Transmission Congestion Management in Electricity Grids

Designing Markets and Mechanisms

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LIST OF ABBREVIATIONS

ABCE	Agent Based Computational Economics
AC	Alternating Current
ANN	Artificial Neural Network
BNetzA	Bundesnetzagentur
CR	Concentration Ratio
DC	Direct Current
DSO	Distribution System Operator
EC	European Commission
EEG	Erneuerbare Energien Gesetz (Renewable Energy Sources Act)
EPEX	European Power Exchange
EU	European Union
EV	Electric Vehicle
Extra-Tree	Extremely Randomized Tree
FTR	Financial Transmission Right
GDP	Gross Domestic Product
HHI	Herfindahl-Hirschmann Index
Inc-dec game	Increase-decrease game
ISO	Independent System Operator
MOP	German Mobility Panel
MRR	Must-Run-Ratio
OTC	Over-the-Counter
PSI	Pivotal Supplier Index
PV	Photovoltaics
ReLu	Rectified Linear Unit
RMSE	Root Mean Squared Error
RSI	Residual Supply Index
SO	System Operator
SOC	State of Charge
TSO	Transmission System Operator
V2G	Vehicle-to-grid

Part I.

Fundamentals

CHAPTER 1

INTRODUCTION

Limiting climate change and thus the reduction of greenhouse gas emissions is one of the greatest and most important challenges of our generation. However, the transition to more sustainable power systems comes with a variety of obstacles such as the integration of regionally clustered, intermittent renewable power generation. The long lead times of transmission grid expansion as well as the occurrence of generation spikes can cause temporal grid congestion that needs to be managed to ensure system stability (Stoft, 2002). Uniform-price electricity markets as operated in Germany and most European countries are cleared without consideration of physical constraints. If the resulting flows exceed the thermal limits of transmission lines, congestion management measures have to be performed (Nüßler, 2012). In Germany, these measures are costly and increase carbon emissions (Staudt et al., 2018c). Thus, they jeopardize the environmental success of the energy transition and the additional system costs have a negative impact on its acceptance (Joos and Staffell, 2018). Furthermore, the related, necessary grid expansions are met with great public opposition (Devine-Wright, 2013). It is therefore of utmost importance to develop new methods for congestion management and to adapt existing methods to the specifics of uniform-price electricity markets with a high share of renewables. Through these methods the inherent short- and long-term welfare loss caused by congestion needs to be efficiently reduced. This dissertation proposes, evaluates and discusses different measures for congestion management and thereby supports the integration of intermittent renewable generation into the electricity system.

1.1. Motivation

The cost for congestion management in the German electricity grid is increasing and has been at a record high of 1.4 billion Euros in 2017 while it has been below 250 million Euro per year until 2014 and even well below 100 million Euro per year until 2011 (Bundesnetzagentur, 2018b). The German government expects these costs to rise to 4 billion Euro in 2023 (Bundesregierung, 2016). The increase is partly caused by the growth in renewable generation capacity (Steinbach, 2013). This capacity can be quickly constructed and the grid is often not prepared for the increased infeed (Hitaj, 2015). For instance, the total wind generation capacity has grown by about 107% from 2010 to 2017 to a total of 56 Gigawatt (GW) and solar generation capacity has increased by 139% to a total of 43 GW in the same period (Bundesnetzagentur, 2017a). Additionally, renewable generation capacity often occurs in clusters. Typically, wind generation capacity is developed in the North of Germany and photovoltaics (PV) capacity in the South (Trepper et al., 2015). However, while these technologies might cause congestion, they are also the backbone of the German energy transition, which is an important cornerstone in the government's strategy towards a decarbonization of the economy (Lauber and Jacobsson, 2016). But, the increasing congestion in the German electricity grids does not only harm the efforts to reduce carbon emissions. The costs also threaten the public support of the energy transition as a whole (Joos and Staffell, 2018).

Grid congestion occurs when the electricity flow on a certain power line exceeds the thermal limit of that line. As electricity cannot be directed over particular lines but flows according to Kirchhoff's laws, the input and output of the grid must be managed correspondingly (Stoft, 2002). A line overload can lead to the destruction of that particular line, which might cause a breakdown of the entire system. To avoid an overload, different actions can be taken. In Germany, the electricity market is cleared centrally and uniformly. That means that the power plant dispatch is determined through an auction process regardless of transmission grid constraints (Trepper et al., 2015). The last dispatched power plant determines the market clearing price (Sensfuß et al., 2008). After the auction, the transmission system operators (TSO) determine whether the market result is feasible. If this is not the case, they instruct individual power plants to refrain from generating. To ensure the balance in the power grid, other power plants are instructed to increase their generation. This process is called redispatch for conventional (Nüßler, 2012) and feed-in management for renewable generation (Schermeyer et al., 2018). It is the main origin of congestion management costs in Germany as the generator that refrains from generating and the generator who has to increase its production are both compensated (German Association of Energy and Water Industries (bdew), 2018).

Most uniform-price electricity markets employ a redispatch mechanism (Nüßler, 2012). This mechanism creates costs and has major consequences for the emissions of the overall energy system (Staudt et al., 2018c). With sufficient knowledge of the individual redispatch deployment, generators can act strategically to optimally schedule their generation within this mechanism. This ability depends on the certainty, with which they can anticipate congestion and the associated redispatch (Hirth and Schlecht, 2018). To evaluate the ability of anticipating redispatch deployment and congestion, forecast models based on artificial neural networks (ANN) and tree-based approaches are developed in this dissertation. Furthermore, strategies that make use of these forecasts are described. The results show that for certain power plants, redispatch can be forecasted day-ahead with a high degree of certainty (see Chapter 4).

The German redispatch mechanism is cost-based. This means that generators only receive their operating costs if they are redispatched and no market premium that would incentivize investors to expand local generation or storage capacity. One major weakness of this mechanism is therefore that it does not provide regional investment signals. This diminishes the long-term efficiency of the mechanism in reducing congestion because it does not incentivize structural changes such as, e.g., the construction of generation or storage capacity (De Vries and Hakvoort, 2002). Recently, the European Commission (EC) has passed legislation that calls to replace the cost-based redispatch with a market-based mechanism (European Commission, 2016). In such a market-based design, generators would place bids on a congestion market platform (Hirth and Glismann, 2018) that could be owned and operated by the four German TSOs as for the ancillary services market (Ocker and Ehrhart, 2017b). Rather than just compensating power plants by their costs, such a market could send price signals for the regional expansion of generation capacity. It also increases the danger of regional market power (Gan and Bourcier, 2002). This is especially true when specific congestion states of the grid can be forecasted that allow operators to derive the necessity of their generation capacity for the operation of congestion management (Hirth and Schlecht, 2018). This knowledge can be used to game the market which would in turn increase the congestion and the cost for its management (see Chapter 5). The design also creates market power potential that can lead to increased power prices for industry and households (Hirth and Schlecht, 2018). Two forecasting models are developed based on previously introduced model families and benchmarked to quantify the possible quality of a congestion forecast in an electricity system that is strongly penetrated with intermittent renewable generation. The results allow to trace the causes of congestion in the German transmission grid and show that the introduction of a market-based mechanism can only succeed if the emerging regional markets are sufficiently competitive (see Chapter 5).

The degree of competition that is necessary to prevent the abuse of market power is hard to determine (Borenstein et al., 1999). Traditional concentration measures based on generation capacity shares need to be adapted to include renewable capacity. It cannot be considered in the same way as conventional capacity since the generation is intermittent and somewhat independent of the capacity (Koschker and Möst, 2016). This raises the question to which extent competition is necessary in a market with a high share of renewables to ensure competitive prices (Gan and Bourcier, 2002). To find the necessary competition, an analysis tool is developed and validated through a case study that simulates a market area with varying numbers of generation agents. The tool allows to evaluate the composition of a group of supply agents with regard to the expected competitive behavior in a limited regional market (see Chapter 6).

Furthermore, new technologies and approaches based on the digitalization of the energy system are evaluated concerning their ability of increasing competition. Information and communication technology are used to connect more resources within the grid and to improve the overall system efficiency. Such a digitalized energy system is introduced as the *Smart Grid* by Farhangi (2010). It includes the use of electric vehicles (EV) as active grid resources through vehicle-to-grid (V2G) technology (Kempton and Tomić, 2005). The expected increasing market penetration of EVs is a challenge for the electricity system but it can also be a blessing if EVs are used in a coordinated manner (Staudt et al., 2018b). To this end, a mechanism is developed and embedded in a simulation of an abstracted version of the German transmission system. The mechanism is intended to reduce the necessary redispatch using V2G technology. EVs are used as a buffer for the congested electricity system and thereby reduce the need for curtailment. It is shown how EVs can support the management of transmission grid congestion (see Chapter 7).

While an improvement to the current congestion management can be achieved through a reform of the redispatch mechanism, it only cures short-term congestion and does not support the elimination of systematic long-term congestion. Short-term congestion is caused by current wind patterns, the solar radiation, the overall generation mix and the current demand pattern. Long-term congestion is a systematic mismatch of available regional generation and storage capacity, the regional differences in demand and the existing transmission grid capacity. In this dissertation, two measures are considered to achieve an overall reduction of long-term congestion: Grid expansions and regional market incentives for the development of cheap generation or storage capacity in load pockets.

As a uniform-price electricity market does not compensate for a specific location, power plants are usually constructed where they can be operated cheaply (Leuthold et al., 2008) and renewable capacity is installed where the ambient conditions are most promising (Pechan, 2017). Grid expansions, on the other hand, are still highly regulated, take a long time to be constructed and public acceptance is low (Mester et al., 2017). Furthermore, the efficiency of reducing congestion through grid expansion is not benchmarked against the cost of short-term alternatives such as redispatch (Kemfert et al., 2016). However, such short-term alternatives are needed if grid expansions have not yet been completed and they might even be an economic long-term solution in times of rare renewable generation spikes. Furthermore, the current regulation incentivizes grid expansion for TSOs over other alternatives (Brunekreeft et al., 2014) as the construction and operation costs are compensated based on a revenue-cap regulation with guaranteed interest on equity (Matschoss et al., 2019). Furthermore, the public opposition against grid infrastructure development is growing (Reusswig et al., 2016), often caused by the "not-in-my-backyard" effect (Komendantova and Battaglini, 2016). Both, the risk of public opposition and of ultimately unnecessary expansion can be transferred to private investors through an innovative market design by compensating an investment in transmission grid capacity based on the avoided redispatch costs in the system. To show how a liberalization could be enabled, a market design for transmission grid expansion is developed. This design results in a welfare optimal system (see Chapter 8).

Another option of avoiding systematic grid congestion in the long-run is the construction of generation and storage capacity in load pockets. Chapter 9 introduces a market design that internalizes congestion into the market clearing and sends regional investment signals through spatially differentiated price signals. This is especially important as the construction of renewable infrastructure can quickly change the nature of grid congestion (Hitaj, 2015).
Congestion has always been a concern in countries where transmission infrastructure is traditionally less developed than in Germany as in the United States. Many of these countries have implemented locational marginal pricing, which differentiates prices over the system nodes based on the congestion state and sends investment signals based on regional scarcity for the regional development of generation and storage capacity (Ott, 2003). Such a design requires a central operator and restricts competition and therefore market freedom (Wu and Varaiya, 1999).
The European electricity market is organized as a so-called zonal market. Grid congestion within the zones is assumed to be minimal and only congestion between zone borders is explicitly considered. This design has grown from the national organization of power systems in European countries such that zone boundaries are often national borders (Kunz, 2018). It has been successful as long as national electricity grids were adapted to the generation portfolio of the particular country.

However, congestion is an increasing problem not only in Germany but also in Europe (Göransson et al., 2014).
For various reasons, it is difficult to implement locational marginal pricing in Europe with the most notable drawback that a supranational institution would have to integrate European Union (EU) member markets but also, for example Switzerland and Norway (Schmitz and Weber, 2013). Another difficulty is the German commitment to a single price zone (Korte and Gawel, 2018). However, less restricted alternatives exist that still allow for explicit consideration of transmission grid constraints (Qin et al., 2017). A driver towards the implementation of such designs is emerging EU regulation. The EC has threatened to divide the national bidding zones if the interconnector capacity between nation states is not sufficiently made available (Bundesregierung, 2018a). However, these designs remain largely untested for effects on welfare distribution and the possibility of exercising market power. Therefore, an electricity market design is introduced in Chapter 9 that takes grid constraints explicitly into account and results in regionally differentiated prices that reflect congestion and send regional investment signals. The design is based on the idea that an optimal dispatch can be achieved with minimal supervision by a system operator. To find the effects of such a design on the welfare distribution and the potential of exercising market power, a simulation study using self-learning agents is performed on various grid topologies. The results show that the design performs equally well as other more restrictive designs and can be an option to reduce congestion in the European electricity system while preserving more market freedom than other market designs.

Overall, this dissertation provides new solutions to transmission congestion management, both, in the short- and in the long-run while especially considering the intermittent nature of renewable generation. In practice, congestion always reduces the global welfare, as the optimal generation schedule cannot be realized. The presented approaches are intended to reduce this welfare loss efficiently. The results of this dissertation can be used to combine different measures for congestion management and to introduce new regulation that ensure the success of the energy transition.

1.2. Research Questions and Outline

The research outline of this thesis is defined along the necessary changes in regulation: First, the current redispatch regulation is evaluated. Then, currently discussed changes of the redispatch mechanism are analyzed and possible weaknesses are addressed. Finally, new market design options are introduced that go beyond the current regulation.
Therefore, the first two research questions relate to redispatch, the current congestion management mechanism in Germany. This mechanism has different implications for the overall market design. The possibility of taking advantage of the mechanism as a generator highly depends on their ability to anticipate the individual deployment of power plants in the redispatch mechanism (Staudt et al., 2018c). Therefore, the initial research question refers to the dependence of redispatch deployment on observable electricity market indices.

Research Question 1 *How accurate can generators anticipate their redispatch deployment under the current German congestion management regulation?*

The answer to this question is supplemented by a critical evaluation of possible generator strategies within the current redispatch mechanism design.
The German cost-based redispatch mechanism does not provide regional investment incentives. Therefore, it has been argued that the mechanism should be reformed and a market-based redispatch should be implemented to increase its long-term effectiveness. This is currently passed as legislation by the EC (European Commission, 2016). As redispatch is a local measure, it can easily provoke regional market power. This is especially important if congestion can be anticipated in the form of regional load and generation pockets (Hirth and Schlecht, 2018). The possibility of implementing such a market-based redispatch mechanism is investigated with the second research question.

Research Question 2 *To what extent can transmission line congestion be identified day-ahead in the German transmission grid?*

To demonstrate gaming opportunities of a consecutive redispatch market, an analytical model is introduced. Using this model, the associated risks of speculating on

higher redispatch prices are derived and discussed.
Redispatch is by definition a spatial phenomenon. Local load and generation patterns and the resulting load flows cause grid congestion and therefore the need for redispatch. As previously discussed, market-based redispatch but also other local congestion management mechanisms can only be introduced if local competition is sufficiently high. However, it is difficult to determine the exact level of competition necessary for competitive behavior, especially in the presence of a relatively high and growing share of renewable generation capacity (Koschker and Möst, 2016). Therefore, the third research question abstracts from the global market perspective and considers a local setup of demand and supply to find the necessary level of competition on electricity markets.

Research Question 3 *What is the influence of the composition of the group of regional electricity supply agents on the possibility to exercise market power in physically limited markets?*

This question needs to be answered for individual regions to support the introduction of market-based redispatch. Therefore, a tool is developed that finds the non-competitive price markup that can be expected. The tool is validated on a case study assuming a disconnected local residential electricity market.
The answer to the previous question still entails the traditional paradigm of electricity markets where suppliers meet the consumer demand, ideally at minimal cost while the consumer demand is largely inelastic (Weidlich and Veit, 2008a). However, with the smart grid and decreasing costs of electrical storage, new solutions to congestion management become available. One possible solution is the application of V2G technology and to use EVs as an active grid resource. Research question 4 considers the possibility of avoiding transmission grid congestion through EVs.

Research Question 4 *How much of the current German transmission grid congestion can be avoided using V2G technology with varying numbers of EVs?*

In this context, EVs can serve as a virtual storage and thus as a buffer to the transmission system and cure congestion without costs for redispatch and feed-in management. Furthermore, they can be seen as another resource in the congestion management market and therefore increase the competition.

The presented approaches are short-term solutions to manage congestion. One way of reducing systematic long-term transmission grid congestion is grid expansion. Currently, the process of expanding the transmission grid is highly regulated and its performance is not evaluated. Furthermore, TSOs are not incentivized to consider short-term congestion management as an alternative to long-term grid expansion (Kemfert et al., 2016; Brunekreeft et al., 2014). It is therefore unclear how much transmission grid expansion is welfare optimal. This is especially important in a public environment in which grid expansions are rejected by an increasing number of citizens (Galvin, 2018). Grid expansions can be evaluated by using the optimal grid expansion under a nodal pricing market design as a benchmark. As nodal pricing leads to the short-term welfare optimal market result (Green, 2007), the corresponding optimized grid expansion leads to a long-term optimization of welfare assuming a static set of generation capacity (Sauma and Oren, 2007). Therefore, the possibility of introducing a market mechanism that incentivizes welfare optimal transmission grid expansion is investigated with research question 5. The assumptions for this welfare optimality are discussed in Chapter 8.

Research Question 5 *Does a mechanism that incentivizes grid expansion through redispatch compensation lead to a welfare optimal transmission grid?*

Finally, all previously introduced mechanisms rely on a correction of the market results by an operator to ensure grid stability using redispatch. With regard to a welfare optimizing development of the electricity system, this is not a satisfying approach as it does not sufficiently send regional investment signals. It is however possible to ensure a feasible market solution at market clearing, avoiding the need for ex-post corrections. With more intermittent generation and a stronger interconnection of European electricity markets, congestion might become an even more pronounced problem (Linnemann et al., 2011). Some researchers argue that in the long-run, locational components in market designs might become unavoidable (Richstein et al., 2018). With the final research question, the market design of Multilateral Locational Pricing is introduced and evaluated. It allows for an elimination of explicit congestion management costs without relying on a central Independent System Operator (ISO) and sends long-term investment signals for regional generation and storage capacity development. It is benchmarked against a nodal pricing approach.

This leads to the final research question.

Research Question 6 *What is the effect of Multilateral Locational Pricing on welfare and market power in contrast to nodal pricing?*

The question is answered using self-learning computational agents that act under the two different market designs with various underlying grid topologies. The agents represent generators, while the demand is assumed to be inelastic. The agents compete for the demand and adapt their ask prices based on the feedback they receive in the market. Furthermore, the implementability and the usefulness of the approach in a future comprehensive congestion management strategy are discussed.

1.3. Thesis Structure

The structure of this thesis is oriented along the major areas of its contributions: The analysis of the redispatch mechanism, the assessment and increase of regional competition for congestion management and the design of markets for the reduction of long-term systematic grid congestion (see Fig. 1.1). Additionally, an introduction into the German electricity system and different congestion management mechanisms is provided in the first part and the overall findings are concluded in the end.

In Part I, the foundations are laid to provide an extensive understanding of the following chapters. An overview of power system economics is given in Chapter 2 with a focus on the current regulation along the electricity value chain. Chapter 3 elaborates on the design of energy markets and congestion management mechanisms from an engineering perspective.

Part II provides an empirical analysis of redispatch in Germany and discusses the current and alternative designs with a focus on generator behavior and strategies. In Chapter 4, strategies for power generators are described that allow them to profit from the current redispatch mechanism design. This includes an evaluation of the accompanying effect on the overall carbon emissions of the energy system. An adjustment of the redispatch mechanism towards a more market-based approach is discussed in Chapter 5. The discussion is supported by an analysis of the possibility to forecast the congestion state of the transmission grid day-ahead. This analysis is performed in order to determine whether it is possible to abuse regional market

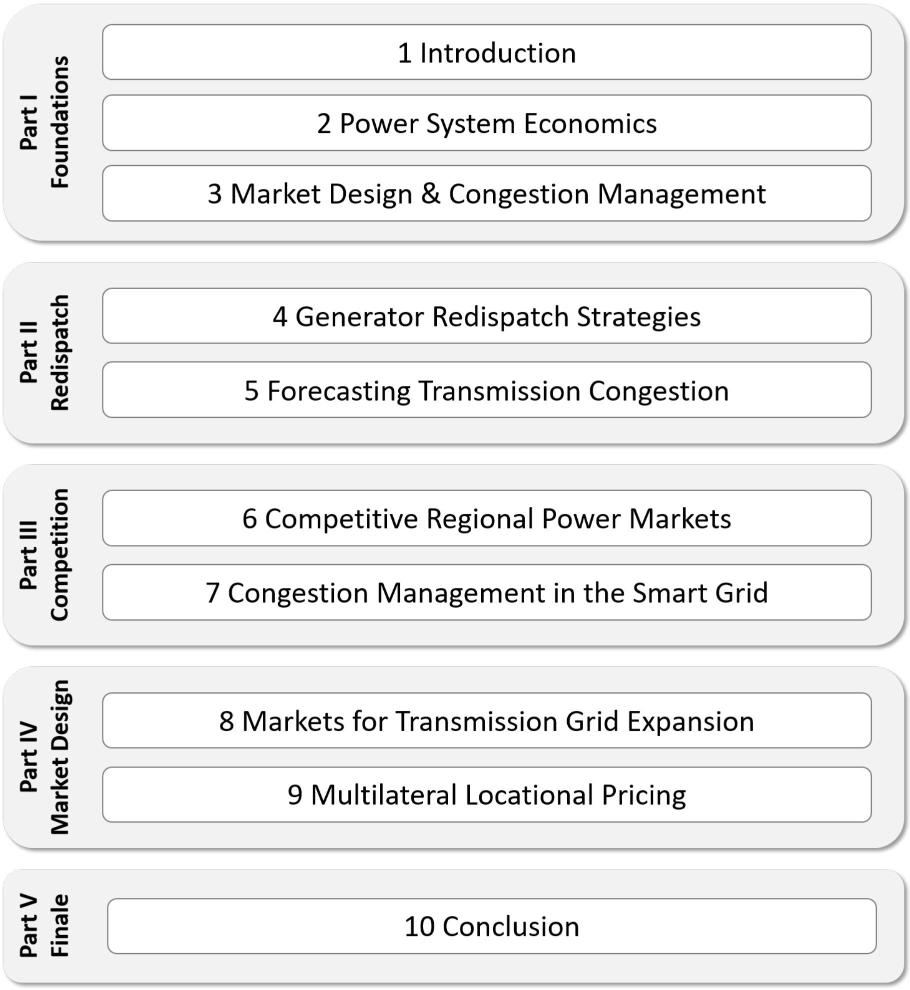


Figure 1.1.: Thesis structure

power with sufficient anticipation of congestion.

The question of market power and countermeasures is treated in Part III. To find the extent of necessary regional competition that ensures competitive behavior, a simulation study is performed in Chapter 6. To assess the strategic behavior of generators, the simulation is based on a set of self-learning agents. Chapter 7 evaluates a heuristic to increase competition for congestion management through the inclusion of V2G technology. Congestion is cleared on an abstracted zonal version of the German transmission grid using EVs and the possible redispatch reduction is evaluated. While this helps to manage congestion in the short-run, market-based approaches to treat systematic long-term congestion are discussed in Part IV. First, Chapter 8 introduces a market mechanism for transmission grid expansion. This approach allows for a liberalization of the transmission capacity market, reduces the risk for energy consumers and leads to a welfare optimal expansion considering short-term alternatives. Second, in Chapter 9, a market mechanism is introduced that takes grid constraints into account at market clearing and thereby provides regionally differentiated prices and thus, long-term investment signals for regional generation investment. This mechanism is evaluated with regard to the welfare distribution and its predisposition to market power and compared to the more restricted design of locational marginal pricing.

Finally, Part V summarizes the key finding, provides a conclusion and discusses avenues for further research.

CHAPTER 2

POWER SYSTEM ECONOMICS

Electric energy is an essential factor for all social and economic activity. Correspondingly, its availability is not only a public but also a political concern. For this reason, power systems have traditionally been strongly regulated. Liberalization of power generation and the unbundling of electricity grids from other activities began in the early 1990s. The objective was to find a balance between security of supply, economic efficiency and ecological sustainability (Umbach, 2012). These dimensions form the triangle of energy system targets depicted in Fig. 2.1.

The process of unbundling divided the electricity value chain into the now liberalized services of generation and retail, and the still regulated transmission and distribution services. This chapter introduces the general setup of the electricity system and the process of liberalization that led to this setup. The chapter allows to put the contributions of this dissertation into the overall context. Furthermore, a few excerpts

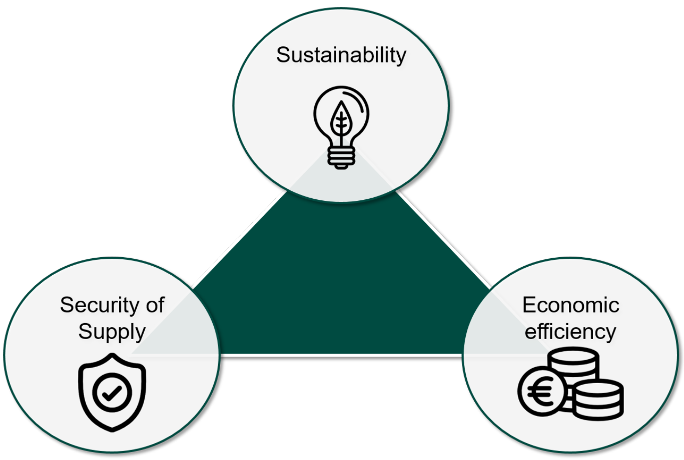


Figure 2.1.: Triangle of targets of the energy system

of regulation are summarized. Most notably, these are the nuclear phase-out, the renewable energy sources act and the latest regulatory reforms intended to support the German energy transition. All of these influence the development of congestion in Germany and the incentives for generation and transmission investment. They are therefore important to judge the results presented in the following chapters. First, the electricity value chain is discussed in the next section.

