\begin{aligned}
FC(y) = &\sum_{m \in M, i \in I} CAP(y,m,i) \cdot \sigma(i) \\
&+ \sum_{y1: y-y1 < econ_lifetime(i)} CAP_{add}(y1,m,i) \cdot \delta(y,i)
\end{aligned} \tag{A.2}$$

Electricity generation (GEN) in each market and timestep (t) has to level the (inelastic) demand (d) minus the trade balance ($TRADE\_BAL$), which depicts the net imports of trade flows ($TRADE$) from other markets. Availability of power plants ($avail \cdot CAP$), which, e.g., considers maintenance shutdowns limit their generation. Trade flows between markets are limited by interconnection capacities ($linecap$). Yearly total variable costs (VC) result from the generation per technology times the technology-specific variable operation costs (γ), which mainly comprise costs for burnt fuel and required CO_2 allowances.

$$\begin{aligned}
\sum_{i \in I} GEN(y,t,m,i) &= d(y,t,m) - TRADE_BAL(y,t,m) \\
GEN(y,t,m,i) &\leq avail(y,t,i) \cdot CAP(y,m,i) \\
TRADE_BAL(y,t,m) &= \sum_{n} (1 - l(n,m)) \cdot TRADE(y,t,n,m) - TRADE(y,t,m,n) \\
TRADE(y,t,m,n) &\leq linecap(y,m,n) \\
&\forall y \in Y, \forall m,n \in M \;\; \& \;\; m \neq n, \forall i \in I \\
VC(y) &= \sum_{m \in M, i \in I, t \in T} GEN(y,t,m,i) \cdot \gamma(y,i)
\end{aligned} \tag{A.3}$$

The presented equations constitute the backbone of SPIDER. Beyond that, the model features, e.g., constraints to depict the utilization of storage as well as constraints on energy potentials, e.g., for biomass.

Grid Modeling

Kirchhoff's current law is implemented directly via mapping active power injections in each market m (which equal the trade balance $TRADE\_BAL$) on line power flows ($FLOW$) via the incidence matrix $\kappa(m,l)$, i.e.:

$$\begin{aligned}
TRADE_BAL(y,t,m) &= \sum_{l \in L} \kappa(m,l) \cdot FLOW(y,t,l) \\
, \kappa(m,l) &= \begin{cases} 1 & \text{if line } l \text{ ends in bus } m, \\ -1 & \text{if line } l \text{ starts at bus m } m, \\ 0 & \text{else} \end{cases}
\end{aligned} \tag{A.4}$$

The transmission grid is assumed to be a directed graph. With $|L|$ representing the number of lines and $|N|$ the number of nodes, the graph is uniquely determined by $|C| = |L| - |N| - 1$ linear independent cycles. To fulfill Kirchhoff's voltage law, power flows ($FLOW$) times line reactances (x) along each of these cycles have to sum up to zero. Thereby, the model considers interactions of electricity generation and power flows endogenously. The cycle matrix ($\phi(l,c)$) assigns lines to the respective cycles.

$$\sum_{l \in L} \phi(l,c) \cdot x(y,l) \cdot FLOW(y,t,l) = 0$$
$$, \phi(l,c) = \begin{cases} 1 & \text{if line } l \text{ is element of cycle } c, \\ -1 & \text{if reversed line } l \text{ is element of cycle } c, \\ 0 & \text{else} \end{cases} \tag{A.5}$$
$$\forall c \in C, \forall y \in Y$$

Regional Scope: Germany's Transmission Network and Neighbors

Figure A.1 visualizes the regional scope. Within Germany, this paper considers a detailed depiction of the transmission network. Connections to neighbors are approximated via Net Trade Capacities (NTC).

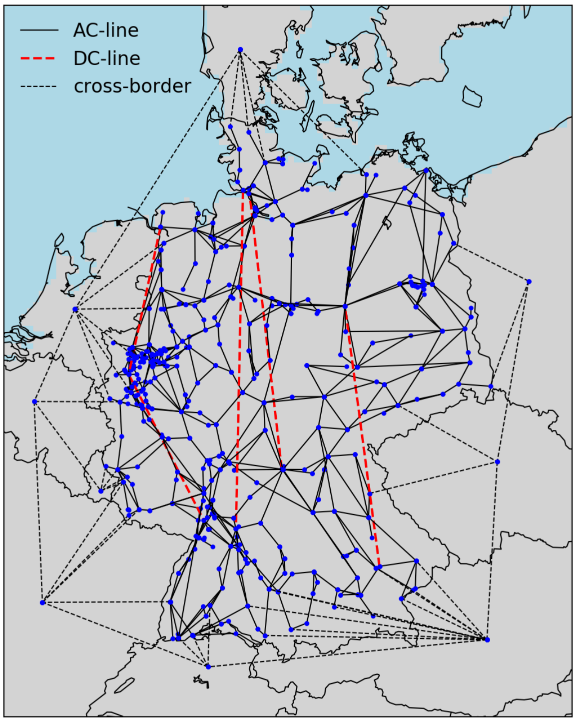


Figure A.1.: Regional scope and considered grid topology in 2030

A.3. Assumptions on Investment Costs, Demand and Fuel Prices

Table A.2.: Development of investment costs [EUR/kW] for onshore wind power plants based on The Boston Consulting Group and Prognos (2018)

Technology	2020	2025	2030
Wind Onshore	1200	1150	1100

Table A.3.: Considered technologies and their techno-economic parameters, assumptions based on scenario *Stated Policies* in World Energy Outlook 2019 (IEA, 2019) and (Knaut et al., 2016)

Technologies	Efficiency	Fixed Operation Costs (EUR/kW/a)
Nuclear	0.33	85
Lignite	0.4	45
Coal	0.45	45
Combined Cycle Gas Turbines (CCGT)	0.5	25
Open Cycle Gas Turbines (OCGT)	0.38	15
Oil	0.4	7
Biomass	0.3	150
PV	1	17
Wind Onshore	1	12
Wind Offshore	1	93
Hydro	1	11.5
Pumped Storage	0.78	11.5

Table A.4.: Development of fuel and carbon prices [EUR/MWh_{th}], based on scenario *Stated Policies* in World Energy Outlook 2019 (IEA, 2019)

Fuel	2019	2020	2025	2030
Uranium	3.0	3.0	3.0	3.0
Lignite	3.9	4.2	5.6	5.6
Coal	7.9	8.1	9.1	9.3
Natural Gas	13.6	15.2	23.2	23.2
Oil	33.1	34.7	42.3	45.9
Biomass	21.0	22.0	22.5	23.0
Carbon [EUR/tCO2]	24.9	26.2	35.5	38.8

Table A.5.: Development of demand [TWh], based on scenario *National Trends* in ENTSO-E (2020a) and *Scenario B* in 50Hertz et al. (2019)

Country	2019	2020	2025	2030
AT	67	69	77	79
BE	85	85	87	91
CH	62	62	62	61
CZ	63	65	73	78
DE	530	529	528	544
DK	35	38	52	46
FR	456	463	496	486
NL	114	114	114	119
PL	156	160	181	182

A.4. Trade Flows

The modeled trade flows underlie three simplifications which are necessary to keep the model tractable: First, the age structure of national power plants fleets is not considered. Second, interconnectors are depicted as NTC constraints without power flow restrictions. Third, other countries than German neighbours are not in the scope of this paper. Due to these shortcomings, the derived trade flows are not realistic. The derived patterns among the three scenarios, however, shed light on the impact of market design on electricity trade between Germany and its neighbours. Figure A.2 visualizes German net imports in the years 2020 and 2030.