2.1. The Value Chain of Electric Energy

The value chain of electric energy broadly consists of four services: Generation, transmission, distribution, and retail (Heck, 2006). Fig. 2.2 shows the value chain and divides the regulated from the liberalized services. The connection between different services is depicted by transformers to show that they are typically performed on different voltage levels of the electricity grid.

2.1.1. Generation

Power generation is the transformation of other forms of energy into electrical energy. It can be classified along different dimensions such as controllability and intermittency or by the carbon emissions. The most common differentiation is between generation from renewable power sources such as wind, solar, hydro or biomass and depletable resources such as coal, gas or uranium. Traditionally, when the security of supply and the economic efficiency were the major objectives of energy policy, most generation would come from large-scale controllable power

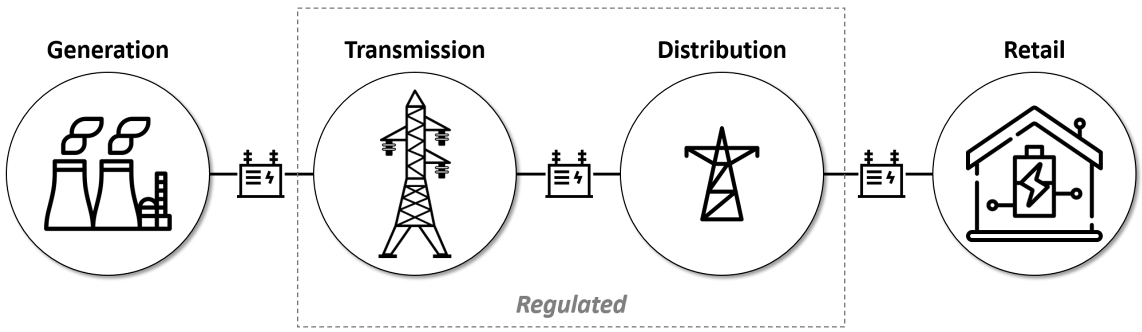


Figure 2.2.: Value chain of electric energy in Germany

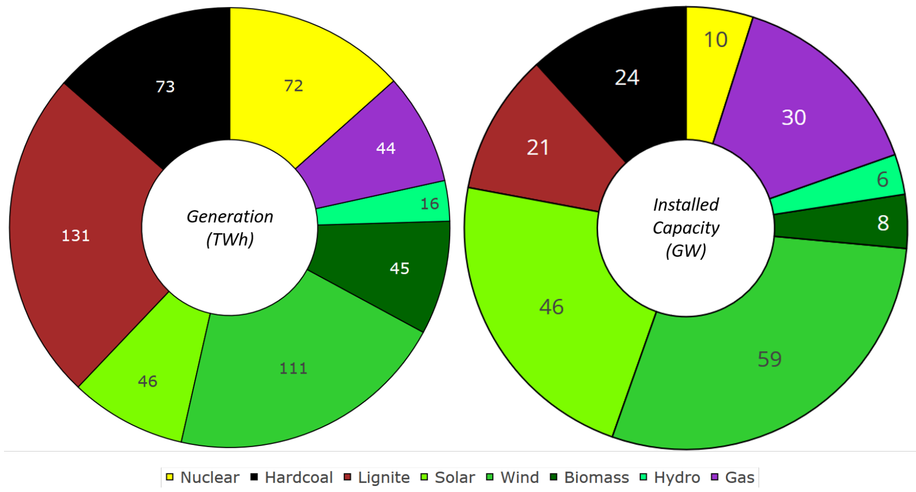


Figure 2.3.: Generation and available capacity in Germany 2018 (Fraunhofer, 2019)

plants. With a greater focus on ecological sustainability came the increase of renewable generation capacity. In the beginning, this has mostly been driven by public policy but recently, the levelized costs of renewable capacity sank below those of conventional capacity (Clauser and Ewert, 2018). The technology mix of the actual generation and the available capacity in Germany in 2018 is shown in Fig. 2.3 with the renewable shares highlighted in green.
About 50% of the installed capacity in Germany is wind or PV power, while about 28% of the generation comes from these sources. The total share of renewable generation in 2018 was 40%. The marginal production cost of wind and solar generation is almost zero. This creates challenges for the liberalized generation markets through the Merit Order effect. The effect describes falling electricity wholesale prices due to a higher share of renewable generation (Sensfuß et al., 2008). Even though generation has been liberalized roughly 20 years ago, the concentration on the market is still high. The CR5 index, which measures the market share of the five largest suppliers in an industry, was at 75.5% in 2017 for conventional capacity the German market (Bundesnetzagentur, 2018b).

In liberalized electricity markets, generation is often traded on a wholesale market. One of the most prominent markets in Europe is the European Power Exchange (EPEX). It performs day-ahead and intraday auctions, sometimes summarized as the spot market. Both are cleared through a uniform-price auction with a Merit

Order dispatch (Graf and Wozabal, 2013). The intraday auction is then followed by a continuous trading period until 30 minutes before physical delivery (Kiesel and Paraschiv, 2017). The Merit Order dispatch is incentive compatible and the clearing price is set by the bid of the marginal generator (Zou et al., 2015). Besides the short-term exchanges with physical delivery, a variety of long-term hedging products have been established. They can be traded through power exchanges or over-the-counter (OTC). The OTC market allows bilateral agreements between generation and consumption outside of the exchanges. On these markets, non-standardized products can be traded which is an advantage over other more restrictive market designs such as nodal pricing (see also Section 3.2.3). The contracts are often only financial, meaning that they are settled based on the market clearing prices on the spot market and no obligation of physically generating electricity is associated to them (Kalantzis and Milonas, 2013). All renewable generation that is compensated through subsidized feed-in tariffs needs to be traded through the spot market (Cludius et al., 2014). The EPEX day-ahead market determines a clearing price for every hour, the intraday auction clears the market for every 15 minutes (Kiesel and Paraschiv, 2017). The latter interval is necessary because balancing power, which is needed for deviations from the anticipated schedule, is financially settled in the same interval (Hirth and Ziegenhagen, 2015). The procurement of balancing power is the responsibility of the TSOs and is further described in Section 2.1.2.

Fig. 2.3 does not provide information on the geographical distribution of the available generation capacity. In Germany, there is a geographical imbalance as wind capacity is often installed in the North close to the coast, while PV capacity is installed in the sunnier South. As wind capacity usually leads to more generation than PV capacity in the geographical area of Germany, more cheap power generation is available in the North (Benhmad and Percebois, 2018). Trepper et al. (2015) and Egerer et al. (2016) confirm the observation and find that consequently, the electricity wholesale price would decrease in the North and rise in the South if Germany would be divided into two bidding zones. This helps in motivating this dissertation: The cheaper electricity generation in the North enters the market through the Merit Order dispatch and needs to be transmitted to the South. However, the transmission grid is not developed to the necessary extent given the increase of wind power generation

Figure 2.4.: Transmission system operators in Germany (Rippel et al., 2017)

in the North (Wohland et al., 2018). This causes congestion in the transmission grid. In the following section, the transmission system is briefly introduced.

2.1.2. Transmission

The transmission system in Europe operates mostly on alternating current with a frequency of 50 Hertz. The transmission grid in Germany operates on 380 and 220 kV (Schmitz and Weber, 2013). The lower voltage levels are operated as distribution grids. The German transmission grid is managed by four TSOs: Tennet, Amprion, 50Hertz, and TransnetBW. They have divided Germany into four transmission system zones as can be seen in Fig. 2.4. These operators emerged from the former regional monopolies for energy supply. The transmission grid operation is a regulated natural monopoly. The operators are compensated using a revenue-cap approach that is discussed in detail in Section 2.2.1. The responsibility of the TSOs is the secure operation of the grid. That includes the operation of preventive emergency measures such as redispatch, feed-in management and the procurement of ancillary services, for example balancing power for operational stability (Bundesnetzagentur, 2018b). The latter is acquired in various products through different auction processes. A detailed description of the mechanism can be found in (Hirth and Ziegenhagen, 2015). The exact process of the redispatch and feed-in management is explained in Section 3.2.2.

2.1.3. Distribution

The German distribution grid is operated by 815 Distribution System Operators (DSOs) that operate a total of 1.8 million kilometers of grid lines on a voltage level of 110 kV or lower. For comparison, the transmission system consists of roughly 37,000 kilometers. Through this grid, the DSOs serve roughly 50 million consumption points. The majority of DSOs serves less than 30.000 consumption points (76%, Bundesnetzagentur (2018b)). In 2014, 98% of all renewable generation capacity was connected to the distribution grid (Buechner et al., 2014). According to §4 of the Renewable Energy Sources Act, DSOs are obliged to connect all new renewable capacity to the grid and transmit all renewable energy that is fed into their grid. This shows that the challenge of integrating renewable generation greatly affects the DSOs as well, which includes the management of reversed power flows from lower voltage to higher voltage grid levels. It requires an increased vigilance regarding possible congestion and grid frequency deviations. Different strategies of dealing with this challenge are discussed in (Von Appen et al., 2013). Distribution is part of the regulated activities of the electricity value chain. This includes the DSO's revenue. The exact regulation and the cost structure of DSOs is described in (BNetzA Bundesnetzagentur, 2015) and by Matschoss et al. (2019). Generally, the focus of this thesis is the transmission system but distribution systems are subject to similar regulation.

2.1.4. Retail

Since the liberalization, every customer in Germany can freely choose her supplier and the retail market for electricity has greatly diversified. After the liberalization, new players entered the market and increased competition (Yadack et al., 2017). This has an impact on the behavior of customers. The share of customers that switch their supplier within a year is rising since 2006 and has reached a record high in 2017 at 11.8%. The CR4 index for the retail market is currently reported as 25% for commercial and 37% for residential customers (Bundesnetzagentur, 2018b).
The most common tariff is a flat volume charge per kilowatt hour (kWh). In 2018 the average rate per kWh was 29.88 Cent. Fig. 2.5 shows the different components of the overall price based on Bundesnetzagentur (2018b). Certain components of the price are regulated and therefore the same for all customers. One of these components is

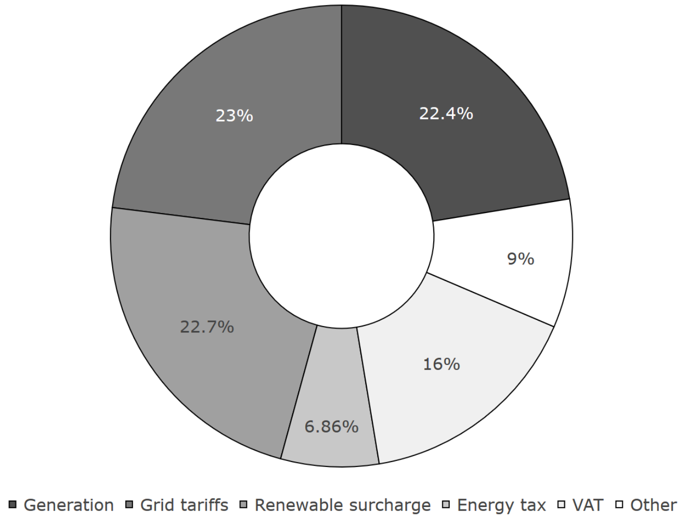


Figure 2.5.: Electricity retail price composition in 2018 (Bundesnetzagentur, 2018b)

the grid tariff that includes the compensation for congestion management measures. The variable component is the procurement cost of retailers. This can be adapted to win over customers. As can be seen in Fig. 2.5, it is only about a quarter of the total price. However, besides the price component, retailers started to differentiate the otherwise homogeneous good of electricity by offering "green tariffs". The amount of energy generation sold through these tariffs has to be backed up by renewable generation over some defined period. The share of green retail customers increased to 24% in 2017 (Bundesnetzagentur, 2018b). Furthermore, new retail tariffs are becoming available. The EC just recently passed legislation forcing all retailers with more than 200,000 customers to offer time-variant tariffs that price electricity based on the real-time market price (European Commission, 2016). In the last few years, the retail sector for electricity has been considered by academics in regard to demand side management, i.e., the determination and pricing of demand side flexibility to increase the price elasticity for electric energy (Palensky and Dietrich, 2011).

2.2. Power Market Liberalization

In this section a brief history of power market liberalization is presented. This includes the current regulation of grid operators, which impacts the discussion on grid expansion and redispatch. The original legislation on power system economics

("Energiewirtschaftsgesetz", EnWG) was passed in Germany in 1935. It included government sanctioned regional monopolies which were believed to ensure a reliable and economically efficient operation of the electricity system (Kment, 2015). The next major reform was passed in 1998 as a reaction to the guideline on the internal energy market of the EU (Eising and Jabko, 2001). The core of the liberalization was the ownership unbundling of generation capacity and grid infrastructure. The underlying idea is that while the transmission and distribution infrastructure are natural monopolies, the generation side can be subject to competition. This has resulted in today's power market regulation. While the unbundling of vertically integrated utility companies was not part of the first reform, it followed in 2003. This created the electricity value chain as depicted in Fig. 2.2. Furthermore, consumers were now free to choose their retailer, grid access had to be provided to third party generators, energy exchanges such as the EPEX were established and the Federal Grid Agency for Electricity, Gas, Mail, Telecommunications and Railroads (BNetzA) was created (Heck, 2006). Today, the BNetzA oversees grid fees and expansions and is the governmental body for the regulation of transmission and distribution grid companies (Bundesnetzagentur, 2018b). This brief introduction is important to understand the context in which congestion management is operated today. Since then, a variety of power market regulation was implemented including the changes in grid regulation towards an incentive regulation, the Renewable Energy Act, the nuclear phase-out and the Power Market 2.0 to name only the most notable pieces of legislation. Those are discussed in the next sections.

2.2.1. Excerpt of Power Market Regulation

In this section, the regulation for electricity transmission grids and the nuclear phase-out are briefly reviewed as they are of importance for this dissertation. The regulation of TSOs impacts the grid expansion and the congestion management. The nuclear phase-out increases the generation imbalance between the North and South of Germany.

Transmission grid regulation After the liberalization of generation and retail, the German grid regulation began with a cost-plus regulation that essentially allowed grid operators to pass through their costs to consumers after they were approved by a regulatory body (Brunekreeft and Bauknecht, 2006). This regulation was later replaced by the revenue-cap as an incentive regulation because the cost-plus regulation led to rising prices and increased the information requirements for the regulator (Brunekreeft, 2003). A more detailed discussion on cost- and price-based regulation is carried out in (Brunekreeft and Meyer, 2011). The revenue-cap, as the name suggests, sets an upper bound for the TSOs' revenue and incentivizes them to reduce their costs gradually. The regulatory body, the BNetzA, determines the revenue-cap and oversees the calculation of grid tariffs for TSOs and DSOs.

The revenue-cap for TSOs mainly consists of two types of costs. Other types considered in the calculation are explained in (BNetzA Bundesnetzagentur, 2015) but they make up less than 10% in the reported period. The two major cost types are long-term non-influenceable costs such as approved investments or balancing activities (e.g., redispatch or ancillary services) and short-term non-influenceable costs which are determined by multiplying an efficiency factor with the cost remaining after subtracting the long-term non-influenceable costs from the total costs. The efficiency factor is determined through a benchmarking process with other European TSOs (§22 ARegV). It is assumed that the short-term non-influenceable costs multiplied with one minus the efficiency factor form the cost that can be reduced by TSOs. For each year in the regulation period this cost component is decreased to reduce inefficiencies. This forces TSOs to reduce their costs to stay below the revenue-cap. As described, the revenue-cap is determined purely based on cost. To account for the economic activity, TSOs receive a regulated interest on their equity that is determined individually for each regulation period. It is currently at 6.91% (Bundesnetzagentur, 2016b). A detailed discussion on the current regulation is provided by Matschoss et al. (2019). This includes a discussion on the incentives for grid operators to favor capital intensive solutions over more efficient possibilities with higher operational costs. The regulation of grid infrastructure is an important aspect for this thesis as grid expansion and redispatch are concurrent ways of solving grid congestion. Both measures are overseen by the TSOs and form part of the non-influenceable costs. However, the interest that is granted to TSOs is only being paid on their capital expenditures, e.g., for investments in grid infrastructure.

Nuclear phase-out In 1998, a total of 19 nuclear reactors were operational for energy generation in Germany. In 2011, after the nuclear accident in Fukushima, the government decided to phase-out nuclear power by 2022 (Jahn and Korolczuk, 2012). The majority of nuclear power stations was and is situated in the South of Germany. This region is characterized by high loads and low potential for wind power generation. Of the total 19 GW nuclear capacity that was still operational in 2011, 67.5% was located in the southern states of Baden-Württemberg and Bavaria and in the South of Hesse close to the border with Baden-Württemberg. Of the currently remaining 9.5 GW of nuclear capacity, 57% is situated in the southern states (Deutsches Atomforum e.V., 2016). The ongoing reduction of secure generation capacity in the South will likely lead to an increased need for congestion management as discussed in (Bruninx et al., 2013) and shown later in Chapter 8. This is especially true as Germany is on the path of phasing out generation from hard coal and lignite as well (Kemfert, 2019).

2.2.2. The Renewable Energy Sources Act (EEG)

The Renewable Energy Sources Act (*Erneuerbare Energien Gesetz (EEG)*) was adopted in April 2000. Since then, it has been amended multiple times. In its original version it defined minimum feed-in tariffs for different technologies of renewable generation. This was implemented such that the renewable generation would be traded on the spot market and the difference between the market clearing price and the minimum feed-in tariff would be subsidized and covered through an additional levy on each consumed kWh over a period of 20 years. The guaranteed feed-in tariff would decrease over time. From an environmental perspective the EEG is a success (Büsgen and Dürrschmidt, 2009). The share of renewable electricity generation increased from 6.3% in 2000 to 40% in 2018. The economic impact is debated (Böhringer et al., 2017). As can be seen in Fig. 2.5, the renewable surcharge that finances the subsidy payments amounts to almost a quarter of retail power prices. Furthermore, the increased generation results in more congestion management costs as previously described, which are covered through the grid tariff portion of the retail electricity price. At the same time, the renewable generation led to decreasing electricity wholesale prices through the Merit Order effect (Sensfuß et al., 2008). It is important to understand the EEG as it was the trigger for renewable generation expansion in Germany, that caused the current congestion difficulty (Steinbach, 2013). As renewable generation capacity can be installed quickly, traditional planning and realization periods for grid infrastructure is lagging behind. In response to a request of the opposition in the German federal parliament, the government declared that "[...] the expansion of renewable energy progressed faster than expected in the EEG. [...] The duration of grid expansion depends on planning and approval procedures, which are highly dependent on public acceptance." (Bundesregierung, 2018c).

2.2.3. Smart Grid Regulation

A major overhaul of the German energy system was prepared in 2015 when the German government published a white paper as a result of a consultation process with various stakeholders that began in October 2014 (Federal Ministry for Economic Affairs and Energy, 2015). The regulatory changes that were initiated in this white paper are discussed in the following paragraph. They include certain considerations for future congestion management and are therefore introduced. However, they do not include an overhaul of the congestion management approach. This dissertation is intended to further contribute to this discussion.

The central question that was answered within the white paper was whether a capacity market should be implemented. The government decided against such a design and explained that it would be too prone to the danger of regulatory mismanagement. In total, the development of the introduced Electricity Market 2.0 contains 20 action items that are divided into three categories: *Strengthening Market Mechanisms*, *Flexible and Efficient Energy Supply* and *Additional Backup*. The first category is a commitment to the forces of the liberalized energy-only market. With this, the government clarifies a few regulatory uncertainties and provides transparent rules to when price markups are acceptable and would not be considered the exercise of market power.

The second category includes a variety of measures to modernize the energy system and to introduce the Smart Grid (Blumsack and Fernandez, 2012). Among others, this includes the introduction of smart meters, the aggregation rules for flexible customers, the increased market penetration of EVs, further transparency of electricity system data and the permission for grid operators to reduce generation peaks of renewable capacity up to 3% of the total expected yearly generation. The latter is justified as "it makes no sense for TSOs to expand the grid for the last kWh" (Federal Ministry for Economic Affairs and Energy, 2015). This is further discussed in Section 9 of this dissertation.

The final category defines a capacity mechanism for the German energy system. The first measure is the introduction of the so-called capacity reserve. Power plants can enter the capacity reserve through a tendering offer and cannot return to participating in the electricity market anymore, afterwards. They are only activated if the total demand cannot be covered on the day-ahead or intraday market and only after all available balancing power is activated. Additionally, TSOs contract the grid reserve. The grid reserve is necessary to ensure that regional scarcity of power generation is avoided. They are used to provide regional redispatch if the regional demand cannot be met due to grid congestion. Power plants in the capacity reserve can also be used in the grid reserve. The cost of contracting the grid and capacity reserves are passed through to customers via the grid tariff portion of the retail electricity price. Especially the grid reserve is therefore another part of the overall congestion costs in the German electricity grid. To conclude, the white paper provides interesting impulses for the future energy system. However, with a strong commitment to the uniform electricity price, no changes in the regulation on grid expansion and no reform of the current and future congestion management, several important areas are not addressed. This dissertation adds to the discussion on the energy market design both in Germany and internationally with new directions for transmission grid congestion management.

CHAPTER 3

MARKET DESIGN AND CONGESTION MANAGEMENT

Congestion management is an essential feature of energy market engineering and has implications for the energy market design. Steven Stoft calls it "one of the toughest problems in electricity market design" (Stoft (2002), p. 24). Congestion in electricity grids occurs when the generation and load patterns lead to more power flow on a transmission line than the thermal limit of that line allows (Stoft, 2002). Alternatively, congestion can occur if a regulatory criterion requires that the power flow cannot exceed a certain limit such as the n-1 criterion. The criterion demands that the grid can remain in operation even after the failure of any particular component (Holttinen et al., 2011). In case of congestion, load pockets (Lesieutre et al., 2005) and generation pockets (Alaywan et al., 2004) can be identified. Load pockets have additional demand that cannot be satisfied and generation pockets have additional generation that cannot be transmitted given the grid constraints. From a market design perspective, two extremes of managing grid congestion can be distinguished: Uniform-price markets and locational marginal pricing (Weibelzahl, 2017).

In uniform-price markets, one single market clearing price is determined for electricity at a specific point in time without consideration of grid constraints. Therefore, it is possible that the market result cannot be realized in terms of feasible power flows. In that case, the TSO needs to intervene and change the schedules of generators if the load is to be fully served (Nüßler, 2012). This redispatch is a deviation from the original market-determined economic dispatch and quantifies the welfare loss induced by the congestion. On the other hand, in markets with locational marginal pricing (also known as nodal pricing), all grid constraints are considered at market clearing (Weibelzahl, 2017). Therefore, different prices emerge at different nodes in the system depending on the marginal unit that is needed to serve these nodes. This usually involves central market clearing by an ISO with mandatory market participation for all loads and generators. A compromise between the two designs is zonal pricing. In zonal pricing, market congestion along the zone boundaries is avoided during market clearing while congestion within the zones needs to be relieved using redispatch (Weibelzahl, 2017).

Most markets in the United States use nodal pricing, whereas many European countries use uniform-pricing and redispatch. The integrated European electricity market uses a zonal setup, in which national boundaries are often also the zonal boundaries (Meeus and Belmans, 2007). However, the EU has threatened to divide national bidding zones if the interconnector capacity between neighboring markets is not sufficiently made available (Bundesregierung, 2018a). Before elaborating on congestion management, this chapter provides an excerpt of the general design choices of liberalized electricity markets. Then, the specifics of congestion management and the resulting implications for the market design are described.

3.1. Energy Market Design

The design of electricity markets is complex and consists of a variety of features. Literature on electricity market design can often only focus on one specific aspect such as Chao and Huntington (2013) who focus on wholesale electricity markets and associated transmission congestion management. A somewhat broader view is provided by Sioshansi (2011), who additionally considers resource adequacy and therefore capacity markets. However, the subject of energy market engineering also includes the design of ancillary service markets, forward markets and the assurance of resource adequacy among other things. In the following section, a non-comprehensive overview of research in the field of energy market engineering is provided. The intention of this section is to provide a brief overview of electricity market design research beyond congestion management and to draw certain connections. This is followed by an overview of the growing field of energy informatics and the associated energy market research. The provided thesis is embedded into the research areas presented in the following sections.

3.1.1. Energy Market Engineering

Capacity mechanisms One of the central concerns of energy market engineering is resource adequacy. This means that incentives need to be designed to ensure that sufficient generation capacity is available to avoid blackouts. First, this is important as electricity is an essential input factor for all social and economic activity. Second, blackouts are problematic from a market perspective as scarcity cannot be priced in such situations because price peaks do not lead to a reduced load as the demand is usually too inelastic to react to such prices. Therefore, a blackout is not avoided due to price spikes and no power delivery is possible, implying reduced payments to generators (Cramton and Stoft, 2005). Regulators are concerned that peak pricing in an energy-only market might not be sufficient to induce incentives for the necessary expansion of capacity (Cramton and Ockenfels, 2016). Opponents of capacity markets argue that the regulatory intervention of determining the necessary provided capacity leads to inflated capacity construction and propose different approaches to recover costs for peak capacity (Hogan et al., 2005). The discussion on the implementation of a capacity market in Germany is resurfacing due to the intermittency of renewable generation (Winkler et al., 2013). Even for renewable generation, some sort of capacity mechanism is implemented: While the feed-in tariff used to be fixed as described in Section 2.2.2, it is now subject to tendering auctions for large units (Kreiss et al., 2017).

Forward markets Another aspect of energy market design is risk management for consumers. As price spikes might occur in certain situations, it is important to design tools for consumers to manage their risk exposure. Again, electric power is a good that can hardly be replaced and many customers are dependent on a steady, secure supply. Stoft (2002) states that the amount of long-term supply contracts is one of the main aspects to reduce market power in electricity markets. Forward markets are designed to acquire electricity well before delivery. Bessembinder and Lemmon (2002) provide an overview of risk hedging activities on electricity forward markets. Furthermore, financial transmission rights are a tool in markets with locational marginal pricing to insure against the risk of locational price differences (Hogan, 1992). However, these tools are unnecessary in uniform-price markets as in Germany.

Ancillary service markets Maintaining a steady frequency is one of the most important tasks of system operators in energy systems. In order to ensure that supply and demand are always balanced, they contract ancillary services in the form of balancing power. Such markets are usually run by the TSOs and have different designs (Ocker, 2017). In the presence of more renewable energy, such balancing power markets are expected to become more important. A critical discussion of renewables and balancing power markets is provided by Hirth and Ziegenhagen (2015). Another balancing responsibility of TSOs is congestion management. A detailed classification of mechanisms and market designs for congestion management is given by Hirth and Glismann (2018). The paper also includes a description of the Dutch redispatch market design. Of the classes of congestion management approaches identified in (Hirth and Glismann, 2018), this dissertation provides solutions in the areas of grid development, dispatch management and trade management.

Wholesale electricity markets In most countries the major electricity market is the wholesale spot market. The controversies around the design of these markets are often related to controversies on the congestion management. Stoft (2002) describes the three controversies between bilateral and centralized markets, exchanges and pools and zonal versus nodal pricing as the main discussions with regard to market architecture. However, in all of these designs one or multiple market reference prices are usually determined at a centralized exchange that allows market parties to submit their bids. These market places are cleared using a Merit Order, such that the cheapest units in terms of marginal cost of generation are dispatched. Most exchanges use a clearing price approach rather than pay-as-bid designs (Cramton and Stoft, 2007). As some uncertainty exists in day-ahead markets, they are usually followed by either an intraday market (Weber, 2010) or a real time power market (Borenstein, 2005), where the latter is usually controlled by a central entity such as an ISO.

Demand side flexibility markets A recent academic and political discussion focuses on the integration of demand side flexibility into the energy system through corresponding market mechanisms and platforms (Papadaskalopoulos and Strbac, 2013). This change of paradigm is triggered by the intermittent nature of renewable generation: As power generation cannot follow the load anymore, the load is supposed to follow supply (Strbac, 2008). This has implications for the tariff (Gärttner, 2016) and auction (Dauer, 2016) design.

This brief overview shows that the landscape of different markets is manifold in energy market engineering. To characterize and categorize these markets, a framework is provided by Weinhardt et al. (2003). This framework has previously been applied to energy market platforms in (Dauer et al., 2016) and (Staudt et al., 2017) among others.

3.1.2. Information Systems and Electricity Markets

The digitalization of energy systems and the increased computational power make information systems an important tool in energy market design and analysis. A broad range of applications has emerged that has been labeled with the term *Energy Informatics* by Watson et al. (2010). One major stream of related research is Agent Based Computational Economics (ABCE). It describes the use of computational agents to assess the economic outcomes of market designs by observing their strategic behavior and their interaction. A comprehensive overview of the different applications of ABCE is provided by Weidlich and Veit (2008a). Veit et al. (2009) analyze the strategic behavior of supply agents in Germany under a locational pricing market design. In (Weidlich and Veit, 2008b), the authors use agents to find interdependencies between different energy markets such as the wholesale and the balancing power market. Kranz et al. (2015) point out that energy informatics should engage stronger in designing markets and regulation for the energy sector. Brandt et al. (2013) emphasize that information systems are a necessary tool for the transition to a more sustainable energy system. The use of information systems to avoid problems with large infeed of renewables at the distribution level is described by Römer et al. (2012). Nieße et al. (2012) use an agent-based approach to show

how information systems can be utilized to form coalitions that ensure distribution grid stability. Overall, this short overview shows that energy informatics is an active research field, but that its reach into energy market design is still limited. This dissertation is a step towards combining the fields of energy market engineering and information systems.

3.2. Mechanisms for Congestion Management

The choice of mechanism for congestion management in an electricity market has implications for the market design in general. A uniform-price market increases competition among generators. At the same time, an additional mechanism for congestion management needs to be introduced. Nodal pricing, on the other hand, sends regional investment signals and is generally considered the short-run welfare optimal market design for electricity markets (Green, 2007). It is however more susceptible to market power abuse in case of regional generation shortages (Gan and Bourcier, 2002). Further disadvantages are the need for an ISO (Wu and Varaiya, 1999) and the system complexity in terms of coordination and prices (Weibelzahl, 2017). Zonal pricing as a compromise between the two designs is also debated, e.g., by Hogan (1999) and Grimm et al. (2016). A general overview of research into grid congestion management is provided by Pillay et al. (2015) and Kumar et al. (2005). An overview of practical implementations of congestion management worldwide is introduced by Krause (2005).

In the following sections, the three major designs for congestion management, uniform-pricing with redispatch, nodal pricing and zonal pricing are briefly introduced along with a motivating example. The example is illustrated in Fig. 3.1. The market setup is such that cheap capacity is available at nodes 1 and 3 with marginal cost functions mc_i. The generation at each node is q_i and the capacity is assumed to be unlimited. The highest load d_i is located at node 2, in the center. The transmission capacity t_{ij} to node 2 is restricted. The simple grid setup allows to ignore loop flows. The power flow is therefore linear and can easily be calculated. Nevertheless, the next section first introduces the calculation of electrical flow.

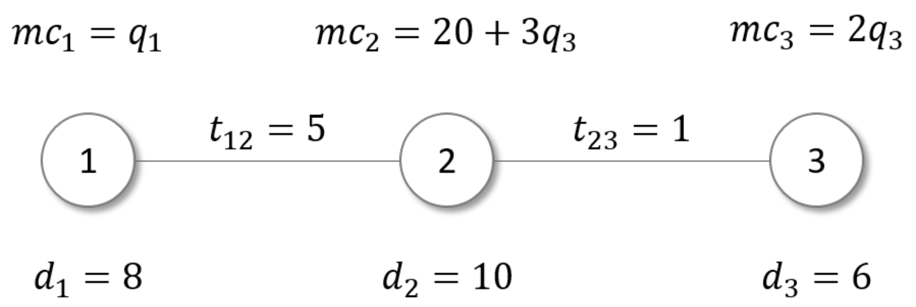


Figure 3.1.: Illustrative example for congestion management

3.2.1. Power Flow

Electric energy cannot be directed through a network along a previously defined path but finds its own way depending on the technical specifications of the network (Weibelzahl, 2017). Electricity flows according to Kirchhoff's current and voltage laws (Stoft (2002), p. 375 ff.). Most electricity grids operate using alternating current (AC) instead of direct current (DC) as it can easily be transformed to higher or lower voltage levels. The German grid operates AC at a frequency of 50 Hertz. If that frequency is not maintained, TSOs allocate contracted balancing power (Müsgens et al., 2014). An overview of optimal power flow models for both AC and DC models is provided by Li and Bo (2007). In this dissertation, all power flow problems are approximated using DC power flow. This is common practice in power system economics (Purchala et al., 2005). The DC power flow ignores reactive power and can be applied if line resistance is small in comparison to line reactance, the voltage amplitude is the same for all nodes and the differences between voltage angles of neighboring nodes are small (Van den Bergh et al., 2014). Furthermore, losses are neglected which is also a common assumption in power economics (Zimmerman et al., 2011). Lossless DC power flows in a meshed system can be calculated using Equ. 3.1 .

$$
\begin{aligned}
z &= H \cdot y \\
H &= \Omega A (A^T \Omega A)^{-1}
\end{aligned}
\tag{3.1}
$$

with

z	$(N_l \times 1)$-dimensional vector of line flows
H	$(N_l \times (N_b - 1))$-dimensional matrix of power distribution factors
y	$((N_b - 1) \times 1)$-dimensional vector of power net injections at all buses (except slack bus)
Ω	$(N_l \times N_l)$-dimensional diagonal matrix of the inverse of line reactances
A	$(N_l \times (N_b - 1))$ reduced network incidence matrix
N_l	Number of lines
N_b	Number of buses (nodes)

The matrix of power distribution factors quantifies the impact of an additional unit of injection at any node but the slack node on every individual line. These factors are very important for congestion management as they need to be considered when generation units are redispatched to relief a specific line of congestion. The slack node can be arbitrarily chosen and ensures the balance of the sum of net injections. The net injections are the generation at a node less the load at that node. The matrix A is the incidence matrix, where each row represents a line and the columns show which nodes are connected by the line. Ideally, the incidence matrix already shows the direction of flow such that a value of 1 represents the node from which the power flows to the node with a value of -1. The slack bus is omitted. The model shows that the line capacities are not considered. The power flows materialize independently of these constraints to the point of the destruction of the line. Therefore, congestion needs to be actively managed.

3.2.2. Redispatch

Redispatch is an adjustment of the economic dispatch to ensure feasibility with regard to grid balance constraints. In essence, an optimized redispatch is the solution to the optimal power flow problem (Maurer et al., 2018). As long as congestion is a rare event, redispatch is a well suited solution to congestion management as it ensures the highest possible competition in the wholesale electricity market. Whether it also sends regional investment signals depends on the redispatch mechanism. A first model based study of redispatch needs in Germany is provided by Nüßler (2012). Germany uses a cost-based redispatch design (Trepper et al., 2015). This means that the redispatch service is only compensated based on costs (and opportunity costs). Other countries such as the Netherlands use a market-based redispatch mechanism (Hirth and Schlecht, 2018). The discussion of introducing a market-based redispatch has emerged due to article 12 of the *'Clean Energy for All Europeans'* package of the EC (European Commission, 2016) that calls for the introduction of "market-based redispatch". Chapter 5 further elaborates on this discussion.

The theoretical welfare implications of cost-based redispatch are displayed in Fig. 3.2. The increasing line represents the marginal production cost of electricity at a specific geographical location. The decreasing line represents the avoided marginal costs due to electricity import through the transmission grid. Economically, the equilibrium is reached when the production cost equals the avoided costs and the intercept determines the uniform market clearing price. Congestion implies that this economic optimum cannot be physically realized even though it represents the economic dispatch in uniform-price electricity markets. The vertical line represents the congestion and the distance between the line and the theoretically optimal market clearing quantity is the necessary redispatch. The dashed triangle area is the lost welfare due to the congestion and represents the total cost of redispatch. The upper triangle above the market clearing price represents the lost consumer welfare and the lower triangle represents the lost producer welfare. The checkered area is the amount of avoided production cost due to necessary down regulation of a power plant for the redispatch. Under the German regulation, this avoided cost of down regulation is reimbursed by the generators to the TSO. However, generators can keep their producer surplus from the central market clearing. The associated costs are socialized and covered by the consumers through grid tariffs. The same is true for the upper dashed triangle which is the additional cost of ramping up replacement generation. Therefore, the entire burden of congestion cost is carried by the consumers. Redispatch is only performed in Germany if topological measures such as grid switching are not sufficient (BMWi, 2015). The compensation components for positive redispatch are provided by the German Association of Energy and Water Industries in (German Association of Energy and Water Industries (bdew), 2018). The compensation includes operating costs, depreciation, fuel costs, emission certificates and ramping costs as well as opportunity costs that arise because of foregone opportunities on the intraday market. The implications of these compensation components are further discussed in Chapter 4.

Finally, the redispatch mechanism is illustrated using the example depicted in Fig. 3.1. The market is now cleared centrally. The overall demand is 24. This implies that the generation occurs at nodes 1 and 3. To find the market clearing price, the intersection of the marginal cost curves needs to be identified by solving the equations $mc_1 = mc_3 \Leftrightarrow q_1 = 2q_3$ and $q_1 + q_3 = d_1 + d_2 + d_3 \Leftrightarrow q_1 + q_3 = 24$. The resulting market price is $p = 16$ with $q_1 = 16$, $q_2 = 0$ and $q_3 = 8$. There is no generation at node 2 as the clearing price lies below the fixed component of the marginal cost function of node 2. The result implies a net injection of 8 at node 1 and 2 at node 3. Both injections cannot be completely transmitted as $t_{12} = 5 < 8$ and $t_{23} = 1 < 2$. This implies a down regulation of 3 units at node 1 and of 1 unit at node 3. The associated lost producer surplus that is covered by consumers is $3 \cdot 3 \cdot 0.5 = 4.5$ at node 1 and $1 \cdot 2 \cdot 0.5 = 1$ at node 3. At node 2, the 4 reduced units need to be generated. The associated welfare loss for consumers is $20 \cdot 4 + 12 \cdot 4 \cdot 0.5 - 4 \cdot 16 = 40$. The total system cost for consumers is then $24 \cdot 16 + (104 - 39) = 449$, where 104 is the cost of the additional ramp-up and 39 is the avoided cost of the generators at nodes 1 and 2. This is equivalent to a per unit price of 18.7.

3.2.3. Locational Marginal Pricing

Locational marginal pricing is based on the original work of Schweppe on liberalized electricity markets (Schweppe et al., 1988). The concept is further developed by Hogan (1992), who describes a market mechanism and the use of financial instruments for the management of regional price differences. The principle is that power can be generated at different prices in different locations. Due to congestion, the marginal unit at different nodes in the network has different prices, which leads to locational marginal or nodal prices (Stoft, 2002). Many authors argue that locational marginal pricing is the welfare optimal option of clearing congestion for a given network (e.g., Weibelzahl (2017), Green (2007) or Krause et al. (2006b)). Locational marginal pricing is usually combined with a pool market model, where all market participants need to trade through the pool, which is organized by an

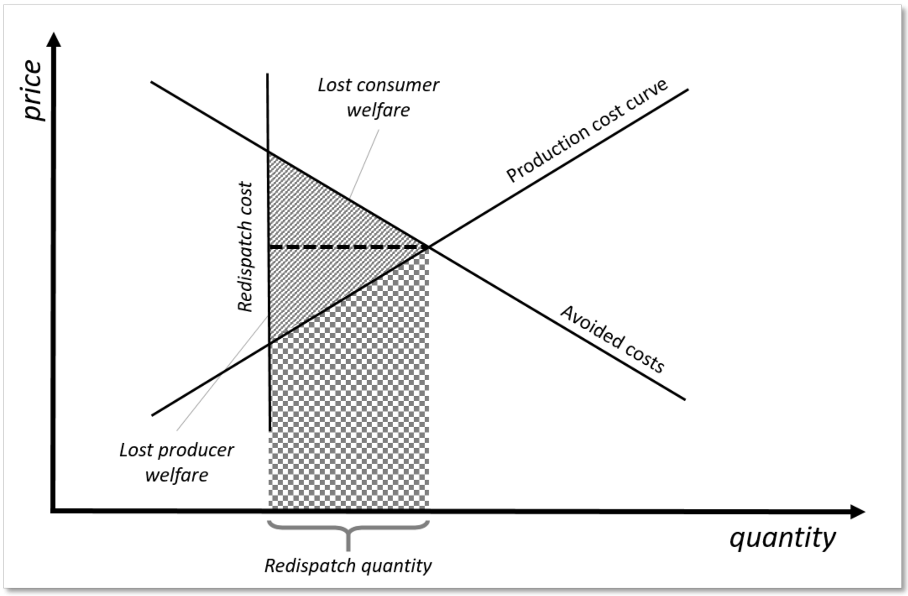


Figure 3.2.: Economics of the redispatch mechanism

ISO that has no financial incentives in the power market (Varaiya and Wu, 1997). The ISO finds the optimal economic dispatch and determines the nodal prices. These prices can be calculated from the dual variables of the market optimization problem. The exact calculation is described in Chapter 8. The concept of the ISO and the related restrictions for the market design are debated (Wu and Varaiya, 1999). Some researchers argue that a more liberalized market can lead to the same competitive prices. This is described as the *Bilateral-Nodal Debate* by Stoft (2002). The locational price differences also set a price for congestion, which is called congestion or transmission rent. The transmission rent payments can be traded as Financial Transmission Rights (FTRs) to insure against nodal price differences. An exhaustive overview of related research is provided by Rosellón and Kristiansen (2013). The income from FTRs can also be used to finance transmission grid expansions (see Chapter 9). However, such payments only occur in case of congestion. Therefore, the individual incentive would be to degrade the line to the point of congestion. A critical review of grid expansion incentives from FTRs is provided in Oren et al. (1995). Leuthold et al. (2008) apply nodal pricing to the German transmission system.

In the example in Fig. 3.1 the ISO would collect bids from all generators in the system and then calculate the optimal dispatch. This dispatch can easily be determined in the given example: Even if the generators at node 1 and 3 produce their own demand and the additional possible amount that can be transmitted, their marginal costs of production are still below the marginal cost of any generation at node 2. Therefore, the generation at node 1 is $q_1 = 13$ and the nodal price is $p_1 = 13$. On node 3, the generation is $q_3 = 7$ and the price is $p_3 = 14$. On node 2, 6 units come from the other nodes. The remaining load needs to be locally generated. Therefore, $q_2 = 4$ and $p_2 = 32$. This leads to the total system costs of $d_1 \cdot p1 + d_2 \cdot p2 + d_3 \cdot p3 = 508$ and therefore an average per unit price of 21.2 for the consumer. Note, that the cost for the consumer is higher than in the uniform-price case. Nodal pricing does not generally lead to higher payments for consumers. However, in the given example the welfare is unequally distributed as producers profit more from the changed market design than consumers. This is further discussed in Chapter 9. The congestion rent emerges from the different payments to generators and by consumers. The generator at node i receives the price p_i at that node. This results in total payments of 395 to all generators. Therefore, the congestion rent is $508 - 395 = 113$. The operator of line 1-2 receives a transmission rent of $t_{12} \cdot (p_2 - p_1) = 5 \cdot (32 - 13) = 95$ and the operator of line 2-3 receives $t_{23} \cdot (p_2 - p_3) = 1 \cdot (32 - 14) = 18$. The advantage of the design lies in the price signals for regional generation investment. Given the market result, it is attractive to invest in generation capacity at node 2. In the previous uniform-price example, the individual profit did not depend on the exact capacity location. Therefore, it would be profitable to develop capacity where it can be cheaply operated instead of where it is most profitable for the system.

3.2.4. Zonal Pricing

Zonal pricing is to some extent a compromise between nodal and uniform pricing. Several nodes are assembled into a zone. The price is determined uniformly for these zones. Only congestion along the borders of the zone is explicitly considered. The approach is useful if congestion within the zone is small, while it is considerable with neighboring zones (Stoft, 1997). However, it is quite difficult to determine the correct zone boundaries. Bjørndal and Jørnsten (2001) analyze the welfare effects of different zone boundary delimitations for simple networks. They find that the

individual surplus greatly depends on the exact delimitation of zones. The decision has therefore political implications. Even the difference in nodal prices is not necessarily a good indicator. This is important as zonal price differences are often used to determine zones (Walton and Tabors, 1996; Burstedde, 2012). The advantages of zonal pricing under certain conditions is also challenged (Hogan, 1999).
In Europe, the national electricity markets are increasingly integrated. The flow-based market coupling implements a coupling of the Western European electricity exchanges and calculates optimal cross-border flows (Van den Bergh et al., 2016). The European zone boundaries are traditionally oriented along the national borders. The EC is further advancing the integration of electricity markets (European Commission, 2016). This is expected to increase intra-zonal congestion in Germany (Bundesregierung, 2018b). The problems in the German transmission grid have been noticed beyond the national borders. Wind generation in the North often flows through the grid of neighboring countries. To prevent this from happening, phase shifters have been installed at the interconnectors (Korab and Owczarek, 2016). The EC has already warned Germany that it would have to be divided into two bidding zones if the cross-border flows are not controlled (Trepper et al., 2015). Recently, the EC has passed legislation that threatens a division of the national bidding zones if the interconnector capacity is not made available at 75% or more of the total possible capacity (Bundesregierung, 2018a). Simulations of the effects of market splitting in Germany are performed by Trepper et al. (2015) and Egerer et al. (2016).

To assess zonal pricing in example 3.1, nodes 1 and 2 are aggregated into a zone. The transmission capacity of line 2-3 is therefore explicitly considered, while congestion along line 1-2 is resolved after market clearing. The demand in zone 1-2 is 18 and 6 in zone 3. Therefore, the regional price of zone 1-2 is 17 as one unit can be imported from the cheaper zone 3. The price in zone 3 is 14 as 6 units are produced for local consumption and 1 is transmitted to zone 1-2. As the intra-zonal congestion is now considered after market clearing, the generation at node 2 now needs to be increased by 4 units and decreased at node 1 by the corresponding 4 units. The welfare loss of this congestion is $4 \cdot 4 \cdot 0.5 = 8$ for the producer surplus at node 1 and $20 \cdot 4 + 12 \cdot 4 \cdot 0.5 - 4 \cdot 17 = 36$ loss of consumer surplus at node 2. The total system cost is then $18 \cdot 17 + 6 \cdot 14 + (104 - 60) = 434$ with 104 being the cost of the additional ramp-up and 60 being the avoided costs of the generator at node 1. The cost per unit for consumers is therefore 18.1. It is the lowest cost in the given example. However, this is not generalizable. Opposing examples could be constructed just as easily.

3.3. Discussion

Congestion is an increasing problem for European electricity markets, while it has been at the center of academic research for years. The expansion of renewable generation capacity makes the problem more complex as temporal intermittent generation can cause spikes in congestion and it is difficult to determine the extent of grid expansion that is still adding welfare to the overall system. The market design choice of the congestion management mechanism has severe implications for the short-term market outcome of electricity markets as shown by the example in the previous section. However, it also has long-term implications for the development of electricity systems. Congestion management mechanisms should set regional incentives to invest in generation capacity at locations where it is most needed in the system. These regional investment signals can then lead to an improved distribution of generation capacity and reduce congestion. For example, wind power capacity can either be installed where it is most profitable in terms of wind speed or where it is most profitable in terms of system costs. Ideally, a market mechanism would send signals that internalize all of theses costs and incentivize optimal investment. However, such regional incentives might come at the expense of more complexity and the risk of regional market power. On the long-run, the desired expansion of renewable generation capacity will likely occur at locations with good availability of the necessary resources such as wind and solar. In the German case, this implies the need for grid expansions, especially if the European electricity market is to be further integrated and electricity needs to be transmitted to Austria, Switzerland or Italy only to name a few. However, just as for generation capacity, the optimal expansion of transmission capacity needs to be correctly incentivized, consider short-term congestion management alternatives and take the intermittency of renewable generation into account. The current grid expansion in Germany occurs according to a centralized plan without efficiency considerations or clearly defined criteria of when a power line should be expanded. Especially, the intermittency of renewable generation causes some congestion to be acceptable, as an expansion to transmit the notorious *'last kWh'* is not economically reasonable (Stoft and Lévêque, 2006). Furthermore, the grid expansion has great opposition within the population making it even more of a difficult task. This indicates that there is no one-size-fits all solution to congestion management. It is important to use a set of mechanisms and tools to reduce the induced welfare loss to an efficient minimum. The following three parts of this dissertation provide new ideas and directions for the future congestion management in Germany and beyond.

Part II.

Redispatch

Introduction to Part II

Cost-based redispatch is the transmission congestion management mechanism currently implemented in Germany and many other European countries. Therefore, the first part of this dissertation analyzes the implications of this mechanism for the behavior of market participants and the system emissions. This includes whether a market-based redispatch can be an alternative to the current mechanism to send regional investment signals for the development of generation capacity. First, the impact of redispatch on emissions in Germany is evaluated and, the strategic implications of the mechanism for generators and regulators are discussed. This includes an assessment of the ability of generators to forecast their own redispatch deployment and corresponding implications for their strategic behavior. Second, the development and the implementation of a market-based redispatch mechanism are discussed. This includes a critical review of the possibility to exert regional market power with sufficient congestion forecasting ability. The possibility of such forecasting is evaluated using publicly available forecasts of fundamental electricity system data. In conclusion, this part provides a critical analysis of the current state of congestion management in Germany and uses empirical data to assess the strategic options for market participants.

CHAPTER 4

GENERATOR REDISPATCH STRATEGIES

In this chapter, the effect of the currently implemented cost-based redispatch on the energy system and market is evaluated. This includes its effect on the carbon emissions of the power system and thus its consequences for the success of the energy transition. The results show that redispatch increases the carbon emissions. As this jeopardizes the success of the energy transition, the strategic behavior of operators in the redispatch mechanism is considered. The possible strategies of profiting from the cost-based redispatch mechanism and their effects are discussed. As all identified strategies are based on knowledge of the individual future redispatch deployment, a model is developed that can be used to forecast the redispatch deployment of individual power plants. The model shows that redispatch deployment can often be forecasted and occurs with high certainty if predicted. This makes the described strategies attractive for generators. Both, the environmental effect of redispatch as well as the ability to anticipate individual power plant redispatch have previously not been investigated. The following chapter is based on (Staudt et al., 2018c).