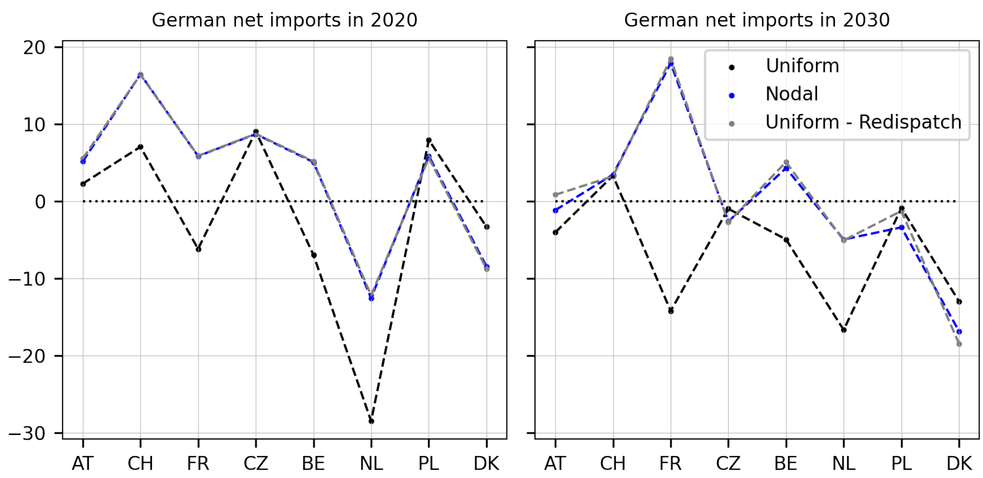


Figure A.2.: Trade between Germany and its neighbour countries in 2020 and 2030

In general, uniform prices trigger higher exports in all directions. Nodal prices incentivize, in particular in Southern and Western Germany, higher imports while exports to Denmark increase. The difference in trade between nodal and uniform prices can be observed best at the example of France. Instead of significant net export under uniform pricing, optimal dispatch under nodal pricing requires high net imports in 2030.

A.5. North-German Federal States

Figure A.3 visualizes the three most Northern federal states of Germany.

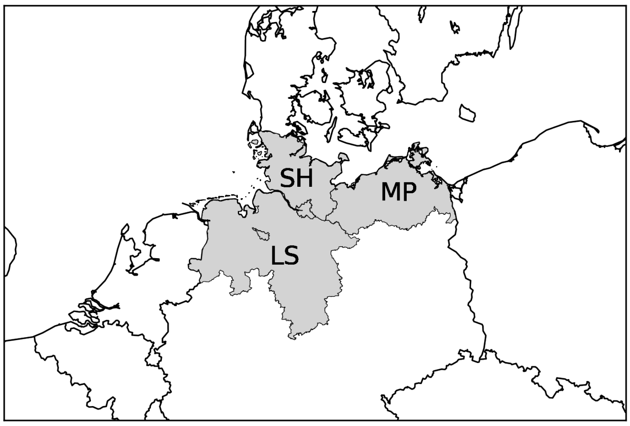


Figure A.3.: The area of the federal states of Mecklenburg-Western Pomerania (MP), Schleswig-Holstein (SH) and Lower Saxony (LS)

A.6. Price times series at exemplary Nodes

Nodal prices differ between nodes if grid bottlenecks occur. To give an idea of the drivers and the structure of nodal prices, Figure A.4 shows the hourly nodal electricity prices and the hourly residual load within the 12 type days at three exemplary nodes, one each in the north, west and south of Germany.

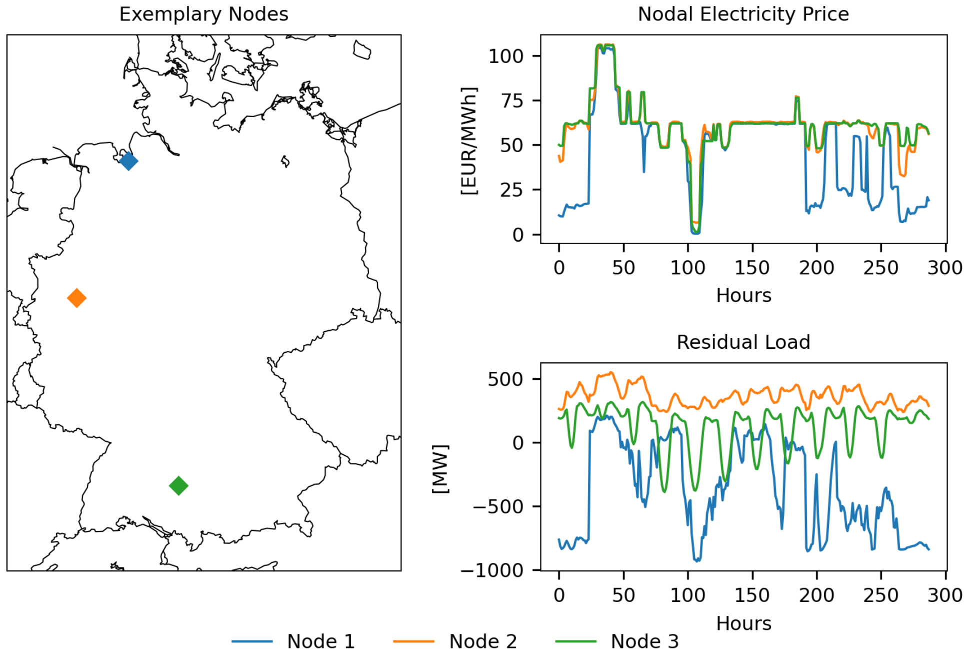


Figure A.4.: Location, hourly nodal electricity prices and hourly residual load of three exemplary nodes

Among the three exemplary nodes, average nodal electricity prices are lowest at *node 1* in the North of Germany. While the installed wind power capacities at *node 1* are large, demand is relatively low. Thus, the residual load becomes negative in hours with high wind availability. If grid bottlenecks occur in these windy periods, the nodal price at **node 1** drops below the nodal prices of *node 2* and *node 3*, e.g., on the first day. If the grid is not congested, prices are the same at all nodes, e.g., between the hours 120 and 180. Nodal prices at *node 2* and *node 3* are mostly equally high. *Node 2* lies Western Germany, where high load prevails. The node has the highest residual load of the exemplary nodes, as electricity demand is relatively high and electricity generation from wind and PV power plants is low. Electricity demand at *node 3* is low while electricity feed-in from photovoltaics is high. Due to the location in Southern Germany, which is rather poorly connected, *node 3* exhibits the highest average nodal prices.

B. Supplementary Material for Chapter 3

B.1. Notation

Throughout the paper at hand, the notation presented in table B.1 is used. To distinguish (exogenous) parameters and optimization variables, the latter are written in capital letters.

Table B.1.: Sets, parameters and variables

Sets		
$i \in I$		Electricity generation and storage technologies
$m, n \in M$		Markets
$l \in L$		Transmission Grid Lines
$c \in C$		Linear independent cycles of modeled grid
$y, y1 \in Y$		Years
$d \in D$		Representative Days
$h \in H$		Hours
Parameters		
$demand(y, d, h, m)$	[MWh]	Electricity demand
$avail(y, d, h, m, i)$	[-]	Availability of technology
$eff(i, m)$	[-]	Efficiency of technology
$linecap(y, m, n)$	[MW]	Available transmission capacity
$\beta(y)$	[-]	Discount factor
$\delta(y, i)$	[EUR/MW]	Annualized investment cost
$\sigma(i)$	[EUR/MW]	Fixed operation and maintenance cost
$\gamma(y, i)$	[EUR/MWh]	Variable generation cost
$cap_{add,min}(y, m, i)$	[MW]	Capacities under construction
$cap_{sub,min}(y, m, i)$	[MW]	Decommissioning of capacity due to lifetime or policy bans
$l(m, n)$	[-]	Relative transmission Losses
$\kappa(m, l)$	[-]	Incidence matrix
$\phi(l, c)$	[-]	Cycle matrix
Variables		
$CAP(y, m, i)$	[MW]	Electricity generation capacity
$GEN(y, d, h, m, i)$	[MWh]	Electricity generation
$CAP_{add}(y, m, i)$	[MW]	Investments in electricity generation capacity
$CAP_{sub}(y, m, i)$	[MW]	Decommissioning of electricity generation capacity
$TRADE(y, d, h, m, n)$	[MWh]	Electricity trade from m to n
$TRADE\_BAL(y, d, h, m)$	[MWh]	Net trade balance of m
$FLOW(y, d, h, l)$	[MWh]	Power flow along line l
TC	[EUR]	Total costs
$FC(y)$ / $VC(y)$	[EUR]	Yearly fixed or variable costs

B.2. Power market model

Basic model

The central planner invests into new power plants and dispatches generation capacities such that the net present value of the variable (VC) and fixed costs (FC) is minimized, where β represents the discount factor.