4.1. Redispatch and Carbon Emissions

In this section, empirical data on redispatch from January 2015 to December 2017 in Germany is evaluated. The data includes information on the redispatched power plant, the direction of the redispatch (positive or negative) and the average and maximum power. It is published by the four German TSOs with an hourly resolution (50Hertz Transmission GmbH et al., 2018). As cross-border redispatch is not fully reported, the analysis is restricted to redispatch performed in Germany and by

Redispatch	Occurrences	Duration [h]	Energy [GWh]
Positive max	1082	5,319	1,380
Positive min	2	5	1
Negative max	1062	5,973	2,746
Negative min	3	12	1

Table 4.1.: Descriptive analysis of the 100 most redispatched generation units

German operators. First, the data is divided into positive and negative redispatch. A total of 137 power plants are deployed for positive and 162 for negative redispatch in the observed period. 74 power plants are used for both positive and negative redispatch. As some cases of negative redispatch are attributed to groups of power plants (especially lignite), they are analyzed in groups if they belong to the same operator and if they are are situated geographically close. To give a general impression of the redispatch occurrences per power plant, the number of redispatch deployments, the overall time of deployment and the total redispatch energy is calculated for positive and negative redispatch individually. Table 4.1 gives a descriptive analysis of the 100 most frequently deployed power plants both for positive and negative redispatch.

In the following, the focus of the analysis will be shifted to the 100 most deployed power plants for both positive and negative redispatch. As Table 4.1 shows, this does not significantly limit the scope as the minimum deployment is already reduced to 2 and 3 redispatch actions, respectively. To be able to determine the effect of redispatch on the power system's emissions, each power plant is associated to its generation technology. This allows to determine the carbon emissions per generated and reduced unit of energy. In Figure 4.1, the positive and negative redispatch per unit is displayed together with the corresponding technology. It allows to visually identify the difference in employed technologies for positive and negative redispatch. The majority of negative redispatch is performed by lignite and hard coal power plants. This has a mixed impact on carbon emissions that can hardly be calculated without additional knowledge on the generation schedule of the power plants: Assuming that these plants are not shut down entirely, then, redispatch forces them to deviate from the optimal point of operation, which causes reduced efficiency and therefore more emissions per generated unit of energy (Turconi et al., 2014). Note that these technologies already have the highest relative emissions as can be seen in Table 4.2. Natural gas is the dominant generation technology for positive redispatch. The switch from hard coal and lignite to natural gas has a decreasing effect on the carbon emissions of the power system (Icha and Kuhs, 2018). Hard coal is the dominant technology among power plants that are used for both, positive and negative redispatch. The redispatch data omits the reduction of renewable generation through feed-in management (Schermeyer et al., 2018). Feed-in management has a considerable impact on the emission effects of congestion management. Between 2015 and 2017, a total of 11,674 GWh of emission free generation have been curtailed (Bundesnetzagentur, 2017b, 2018a, 2017a, 2016a). To ensure grid balance, this generation needs to be replaced by conventional generation. The difficulty in determining the exact effect of redispatch on carbon emissions is that cross-border redispatch is not reported (BDEW, 2018). The total reported positive redispatch energy is 10.5 TWh while the reported negative amount is almost twice as high with 19.2 TWh. It is therefore not possible to give a complete account of the emission effect of the redispatch. This is confirmed by the German government who answered to a request of the opposition that "[...] data for international redispatch is not reported on power plant basis [...]" and that there is "[...] no concrete information on the fuel that is used to replace curtailed renewable generation" (Bundesregierung, 2018a). The missing data has no impact on the final strategy analysis of this chapter as redispatch deployment is analyzed on generation unit level. As the considered units are located in Germany or operated by German companies this data is complete. In order to still give an indication of the environmental effect of redispatch, the emissions of positive and negative redispatch are calculated based on an average redispatched GWh. The specific emissions of each technology are based on Icha and Kuhs (2018) and are displayed in Table 4.2. The analysis reveals that each GWh of positive redispatch over the considered horizon causes 714 tons of carbon emissions. At the same time each negative GWh of redispatch reduces the carbon emissions by only 576 tons on average. This allows to conclude that redispatch has an overall negative environmental effect. It therefore does not only reduce the public acceptance of the energy transition as it causes additional costs, but also weakens the environmental effect of transitioning to more renewable electricity generation. This makes an efficient congestion management even more important. The shift between conventional generation technologies for redispatch is mostly from lignite and hard coal to natural gas generation, which has a reducing effect on carbon emissions. The negative overall effect is caused by the curtailment of renewable generation. As renewables have the lowest marginal cost of production, any efficient congestion management would avoid the curtailment of these sources. This is further motivation for the approaches suggested in this dissertation.

Fuel	Carbon emissions
Lignite	1,148 tons/GWh
Hard coal	847 tons/GWh
Natural gas	382 tons/GWh

Table 4.2.: Specific carbon emissions of electricity generation based on Icha and Kuhs (2018)

So far, this analysis only considers the replacement of one generation technology by another as driver for increased emissions through redispatch. However, as previously pointed out, the effect of redispatch goes beyond this increase as the efficient operation of power plants is disturbed. Lignite power plants do not only use the most emission intensive technology (Icha and Kuhs, 2018) but are also much more often ramped down than ramped up (14.0 TWh to 0.05 TWh). Their loss in efficiency by reducing their generation from maximum to minimum load is roughly 10% (Schröder et al., 2013). This is equivalent to roughly 100 tons of carbon emissions per GWh of generation. Furthermore, TSOs have announced that in the future, power plants of the network reserve will have to be operated in partial load to provide short-term curative redispatch in order to reduce ramp-up times. This does not only increase the cost of redispatch but also greatly increases emissions, as pointed out by the TSOs in (50Hertz Transmission GmbH et al., 2017). In conclusion, this section shows that redispatch does not only harm the public opinion of the energy transition but negatively affects its objectives. It is therefore crucial to minimize the negative effects of the redispatch mechanism to an efficient minimum. To do so, mechanisms need to be introduced that optimize the short- and long-term environmental and financial costs of congestion management. The following section discusses misplaced incentives of

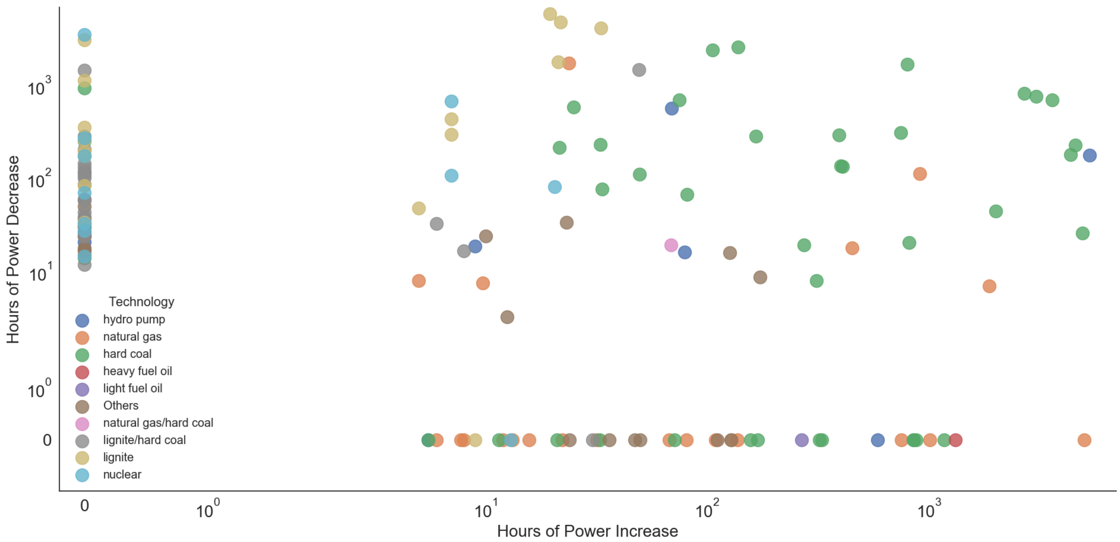


Figure 4.1.: Increasing and decreasing redispatch by generation technology

the cost-based redispatch.

4.2. Redispatch and Strategies

In this section, possible operator strategies are discussed that allow to profit from the cost-based redispatch mechanism as described in Section 3.2.2. These strategies are an important issue when implementing congestion management mechanisms. The most prominent example for strategic behavior in congestion management markets is the Californian case (Alaywan et al., 2004). The so-called increase-decrease (inc-dec) gaming led to a breakdown of the market and the financial default of some of its participants (Woo, 2001). This strategy is further described in Chapter 5. The strategic actions related to congestion management are again discussed today as the EC has called for a market-based procurement of redispatch capacity (European Commission, 2016). Some of the related concerns such as holding back capacity from the wholesale market are expressed by Hirth and Schlecht (2018). This discussion addresses market-based redispatch, but even the cost-based mechanism has weaknesses that allow for a strategic exploitation. Each of the following paragraphs discusses one strategy that can potentially be used in the current design of the redispatch mechanism.

Redispatch Decremental Game The inc-dec game was observed in California after the liberalization of the electricity market. It is a strategy for anticipated down-regulation of power plants. Originally, it describes the behavior of generators to bid high in the day-ahead market and low in the real-time market if they can anticipate to be redispatched down (Alaywan et al., 2004). In the Californian market, this allowed them to pocket the difference between the bids. In the German market, the generators do not have the possibility of setting a low bid in a real-time market but they can still use a similar strategy: By selling more on the spot market than is actually available, operators can achieve additional profits. A power plant that cannot operate at full load due to maintenance or other related issues, can still be sold at full capacity. The redispatch then reduces the output and the operator can keep the difference between the market clearing price and the marginal production cost. Furthermore, power plants operate more efficiently at full capacity. Therefore, the marginal production cost that needs to be reimbursed is lower than it would be at partial load operation. Overall, this incentivizes power plants that already operate in a generation pocket to generate even more, thus aggravating the congestion. This strategy bears a certain risk. If congestion is forecasted but does not occur, the sold amount needs to be procured on the intraday market or balancing power needs to cover the difference, which can be expensive. Therefore, such strategies would only be followed if the redispatch deployment can be accurately forecasted. This chapter shows that this is indeed possible.

Reducing Intraday Exposure The compensation for positive redispatch is regulated. It includes among other things the fuel cost, the wear and tear of power plants but also the foregone profits that could have been achieved on the intraday market as previously introduced in Section 3.2.2. The latter includes both the intraday auction and the continuous intraday trading. The compensation is calculated ex-post after market closure. This reduces the risk exposure of operating power plants as any missed profit opportunity would be reimbursed. A power plant that forecasts to be redispatched can therefore choose riskier day-ahead market strategies as they can expect to be compensated with the intraday price. As the intraday price is highly correlated to the day-ahead price (Gürtler and Paulsen, 2018), the risk of lost revenue on the day-ahead market is small for the operator. The risky behavior in the day-ahead market might lead to the power plant falling out of the Merit Order, even if only partially. Given that the grid situation already suggests that the power plant would be needed for redispatch, this again aggravates the congestion situation: There is less generation in an area that can already be identified as load pocket. Furthermore, it increases both the wholesale electricity price and the redispatch costs and therefore puts the acceptance of the energy transition at risk.

Cost Exceeding Compensation A similar effect can be caused by regulatory mistakes. Power plant operators do not have to foreclose all information on their production costs to regulators. Richstein et al. (2018) argue that the German cost-based redispatch can only be successful when "costs can be tracked easily by third parties". It is therefore possible that redispatch compensation is set too high. This is additionally pointed out by Richstein et al. (2018). The authors state that if "[...] cost based redispatch has issues of determining the exact cost-basis the inc-dec game also exists [...]". Such a miscalculation would of course change the opportunity costs of operators. If a power plant expects to be redispatched, it would only market its capacity on the spot market at the redispatch compensation. This can cause the power plant to fall out of the market, again intensifying the congestion and causing the negative externalities described in the previous section. As for all other strategies, the success is dependent on a reliable forecast of redispatch deployment.

Ramp-up and Bridging Low Prices Sometimes it makes sense for power plants to be marketed below their marginal cost of production. This is true when the ramp-down would cause long idle times or when the ramp-up occurs in hours with low prices, to fully profit from proceeding hours with high prices. The extreme form of such situations are negative prices when power plant operators accept to pay the market for staying online (Genoese et al., 2010). Furthermore, Pape et al. (2016) find that start-up costs have a considerable impact on market prices. Redispatch can be used to avoid these costs for operators as ramp-up costs are compensated and in low price periods the variable costs of generation are covered. A power plant that anticipates to be redispatched in a certain hour can profit from the ramp-up compensation by marketing its generation cheaper over the consecutive hours. If the operator can anticipate that the plant would be redispatched in low price periods over a few hours, she can save the costs that would incur from operating at a price below the marginal production costs. This means that the losses that incur while operating a power plant in difficult market conditions are socialized while the associated market profits are privatized. This jeopardizes the acceptance of the energy transition. Lignite and coal power plants mainly profit from this regulation as ramp-up costs and idle times are typically a major concern for these technologies (Staudt et al., 2018c).

4.3. Forecasting Redispatch

The previous section shows that strategies to profit from the cost-based redispatch mechanism exist under the assumption that redispatch deployment can in fact be anticipated. In this section, two forecasting models based on an ANN and an *Extremely Randomized Tree* (Extra-Tree) are developed and evaluated that allow power plant operators to forecast their redispatch deployment. Both, *recall*, which assesses the correctly predicted occurrences of redispatch, and *precision*, which evaluates how often redispatch actually occurs if predicted, are evaluated. The results empirically show that redispatch can be forecasted based on fundamental system data which highlights potential weaknesses of the cost-based redispatch approach that need to be considered by regulators.

4.3.1. Empirical Feature Data

The intention of this chapter is to assess whether redispatch deployment can be forecasted through classification models using fundamental system data. A descriptive analysis of this data is provided in Table 4.3. For all features, only publicly available forecasts are used instead of actuals. This means that the data is available day-ahead and it is available to all market participants. The features are: forecasts of the load, overall generation, wind generation and solar generation. As no public forecast exists for the market clearing price, the current price is used as the naïve forecast for the next day's price. All data is publicly accessible at the transparency platform of the European Transmission System Operators (European Network of Transmission System Operators, 2018), the European Energy Exchange (European Energy

Feature	Min	Max	Mean	q25	q50	q75
Load [MW]	29,014	74,846	54,672	46,772	54,710	63,023
Solar [MW]	0	27,604	4,060	0	93	6,563
Wind [MW]	284	39,421	9,941	3,919	7,709	133,781
Generation [MW]	32,604	99,606	66,894	57,034	66,483	76,950
Price [$\frac{€}{MWh}$]	-130	163	32	24	31	39
Neg. Redispatch [MW]	0	7,964	729	0	265	1,065
Pos. Redispatch [MW]	0	5,481	398	0	199	559

Table 4.3.: Descriptive analysis of feature data for redispatch deployment forecast

Exchange AG, 2018) and the data platform of the German Federal Grid Agency (Bundesnetzagentur, 2019). Furthermore, two factor variables are introduced to differentiate between weekday and weekend (binary) and the season (factor variable). The observed period is January 2015 to December 2017. The model has an hourly resolution.

This results in a feature matrix with 26,304 data points over the considered period. Deleting data points with missing values results in a data set of 26,040 data points. The feature data is scaled to ensure that the value range has no impact on the activation functions in the ANN. Standardization with zero mean and unit-variance is used as scaling function.

To better understand the data, an initial descriptive analysis is performed. Negative redispatch shows a positive Pearson correlation coefficient r ($\in [-1, 1]$) with wind generation (0.27), overall generation (0.26) and load (0.26). This shows that there is a positive linear relationship between the features. Positive redispatch is positively correlated to wind generation (0.33) and slightly negative with solar generation (-0.07). This supports the suspicion that congestion especially occurs along the North-South line in Germany: Wind infeed in the North causes congestion, while solar generation in the South rather leads to a reduction. Furthermore, load and generation are strongly correlated (0.91) as well as load and price (0.57). This is expected as more demand leads to more supply and higher prices. Other correlations lie below 0.43. The conclusion from the initial analysis is that there is predictive power in the chosen model input features.

4.3.2. Forecasting Models

Redispatch occurs when transmission grids are congested by a pattern of inputs that leads to line flows which exceed the capacity. The inputs depend on the market results, which are in turn dependent on weather conditions, electric load and fuel prices among others. Furthermore, one or more of the features might be dominant. Therefore, the anticipation of redispatch for a specific power plant is a non-linear problem and classification models need to be employed that are able to handle non-linear dependencies.

An ANN and an Extra-Tree classifier are chosen to forecast redispatch deployment day-ahead as they achieve good classification results using their initial configuration. Furthermore, they are able to classify non-linear dependencies and do not require any assumptions on the underlying distribution. The advantages of ANNs for congestion management are furthermore outlined by Satpathy et al. (2015) and Sharma and Srivastava (2008). Additionally, ANNs allow for a flexible representation of other time series models (More and Deo, 2003) and show superior performance over other models in the prediction of zonal prices which is a related problem in energy economics (Daneshi and Daneshi, 2008). ANNs are frequently used in electricity system research for tasks such as price (Amjady, 2006) or wind forecasting (Chitsaz et al., 2015). Extra-Trees are less commonly used in the energy community but have been successfully applied to classification tasks (e.g., Désir et al. (2012)). Furthermore, they allow for an evaluation of feature importance and their interpretability is superior to ANNs. Both models are trained individually for each power plant in the following application.

ANNs are motivated by the processes of the human brain. Several nodes pass information using weights and activation functions and can approximate any mathematical function if configured correctly (Hassoun et al., 1995). A schematic depiction of an ANN as used in this chapter is shown in Fig. 4.2. The information calculated in each node needs to be passed based on by a function. For the described model, the rectified linear unit (ReLu) function is used because of its good performance when applied to classification tasks in input and hidden layers (Glorot et al., 2011).

The ReLu function transforms the signal x to $f(x) = max(0, x)$. The output neuron uses the sigmoid function to obtain the desired classification. The weights between the neurons are randomly initialized in the first iteration. They are then optimized using a backpropagation algorithm that minimizes the classification error given by the loss function along the steepest decline of the stochastic gradient based on the given training data. For this model, the ADAM algorithm is chosen, which is a particular form of the gradient descent (Kingma and Ba, 2014). The weight update per iteration using the ADAM algorithm is performed as follows:

$$\omega_{t+1} = \omega_t - \frac{\alpha \cdot m_t}{\sqrt{v_t} + \epsilon} \tag{4.1}$$

with

ω_t	Weight in period t
α	Step length
m_t	Moving average of gradient
v_t	Moving average of uncentered variance of gradient
ϵ	Constant disruptive term

The gradient g_t with regard to the loss function $L_t(\omega_t)$ and its partial derivatives with regard to the weights ∇_ω are calculated using the following formula:

$$g_t = \nabla_\omega L_t(\omega_{t-1}) \tag{4.2}$$

Finally, a loss function needs to be chosen to define the difference between the predicted label and the true label to improve the model. A common measure for classification tasks is binary cross entropy (De Boer et al., 2005). The objective function for the ANN is therefore the minimization of the following:

$$L(\omega) = -\frac{1}{T}\sum_{t=0}^{T} y_t log(\hat{y}_t) + (1 - y_t) log(1 - \hat{y}_t) \tag{4.3}$$

with $\hat{y}_t$ being the sigmoid estimation for the class, and y_t being the actual class for data point t with batch size T.

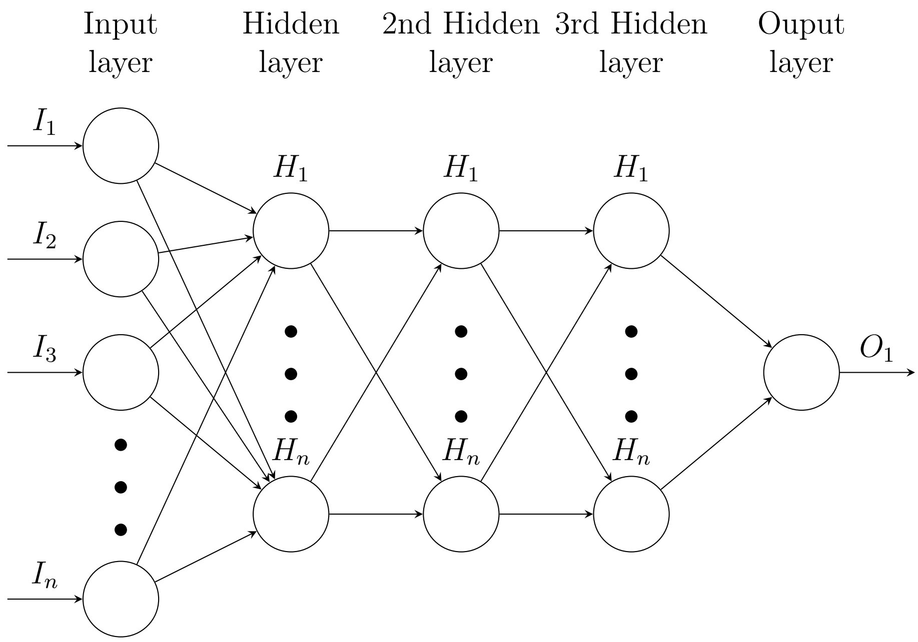


Figure 4.2.: Stylized architecture of the applied ANN

The exact configuration of an ANN is subject to trial and error. There is no clear indication on the exact parameter combination that is ideal for a given problem (Sharpe et al., 1994). One common concern is to avoid overfitting. This means that the model is so well adapted to training data, that it does not perform well on unseen data. At the same time the given information needs to be used as good as possible (Srivastava et al., 2014). Beyond the introduced specifications, the configuration includes the number of layers, the epoch and batch size and the number of nodes in the hidden layers. The batch size describes the number of data points for one training instance or epoch. The epoch size determines the number of runs through the entire data set. The specific configuration for the classification of redispatch deployment is described in the following section 4.3.3.

The Extra-Tree is an ensemble classifier that is based on random forests and therefore ultimately decision trees (Breiman, 2001). Extra-Trees add another level of randomness compared to random forests. Random forests use a randomly chosen subset to create decision trees and then calculate the optimal cut point for each feature of the tree. Extra-Trees additionally randomize the cut point for each feature. Therefore, training times are reduced. Geurts et al. (2006) show that Extra-Trees perform at least as good or better than random forests. Extra-Trees only need a few specifications. The configuration includes the number of decision trees, the maximal depth of the tree and the minimal data points allowed at one leaf. The optimization of the decision tree is performed using the Gini impurity $I_G(p)$ (Breiman, 2017) as an error measure. It measures the probability that a randomly chosen item from a subset would be misclassified by randomly classifying it according to the probability distribution of the corresponding subset at the node or leaf. This implies that it is zero if all items at a node or leaf belong to one class. It is calculated according to Equ. 4.4 with i being a specific class and J the number of classes. In the specific case of binary classification this implies $J = 2$.

$$I_G(p) = \sum_{i=1}^{J}(p_i \cdot (\sum_{k \neq i} p_k)) \tag{4.4}$$

Two types of models are trained to differentiate between the importance of regional and autoregressive components of redispatch deployment. The regional model uses data on TSO level (if available) to forecast redispatch deployment as it is a regional phenomenon. The autoregressive model uses the day-ahead deployment for redispatch as an additional feature to find consecutive occurrences of redispatch, which can often be traced to faulty infrastructure such as transformer outages (50Hertz Transmission GmbH et al., 2017). The results in the following section show that the regional component has a stronger influence than the autoregressive component. Therefore, Fig. 4.3 and Fig. 4.4 report the results using the regional feature data model.

The validation of the models is done using stratified k-fold cross-validation (Kohavi et al., 1995) with k set to 10. 80% of the data is used for training and validation. The data set is being split into 10 mutually exclusive subsets with the same number of data points. It is split such that the average number of occurrences of each class, in this case *deployment* and *no deployment*, is roughly respected for each created subset. Using the cross-validation approach, the model is trained and tested 10 times. Each time one subset is omitted in the training process and then used for testing. Finally, the remaining unseen 20% of the data is used for the final testing.

4.3.3. Results

After pre-processing the data, the models are trained. Initially, both models, the ANN and the Extra-Tree, are trained individually for positive and negative redispatch to find peculiarities of power plants used for positive and negative redispatch. However, the same configuration of hyper-parameters performs best for the two directions of redispatch. This might be caused by the fact that the TSOs react with similar measures in similar environments and therefore the same model can identify both the instructed increase and decrease of redispatch. Because the computational effort of training and evaluating the models is high, the analysis is restricted to the 25 most deployed power plants for positive and negative redispatch. This covers at least 80% of the time and energy of upward and downward redispatch and each considered power plant has at least 200 hours of redispatch deployment. This is important for the models to have sufficient training data. Five power plants appear in both sets. As performance measure we use the recall r, the precision p and the F1 score (see Equ. 4.5).

$$r = \frac{true\ positives}{true\ positives + false\ negatives} \tag{4.5a}$$

$$p = \frac{true\ positives}{true\ positives + false\ positives} \tag{4.5b}$$

$$F1 = 2 \cdot \frac{p \cdot r}{p + r} \tag{4.5c}$$

In this context, *true positives* are correctly forecasted redispatch occurrences, *false negatives* are data points that indicate redispatch but have not been forecasted as such and *false positives* are incorrectly, as redispatch forecasted data points. Therefore, the recall measures the share of actual redispatch occurrences that are forecasted and precision measures what share of the redispatch forecasts is correct. These measures are used instead of, for example, the accuracy, which simply measures the share of correctly forecasted instances, as redispatch is still a rare event (see Table 4.1) and the class distribution is imbalanced. Therefore, always forecasting *no redispatch* yields a relatively high accuracy but does not answer the question if generators can forecast their redispatch deployment. In this section, the results are not only compared between the models but also against the naïve forecast, which is a seasonally adapted version of a random walk where the realization of the previous day serves as a forecast for the current prediction. This is a widely accepted benchmark in forecasting literature (Hyndman and Koehler, 2006).

The ANN has an input layer with one neuron for each feature. It has three hidden layers with 100, 50 and 25 neurons and a single output neuron that uses the sigmoid function to classify. The network is trained in 150 epochs with a batch size of 25. The learning rate is set to $\alpha = 0.001$. The Extra-Tree is specified with a number of trees of 500, a maximal depth of 30 and a minimum of one data point per leaf. The configuration of the Extra-Tree is found using grid search (the systematic detection of the optimal configuration from a range of parameters (Bergstra and Bengio, 2012)). The configuration of the ANN is found using grid search on the global data instead of the regional data as the repeated training of ANNs with this high number of features is computationally too expensive (one model run with 25 power plants on a machine with 12GB RAM, 4 processors and 2.4 GHz takes 53 hours). The models are trained and validated using 10-fold cross validation on 80% of the data. The remaining 20% are kept for the test set. The results are reported on the test data in Table 4.4. The results from the cross-validation are shown in the Appendix for validation purposes. The results for a power increase are shown in Table A.1 and for a power decrease in Table A.2.

The results in Table 4.4 show that the individual power plant redispatch deployment can be predicted with a high precision even on average. Using the Extra-Tree, the precision for the redispatch deployment is higher than 90%. That means that operators can highly trust in a prediction of redispatch and thus adapt their bidding strategy correspondingly. The ANN achieves a precision of almost 90%, meaning that forecasted redispatch actually occurs with a probability of 90%, while predicting redispatch occurrences with a probability of over 80%, as shown by the recall. The results for individual power plants are displayed in Fig. 4.3 for positive redispatch and in Fig. 4.4 for negative redispatch. The individual results underline the possibility for power plant operators to anticipate their redispatch deployment. Therefore, the strategies introduced in the beginning of the chapter can easily be

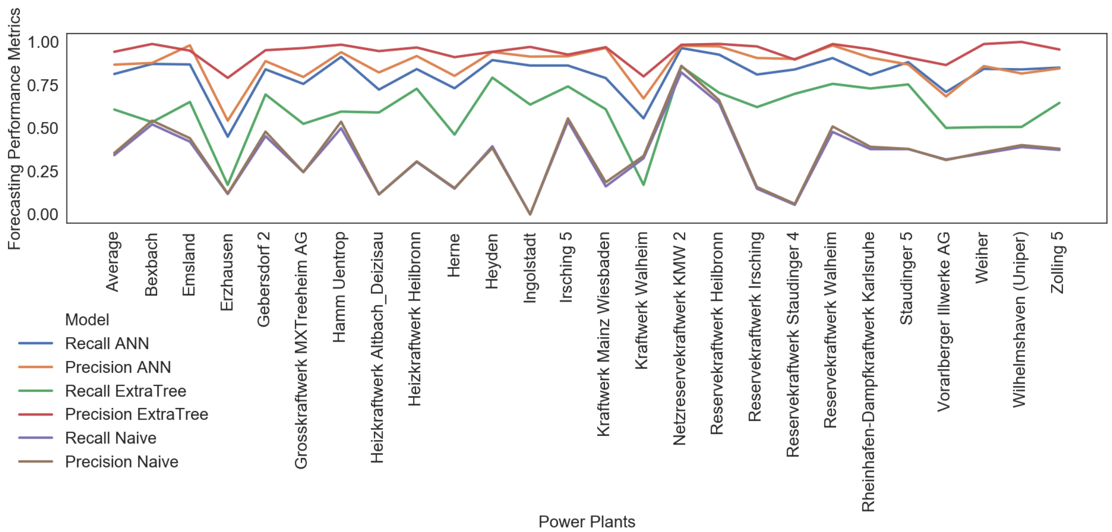


Figure 4.3.: Forecasting results for positive redispatch

Model type	ANN				Extra-Tree			
Data type	Regional		Autoregressive		Regional		Autoregressive	
Redispatch	Pos.	Neg.	Pos.	Neg.	Pos.	Neg.	Pos.	Neg.
Recall	**0.81**	**0.76**	0.54	0.47	0.61	0.52	0.47	0.37
Precision	**0.87**	**0.84**	0.66	0.62	**0.94**	**0.94**	0.78	0.75
F1-Score	0.84	0.81	0.59	0.53	0.73	0.66	0.58	0.49

Table 4.4.: Average forecasting results of both models using different data sets

followed.

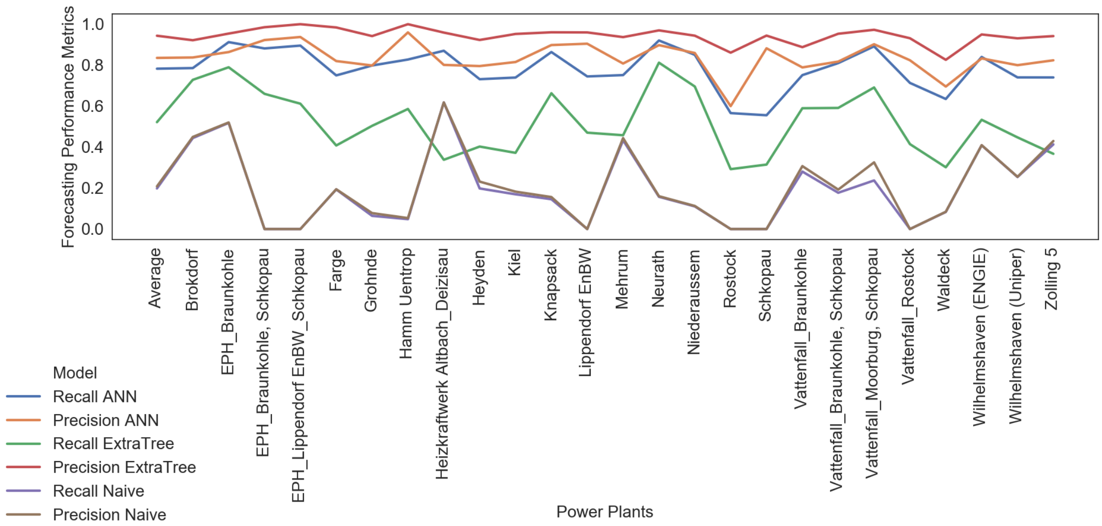


Figure 4.4.: Forecasting results for negative redispatch

4.4. Summary of Chapter 4 and Discussion

The objective of this chapter is to discuss the impact of the redispatch mechanism on the carbon emissions of the electricity sector and on market behavior of participants. The results show that, even though emission intensive power generation is often reduced, the overall ecological balance of the redispatch mechanism is negative. The application of the mechanism leads to more emissions. Then, the strategic implications of the mechanism are discussed. Several possible generator strategies are described to profit from cost-based redispatch. It is shown that some of these strategies might even aggravate grid congestion. All strategies are based on the correct anticipation of individual redispatch deployment. Therefore, it is evaluated whether individual power plants can anticipate their redispatch deployment given the fluctuation of renewable generation, load and other factors. To this end, two models are developed and applied to three years of empirical data. They are benchmarked against each other and a naïve forecast. The results show that certain operators can indeed forecast their redispatch deployment using publicly available data. This is true even though information on technical failure of system components (such as transformer outages or line failures) is not included in the model. While a majority of redispatch occurrences can be correctly anticipated, a prediction of redispatch is

almost certainly true on the evaluated data. In the following chapters, adjustments of the redispatch mechanism are proposed. However, the presented models can already be used to better oversee the current redispatch regulation. Using the model, regulators can identify power plants and situations for which redispatch could be anticipated. These situations could than be overseen more closely, which could be combined with additional regulation on the allowed behavior for redispatch.
The results already reveal a few weaknesses of the cost-based redispatch mechanism. However, one of the major drawbacks of the mechanism is the lack of regional investment incentives. Even though it can be gamed to some extent, the revenues would not warrant the construction of additional generation capacity in load pockets. Therefore, the mechanism has no effect on the long-term reduction of transmission grid congestion. This is a serious concern as this might ultimately result in a distribution of generation assets that cannot guarantee a balanced grid operation at all times and makes expensive and unpopular grid expansion indispensable. Additionally, it may lead to a division of the German bidding zone as the EC has announced to split bidding zones if congestion prevents interconnector capacity from being made available at at least 75% (Bundesregierung, 2018a). The following chapter discusses a currently considered reform of the redispatch to a market-based mechanism.

CHAPTER 5

FORECASTING TRANSMISSION CONGESTION

One of the major weaknesses of the cost-based redispatch mechanism is that it does not provide regional investment signals (Hirth and Schlecht, 2018). However, redispatch is currently the only locational signal in the German electricity market. It could thus be used to steer the expansion of generation capacity to regions where it is needed if renewable generation is low. Therefore, and due to legislation by the EC (European Commission, 2016), the German government evaluates the transition to a market-based redispatch. Such a market exists for example in the Netherlands (Hirth and Glismann, 2018). The design of redispatch congestion markets is introduced in Section 5.1. The market can only be successful if persistent regional market power beyond usual scarcity rents is avoided and if congestion cannot be anticipated. In the latter case, a power plant might not sell its capacity on a less profitable spot market and instead only bid into the congestion market. Thus, the congestion is aggravated as described for several strategies in the previous section. Richstein et al. (2018) point out that "actors will for example avoid selling electricity in the day-ahead market and choose to be remunerated at the short-term locational (re-dispatch) market price if wind and solar generation patterns allow market participants to anticipate grid constraints and therefore profit from more attractive prices in the redispatch markets". The difficulty in today's electricity markets is that grid constraints cannot be forecasted based on outages but need to consider load and renewable generation patterns. In this chapter, the possibility to anticipate grid congestion is therefore evaluated and combined with a critical appraisal of a market-based redispatch mechanism. The chapter is in part based on (Staudt et al., 2019b).

5.1. Market-Based Redispatch

One of the major weaknesses of the cost-based redispatch is that it does not provide long-term signals for regional generation investment. Therefore, a wind turbine is most profitable where most wind energy is generated and not where it is most useful to the system. A gas power plant might be more attractive at harbours in the regional periphery, where liquified natural gas can directly be delivered to the power plant. Market-based congestion management causes regional congestion prices to emerge that should set incentives for the expansion of regional generation capacity. This does not help to overcome other weaknesses of the redispatch mechanism such as the lost producer surplus, which is covered by consumers, but it does at least ensure that regional capacity for redispatch is available.

Market-based redispatch is discussed in Hirth and Schlecht (2018) as part of a federal project in Germany that assesses the market-based procurement of congestion management capacity. This initiative is necessary as the EC requires member states to assess market-based redispatch mechanisms (European Commission, 2016). Glismann (2018) proposes to use a framework for the procurement of ancillary services including redispatch. The framework is first introduced in Glismann and Nobel (2017) and evaluation criteria for the related market design options are presented by Rieß et al. (2017). Several papers such as (Richstein et al., 2018) address the inc-dec game that is discussed for the cost-based redispatch mechanism in Chapter 4, which is a major impediment for market-based redispatch. In essence, generators bid low prices in the day-ahead market if they can expect to be in a generation pocket. They are then dispatched and compensated based on the market clearing price that is higher than their bid. As they are in a generation pocket, they are instructed to reduce their generation. In designs that allow the traditional inc-dec game, they then need to reimburse the operator with their bid price as this is assumed to be their marginal cost of production. The design of the Dutch redispatch market is described by Hirth and Glismann (2018). The German Federal Association of the German Energy and Water Industries has published a statement that welcomes the initiative of the EC to liberalize the congestion management market but argues that the national regulatory agencies need to oversee whether sufficient competition can be ensured (Bundesverband der Energie- und Wasserwirtschaft e.V., 2018). A critical review of market-based redispatch is brought forward by Grimm et al. (2018) and Hirth and Schlecht (2018). The authors of both publications argue that market-based redispatch results in an inefficient power plant dispatch. In (Grimm et al., 2018), the authors emphasize that market-based redispatch has the advantage of providing long-term investment signals. However, they show that if redispatch is procured using marginal cost pricing at each node, the TSO might have an incentive to dispatch generators who clear congestion less efficiently but lead to lower overall payments. They argue therefore that the TSO needs to procure redispatch by clearly defined rules and without price considerations and that the prices should then be determined afterwards given the efficient redispatch. In (Hirth and Schlecht, 2018) the authors show how the inc-dec game leads to inefficient dispatch. The authors conclude that market-based redispatch can only be successful if congestion is rare and unpredictable. This chapter shows however that anticipation is indeed possible. Therefore, ample competition is necessary to ensure competitive behavior on which Chapter 6 further elaborates. An extended example including details on the strategic decision problem faced by the operator is provided in the following.

Consider the example in Fig. 5.1. The system node on the left side is connected to the overall transmission grid by a limited line capacity. Assume that the capacity is sometimes sufficient to supply the node and sometimes it is not. Therefore, the node is a potential load pocket. Connected to the node is renewable generation with marginal production cost of zero, a cheap conventional generator with marginal production cost of $mc = p_{low}$ and capacity c_{low} as well as an expensive generator with marginal production cost of $mc = p_{high} > p_{low}$ and capacity c_{high}. Now, the strategic decisions of the cheap generator in a sequential two stage spot and congestion market are considered. For simplicity, the market clearing price is assumed to be $p_{low} < p_{market} < p_{high}$ and all generators at the considered node are price takers on the spot market. It is uncertain whether congestion will occur at the node. That depends on the uncertain load and the uncertain generation from the renewable capacity. Assuming that the generation capacity is not partly marketed in both market stages, which would only be reasonable as a mixed strategy under uncertainties, the cheap generator has two options: Its capacity can be sold on the spot market or it can be retained for the congestion management in the second market stage. On the spot market, the cheap generator can obtain a revenue of $p_{market} \cdot c_{low}$. On the congestion market, the cheap generator can increase its price up to the expensive generator p_{high} as no other alternative to manage congestion exists. However, the needed energy to clear congestion $q_{congestion}$ might be below the capacity of the cheap generator. If the cheap generator holds out for the congestion market, the potential congestion would be aggravated as there is less generation at the node. In fact, the cheap generator needs to consider how much electricity would be needed on the congestion market if its capacity is not sold on the spot market and calculate if $p_{high} \cdot \mathbb{E}(q_{congestion}|b_{market} = 0) > p_{market} \cdot c_{low}$, where b_{market} is the bid quantity on the spot market by the operator. This strategic consideration already shows that such a two stage market provides mixed incentives. Note that a deviation of the cheap generator from its ideal behavior of bidding in the spot market causes market inefficiencies and additional costs for consumers. After the cheap generator has chosen where to sell its capacity, the spot market is cleared and it becomes apparent whether congestion occurs. Four outcomes are now possible as shown in Table 5.1. The difference between the theoretical congestion income and the spot market income cannot be determined without knowledge of further parameters. Assuming however, that the expensive generator does not compete for the congestion management, e.g., due to maintenance, the congestion price would be set by the cheap generator, which would allow to make up for any losses in sold quantity compared to the spot market. This shows that both the anticipation and a market controlling position play an important role in abusing the market-based redispatch mechanism. In the given example, the outcome which is to be avoided by the generator at all cost, is that congestion is forecasted but does not occur as this leads to a payout of zero. This chapter empirically evaluates whether congestion can be anticipated to the extent that this strategic behavior can be profitable. To this end, the possibility of anticipating congestion in the German transmission grid is investigated to assess whether strategic considerations could harm any implementation of a market-based congestion management mechanism.

Strategy/Congestion	Congestion	No Congestion
Spot market	$p_{market} \cdot c_{low}$	$p_{market} \cdot c_{low}$
Congestion market	$p_{high} \cdot q_{congestion}$	0

Table 5.1.: Revenue based on market results and strategy

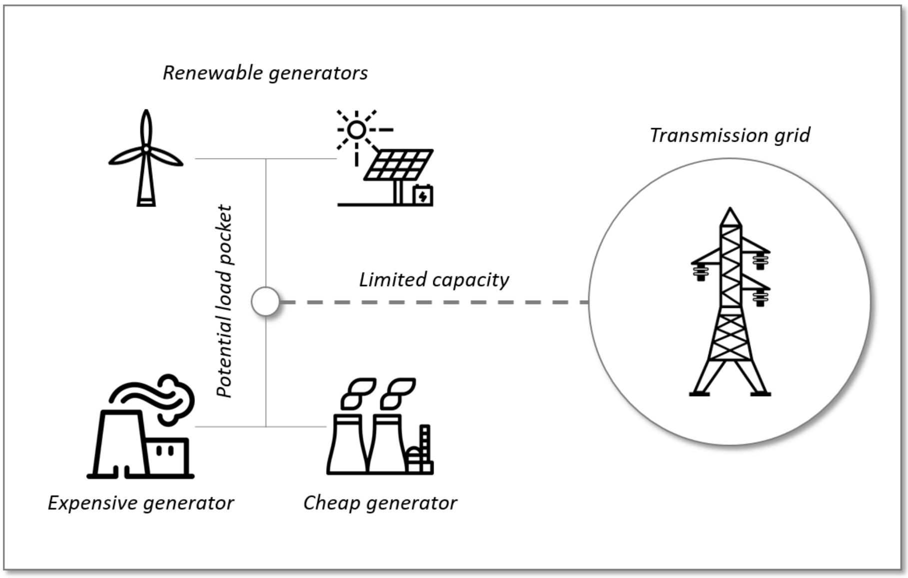


Figure 5.1.: Exemplary depiction of a node connected through a single transmission line

5.2. Congestion in the 50Hertz Transmission Grid

The empirical data used in this chapter comes from the German TSO 50Hertz, which is the only the German TSO publishing its congestion data (50Hertz, 2018a). The transmission system of 50Hertz is situated in the Northeast of Germany. In the first quarter of 2016, 50% of all redispatch operation was conducted in the control area of 50Hertz (Bundesnetzagentur, 2016c). The TSO is therefore of special interest as it greatly contributes to the North-South division of the German electricity system. The considered period is January 2015 to December 2017 as in the previous chapter. Congestion of a transmission line is reported in three states: green, yellow and red. Green implies a load of less than 50% of the thermal capacity, yellow means between 50% and 70% and red above 70% (50Hertz, 2018a). In Germany, the n-1 criterion applies. It means that in case of any single system component failure, a stable system operation has to be guaranteed (Holttinen et al., 2011). According to the explanation provided by 50Hertz (50Hertz, 2018b), yellow implies an operation close to the limit imposed by the n-1 criterion and red implies an operation at the limit. Therefore, both states can be classified as congestion and the presented model is intended to classify between the save system operation (green) and the case of congestion (yellow or red). As in the previous chapter, only forecasted, publicly available data is used. This ensures that operators could profit from an anticipation of congestion through bids in the spot auction. The used features are the net grid input, the net load (for 50Hertz and Germany), the wind and solar generation, the scheduled generation, the scheduled export (import in case of negative values) to the Czech Republic, Poland and Denmark, the German market clearing price of the previous day and a binary variable for weekend and weekday. All data is from the 50Hertz region if not specified differently. The intention of this data set is to include all factors that could influence the grid state. In order to evaluate the impact of forecasting errors in the data on the final prediction results, the developed model is also trained separately with realized data. This helps to evaluate the impact of improved private forecasts on the ability to anticipate congestion and to find whether the set of input features is sufficient to describe congestion. All features are mapped to hourly values as the congestion data is provided on an hourly basis. The German net load is corrected to the German net load without the 50Hertz control area to avoid multicollinearity. Data points with missing values are eliminated. This results in a total of 19,146 values. A descriptive analysis over the input features is provided in Table 5.2.

The developed models predict congestion on individual lines. This is more detailed than needed for individual power plants to know whether they are in a load or generation pocket. Instead, it is often precise enough to know of one congested line that cannot be relieved by many other operators. In total, 90 out of 200 lines are considered which have at least 80 congestion events. A certain number of congestion events is important to distribute them among the training, validation and test set for the model training. 45% of all lines have at least 80 congestion events over the observed period, which gives an indication on the extent of congestion. The distribution of congestion events is depicted in Table 5.3. The data for each line is not necessarily always complete. Of the total 19,146 data points, the congestion

Feature	μ	σ	Min.	Max.	Unit
Net input	12478	1579	81	18530	MWh
Net load (50 Hertz)	9256	1858	0	13452	MWh
Net load (Germany)	45327	7994	27347	61256	MWh
Wind generation	3073	2734	45	13360	MWh
Solar generation	985	1519	0	7249	MWh
Scheduled generation	11755	2298	4410	21131	MWh
Export CZ	-111	345	-1400	1184	MWh
Export PL	-108	254	-1688	580	MWh
Export DK	-185	458	-600	601	MWh
Spot prices	32	14	-130	164	EUR/MWh

Table 5.2.: Descriptive analysis of features for congestion prediction

Feature	μ	σ	Min.	Max.	q25	q50	q75
Red & Yellow	1480	1973.6	80	7830	644	184.3	2149
Red only	355.6	450.7	56	1857	181	81	380.5

Table 5.3.: Descriptive analysis of congestion events in the 50Hertz control area

data of the transmission lines is on average available for 16,702 cases. The maximum is 19,097 and the minimum is 408.

As described, the analysis also considers actuals for certain input features to simulate improved forecasts of specific key figures. The aim is to better judge the potential of anticipating congestion for private actors with access to improved forecasts. To do so, after an initial model evaluation, some forecasted features are replaced by the actuals. Using only forecasted data is the base data set and scenario 1. In the following scenarios, the the wind generation forecast is replaced by actuals (scenario 2) and finally wind generation, net load and exports are replaced (scenario 3).

5.3. Forecasting Models and Results

The classification forecast of congestion is done using the same models as in the previous chapter: An ANN with backpropagation and an Extra-Tree classifier. A logistic regression model is used as benchmark as well as a naïve forecast. The used features are all forecasts, which are available day-ahead and can be accessed by market participants.

5.3.1. Model Parameterization

As in the previous chapter, an ANN and an Extra-Tree are trained to forecast the congestion state of a line. These models are used due to their ability to represent non-linear dependencies without needing ex-ante assumptions on their distribution. The models are benchmarked using a naïve forecast which assumes the congestion state of the line on the previous day (or weekend/holiday in case of Saturday, Sunday or a public holiday) and a logistic regression. Not all results for the logistic regression can be reported but an excerpt is shown in Table A.7 of the Appendix to provide some insights. Every line is trained with the same configuration of the ANN which results in an individual model for each line. The ANN has three hidden layers with 100 neurons in the first hidden layer, 50 in the second and 25 in the third. The batch size is 25 with 100 epochs. The configuration is chosen based on a trial and error process (Sharpe et al., 1994) as grid search is too computationally expensive (see also the previous chapter). An excerpt of the iterative process that led to the design is presented in Appendix A.3. The used activation functions are ReLu in the hidden layers and the sigmoid function in the output neuron. ADAM is the optimization algorithm for the backpropagation of the model error. The training-validation-test split is 64%-16%-20%, implying the hold-out method (Kim, 2009). This split is computationally less expensive than cross-validation and can be used as the variance of cross-validation results in exemplary test runs is low, allowing to do a less extensive validation (Refaeilzadeh et al., 2009). The corresponding cross-validation results for 15 exemplary lines are provided in Appendix A.4. The Extra-Tree is parameterized with a number of trees of 10, no maximum depth and at least two samples per leaf.

5.3.2. Base Case Results

In order to get a better understanding of the causes for congestion, the empirical data is analyzed with regard to its importance for the given classification task. This is done using the Gini impurity which is the error measure of the Extra-Tree. It describes the decrease in impurity of the classification data set that is achieved using the respective feature. The results are displayed in Table 5.4. It shows that wind generation is the most influential factor for congestion in the 50Hertz area. This can be expected as the 50Hertz zone has a high capacity of wind generation, while the grid has been designed to transmit the power generated by the local lignite power plants. Furthermore, the power flow to the Czech Republic plays an important role. This might be because it is another proxy for wind generation: If lots of wind energy is generated, the abundant power flows through the Czech grid. Furthermore, the price and net load are important features. The seasonal dummy feature, the weekday and the solar generation play only a minor role.

Feature	Gini impurity decrease	Feature	Gini impurity decrease
Wind	0.141	Price (EPEX)	0.089
Im/Export DE-CZ	0.107	Im/Export DE-DK	0.076
Net load	0.10	Im/Export DE-PL	0.076
Net input	0.099	Solar	0.059
Sched. generation	0.096	Season	0.049
Net load Germany	0.092	Weekday/-end	0.019

Table 5.4.: Mean feature importance for all lines of the 50Hertz control zone

As in Chapter 4, the performance of forecasting congestion is evaluated as congestion is a rare event. The precision and recall for no congestion are around 97.5% for the ANN. Table 5.5 shows the results using the base data set, which only contains forecast or previous-day data. The results show a good average performance of the ANN. The Extra-Tree exhibits particularly high precision values. High precision is a valuable characteristic as it provides the user of the forecast with a high certainty in case of a congestion forecast and it helps to avoid a complete loss of revenue as described in Example 5.1. Fig. 5.2 displays the results per line. It shows that certain congestion can be forecasted with very high values of recall and precision. This demonstrates that particular power plants can easily forecast their position in a hypothetical redispatch market given that they know about their power distribution factor impact on the congested line. This implies severe danger of gaming if such a redispatch market is to be implemented. The high precision values of the Extra-Tree also minimize the risk associated with betting on the redispatch market as shown in Section 5.1. The following section provides an analysis of the impact of improved forecast ability of the feature values on the forecast ability of line congestion.