The objective is hence:

$$min!\ TC = \sum_{y \in Y} \beta(y) \cdot [VC(y) + FC(y)].$$

Installed electricity generation capacities (CAP) are modeled endogenously: The model invests in new generation capacities (CAP_{add}) and decommissions capacities (CAP_{sub}), which are not profitable. For a realistic depiction of European energy markets, existing as well as under construction capacities ($cap_{add,min}$) and decommissioning due to end-of-lifetime or technology bans ($cap_{sub,min}$) are given exogenously. These parameters serve as lower bounds for building or decommissioning capacities, respectively. The fixed costs per year comprise the annualized investment costs (δ) plus fixed operation and maintenance costs (σ) per installed capacity. The following equations describe these interrelations.

$$\begin{aligned}
CAP(y,m,i) &= CAP(y-1,m,i) + CAP_{add}(y,m,i) - CAP_{sub}(y,m,i) \\
CAP_{add}(y,m,i) &\geq cap_{add,min}(y,m,i) \\
CAP_{sub}(y,m,i) &\geq cap_{sub,min}(y,m,i) \\
&\forall y \in Y, \forall m \in M, \forall i \in I
\end{aligned}$$

$$\begin{aligned}
FC(y) = &\sum_{m \in M, i \in I} CAP(y,m,i) \cdot \sigma(i) \\
&+ \sum_{\substack{y1: y-y1 \\ < econ_lifetime(i)}} CAP_{add}(y1,m,i) \cdot \delta(y,i)
\end{aligned}$$

Electricity generation (GEN) in each market, day (d) and hour (h) has to level the (inelastic) *demand* minus the trade balance ($TRADE\_BAL$), which depicts the net imports of trade flows ($TRADE$) from other markets. Availability of power plants ($avail \cdot CAP$), which, e.g., considers maintenance shutdowns limit their generation. Trade flows between markets are limited by interconnection capacities (*linecap*). Yearly total variable costs (VC) result from the generation per technology times the technology-specific variable operation costs (γ), which mainly comprise costs for burnt fuel and required CO_2 allowances.

$$
\begin{aligned}
\sum_{i \in I} GEN(y,d,h,m,i) &= demand(y,d,h,m) - TRADE\_BAL(y,d,h,m) \\
GEN(y,d,h,m,i) &\leq avail(y,d,h,i) \cdot CAP(y,m,i) \\
TRADE\_BAL(y,d,h,m) &= \sum_{n} (1 - l(n,m)) \cdot TRADE(y,d,h,n,m) \\
&\quad - TRADE(y,d,h,m,n) \\
TRADE(y,d,h,m,n) &\leq linecap(y,m,n) \\
&\forall y \in Y, \forall m,n \in M \;\; \& \;\; m \neq n, \forall i \in I \\
VC(y) &= \sum_{\substack{m \in M, i \in I, \\ d \in D, h \in H}} GEN(y,d,h,m,i) \cdot \gamma(y,i)
\end{aligned}
$$

Storage equations

The charging level of storage ($STORLEVEL$) is determined by the level in the previous time step and the net-balance of electricity charged and withdrawn. The level cannot exceed the storage volume which is given by the installed capacity and an exogenous ratio of capacity and volume (vol_factor).

$$
\begin{aligned}
STOR\_LEVEL(y,d,h,m,i) &= STOR\_LEVEL(y,t-1,m,i) \\
&- eff(m,i)\cdot GEN(y,d,h,m,i) \\
&+ eff(i,m)\cdot GEN(y,d,h,i,m) \\
STOR\_LEVEL(y,d,h,m,i) &\leq STOR\_VOL \\
STOR\_VOL &= avail(y,d,h,i)\cdot vol\_factor(i)\cdot CAP(y,m,i) \\
&\forall y \in Y, \forall d \in D, h \in H, \forall m \in M, \forall i \in I_{Storage}
\end{aligned}
$$

The amount of energy which can be shifted between typedays (DAY_SALDO) is limited according to the number of days that a typeday represents (d_rep). The total of the energy shifted by storage must add up to zero.

$$
\begin{aligned}
DAY\_SALDO(y,d,m,i) &= \sum_{h\in H}(GEN(y,d,h,i,m) \\
&\quad - GEN(y,d,h,m,i)) \\
DAY\_SALDO(y,d,m,i)\cdot d\_rep(d) &\leq STOR\_VOL(y,m,i) \\
DAY\_SALDO(y,d,m,i)\cdot d\_rep(t) &\geq -STOR\_VOL(y,m,i) \\
\sum_{d\in D} DAY\_SALDO(y,d,m,i) &= 0 \\
&\forall y \in Y, \forall d \in D, \forall m \in M, \forall i \in I_{Storage}
\end{aligned}
$$

B.3. Assumptions on technologies, demand and fuel prices

Table B.2.: Considered technologies and their generation efficiency, assumptions based on scenario *Stated Policies* in World Energy Outlook 2021 (IEA, 2021) and Knaut et al. (2016)

Technologies	Efficiency
Nuclear	0.33
Lignite	0.4
Coal	0.45
Combined Cycle Gas Turbines (CCGT)	0.5
Open Cycle Gas Turbines (OCGT)	0.38
Oil	0.4
Biomass	0.3
PV	1
Wind Onshore	1
Wind Offshore	1
Hydro	1
Pumped Storage	0.78
Battery Storage	0.95

Table B.3.: Development of fuel and carbon prices [EUR/MWh_{th}], based on scenario *Net Zero Emissions* in World Energy Outlook 2022 (IEA, 2022)

Fuel	2019	2030
Uranium	3.0	3.0
Lignite	3.9	4.0
Coal	7.9	7.7
Natural Gas	13.6	25.9
Oil	33.1	44.9
Biomass	21.0	23.0
Carbon [EUR/tCO2]	24.9	95.0