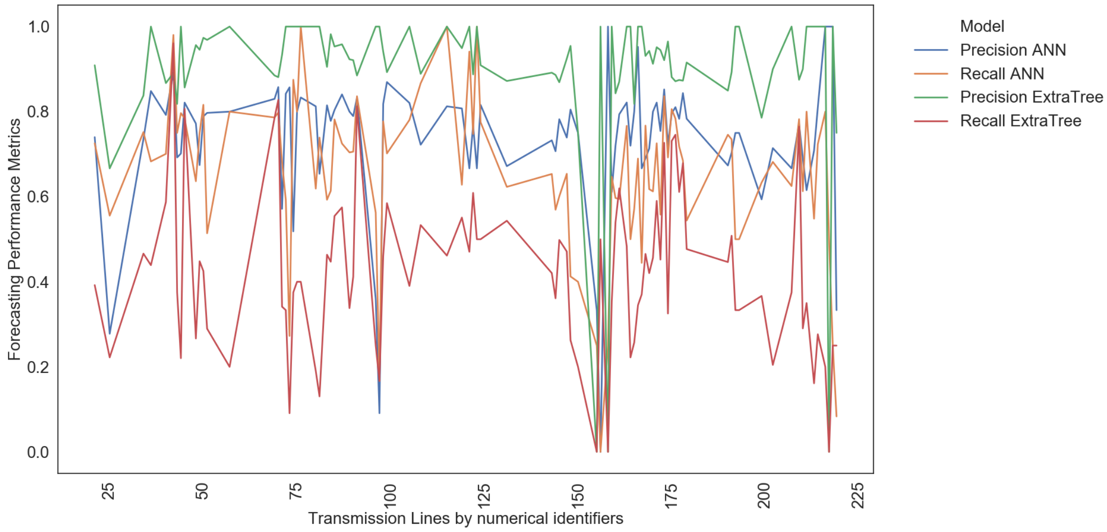


Figure 5.2.: Precision and recall for different forecasting methods

Classifier	Precision	Recall	F1-score
ANN	73.6%	65.6%	67.9%
Logistic regression	34.1%	13.2%	16.7%
Naïve forecast	6.7%	8.8%	7.3 %
Extra-Tree	89.8%	41.9%	54.8%

Table 5.5.: Congestion classification results using only forecasted features

5.3.3. Forecast Improvement

In this section, the forecasted feature values are partly replaced by their actuals to identify the impact of wrongly forecasted features on the final outcome of the congestion forecast. This is especially interesting as the used forecast values are publicly available. However, private companies possess the ability to forecast such figures with more accuracy (Connolly et al., 2010). Table 5.6 shows the errors of public load and renewable generation forecasts for Germany from 2015 to 2017. The displayed values are the root mean squared error (RMSE) and the RMSE normalized by the mean of the actual values. It can be seen that especially the renewable generation forecasts have a considerable error margin. At first, the wind generation is replaced by actuals as many commercial wind power generation forecast providers exist. Table 5.7 shows the results. As can be seen, both, the recall and precision increase for the ANN and the Extra-Tree. The naïve forecast is not displayed as the results stay the same as in the base case. The precision of the Extra-Tree becomes very high, such that the reliance on the forecast has almost no associated risk. Replacing wind generation, net load and exports by their actuals improves the classification greatly, especially in the case of the Extra-Tree as can be see in Table 5.8. This leads to a state where almost all occurrences of congestion are correctly classified and the certainty with which a forecasted congestion actually occurs is close to 100%. This raises the suspicion of overfitting. However, the results are achieved on unseen test data. One probable reason is the relation between physical cross-border flows and congestion. An analysis of the correlation reveals that the load on some lines has a linear relationship with the cross-border flows. The average absolute Pearson correlation of all lines with the cross-border flow is 0.22 with individual values above 0.6. These are high values considering that the relationship between cross-border flows and line load is not linear. The findings might be useful for other applications of the model such as optimal grid switching. Both results show that congestion forecasting is possible and that this needs to be considered when designing and implementing congestion management markets.

Feature	Mean	RMSE	Normalized RMSE
Load	13,802	539	3.91%
Wind Onshore	2,083	340	16.3%
Wind Offshore	356	71	20.0%
PV	1,000	172	17.2%

Table 5.6.: Evaluation of public forecasts for Germany from 2015-2017

Classifier	Precision	Recall	F1-score
ANN	81.4%	78.1%	78.5%
Logistic regression	37.9%	17.8%	21.7%
Extra-Tree	95.1%	57.7%	69.5%

Table 5.7.: Classification results of data set 2 with wind generation actuals

Classifier	Precision	Recall	F1-score
ANN	80.8%	80.4%	80.1%
Logistic regression	62.5%	35.9%	41.8%
Extra-Tree	99.9%	99.3%	99.6%

Table 5.8.: Classification results of data set 3 with wind, net load and export actuals

5.4. Summary of Chapter 5 and Discussion

In this chapter, the implementation of a market-based redispatch mechanism is discussed. This consideration is driven by directives of the EC and the advantage of providing regional investment signals for the installation of generation or storage capacity. However, as shown in the beginning of the chapter and as assumed by other scholars, the possibility of anticipating congestion coupled with regional market concentration leads to severe drawbacks of the market-based redispatch. Using an illustrative example, it can be understood that such a mechanism in combination with the described characteristics leads to adverse incentives for system stability. The threat of loss from gaming the market needs to be sufficiently high to ensure competitive behavior. In order to assess the actual ability of generators to anticipate congestion, empirical data from the German transmission grid is used. To this end, two forecasting models are designed and benchmarked. Based on publicly available forecasting data, the congestion of individual lines in the area of the 50Hertz TSO is forecasted day-ahead. This ensures that the knowledge gained from the models is available before the day-ahead market clearing. The results show that the threat of congestion anticipation is fairly high. On some lines, the threat of falsely forecasting congestion can almost be eliminated. As in Chapter 4, the Extra-Tree classifier leads to high precision values which characterize the certainty of congestion if it is forecasted. It should be noted that as in the previous chapter it cannot be claimed that these are the most powerful models. It is possible and likely that other configurations could lead to slightly better results. However, the model performance is sufficient to show how they can be used to reduce the risk of strategic reactions to anticipated congestion. The results of this chapter force regulators to be careful with the implementation of regional market-based redispatch. It needs to be ensured, as proposed by the EC, that regional competition is sufficiently high. This would greatly increase the expected value of opportunity costs from gaming. Therefore, in the next part of this dissertation, a tool to identify regional market power is introduced and a way to increase competition through smart grid technology is investigated.

Part III.

Competition

Introduction to Part III

Part II discusses the redispatch mechanism and shows that it has weaknesses due to the possible anticipation of redispatch deployment and network congestion. These weaknesses are especially serious for market-based redispatch. Such a design could send investment signals to expand necessary regional generation capacity but it could also lead to the abuse of regional market power. The inherently regional phenomena of load or generation pockets reduce the market competition as only a limited number of generators can counter a specific congestion. This raises the question of the necessary extent of market competition to ensure that no market controlling position of individual generators emerges. In Chapter 6, a model is developed and validated that can be used to detect market power and to simulate the necessary addition of generation capacity to reduce such effects. Chapter 7 then introduces possible new participants for the redispatch market to increase competition. Smart grid technology is proposed to employ EVs using V2G technology to relief the grid of congestion. In this design, EVs are used as a buffer for the transmission grid, thus advancing the concept of the internet of energy.

CHAPTER 6

COMPETITIVE REGIONAL POWER MARKETS

Market power is an often considered research area in electricity market design. This is due to the rather recent market liberalization and the traditionally high entry barriers in terms of initial investment (Von Hirschhausen et al., 2007). Renewable generation has changed the perspective in the way that competition only needs to be considered for the residual load that persists after renewable generation has been subtracted from the overall load (Schill, 2014). This chapter introduces a model that can help to identify market power in electricity markets with a high penetration of renewable generation capacity. The purpose of the model in the context of this dissertation is to identify regional market power that can arise with respect to congestion management. The presented case study is therefore carried out in a regional consumption scenario of a small city that is disconnected from the transmission grid. However, the model can also be used to analyze regional wholesale or redispatch markets if a full network model including power distribution factors is available. In the following, the research on market power in electricity markets is briefly discussed. Then, the developed model is presented and finally evaluated in a case study. The chapter is largely based on (Staudt et al., 2018a).

6.1. Market Power on Power Markets

In his book Steven Stoft advocates (Stoft, 2002) to take an economic perspective to market power and to use the definition by Mas-Collel, which states that market power is "the ability to alter profitably prices away from competitive levels" (Mas-Colell et al. (1995), p. 383). Often, competitive behavior on electricity markets is characterized as the bidding of marginal generation costs (Borenstein, 2000). This implies that the market clearing price or the locational marginal price is being set by the marginal cost of production of the last necessary power plant to cover the load. However, a deviation from the marginal price in the case of load peaks is not necessarily covered by this definition and is usually not considered the exercise of market power (Borenstein et al., 1999). Such price peaks are needed to recover investment costs of peak power plants that only come online in rare scarcity situations (Hogan et al., 2005). The exercise of market power in electricity markets is mostly characterized by withheld capacity, either physically or financially by bidding above the marginal cost of production (Ockenfels, 2007). Stoft finds three main drivers of market power in electricity markets: Demand elasticity, generation concentration and the volume of long-term contracts (Stoft, 2002). Low demand elasticity allows generators to greatly increase their prices if competition with other generators does not make this unprofitable. But even with increasing price elasticity, the increase of prices might still be profitable if competition is very low. In the analysis of this chapter, the demand elasticity is assumed to be greatly below the electricity prices and therefore zero in the given action space. This is a common assumption in electricity market research (Weidlich and Veit, 2008a). However, at this point, it should be noted that elasticity is assumed to increase in future scenarios with more flexible loads in a smart grid (Aghaei and Alizadeh, 2013).

6.1.1. Regional Market Power

While market power is generally a noteworthy problem of electricity markets, it is even more severe considering network constraints and hence regional market power. Certain capacity might be needed to run at all cost in order to relief the grid of a load pocket. This leads to a variety of regulation. In the original Californian market design, such capacity was labeled *reliability-must-run* and was contracted individually (Bushnell and Wolak, 2000). In this specific case, it led to gaming opportunities for generators that proved to be very expensive (Woo et al., 2003). This is just one empirical example to demonstrate the regulatory dilemma: Generation should be acquired based on market mechanisms, but the regional necessities of the electricity system might create regional market controlling positions. Borenstein et al. (1999)

discuss the weaknesses of short-run concentration measures for market power but point out that long-term measures need to perform on similar assumptions. They also highlight that regional considerations are much more important than the general ownership concentration of generation assets. David and Wen (2001) extensively describe how transmission constraints create regional market power. They report that this market power might even lead to necessary signals to reinforce the transmission system. This particularity of congestion is discussed in Chapter 8. Further discussion on local market power is presented by Harvey and Hogan (2000). The authors argue for the implementation of nodal pricing over zonal pricing, even though this would decrease the market size. It would send the necessary economic signals for regional generation investment and reduce the necessary regulation for congestion management. Johnsen et al. (1999) find empirical evidence of an increased exercise of market power in case of congestion in Norway. Trepper et al. (2015) propose a market splitting for Germany to reduce the cost of congestion management but point out that additional research is needed to assess potential effects on market power in the electricity market.

6.1.2. Measuring Market Power

Measuring market power on electricity markets is difficult as it has a spatial and a temporal component. Most established measures are rather static in the sense that they measure market concentration based on capacities (Bataille et al., 2014). One of the more popular measures is the Herfindahl-Hirschmann-Index (HHI) (Rhoades, 1993). It is calculated as the sum of squares of individual market shares. Another popular measure is the concentration ratio (CR), which is defined as the sum of the market shares of the most dominant market participants (Hall and Tideman, 1967). Both indices do not take specifics of the available capacities into account. For example, an inclusion of wind and PV generation capacity does not seem appropriate as it is not necessarily always generating energy. Therefore, the German Federal Grid Agency only measures the market shares of conventional capacity using the CR instead of the full capacity (Bundesnetzagentur, 2018b). Even this approach has weaknesses as a gas power plant is fundamentally different from a lignite power plant (Hentschel et al., 2016). An approach beyond the ownership concentration of capacity is the Lerner Index, which concentrates on the market results (Elzinga and Mills, 2011). It defines the market deviation from efficient competition by the deviation from the theoretical marginal price based on the available generation capacity. The index is therefore a useful measure as it can be differentiated by time and region. It allows to measure temporal and regional market distortions. Recently, the Pivotal Supplier Index (PSI) and the Residual Supply Index (RSI) have become popular (Bataille et al., 2014). The PSI is an indicator variable that expresses whether one particular supplier is necessary to cover the entire demand. Due to the virtual price inelasticity of power demand, this creates great market power potential. The RSI measures the ratio of total capacity to demand without the analyzed supplier. Therefore, the value shows how much of the total demand could be covered without the considered generator. A similar approach to the RSI is developed in (Gan and Bourcier, 2002). The authors define the must-run-ratio as the regional capacity of an individual supplier that needs to run to cover the regional demand given the capacity of the competitors, the regional load and the limited import ability. An overview over different market power measures such as the HHI, the concentration ratio, the Lerner Index and other indices in the context of electricity markets is provided in (Möst and Genoese, 2009). In Section 6.3 of this chapter, the HHI and a variation of the Lerner Index are considered to describe the market power distortions in the simulation environment.

6.1.3. Agent behavior and Analysis

Agent-based models are used to investigate a variety of questions on electricity markets. A comprehensive overview of agent-based models in electricity market research is provided by Weidlich and Veit (2008a). The authors define four dimensions of research in the area of agent-based computational economics (ABCE) for energy markets: Empirical and descriptive ABCE, normative ABCE, theory generation and methodology improvement. The following model can be classified into empirical and descriptive ABCE as it evaluates the forming of global regularities from the interaction of agents on the micro scale. Another more recent discussion on ABCE in energy economics is provided by Tesfatsion (2018). Other authors have previously investigated market power on electricity markets using agent-based designs. In (Nicolaisen et al., 2000), the authors use an evolutionary algorithm to measure the use of market power under different ratios of demand and supply agents, keeping load and capacity constant. They assume an elastic demand and find evidence of market power on the supply side which is atypical for electricity markets. Furthermore, they find no effects of supplier concentration, which is opposed to basic economic theory. The value of ABCE in energy economics for the investigation of systems with high renewable penetration, as in the provided study, is highlighted by Gallo (2016). Krause et al. (2006b) find evidence of the exercise of market power in nodal pricing electricity markets using a Q-learning approach. While this is a considerable finding, the weakness of Q-learning is that it only allows for discrete strategies that need to be defined ex-ante (Lin and Mitchell, 1993). A continuous learning algorithm for agents on electricity markets is developed and evaluated by Kimbrough and Murphy (2013). The authors find that the algorithm works as expected and that agents find profit maximizing strategies when they posses market power. The authors use a static environment, which ignores the dynamics of an actual electricity market. For the presented model, a variation of the algorithm is used. More ABCE research on electricity markets can be found in (Lopes and Coelho, 2018).

In order to understand strategic behavior on electricity markets, tacit collusion needs to be considered. Tacit collusion is based on signaling theory (Connelly et al., 2011). Game theoretically, it means that a sender chooses an action that can be interpreted as a signal by the receiver, who then chooses her action correspondingly. Tacit collusion using signaling is investigated by Horstmann (2016). It is rarely applied in electricity market research. One study is conducted by Liu et al. (2010): The authors evaluate two auction mechanisms while allowing signaling. The approach is interesting as it allows to process the bids of competitors to learn their marginal cost and act correspondingly. The employed agent learning mechanism in this chapter shows that the agents implicitly do the same.

To conclude, market power is an important topic in energy market research and it is extensively investigated. However, a simulation model to screen the potential of regional market power in a dynamic environment has not yet been developed. The presented model fills this gap.

6.2. Identifying Market Power

In this section, the model for identifying market power in regional electricity markets is introduced. In the presented setup, a uniform-price electricity market is assumed. The price finding mechanism is the Merit Order with inelastic demand. However, this can easily be replaced by more sophisticated models such as zonal markets, pay-as-bid designs and elastic demand. The supply side consists of a set of agents $A = \{a_1, ..., a_n\}$. Each agent has a specific generation capacity c_i. To account for the difference between conventional and renewable capacity, the set of supply agents is split up into two subsets of controllable conventional agents $S = \{s_1, ..., s_m\}$ and non-controllable renewable agents $R = \{r_1, ..., r_l\}$ such that $S \cup R = A$. The controllable generation agents are further divided into subsets of generation classes. This division should be done according to the available generation technologies and therefore the marginal cost of generation. For the presented model, only base generation agents $B = \{b_1, ..., b_k\}$ and peak generation agents $W = \{w_1, ..., w_h\}$ are differentiated. For specific use cases, this might be too broad of a classification, but it suffices for the purpose of the model validation. The marginal cost of production of base and peak agents are such that $mc_B < mc_W$. The marginal costs of production of renewable agents are assumed to be zero (Taylor et al., 2016).

6.2.1. Setting Supply Bids

In every time step $t \in 1, ..., T$, each agent $i \in A$ submits an ask price $q_{i,t}$. As described, market power can be exercised by bidding prices above the marginal cost of production or by withholding capacity. The model employs price competition but might be adjusted to reflect competition in quantity. Agents act strategically if they anticipate their generation class as price setting. Otherwise, they simply bid their marginal cost of production mc_i. The rationale is that agents in generation classes which are cheaper than the setting class would risk to fall out of the Merit Order by acting strategically and are already making a profit. If agents do not expect to be dispatched at all because the market clearing price is below their marginal cost of production, strategic behavior does not increase their profit. Generation agents are aware of the available market capacity and their marginal cost of production. This allows them to anticipate whether their generation class is price setting.

However, they cannot forecast the actual load with absolute certainty. In markets with a high penetration of renewable generation, another element of uncertainty is introduced. Therefore, each agent forecasts the actual load d_t and the generation from renewable generation ρ_t. The default distribution of these forecasts is set to $f^d \sim N(\mu, \sigma) = N(d_t, \frac{0.1 d_t}{3})$ and $f^\rho \sim N(\mu, \sigma) = N(\rho_t, \frac{0.1 \rho_t}{3})$. This implies, that the mean forecast is correct and that the forecast errors are almost certainly within an error margin of 10%. The distribution of the forecast errors can easily be adapted to empirical values of any environment. This is especially important considering the example for market-based redispatch in Chapter 5. Here, the uncertainty of redispatch quantities can be included instead of demand uncertainty. With increasing uncertainty, a speculative strategy might become less attractive for the power plant operator.

The agents adapt their bids according to the success of their strategy. The strategy adjustment is performed using a reinforcement learning mechanism. The agents use the *Probe and Adjust* Algorithm introduced by Kimbrough (2011). The reinforcement algorithm is chosen because it has been proven to converge for electricity market supply curves (Kimbrough and Murphy, 2013). The evaluation in Section 6.3 also shows that the algorithm can reflect collusive behavior.

The algorithm is initialized with a base bid value $v_{i,0}$ for each agent a_i. For simplicity, each agent is initialized with its marginal cost of production as base bid value, such that $v_{i,0} = mc_i$. In every strategic trading period, the base bid is varied randomly by drawing from a uniform distribution with a learning parameter δ_t such that $\hat{q}_{i,t} \sim U(v_{i,e} - \delta_t, v_{i,e} + \delta_t)$. The index e is different from t as the base bid is not updated in each period. The actual bid is then determined as $q_{i,t} = max(\hat{q}_{i,t}, mc_i)$ to ensure that agents do not bid below their marginal cost of production. The learning parameter decreases over time from its original value to avoid temporal deviations from optimality after convergence as proposed by Kimbrough (2011). The parameter

δ shrinks to 10% of its original value over time, such that $\delta_t = \delta \cdot (1 - 0.9\frac{t}{T})$, where 10% is arbitrarily chosen. The bid is then two dimensional comprising the price and the quantity bid $(c_i, q_{i,t})$. As previously mentioned, the model can easily be adjusted to quantity competition. In that case, the price bid would be kept constant. The generation of renewable generators is intermittent and varies over the time steps t. Therefore, their capacity cannot be used in the bid. Instead, the actual varying generation is used such that the bid can be formulated as $(g_{i,t}, q_{i,t})$.

6.2.2. Market Model and Power

After all bids are determined, they are submitted to the market and the market is cleared. The Merit Order supply curve is determined by bringing the bids in ascending order, which leads to $((h_{(1)}, q_{(1),t}), ..., (h_{(n)}, q_{(n),t}))$ with $h_{(i)}$ as place holder for the conventional capacity or the renewable generation depending on the supply agent and $q_{(i),t}$ such that $q_{(1),t} \leq q_{(2),t} \leq ... \leq q_{(n),t}$. The uniform market clearing price is determined through a Merit Order dispatch, such that $p_t = q_{(J),t}$ with $\sum_{j=1}^{J-1} h_{(j)} < d_t$ and $\sum_{j=1}^{J} h_{(j)} \geq d_t$. The profit of each agent is determined using Equ. 6.1, with generator J being the price setting agent.

$$y_{(i)} = \begin{cases} h_{(i)} \cdot (p_t - mc_{(i)}), & i \in \{1, ..., J-1\} \\ (d_t - \sum_{j=1}^{J-1} h_{(j)} \cdot (p_t - mc_J)), & i = J \\ 0, & otherwise \end{cases} \tag{6.1}$$

Market power is measured using a variation of the Lerner Index. In each round, the markup is calculated as the difference between the market clearing price and the virtual competitive market clearing price such that $m_t = (p_t - p_t^{mc})$, which is equivalent to the Lerner Index without correcting by the market price. This allows to calculate the additional costs for consumers caused by strategic behavior. The overall markup m over T periods is calculated as the sum of all markups $m = \sum_{t=1}^{T} m_t$. Furthermore, the concentration is measured using the HHI of the available generation, which will be called generation HHI. The available generation is defined as the sum of the controllable capacity and the actual renewable generation. The generation HHI for trading period t is therefore calculated according to Equ. 6.2.

The overall generation HHI of the simulation run is then calculated as the mean of the HHI_t in all trading periods.

$$
\begin{aligned}
HHI_t &= \sum_{i=1}^{n} \left(\frac{h_i}{\sum_{j=1}^{n} h_j}\right)^2 \\
HHI &= \frac{\sum_{t=1}^{T} HHI_t}{T}
\end{aligned}
\tag{6.2}
$$

6.2.3. Learning and Signalling

One of the cornerstones of the model is the adjustment of supply bids using reinforcement learning. In each round, in which an agent assumes to be price setting and acts strategically, the chosen bid and the achieved profit from Equ. 6.1 are registered as a tuple. After a number of rounds Ω with strategic actions, called batch, the agent evaluates the results. The agent then sorts the achieved profits in descending order such that $y_{i,(1)} \geq y_{i,(2)} \geq ... \geq y_{i,(\Omega)}$. From this, the agent calculates the new base bid value using Equ. 6.3 with $\omega < \Omega$, meaning the evaluation set needs to be smaller than the batch size. In the following case study, Ω is set to 10 and ω is equal to 3.

$$
v_{i,e+1} = \frac{\sum_{j=1}^{\omega} q_{i,(j)}}{\omega} \tag{6.3}
$$

Finally, to include the strategic option of signaling into the strategic option portfolio of generators, the signal needs to be defined. In the proposed model, a signal is sent by submitting an increased bid to the competitors. This bid is supposed to show the receivers that collusive behavior would lead to higher profits along the Merit Order. To do so, a signaling agent would always add the current learning parameter δ_t to the original bid price such that $q^s_{i,t} = q_{i,t} + \delta_t$. In order to not distort the bid evolution of the signaling agent, learning is still performed using the original bid and the theoretically resulting profit from the original bid $q_{i,t}$. The implemented approach is slightly different from traditional signaling theory in the sense that the profit of the receiver does not depend on the sender's type but on its own type. Using the signal, they try to maximize their own profit as it becomes more probable that randomly chosen high bids are successful, which might then lead to a general shift of the Merit Order to the left, resulting in higher prices and markups.

6.3. Evaluating Market Power

To evaluate the validity of the model, a case study is performed that captures sufficient market dynamics in terms of renewable and load variation. To do so, empirical data from the German electricity market in 2015 is used. The chosen scenario is that of a small German city, that needs to cover the residential demand locally due to congested lines. As previously pointed out, the case can easily be transferred to the assessment of regional market power in redispatch markets.

6.3.1. Case Study Simulation

The small city is assumed to consist of 10,000 households. They are represented by generic load profiles from the German Federal Association of the German Energy and Water Industries (bdew) (Meier, 1999) that can be assumed as an average individual consumption if 10,000 or more households are considered (Wagner et al., 2016). The daily profiles are available for summer, winter and the time in between (spring and fall). Beyond the differentiation for competition, the simulation is also differentiated by season.

The conventional capacity is split up into base and peak capacity. The split is motivated by the split in the German electricity market. Base capacity is represented by nuclear power, lignite and 50% of the hard coal capacity. This sums up to 51.9% of the total conventional capacity. Peak power plants are the other half of hard coal power plants and gas power plants, which make up 48.1%. The total conventional capacity is determined based on the ratio of available capacity to the maximum demand in Germany in 2015. This factor is 1.14 (European Network of Transmission System Operators, 2018). Renewable capacity and generation are scaled correspondingly based on data from 2015. Wind capacity is set to 57.6% of the maximum load and PV capacity to 50.7%. In order to achieve representative daily renewable generation profiles, the average generation on a summer, winter and

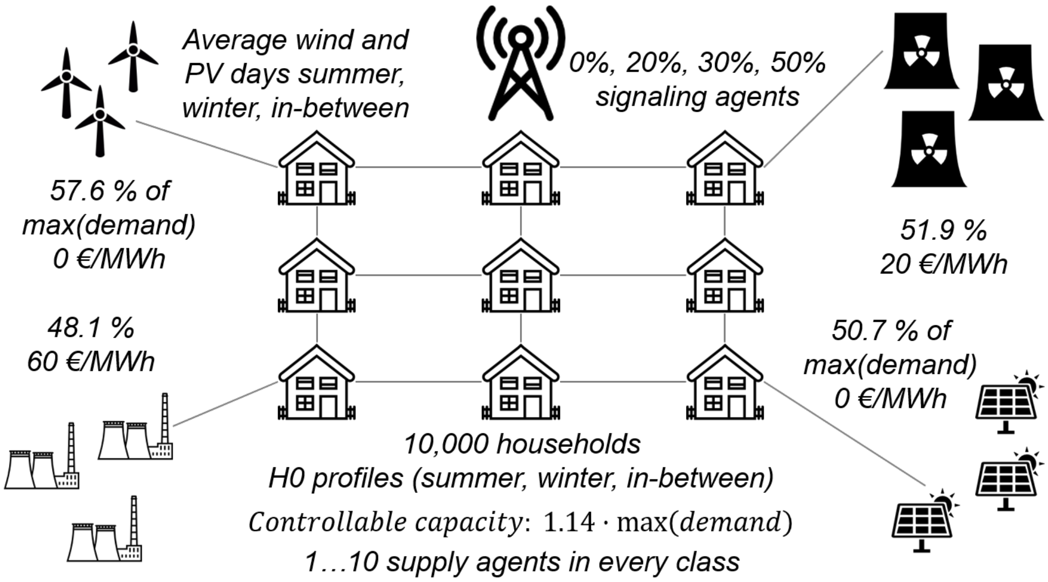


Figure 6.1.: Representation of the case study

in-between day in 2015 is calculated for a 15 minutes resolution based on empirical generation data (Bundesnetzagentur, 2019).

As mentioned, the simulation is run individually for every season. The generation classes are wind, solar, base and peak generation. The number of agents in each generation class is altered between 1 and 10. It is furthermore differentiated by the share of signalling agents. These make up 0%, 20%, 30% or 50% of the agents in each generation class. The number is always rounded down to the next integer. In total, this leads to 120,000 scenarios. Trading occurs in 15 minutes slots to represent the intraday trading on the German wholesale power market. This means that 96 trading rounds are performed per day. For every simulation scenario, 30 days are simulated to train the agents and the 31^{st} day is evaluated. Adopting the values for the marginal cost of production from De Jonghe et al. (2011), the marginal cost for base generators is set to $mc_b = 0.02\frac{€}{kWh}$ and the marginal cost of peak generators is set to $mc_p = 0.06\frac{€}{kWh}$. Renewable generators have marginal costs of zero. The learning parameter δ is initialized with 0.01.

6.3.2. Market Concentration Results

The result of the simulation is one data point for each scenario. This can be used to evaluate the relation between temporal market concentration and the resulting exercise of market power. An initial evaluation is performed through a factor regression to find the linear relationship between the input factors and the resulting markup. The explanatory variables are the generation HHI, the number of agents in each generation class, the season and the share of signalling agents. The detailed regression result is presented in Table 6.1. The adjusted R^2 of the regression is 0.87. This implies a strong dependence between the markup and the regression features. The influence of almost all factor values is significant based on their p-values to the significance level of 0.001. An increasing number of base and peak agents leads to lower markups. More signalling agents increase the markup. Surprisingly, more renewable generation agents also increase the markup. Partly, this phenomenon is caused by the fact that renewable generators never set the price in the simulation. Therefore, a higher number of renewable generators has no impact on the market result but might lead to more signalling agents in combination with the signaling share, which in turn leads to higher prices. The markup is higher in the summer and fall/spring time than in the winter. This is due to the fact that peak power plants are needed more often in the winter and competitive prices are therefore already higher. This reduces the markup. Furthermore, the market concentration correlates with the overall markup. To isolate the linear relationship between the concentration measures and the overall markup, further analyses are performed in the following. The Pearson correlation coefficient between the generation HHI and the markup is 0.61. However, this shows that the overall concentration is not necessarily the driving factor of market power. Even though the generation HHI was used, which is a more precise measure than the capacity HHI, a linear regression with the generation HHI as explanatory variables and the markup as dependent variable only yields an adjusted R^2 of 0.37. Additionally, the maximal average must-run-ratio (MRR) as defined by Gan and Bourcier (2002) is calculated per simulation run. To do so, it is calculated in every time step for every agent. In the end, the highest average MRR among all agents is recorded for the simulation run. The correlation between the maximal MRR and the markup is 0.43 and hence lower

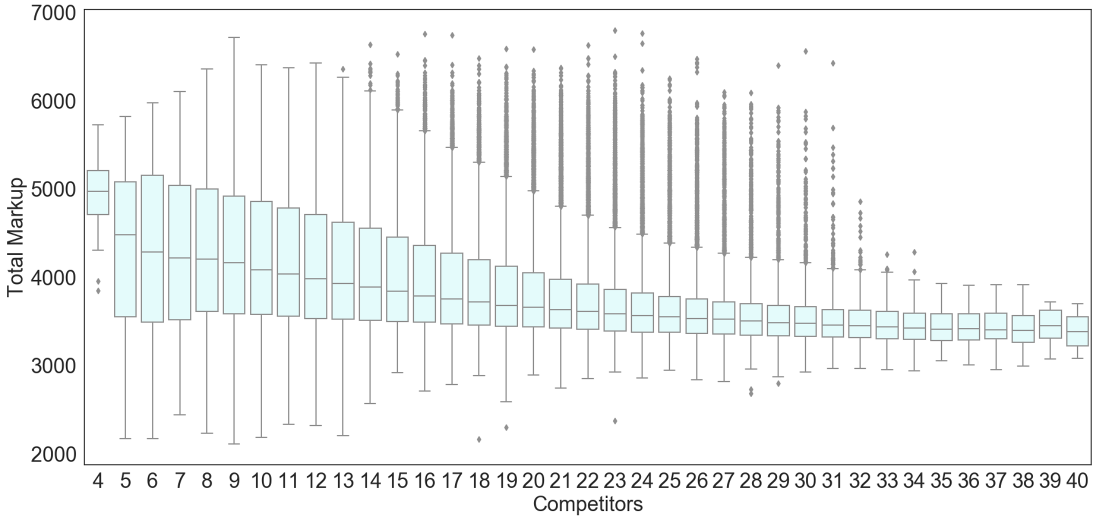


Figure 6.2.: Markups dependent on number of competitors

than for the HHI. A regression yields an adjusted R^2 of 0.18. A combined regression of HHI and MRR has an adjusted R^2 of 0.40, demonstrating that both measures account for roughly the same variance in the data. This suggests that even slightly dynamic concentration measures can only partially explain the strategic market behavior of agents.

Fig. 6.2 shows the simulation results based on the total number of competitors. The minimum is four competitors if every generation class is represented by one agent and the maximum is 40 if ten agents represent each class. It can easily be deducted from the figure that more competition tends to decrease the markups. The median and the upper quartile generally decrease.

To allow for a more detailed evaluation, the markup is now divided into the markup caused by base generators and the markup caused by peak generators. The results are shown in Fig. 6.3 and Fig. 6.4. Again, the general tendency is a markup decreasing effect of competition. However, the base markup is more resistant against competition than the peak markup. The differences between the minimal and the maximal median markup are 5% for base suppliers and 87% for peak suppliers. The explanation is that 60.2% of the base capacity is used on average over the

Variable	Estimate	Std. Error	t-Values
HHI Value	-4352.363***	283.162	-15.371
BaseAgents-2	-443.609***	27.069	-16.388
BaseAgents-3	-590.167***	36.012	-16.388
BaseAgents-4	-692.12***	40.49	-17.094
BaseAgents-5	-770.875***	43.177	-17.854
BaseAgents-6	-831.753***	44.969	-18.496
BaseAgents-7	-885.06***	46.249	-19.137
BaseAgents-8	-911.643***	47.21	-19.311
BaseAgents-9	-931.181***	47.956	-19.417
BaseAgents-10	-944.531***	48.554	-19.453
PeakAgents-2	-1169.215***	23.261	-50.264
PeakAgents-3	-1806.634***	30.922	-58.425
PeakAgents-4	-1991.01***	34.759	-57.28
PeakAgents-5	-2162.998***	37.063	-58.36
PeakAgents-6	-2182.881***	38.599	-56.552
PeakAgents-7	-2210.773***	39.697	-55.692
PeakAgents-8	-2232.908***	40.52	-55.107
PeakAgents-9	-2238.672***	41.16	-54.389
PeakAgents-10	-2258.888***	41.672	-54.206
WindAgents-2	166.495***	3.427	48.59
WindAgents-3	188.651***	3.889	48.511
WindAgents-4	192.191***	4.144	46.373
WindAgents-5	192.138***	4.304	44.642
WindAgents-6	190.009***	4.413	43.06
WindAgents-7	187.013***	4.491	41.639
WindAgents-8	184.531***	4.551	40.55
WindAgents-9	188.901***	4.597	41.089
WindAgents-10	189.815***	4.635	40.955
PVAgents-2	3.293	2.786	1.182
PVAgents-3	8.573**	2.837	3.022
PVAgents-4	17.312***	2.867	6.037
PVAgents-5	19.811***	2.887	6.861
PVAgents-6	24.079***	2.901	8.3
PVAgents-7	27.942***	2.911	9.597
PVAgents-8	28.757***	2.919	9.851
PVAgents-9	34.245***	2.925	11.706
PVAgents-10	36.197***	2.93	12.352
Summer	428.81***	2.322	184.689
Spring/Fall	136.484***	1.812	75.321
Signalling-0.2	3.569*	1.72	2.075
Signalling-0.3	22.644***	1.72	13.168
Signalling-0.5	59.927***	1.72	34.848
N	120,000	$^{***}p < 0.001$	$^{**}p < 0.01$
Adjusted R^2	0.8703	$^{*}p < 0.0.5$	

Table 6.1.: Factor regression of markup results using the input features

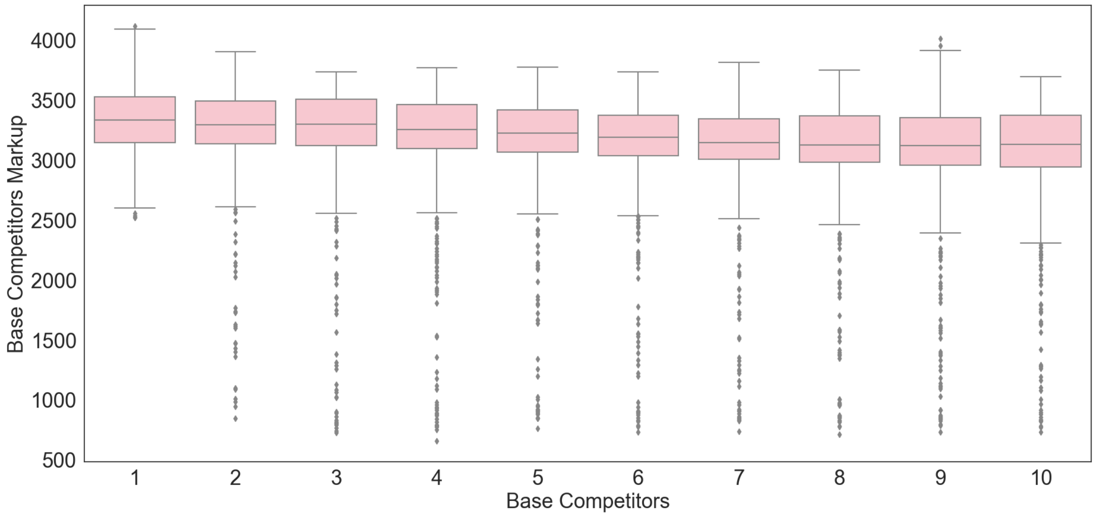


Figure 6.3.: Markups caused by base suppliers

simulation scenarios. Therefore, agents increase their bids as long as they do not surpass peak generators. But until then, they are dispatched even with high bids as the competition between base agents is low.

On the other hand, only 23.2% of the peak capacity is needed on average over all time steps and seasons. This makes competition fiercer and causes markups to decrease quickly with increasing competition. Furthermore, base suppliers set the price in 80.9% of trading rounds. In the final round, the base bid is on average 0.06 € away from the marginal cost of production, while it is only 0.034 € away for peak agents. Therefore, the share of the the markup caused by base supply is much higher than for peak capacity. It is hard to determine whether this markup is sufficient to cover the fixed costs of power plants. As this is not necessarily a question of competition it is not considered in this chapter. However, some guidance is provided in the following. One measure to consult are the levelized costs of electricity that include all costs associated with the generation of one kWh for a specific technology. In (Kost et al., 2018) the authors report the levelized costs of lignite, hard coal and combined-cycle gas turbines in a range with an upper bound of less than $0.1\frac{€}{kWh}$. With the average simulated price of roughly 0.08 to $0.09\frac{€}{kWh}$ the levelized costs of most power plants would be covered, while the cheaper power plants achieve profits beyond their costs. Note that no unanticipated peaks are considered in this case

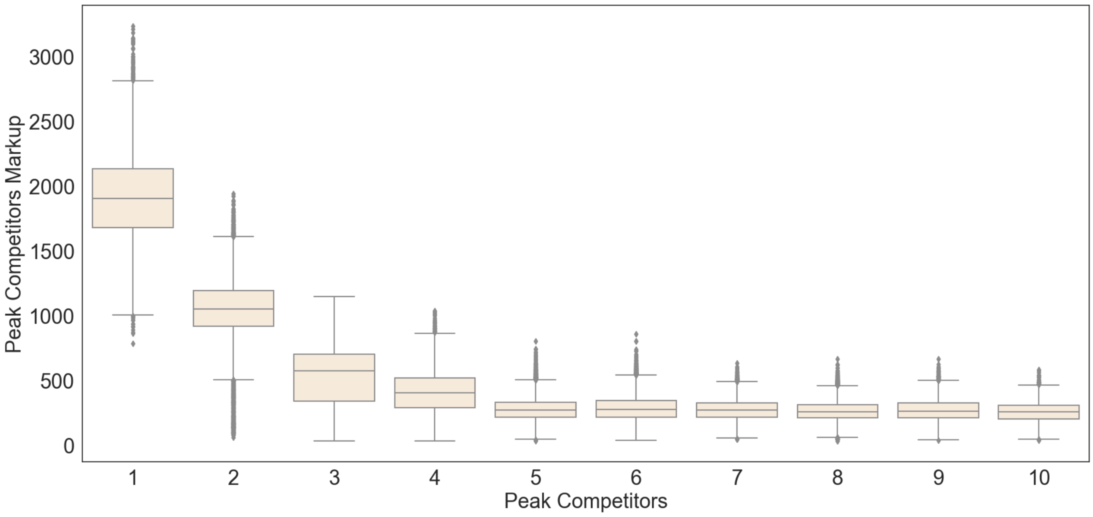


Figure 6.4.: Markups caused by peak suppliers

study but a rather smooth portfolio of household customers with standard load profiles. Such peaks would give the opportunity of further profit margins for peak generation power plants.

6.3.3. Signalling Effects

Finally, the effect of signaling on tacit collusion is evaluated. An initial analysis shows little to no impact of signaling. The difference between the lowest and the highest median markup is 1.6%. This has two main reasons: First, in scenarios with little competition, which lead to high markups, there are only few signaling agents due to the rule of rounding down to the next integer. Second, when there are many agents, competition prevails even if signals are sent. Furthermore, for base agents, the markup usually rises up to the peak prices anyway. Therefore, the additional effect of signaling agents is minimal. Fig. 6.5 shows that in the case of two base or peak agents, signaling has an effect on the markup of peak agents, while the markup is roughly the same for the base agents (even though there are less smaller outliers). The difference in the mean markup in the case of two peak agents with and without a signaling agent is 26%. Again, the effect wears off with more competition. The difference falls to 15% for three peak agents with one signaling and to 9% with four peak agents and one signaling. The results confirm the findings of Horstmann (2016)

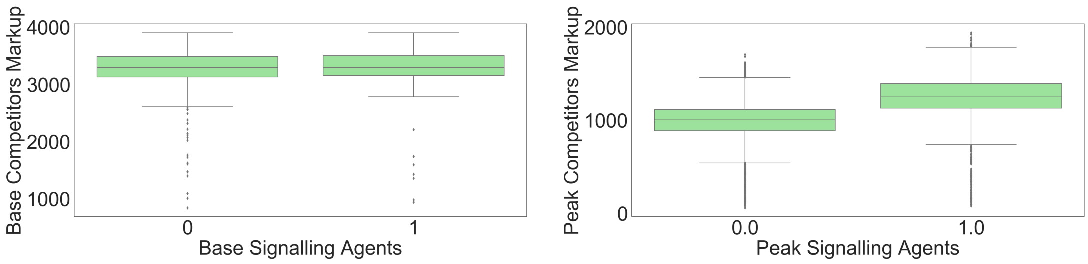


Figure 6.5.: Markups for one signaling agent among two generation class competitors

that few agents can already obstruct tacit collusion.

6.4. Summary of Chapter 6 and Discussion

In this chapter, a model is introduced to evaluate regional temporal market power. The model is based on self-learning computational agents that adjust their bids based on the market feedback. The model can be used to evaluate regional implementations of market-based congestion management. It can also be useful for any other assessment of regional market power such as new market zones as proposed for Germany by Trepper et al. (2015). The model is validated using a case study of a hypothetical small German city. The evaluation shows that the model works as intended. Market power situations can be identified by measuring the expected markup caused by agent behavior. The model results show that increased concentration leads to an increased abuse of market power. It implies that competition is especially important for peak power plants. Furthermore, it shows that a varied generation portfolio is important to reduce the possibility of gaming the supply curve by bidding up to the next marginal cost step. The model also shows the susceptibility of electricity markets to market power. It can serve as an indication of the reaction of power plant operators to market power. It has to be noted that the agents in this tool learn their behavior iteratively. Actual operators can anticipate market controlling situations of their power plant even for short time periods and exploit these situations. However, the model can correctly predict an overall competitive or non-competitive environment. As stated by the EC, it is important to ensure sufficient competition to introduce regional redispatch markets (European Commission, 2016). The introduced tool helps to identify the extent of market power. This needs to be accompanied by solutions for congestion management if competition is not sufficiently high. The next chapter therefore introduces ways to increase competition for congestion management using smart grid technology and EVs.

CHAPTER 7

CONGESTION MANAGEMENT IN THE SMART GRID

The previous chapter introduces a tool to identify market power on regionally limited electricity markets. This helps to identify suitable regions for market-based redispatch. However, in areas with too little competition alternative approaches are needed. One possibility is to use the advances of digitalization in the energy sector and to employ digital technology to relieve congestion. To this end, the chapter assesses the potential of V2G technology to act as a virtual buffer for the transmission grid and to increase the competition for congestion management services. Jochem et al. (2014) already describe the fundamental decision to either expand the network to deal with increased electrical load due to EVs or to adopt a coordinated charging approach. An online heuristic is introduced that can be used in real time and it is tested on a stylized version of the German transmission grid. In this case study, the possible compensation for EV owners is calculated based on the virtual redispatch that is avoided. In the next section, the concept of V2G is introduced. Then, the model and the simulation are introduced before the results are discussed. This chapter is based on (Staudt et al., 2018b).

7.1. V2G Technology and Research

The concept of V2G is first described by Kempton and Letendre (1997). The underlying idea is to use EVs as bi-directional grid resources. In other words, the EV charges when power is available, and it provides energy to the grid if there is a lack of it. Kempton and Tomić (2005) provide an overview of different V2G mechanisms and applications. The load shift potential of EVs in Germany is evaluated by Babrowski et al. (2014). The integration of renewable energy through V2G technology is described by Schuller et al. (2015) and Seddig et al. (2017), which is a basis for the research in this chapter. The linking of EVs with the electricity system through the smart grid is first introduced by Blumsack and Fernandez (2012). The general idea of demand side management as a tool for the integration of renewable energy is proposed by Strbac (2008). He already discusses the advantages of curtailing load at specific locations in the network. Various authors, such as Cao et al. (2012), have developed charging strategies to optimally react to time of use tariffs. The model in this chapter lets EVs react to grid signals depending on the congestion situation. Bessa and Matos (2012) give a broad overview of the technical and economical grid integration of EVs. Previous research on using EVs as grid resources is often focused on ancillary services (Andersson et al., 2010). An overview of such approaches is given by Hoogvliet et al. (2017). However, as Peterson et al. (2010) note, the use of EVs would quickly saturate the market and only allow a small number of EVs to participate. The case study of this chapter will show that congestion management has the potential of involving more EV owners. In Wu et al. (2012), the authors show that distributed decisions of EV coordination can achieve equal optimality as central coordination. This is an important result for the heuristic in this chapter, which is based on decentralized actions. Most studies that focus on the grid impact of EVs consider the impact on the distribution grid such as (Flath et al., 2013). The impact of EVs on the transmission grid is studied by Heinrichs and Jochem (2016). A study on avoiding transmission grid expansion through EVs is performed by Verzijlbergh et al. (2014). However, the authors focus on cross-border transmission capacity and therefore do not need to take redispatch into account and can include regional price differences. Note that stationary storage is an equally well suited approach to congestion management (Khani et al., 2016). The reason why EVs are considered in this chapter is that they have an additional political driver as they are an important cornerstone of the European strategy to reduce emissions in the transportation sector (Jochem et al., 2015) and can be used bi-directionally as grid resources.

7.2. V2G Redispatch Model and Simulation

In this section, the developed redispatch model and the simulation are introduced. The algorithm is intended to work online. Therefore, a heuristic is developed that does not require computationally expensive optimization (Berizzi et al., 2009). It is based on the intuition that redispatch is performed by decreasing generation in front of a bottleneck and increasing it behind the bottleneck. To this end, a search algorithm is introduced that finds EVs available for redispatch and deploys them correspondingly. The model uses EVs as a buffer for the electricity grid. They always return to their planned charging state as soon as it is permitted by the congestion state of the grid. This way, no electricity generation is lost and technically no welfare loss occurs (ignoring wear and tear of the batteries and losses). Besides the increased competition, this is a major advantage of the presented mechanism over redispatch. It is assumed that customers voluntarily set a lower and an upper bound for the state of charge (SOC) because such behavior is beneficial for the lifetime of the battery (Schoch et al., 2018).

7.2.1. Redispatch Model and Online Algorithm

The model is based on a uniform-price electricity market with Merit Order dispatch as implemented in Germany and most European countries. As introduced in Chapter 3, the most expensive plant in terms of marginal cost that is still dispatched to cover the demand, sets the price. Demand and supply bids are cleared centrally without consideration of transmission constraints. To relief congestion in the grid, a two-stage redispatch heuristic is developed. The corresponding algorithms are favored over a system optimization to allow for online implementation and to reduce the overall complexity as a large number of EVs might be involved in clearing congestion. In the first stage, the congested lines are identified that can be cleared through redispatch. The entire process of finding overloaded lines for redispatch is described as pseudo-code in the *linefinding* Algorithm 1. Redispatch can be performed at line (i, j) from node i to node j if the flow on the line is positive, i.e., $f(i, j) > 0$, with a positive generation q in front of the congestion ($q_i > 0$) and remaining capacity c behind the congestion $c_j - q_j > 0$. Defining K_i as the set of nodes that node i is connected to with transmission capacity $u(i,j)$ greater zero such that $j \in K \Leftrightarrow u(i,j) > 0$, allows to iterate through the network. The vector of all edges is defined as e, the corresponding vector of all line capacities is denoted as u, and f is the vector of all line flows. To iterate through all flows into a specific node, $f(K-i,i)$ is defined as the vector of all flows into node i. In the algorithm, a few additional functions are defined: The function *sorted* sorts an array by its first column in descending order. The function *calculateLoadFlow* returns the line flows in the electrical system provided. The command *break* ends the current iteration. The algorithm finds the line with the strongest transmission constraint violation and examines the possibility to perform redispatch along the line. If this is not possible because either, there is no more generation in front of the congestion or, no more idle capacity behind the congestion, the algorithm first tries to increase the generation at the node in front of the congestion or decrease the production behind the congestion by moving out to other connected nodes.

With the second stage, the generation is adjusted such that all constraints are respected. The exact algorithm is displayed as pseudo-code in the *redispatch* Algorithm 2. To achieve the objective, the energy generation in front of the congestion is decreased by ϵ and increased by the same amount behind the congestion. The value of ϵ is chosen heuristically to iteratively resolve congestion. It is set to the minimum of half of the exceeding transmission flow, the generation in front of the congestion or the remaining idle capacity behind the congestion such that $\epsilon = min(\frac{1}{2}(f(i,j) - u(i,j)) + \gamma, q_{l[0]}, c_{l[1]} - q_{l[1]})$. The fixed parameter γ is added to increase convergence speed. The generation is then adjusted and with the adjusted schedules, the load flow is recalculated. If congestion persists, the heuristic is repeated. This iterative process continues until all congestion is cleared or no more adjustments are possible.