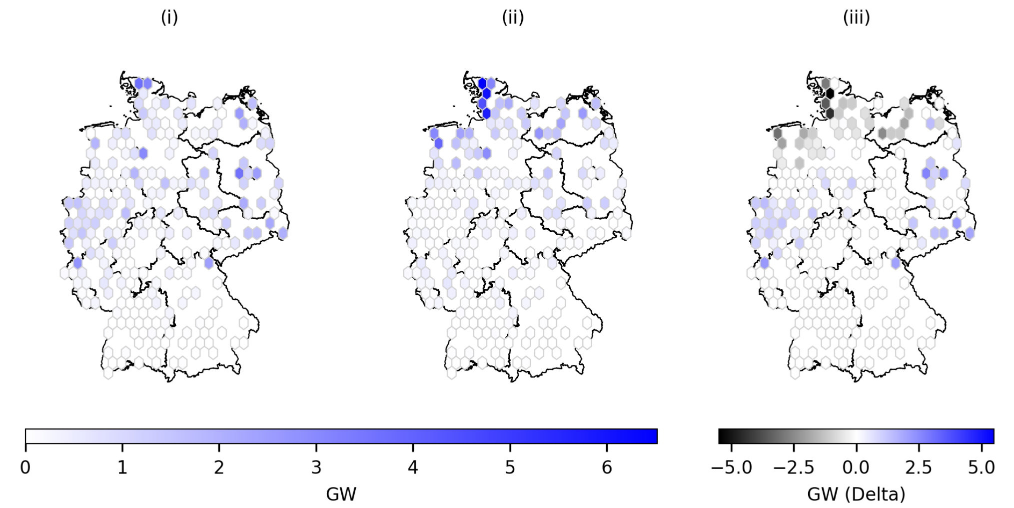
Table B.4.: Development of demand [TWh], for Germany based on BMWK (2022a) and for all other countries on scenario *National Trends* in ENTSO-E (2020a)

Country	2019	2025	2030
AT	67	77	79
BE	85	87	91
CH	62	62	61
CZ	63	73	78
DE	524	600	715
DK	35	52	46
FR	456	496	486
NL	114	114	119
PL	156	181	182

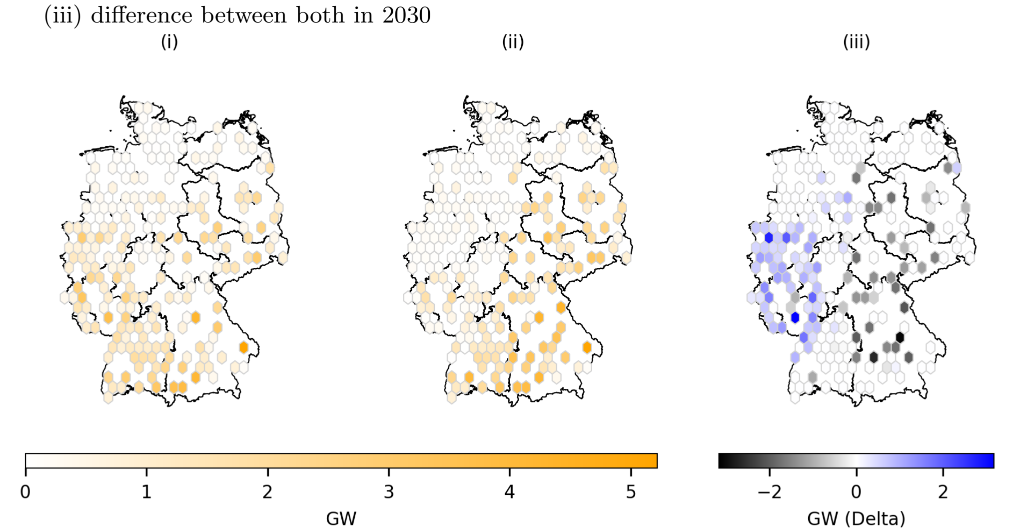
B.4. Additional results and sensitivity analyses

Renewable allocation

Solar and wind power allocation is primarily driven by the consideration of transmission capacity. In the nodal setting, grid constraints are considered when siting new capacity. However, in the uniform case, investment decisions depend mainly on resource quality and, to a lesser extent, on feed-in patterns and resulting balancing effects. As a result, wind and solar capacity are distributed more broadly and closer to demand under the nodal setup. At the same time, it is concentrated at sites with high resource quality in the uniform setting. Figures B.1a and B.1b compare the spatial distribution of wind and solar capacity in both cases. Total capacity is exogenous for both settings and reflects Germany's 2030 capacity targets.



(a) Spatial distribution of wind capacity expansion in the (i) nodal and (ii) uniform setting and (iii) difference between both in 2030



(b) Spatial distribution of solar capacity expansion in the (i) nodal and (ii) uniform setting and (iii) difference between both in 2030

Figure B.1.: Spatial distribution of wind and solar capacity expansion in the nodal and uniform setting

In the nodal setting, wind capacity peaks in the very north of the country, where resource quality is high. The rest of the capacity is widely distributed above the 50th parallel. Solar capacity is relatively evenly distributed below the 52nd parallel, despite higher resource quality in the south of Germany. All in all, significant shares of wind and solar capacities are allocated close to the demand centers in western Germany.

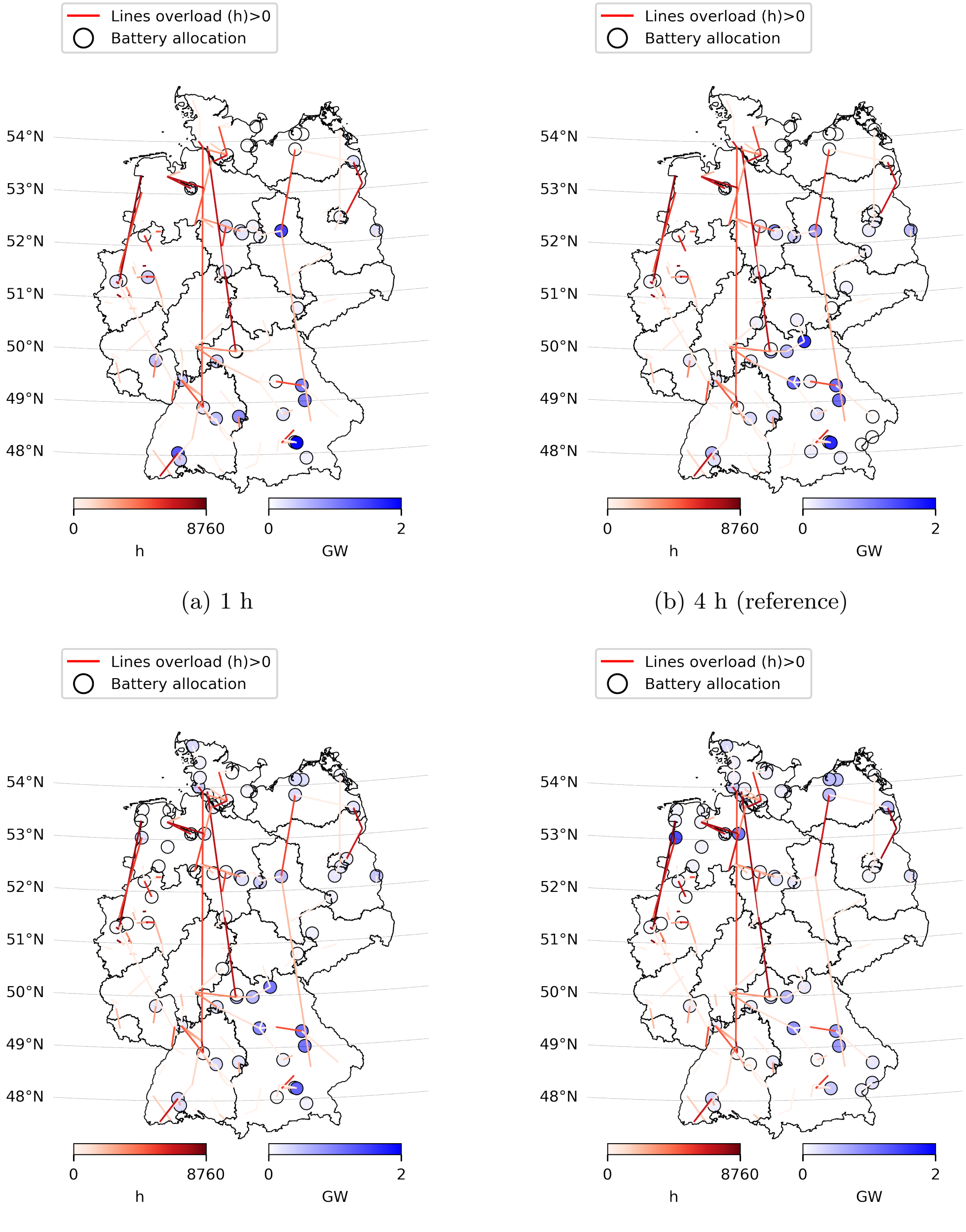
In the uniform setting, investment in wind power concentrates above the 53rd parallel. Solar capacity concentrates in Germany's south and east, with the majority of capacity installed below the 50th parallel. The lack of coordination of renewable feed-in and grid bottlenecks under the uniform setup leads to high curtailment. This especially affects wind power, which is separated from demand by a structural north-south grid bottleneck. In total, 109 TWh of renewable electricity are curtailed under the uniform setup in 2030, compared to only 30 TWh under the nodal setup.

Volume factor

Figure B.2 shows variations of the volume factor, i.e., the ratio between connected power (GW) and the energy volume (GWh) of a storage technology. Low volume factors correspond to battery storage, while higher factors can be seen for technologies using a different energy carrier for storage, e.g,. hydrogen. Storage allocation depends significantly on the volume factor. For higher volume factors (¿4h), storage moves northwards and closer to wind generation. Here, they buffer volatile wind generation and increase utilization of the congested lines along the structural grid bottleneck. However, even for higher volume factors, significant capacities are allocated in the south of Germany. Even when volume factors are above 100h and the majority of storage is located above the 52nd parallel, storage is needed to buffer volatile PV infeed in the south.

Battery capacity

Figure B.3 shows sensitivity analyses for the total installed capacity of batteries for a given distribution of wind and solar generation according to the nodal setting. The allocation of batteries close to grid bottlenecks along the 53rd parallel as well as in the south of Germany is robust. In the case of 15 and more GW of batteries, saturation in those areas leads to an allocation in the north, close to wind generation centers. The sensitivity analyses, therefore, highlights again the role of batteries in balancing short-term volatility from demand and solar feed-in time series as opposed to wind generation that requires longer storage of electricity.



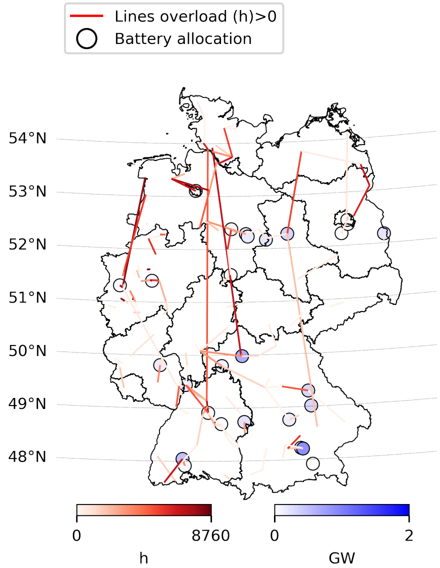
(a) 1 h

(b) 4 h (reference)

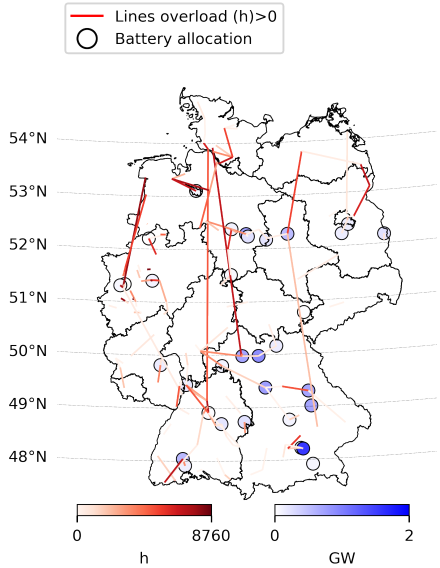
(c) 50 h

(d) 200 h

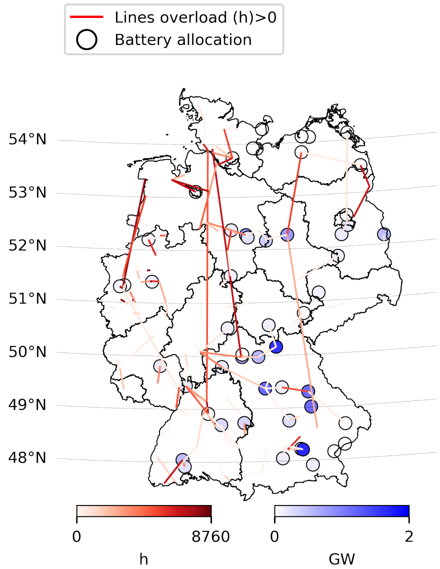
Figure B.2.: Optimal battery allocation based on the distribution of wind and solar in the uniform setting for different battery volume factors



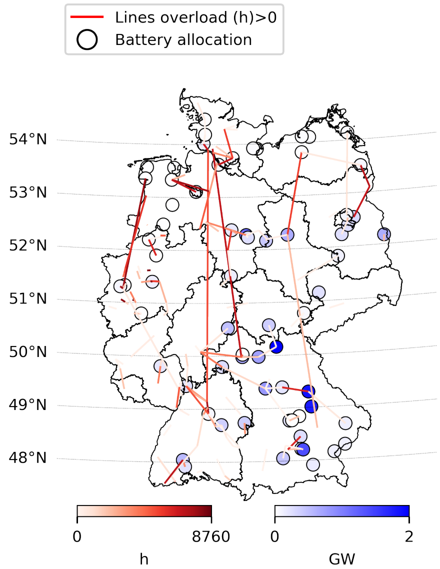
(a) 5 GW



(b) 10 GW



(c) 15 GW (reference)



(d) 20 GW

Figure B.3.: Optimal battery allocation based on the distribution of wind and solar in the uniform setting for different battery capacities

C. Supplementary Material for Chapter 4

C.1. Notation

Throughout the paper at hand, the notation presented in table C.1 is used. To distinguish (exogenous) parameters and optimization variables, the latter are written in capital letters.

Table C.1.: Sets, parameters and variables

Sets		
$i \in I$, $j \in J$		Electricity generation and consumption technologies
$z \in Z$		Zones
$n \in N$		Nodes
$l \in L$		Transmission Grid Lines
$t \in T$		Timesteps
Parameters		
$f^{max}(l)$	[MW]	Line capacity
$ram(t,l)$	[MW]	Remaining Available Maring (RAM)
$f^{ref}(t,l)$	[MW]	Reference flow in base case
$frm(l)$	[MW]	Flow Reliability Margin (FRM)
$fav(l)$	[MW]	Final Adjustment Value (FAV)
$nPTDF(t,z,l)$	[-]	nodal Power Transfer Distribution Factor
$zPTDF(t,z,l)$	[-]	zonal Power Transfer Distribution Factor
$gsk(t,n,z)$	[-]	Distribution of zonal generation among nodes
$\gamma(t,i)$	[EUR/MWh]	Variable generation cost
$\kappa(m,l)$	[-]	Incidence matrix
Variables		
$GEN(t,z,i)$ / $CONS(t,z,j)$	[MWh]	Electricity generation / consumption
$SALDO(t,z)$	[MWh]	Net position of zone z
$FLOW(t,l)$	[MWh]	Power flow along line l
$VC(y)$	[EUR]	Variable costs

C.2. Assumptions on technologies, fuel prices and demand

Table C.2.: Considered technologies and their generation efficiency, assumptions based on scenario *Stated Policies* in World Energy Outlook 2021 (IEA, 2022) and Knaut et al. (2016)

Technologies	Efficiency
Nuclear	0.33
Lignite	0.4
Coal	0.45
Combined Cycle Gas Turbines (CCGT)	0.5
Open Cycle Gas Turbines (OCGT)	0.38
Oil	0.4
Biomass	0.3
PV	1
Wind Onshore	1
Wind Offshore	1
Hydro	1
Pumped Storage	0.78
Battery Storage	0.95

Table C.3.: Assumptions on fuel and carbon prices [EUR/MWh_{th}], based on scenario *Stated Policies* in World Energy Outlook 2022 (IEA, 2022)

Fuel	2021	2025	2030	2035
Uranium	5.5	5.5	5.5	5.5
Lignite	4.5	4.5	5.0	5.0
Coal	15.3	11.5	7.7	7.8
Natural Gas	28.8	27.3	25.8	26.3
Oil	37.7	41.2	44.8	46.5
Biomass	20.0	21.0	22.0	23.0
Carbon [EUR/tCO2]	54.0	90.0	100.0	110.0

Table C.4.: Development of demand [TWh], for Germany based on scenario *Global Ambition* in ENTSO-E and ENTSOG (2022)

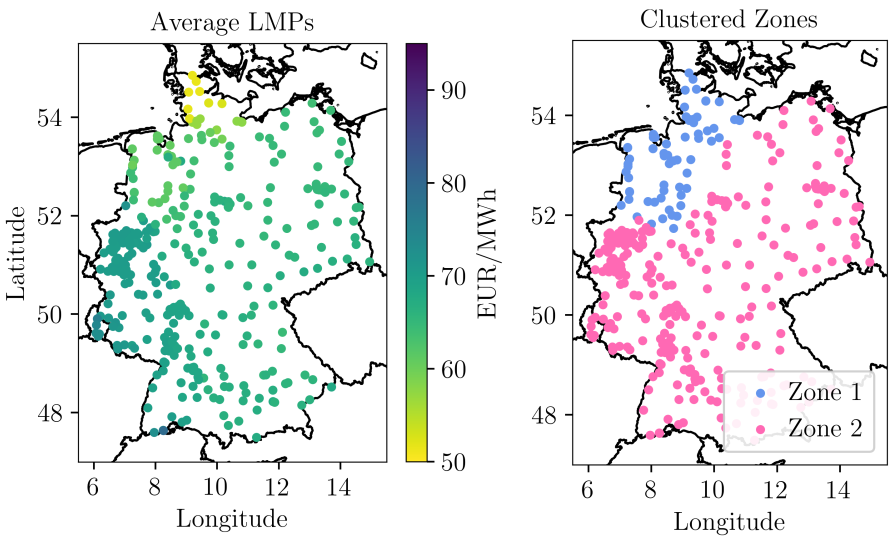
Country	2021	2025	2030	2035
AT	70	78	85	91
BE	88	95	103	108
CH	62	62	62	65
CZ	66	65	65	68
DE	531	592	652	686
DK	35	42	49	52
FR	482	502	523	547
HU	47	46	45	47
HR	19	18	17	17
IT	320	319	317	335
LU	7	7	8	9
NL	119	145	171	182
NO	122	122	122	122
PL	167	169	171	178
SE	142	143	144	148
SI	14	15	15	16
SK	28	30	32	33

C.3. Additional results

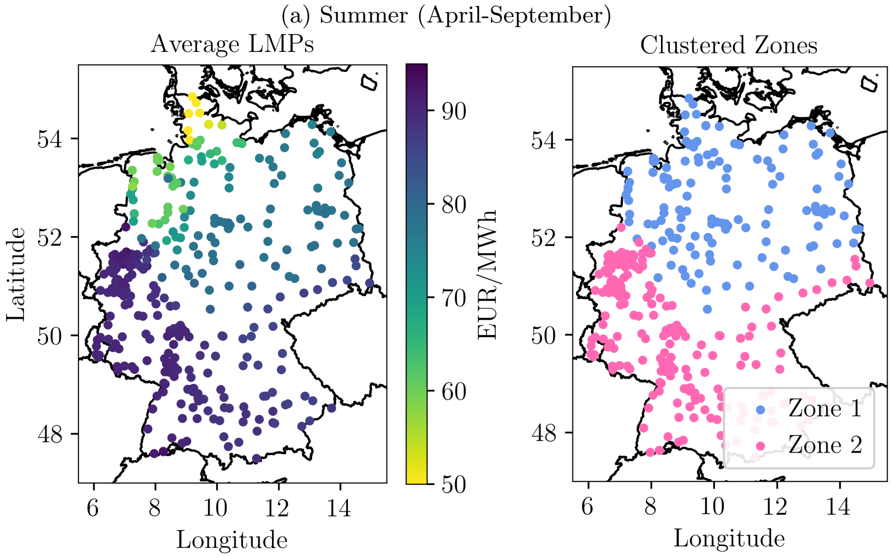
Season-specific bidding zone configuration

Changing the bidding zone configuration depending on the time of year could further reduce redispatch costs without increasing uncertainty. This would be particularly beneficial if the structural congestion shifts significantly throughout the year due to different seasonal renewable generation and load patterns. Figure C.1 shows an example of a season-specific split resulting from the separate clustering of the summer and winter season LMP time series for the scenario year 2030.

During the summer season, average LMPs are lower due to higher solar generation and lower electricity demand. In addition, wind generation is lower, especially at greater distances from the North Sea coast. As a result, the low-price summer bidding zone is a smaller area close to the North Sea. In contrast, the winter configuration is the same as that identified for the entire year (see figure 4.3 in section 4.4.2). This is because the regional differences in LMPs are higher in the winter months.



(a) Summer (April-September)



(b) Winter (October-March)

Figure C.1.: Season-specific split for the scenario year 2030

Discounting in the clustering of a stable split

In this paper, a discount rate of 0% is assumed for clustering the stable bidding zone split across multiple scenario years, as it simplifies the comparison of the split's impact between scenario years. Considering a discount rate weighs the present higher than the future and thus, the resulting bidding zone configuration changes. For example, a discount rate of 3% would result in a 4.6% (16 nodes) larger northern bidding zone, equivalent to the year-specific one of the year 2025 (see figure C.2).

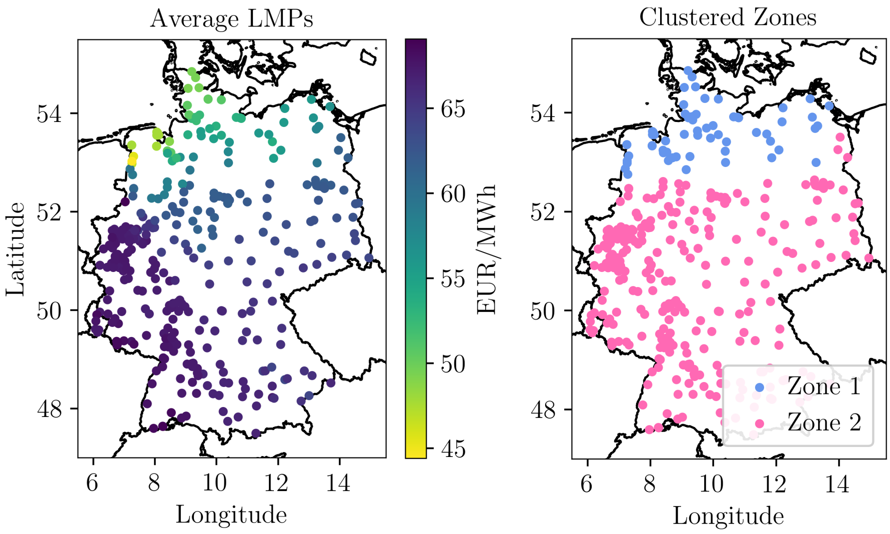


Figure C.2.: Spatial distribution of average LMPs across all scenario years (left) and resulting bidding zone split (right) when applying a discount rate of 3% in the clustering

D. Supplementary Material for Chapter 5

D.1. The Power Market Model DIMENSION

Table D.1 presents the notation used within this paper. Capitalized terms represent endogenous decision variables. Lowercase terms denote exogenous parameters.

Table D.1.: Sets, parameters and variables

Sets		
$i \in I$		Electricity generation and storage technologies
$m, n \in M$		Countries
$y \in Y$		Years
$t \in T$		Representative time steps
Parameters		
$d(y,t,m)$	[MWh]	Electricity demand
r	[-]	Discount rate
$avail(y,t,m,i)$	[-]	Availability of electr. generation
$ntc(y,m,n)$	[MW]	Net transmission capacity
$\eta(i)$	[MWh/MWh_th]	Generation efficiency
$\delta(y,i)$	[EUR/MW]	Annualized investment cost
$\sigma(i)$	[EUR/MW]	Fixed operation and maintenance cost
$\gamma(y,i)$	[EUR/MWh]	Variable fuel cost
$\tau(y)$	[EUR/tCO2eq]	Carbon price
$\nu(i)$	[tCO2eq/MWh_th]	Fuel-specific emission factor
$cap_{add,min}(y,m,i)$	[MW]	Existing or under construction capacity
$cap_{sub,min}(y,m,i)$	[MW]	Decommissioning due to lifetime or policy
$l(m,n)$	[-]	Relative transmission losses
Variables		
$CAP(y,m,i)$	[MW]	Electricity generation capacity
$GEN(y,t,m,i)$	[MWh]	Electricity generation
$EM(y,t,m,i)$	[tCO2eq]	Emissions
$CAP_{add}(y,m,i)$	[MW]	Investments in electr. generation capacity
$CAP_{sub}(y,m,i)$	[MW]	Decommissioning of electr. generation capacity
$TRADE(y,t,m,n)$	[MWh]	Trade flow of electr. from m to n
TC	[EUR]	Total costs
$FC(y)$	[EUR]	Invest and fixed operation & maintenance costs
$VC(y)$	[EUR]	Variable generation costs

The central planner minimizes total discounted costs for serving the electricity demand. Consequently, she decides on the investment in capacity and the dispatch of power plants. The total discounted costs consist of fixed (FC) and variable (VC) costs, i.e.,

$$TC = \sum_{y \in Y} (1+r)^{-(y-y_0)} \cdot [FC(y) + VC(y)], \tag{D.1}$$

where the fixed costs per year comprise the annualized investment costs and the fixed operation and maintenance costs for installed capacity. The variable costs embody generation-dependent costs, namely for fuel and emission allowances.The installed capacity of electricity generators develops endogenously according to equation D.2.

For a realistic depiction of European energy markets, equations D.3 and D.4 account for existing as well as under construction capacities ($cap_{add,min}$) and decommissioning due to end-of-lifetime or technology bans ($cap_{sub,min}$). Equation D.5 formally defines the fixed costs.

$$CAP(y,m,i) = CAP(y-1,m,i) + CAP_{add}(y,m,i) + CAP_{sub}(y,m,i) \tag{D.2}$$

$$CAP_{add}(y,m,i) \geq cap_{add,min}(y,m,i) \tag{D.3}$$

$$CAP_{sub}(y,m,i) \geq cap_{sub,min}(y,m,i) \tag{D.4}$$

$$\begin{aligned} FC(y) = & \sum_{\substack{\tilde{y}: \\ y-\tilde{y}<lifetime(i)}} CAP_{add}(\tilde{y},m,i) \cdot \delta(\tilde{y},i) \\ & + \sum_{m \in M, i \in I} CAP(y,m,i) \cdot \sigma(i) \end{aligned} \tag{D.5}$$

Further, technical constraints restrict the dispatch of installed capacities. First, for every time step, electricity generation has to balance the inelastic demand adjusted by the trade flows from and to neighboring countries (Equation D.6). Second, electricity generation of each technology and in each time step is bound by the available capacity (Equation D.7). The availability factor accounts for maintenance shutdowns of conventional power plants or the infeed profile of renewable energy. The trade flows are restricted by the net transfer capacities between countries and have to be symmetric, i.e., exports from m to n are imports from n to m (Equations D.8 and D.9). Variable costs comprise fuel costs and costs for emissions (Equation D.10). The former is calculated as the product of generation per technology and the technology-specific variable fuel costs. The latter is the product of the carbon price and realized emissions which are calculated through the fuel input and the fuel-specific emission factor (Equation D.11).

$$\sum_{i\in I} GEN(y,t,m,i) = d(y,t,m) + \sum_{n\neq m}(1-l(m,n))\cdot[TRADE(y,t,m,n) - TRADE(y,t,n,m)] \tag{D.6}$$

$$GEN(y,t,m,i) \leq avail(y,t,i)\cdot CAP(y,m,i) \tag{D.7}$$

$$TRADE(y,t,m,n) \leq ntc(y,m,n) \tag{D.8}$$

$$TRADE(y,t,m,n) = -TRADE(y,t,n,m) \tag{D.9}$$

$$\forall y\in Y, m,n\in M,\ i\in I$$

$$VC(y) = \sum_{m\in M, i\in I}\sum_{t\in T}[GEN(y,t,m,i)\cdot\gamma(y,i) + EM(y,t,m,i)\cdot\tau(y)] \tag{D.10}$$

$$EM(y,t,m,i) = GEN(y,t,m,i)\cdot\frac{\nu(i)}{\eta(i)} \tag{D.11}$$

The presented equations constitute the core functionality of DIMENSION: The objective function in equation D.1 is minimized over the feasible region, which is defined by the constraints D.2-D.11.

Moreover, the model incorporates features such as ramping and storage constraints as well as area restrictions for RES. For a thorough introduction of DIMENSION and its characteristics, the reader is referred to Richter (2011).

D.2. Numerical Assumptions

Table D.2.: Technological learning regarding investment costs [EUR/kW], based on the World Energy Outlook 2019 (IEA (2019))

Technology	Status quo	Near Future	Far Future
Wind Onshore	1580	1503	1430
Wind Offshore	3985	3038	2600
PV (roof)	883	688	580
PV (base)	750	585	480
OCGT	412	412	412
CCGT	900	900	900

Table D.3.: Considered technologies and their techno-economic characteristics based on Knaut et al. (2016) and Peter (2019)

Technologies	Efficiency	Fixed Operation Costs (EUR/kWa)
Nuclear	0.33	101 - 105
Lignite	0.32 - 0.46	45 - 60
Coal	0.37 - 0.46	40 - 60
CCGT	0.39 - 0.60	24 -30
OCGT	0.28 - 0.40	12 - 17
Oil	0.4	7
Biomass	0.3	120
PV	1	15 - 17
Wind Onshore	1	13
Wind Offshore	1	93
Hydro	1	11.5
Pumped Storage	0.76	11.5

Table D.4.: Assumptions on fuel prices [EUR/MWh$_{th}$]

Fuel	Price
Uranium	3
Lignite	3
Coal	10
Natural Gas	20
Oil	33

Table D.5.: Assumed electricity demand per country [TWh], based on 2019 levels according to ENTSO-E (2020b)

Country	Demand	Country	Demand
AT	67	IE	29
BE	85	IT	307
BG	32	LT	12
CH	62	LV	7
CZ	63	NL	114
DE	530	NO	128
DK	35	PL	156
EE	8	PT	49
ES	248	RO	52
FI	86	SE	132
FR	456	SI	14
GR	51	SK	28
HR	17	UK	263
HU	41		

D.3. Impact of Fuel Prices on Short-term MAC Curves

Figure D.1 depicts the impact of different gas prices (10, 20 or 30 EUR/MWh$_{\mathrm{th}}$) on short-term MAC curves, i.e., if no investments are possible.

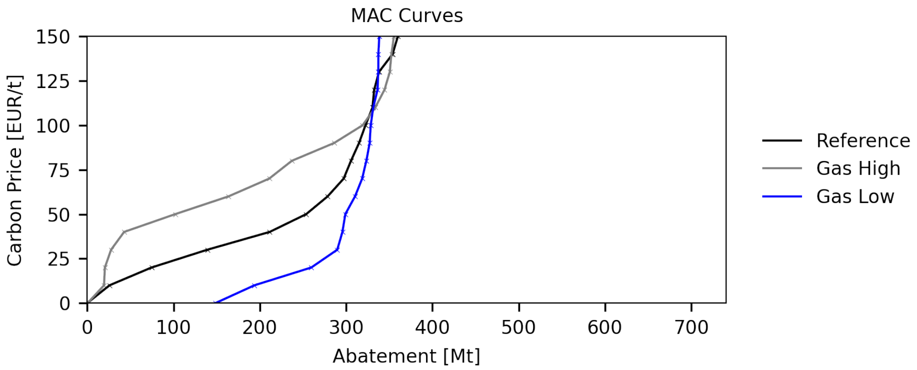


Figure D.1.: Short-term MAC curves for different coal/gas price spreads

The lower part of the MAC curve reflects the margin between coal and gas prices. Under lower gas prices, modern gas power plants replace inefficient coal generation even without a carbon price signal. Higher gas prices have the opposite effect. Only below 10 EUR/t, higher gas prices do not impact fuel switching as the margin between coal and gas is not closed by such low carbon prices. The upper part of the MAC curve is similar since the fuel-switching potential is reached independently of the gas price. Only minor shifts in the dispatch of, e.g., biomass affect the MAC curve.

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Curriculum Vitae

CURRICULUM VITAE

Jonas Zinke

PERSONAL DATA

Date of Birth	8th March 1993
Place of Birth	Berlin
Nationality	German

RESEARCH INTERESTS

Market Design, Electricity Markets, Energy System Modeling

EDUCATION

since 10/2018	**Institute of Energy Economics (EWI)** and **Department of Economics, University of Cologne** Doctoral Candidate in Economics
10/2016 - 09/2018	**RWTH Aachen University** Master of Science in Business Administration & Engineering: Electrical Power
08/2015 - 12/2015	**Pohang University of Science and Technology, South Korea** Study abroad
10/2012 - 09/2016	**RWTH Aachen University** Bachelor of Science in Business Administration & Engineering: Electrical Power
06/2009	**Amos-Comenius-Gymnasium, Bonn** Maturity/Abitur

WORKING EXPERIENCE

since 02/2024	**E.ON SE** Manager Strategic Market Analysis
10/2018 - 01/2024	**Institute of Energy Economics at the University of Cologne (EWI)** Research Associate
09/2021 - 12/2021, 07/2022 and 09/2022 - 10/2022	**IEA - International Energy Agency, Paris** Consultant
10/2017 - 01/2018	**PwC - PricewaterhouseCoopers GmbH WPG, Düsseldorf** Internship
07/2016 - 09/2017	**Institute for High Voltage Technologies, RWTH Aachen University** Student Assistant
04/2015 - 07/2015	**SAG GmbH (today part of SPIE Group), Langen** Internship

LANGUAGES

German	Mother tongue
English	Proficient
Spanish	Basic

PUBLICATIONS

Articles in Peer-Reviewed Journals:

- Schmidt, L. and Zinke, J. (2023). One Price Fits All? On Inefficient Siting Incentives for Wind Power Expansion in Germany under Uniform Pricing. *The Energy Journal* Vol. 44, DOI: 10.5547/01956574.44.4.lsch.

Working Papers:

- J. Zinke (2023). Two prices fix all? On the Robustness of a German Bidding Zone Split. *EWI Working Paper* 23/07.
- B. Czock, A. Sitzmann, J. Zinke (2023). The place beyond the lines – efficient storage allocation in a spatially unbalanced power system with a high share of renewables. *EWI Working Paper* 23/01.
- L. Schmidt, J. Zinke (2020). One price fits all? − Wind power expansion under uniform and nodal pricing in Germany. *EWI Working Paper* 20/06.
- M. Hintermayer, L. Schmidt and J. Zinke (2020). On the time-dependency of MAC curves and its implications for the EU ETS. *EWI Working Paper* 20/08.

Further Publications:

- C. Fernández Alvarez, J. Zinke, A. Lilienkamp (2022), Coal 2022 (2022), *Report on behalf of the International Energy Agency (IEA).*
- C. Fernández Alvarez, J. Zinke (2022), Coal Market Update, *Report on behalf of the International Energy Agency (IEA).*
- M. Gierkink, E. Cam, H. Diers, J. Keutz, J. Kopp, A. Lilienkamp, M. Moritz, M. Wiedmann, J. Zinke (2022), Szenarien für die Preisentwicklung von Energieträgern, *Study on behalf of the academy project "Energy Systems of the Future" (ESYS).*
- C. Fernández Alvarez, F. Arnold, J. Zinke (2021), Coal 2021 (2021), *Report on behalf of the International Energy Agency (IEA).*
- M. Gierkink, Wagner, Berit Hanna Czock, A. Lilienkamp, M. Moritz, l. Pickert, T. Sprenger, J. Zinke, F. Fiedler (2021), dena-Leitstudie Aufbruch Klimaneutralität, *Study on behalf of the German Energy Agency (dena).*
- O. Hennes, S. Jeddi, R. Madlener, H. Schmitz, J. Wagner, S. Wolff, J. Zinke (2021), Auswirkungen von CO2-Preisen auf den Gebäude-, Verkehrs- und Energiesektor (*Implications of CO2-Pricing on the Buildings, Mobility and Energy Sector.*), *Zeitschrift für Energiewirtschaft*, Vol. 45 (3).
- E. Künle, J. Zinke, A. Lilienkamp, N. Namockel (2020), Auswirkungen von Kälteperioden auf die Spitzenlast im nordwesteuropäischen Stromsystem in 2030 (*Impact of cold spells on peak load in the Northwest European power system in 2030.*), *et – Energiewirtschaftliche Tagesfragen*, Vol. 70 (12), pp. 52-54.
- P. Abiven, M. Blondel, M. Taoufiki, E. Künle, J. Zinke, A. Lilienkamp, N. Namockel (2020), 2030 Peak Power Demand in North-West Europe, *Study on behalf of ENGIE.*

PRESENTATIONS AND TALKS

- The place beyond the lines - efficient storage allocation in a spatially unbalanced power system with a high share of renewables. *16th YEEES Workshop.* May 2021. Ghent, Belgium.
- One price fits all? Wind power expansion under uniform and nodal pricing in Germany. *16th International Ruhr Energy Conference.* September 2020. Online.
- One price fits all? Wind power expansion under uniform and nodal pricing in Germany. (accepted but postponed due to COVID-19). *16th IAEE International Conference.* June 2020. Paris, France.

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"Hiermit versichere ich an Eides Statt, dass ich die vorgelegte Arbeit selbstständig und ohne die Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe. Die aus anderen Quellen direkt oder indirekt übernommenen Aussagen, Daten und Konzepte sind unter Angabe der Quelle gekennzeichnet. Bei der Auswahl und Auswertung folgenden Materials haben mir dienac hstehend aufgeführten Personen in der jeweils beschriebenen Weise entgeltlich/unentgeltlich (zutreffendes unterstreichen) geholfen:

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Düsseldorf, 17.01.2024

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