The cost of congestion management is calculated as the welfare loss resulting from redispatch as introduced in Section 3.2.2. The cost for redispatching the quantity ϵ is composed of the cost of ramping down generation at node i as k_i^d and the cost of ramping up at node j as k_j^u. Assuming that the ramped down power plant at node i generates at a marginal cost of production below the market clearing price p of $m_a \leq p$ and the increasing power plant at node j generates at $m_b \geq p$, the costs of

Algorithm 1: linefinding

```
Input: f, u, e, q^c, q^r, c^c
Output: f, q^c
r = sorted[max(f − u, 0), e]
i = 0
while i < length(r[0]) and r[0][i] > 0 do
    l = r[0][i]
    if (f(l) > 0 and q^c_{l[0]} ≠ 0 and c^c_{l[1]} − q^c_{l[1]} ≠ 0) then
        redispatch(f, u, e, q^c, q^r, c^c, l)
        break
    i=i+1
i = 0
while i < length(r[0]) and r[0][i] > 0 do
    l = r[0][i]
    if (f(l) > 0 and q^c_{l[0]} = 0 and c^c_{l[1]} − q^c_{l[1]} ≠ 0) then
        h = sorted[f(K, i), K]
        l = h[0][1]
        redispatch(f, u, e, q^c, q^r, c^c, l)
        break
    if (f(l) > 0 and c^c_{l[1]} − q^c_{l[1]} = 0) then
        h = sorted[f(i, K), K]
        l = h[0][1]
        redispatch(f, u, e, q^c, q^r, c^c, l)
        break
    i=i+1
return f, q^c
```

Algorithm 2: redispatch

```
Input: f, u, e, q^c, q^r, c^c, l
Output: −
ϵ = min(1/2 (f(i, j) − u(i, j)) + γ, q^c_{l[0]}, c^c_{l[1]} − q^c_{l[1]})
q^c_{l[0]} = q^c_{l[0]} − ϵ
q^c_{l[1]} = q^c_{l[1]} + ϵ
f = calculateLoadFlow(q^c, q^r)
linefinding(f, u, e, q^c, q^r, c^c)
break
return ()
```

redispatching the quantity ϵ can be calculated as follows:

$$
\begin{aligned}
k_i^d &= (p - m_a) \cdot \epsilon \\
k_j^u &= (m_b - p) \cdot \epsilon
\end{aligned}
\tag{7.1}
$$

This allows to calculate the redispatch cost for each node. In theory, this amount could be cost-neutrally redistributed to EV owners that help resolving congestion.

So far, the described algorithm does not consider EVs but can be used for conventional redispatch. In the following, EVs are considered as a virtual power plant (Jansen et al., 2010) with zero marginal cost of production. To this end, a fixed share α of the battery capacity is reserved from EVs participating in the mechanism that can be used for redispatch purposes. Note, that this does not mean that energy is taken from the EVs but the original SOC is always re-established after the congestion is resolved. The time to return to the original SOC is discussed in Section 7.3. The capacity of the virtual EV power plant is limited by the sum of the energy of the corridor and the maximum charging power. Additionally, the driving patterns of the EVs are considered, such that they can only be used for congestion management if they are stationary, i.e., not driving. The current absolute difference between the actual SOC, including congestion management soc^a, and the required SOC soc^r is referred to as the *EV gap*. The intention is to keep the EV gap low and to close it as quickly as possible. The time during which a non-zero EV gap exists is referred to as the EV gap duration in the following.

7.2.2. Simulation

A simulation is performed to show the practicability and the implementability of the mechanism. Furthermore, it is meant to give an indication of the possible compensation payments to EV owners. The simulation is carried out on a stylized German transmission grid with five bidding zones: One zone for each TSO except for TenneT which is divided into two zones. This division into bidding zones is similar to the results of Breuer et al. (2013). It is chosen to illustrate the North-South division of the German grid with regard to congestion (Trepper et al., 2015). The inter-zonal thermal transmission capacities are based on the static network models of the TSOs (TransnetBW - Statisches Netzmodell, 2017; TenneT - Statisches Netzmodell, 2017; 50Hertz - Statisches Netzmodell, 2017; Amprion - Statisches Netzmodell, 2017). Fig. 7.1 shows the schematic setup of the transmission system model. The exact transmission capacity values of the system are given in Fig. A.1 of the Appendix. Intra-zonal congestion is not considered. To account for the n-1 criterion of the German TSOs, which means that the system needs to be stable if any one system component fails, the transmission capacity is reduced to 50% of the original value. These two measures are not necessarily equivalent as the used transmission grid is only an abstracted version, but it mimics the case where two parallel transmission lines with equal capacity exist for each network branch. The reactance is assumed to be the same on all lines. The load flow calculations are done using a DC approximation with lossless transmission as introduced in Section 3.2.1.

The regional generation capacity is based on the location of power plants in Germany derived from Bundesnetzagentur (2017b). The exact division is shown in Appendix A.6. The load is distributed to the bidding zones according to the regional gross domestic product (GDP) (Destatis, 2016). The technology specific marginal costs of power plants are based on Leuthold et al. (2008). For the simulation, the plant operators are assumed to not act strategically and bid their marginal cost of production. This leads to reduced redispatch costs, because a higher variance in bids leads to higher redispatch payments as can be concluded from Equ. 7.1. The capacity share α that is available for congestion management from EV battery capacity is set to 20% on average. As we do not consider individual EVs, but the overall available capacities, more capacity might be contracted from individual EVs and less from others. All EVs which are currently not on the road, can theoretically be called to support the congestion management.

To determine whether an EV is driving, data from the German mobility panel (MOP) is used, which provides a wide range of driving profiles over a week (Zumkeller et al., 2011). A detailed analysis of the MOP is provided by Schuller et al. (2014). The MOP is divided by socio-economic groups. The simulation is

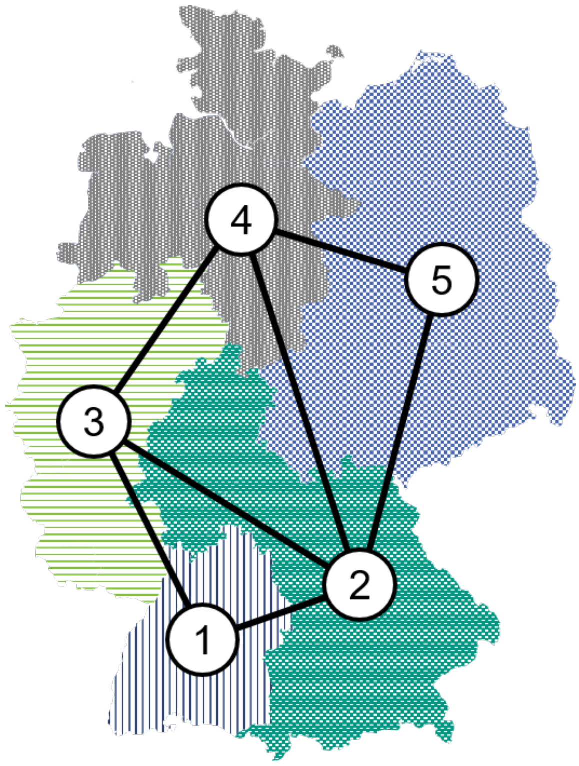


Figure 7.1.: Stylized representation of the German transmission grid

based on full-time employees, who are the most frequent drivers. The availability of EVs is shown in Fig. 7.2. The figure shows that at least 80% of all EVs are always available. The battery capacity of each individual EV is assumed to be 40 kWh (Zhang et al., 2018). The simulation has an hourly resolution and is based on load and renewable generation data from 2016. The number of EVs is distributed among the zones by the share of the national GDP of the respective zones (Destatis, 2016) in line with the distribution of the load. The renewable generation by TSO is provided by the European Energy Exchange (EEX Transparency, 2013). The renewable generation in the TenneT area is divided into the North and South zone according to the renewable generation capacity in the respective zones.

Besides an analysis of the possible compensation, the simulation also shows whether congestion can be sustainably avoided through EVs or if the additional demand in the consecutive periods only moves congestion from hour to hour. A detailed description of the simulation process is shown in the flow chart of Fig. 7.3.

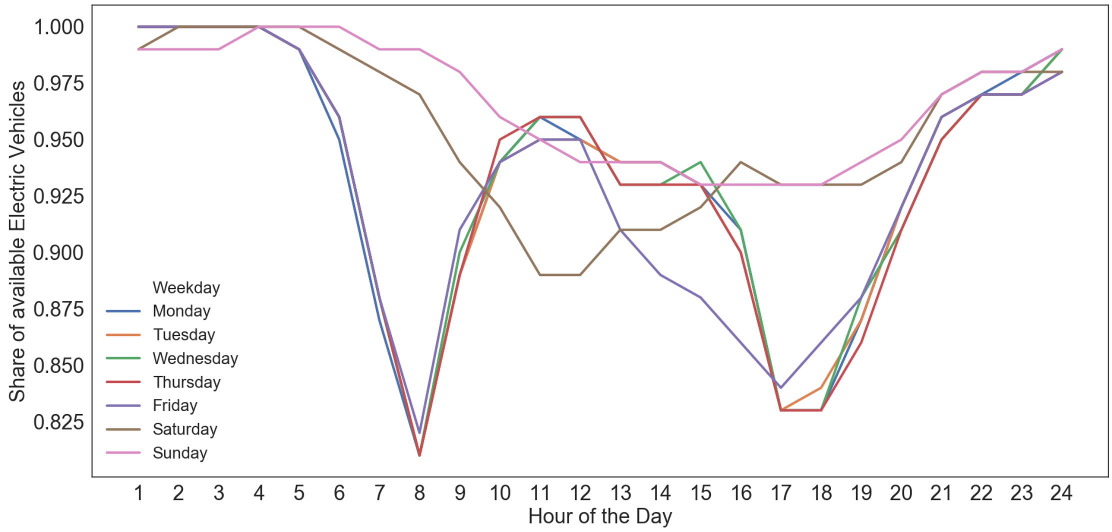


Figure 7.2.: Share of EVs available for redispatch

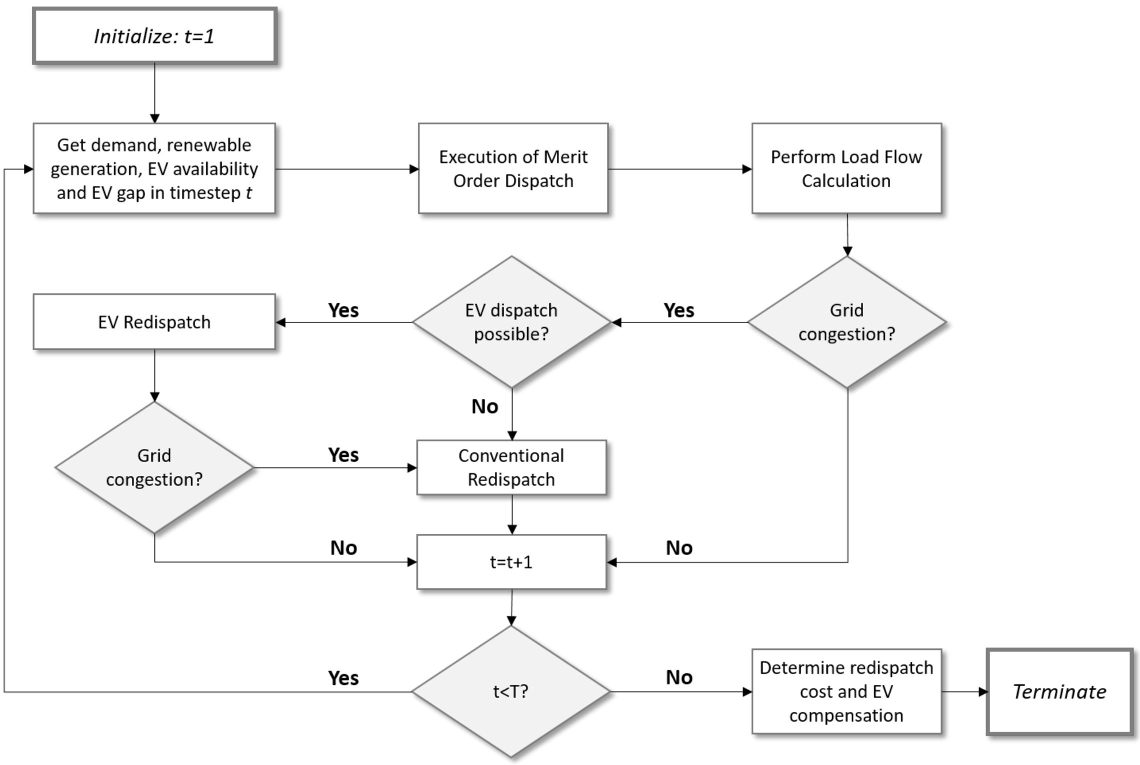


Figure 7.3.: Simulation flow chart

7.3. Simulation Results

The model is initially run without considering EVs for congestion management to find a baseline for the possible overall cost-neutral financial compensation. In this scenario, the redispatch and the associated costs are calculated. In the following scenarios, different market penetrations of EVs are assumed and they are allowed to participate in the congestion management. The saved costs for congestion management are redistributed among the participating EVs to find the possible compensation for a cost-neutral inclusion of EVs into the congestion management.

7.3.1. Baseline Scenario

In this scenario, a conventional congestion management is performed by redispatching thermal power plants. The redispatch is performed according to the introduced algorithms in Section 7.2.1. In the simulation, roughly 28 TWh of redispatch are necessary, which causes a welfare loss of 147 million €. The actual amount of adjusted energy feed-in for congestion management in 2016 was about 16.5 TWh (Bundesnetzagentur, 2018b). The considerable differences can be attributed to two causes: First, system operators try to reduce congestion through grid switching before employing redispatch (BMWi, 2015). This is not simulated in the given model as no explicit information on existent switches is available. Second, the given system abstracts from reality in the way that we only consider the German transmission system. However, the German power system is connected to its European neighbors that can sometimes reduce congestion in the German system (Kunz, 2018). To allow for a better understanding of the redispatch and to judge the validity of the model, the regional distribution of redispatch is evaluated. The detailed results can be found in Table 7.1. It shows that the redispatch welfare loss occurs in specific regions. Most congestion occurs along the North-South division as suggested by Trepper et al. (2015), i.e., between TenneT North and TenneT South and at the link between 50Hertz and TenneT South. Therefore, bidding zones 2, 4 and 5 are most affected by congestion management measures. These results show the validity of the simulation model as the real congestion situation in Germany is reflected. Fig. 7.4 displays the average redispatch per day over the simulation period. As expected, most redispatch is

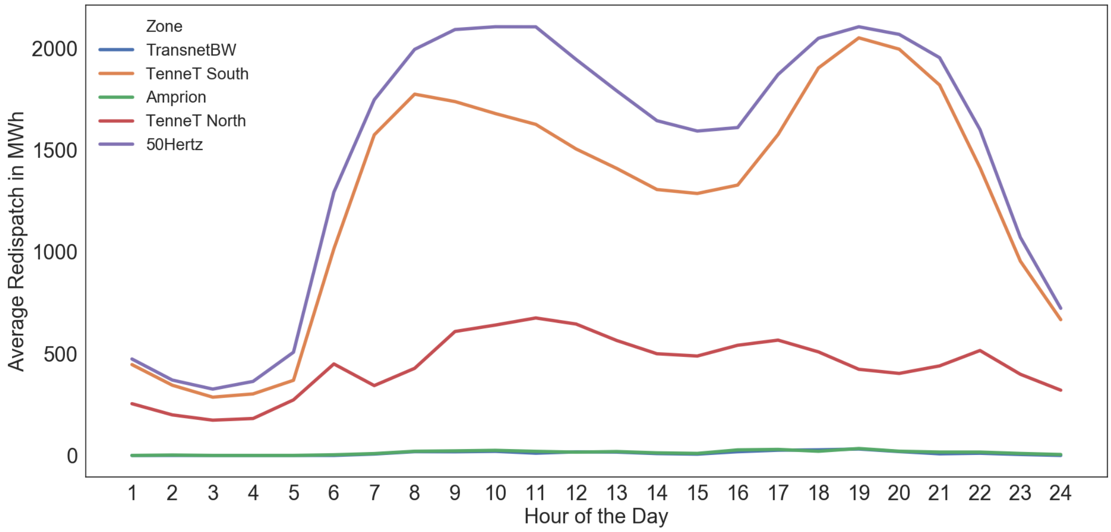


Figure 7.4.: Avg. daily redispatch per node

Bidding area	**Redispatch (GWh)**	**Additional Costs (Thousand €)**
TransnetBW	98	28
TenneT South	11,125	117,856
Amprion	124	74
TenneT North	3,861	6,591
50 Hertz	12,969	22,701
Total	28,179	147,252

Table 7.1.: Model results for redispatch needs and additional costs

needed during times of high demand, namely, in the morning at around 8am and in the early evening around 6pm. Unfortunately, this also corresponds to the times when many EVs are on the road and not available for congestion management (see Fig. 7.2). However, as the next section will show, the EV availability is still mostly sufficient to provide the necessary capacity for redispatch. The observation of the charging corridor occurs globally instead of on individual EV level. A complimentary scheduling mechanism is presented by Jian et al. (2015).

7.3.2. EV Contribution to Congestion Management

Besides the general contribution of EVs to congestion management, this section also analyzes the differences of EV market penetration levels. The scenarios of 2, 4, 6 and 8 million EVs are considered. This can also be understood as different numbers of EV owners who choose to participate in the mechanism. The results of the EV simulations are shown in Table 7.2. For each simulation, it provides the remaining redispatch costs after involving EVs and the possible compensation for EV owners in each bidding zone. The results show that even with only 2 million EVs, the redispatch costs can be considerably reduced. However, more EVs still contribute to a further decrease of redispatch costs, even though with a falling rate. The average EV gap duration is 7 hours. The maximum varies between 142 and 161 hours for the different bidding areas. This implies that the SOC desired by the user, from which is deviated during congestion periods, is re-established in less than one week, even in the worst case. Fig. 7.5 shows the EV gap in December. As can be observed, it always returns back to zero.

EV owners receive a compensation for their contribution to congestion management depending on their location in the network. In some bidding areas, the compensation would likely not incentivize participation. However, this is due to the fact that only little redispatch is necessary in these zones. In practice, the compensation might be even higher as the redispatch costs in the modelled simulation environment are rather low in comparison to reality. In 2016, the congestion management costs in Germany amounted to 591 million Euro (Bundesnetzagentur, 2017). The low simulated values might have several reasons. First, there is no differentiation between conventional redispatch and feed-in management of renewable generation. The costs for the latter are significantly higher. Secondly, the marginal costs reported by Leuthold et al. (2008) likely do not reflect the actual marginal production costs in 2016. The average market clearing price in the simulation is 21 €/MWh while the actual clearing price in 2016 was 30 €/MWh (European Energy Exchange AG, 2018). Errors in the assumptions on marginal costs of production are directly reflected in the cost for redispatch. And finally, the technology specific marginal costs of production are a simplifying assumption. In reality, each power plant has

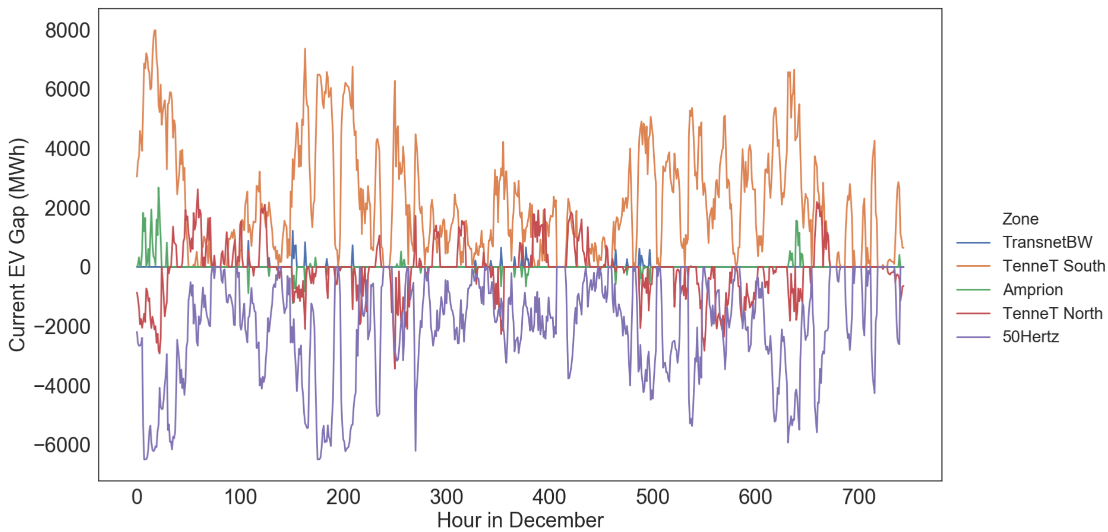


Figure 7.5.: Model results for the EV gap (sum of difference between preferred user SOCs and actual SOCs) per node in December 2016

different marginal cost of production even if the generation technology is the same. However, if the market clearing price and the marginal costs of redispatch power plants coincide, this leads to lower welfare losses in the simulation. Therefore, this assumption leads to lower costs. Overall, the simulation demonstrates the feasibility of managing congestion using EVs. The different compensation payments allow to introduce a spatial component in the German electricity system without the risk of market power abuse. This can help to temporarily support the management of congestion in the transmission system. As the approach is very flexible, it can be used as a short-run curative measure similar to balancing power. However, the presented simulation has certain limitations which are discussed in the following section.

		Transnet	TenneT South	Amprion	TenneT North	50Hertz	Total
2M EVs	Redispatch cost (k€)	0	27,924	7	1,010	5,672	34,613
	Compensation EV (€)	0.09	167.43	0.12	17.41	56.63	56.32
4M EVs	Redispatch cost (k€)	0	6,304	0	156	1,133	7,593
	Compensation EV (€)	0.05	103.84	0.07	10.04	35.86	34.91
6M EVs	Redispatch cost (k€)	0	747	0	26	150	924
	Compensation EV (€)	0.03	72.68	0.05	6.83	25,00	24.39
8M EVs	Redispatch cost (k€)	0	24	0	0	11	36
	Compensation EV (€)	0.02	54.84	0.03	5.14	18.86	18.40

Table 7.2.: Redispatch cost and benefit for every EV per scenario per year

7.4. Summary of Chapter 7 and Discussion

In this chapter, a mechanism to resolve congestion in the transmission grid using EVs is introduced and evaluated using a stylized version of the German transmission grid with empirical load and generation data. EVs are chosen for this application of demand side management for two reasons: First, Germany has implemented a national strategy to increase the use of EVs (Pfahl et al., 2013). Second, EVs can be used bidirectionally, meaning that they can consume abundant electricity in a generation pocket and provide additional energy in load pockets. However, other strategies of demand side management using other technologies should equally be evaluated (Dengiz et al., 2019). The results of the simulation show that EVs can support congestion management considerably and that cost-neutral compensation payments are possible that might incentivize owners to participate. The approach is especially attractive since the EVs serve as a buffer for the transmission system. Therefore, no electricity needs to be paid that is not produced and therefore no welfare is lost. This is an application of the internet of energy and reminds of online buffering. The calculated compensation is a cost-neutral upper bound that can be paid to EV owners. The actual attractiveness of the approach needs to be evaluated by including battery degradation with regard to the V2G activity. However, the Dutch TSO already experiments with a similar setup[1] and a first initiative is also underway in Germany[2].

However, the technical as well as the regulatory development of V2G is still in its early stages. Currently, only one protocol allows for bi-directional charging and first prototypes are currently being implemented (Zecchino et al., 2019). Furthermore, there is no specific regulation for V2G in Germany. It is unclear whether EVs qualify as stationary storage. These technical and legal issues need to be resolved before V2G can be implemented for the described purposes (Steinhilber et al., 2013). One simplifying assumption is that there is no congestion on lower voltage levels in the way that the actions of EVs are directly reflected and not hindered by system constraints other than from the transmission grid. Another improvement might be the optimization of redispatch instead of using a heuristic, which is however more computationally expensive (Berizzi et al., 2009). The individual compensation is based on participation instead of actual energy contribution. This might be changed to make the mechanism more attractive for certain individuals. Finally, the study shows that it is possible to reduce congestion using EVs, but it is unclear whether customers would participate in such a mechanism.

The presented approach can help to temporarily resolve congestion. It can also be used to supplement regional market-based redispatch to ensure sufficient competition. Furthermore, it allows to avoid the negative effects on welfare of the redispatch mechanism overall. However, it remains unclear in which situations redispatch or EV redispatch is the more efficient long-term solution and in which situations grid expansion is a more suitable avenue. This depends on the theoretical costs of redispatch and on the persistence of the congestion. Such considerations are difficult

[1] https://www.tennet.eu/news/detail/electric-vehicles-replace-power-plants-to-maintain-supply-demand-balance-on-high-voltage-grid/

[2] https://www.tennet.eu/news/detail/tennet-the-mobility-house-and-nissan-work-together-on-stabilising-the-power-grid/

and the outcome is inherently uncertain. The next part of this dissertation therefore introduces a mechanism to privatize the risk of such grid expansions as well as a wholesale market mechanism that can potentially internalize transmission grid congestion and send regional generation investment signals similar to nodal pricing.

Part IV.

Market Design

Introduction to Part IV

In Part III, different aspects of competition in congestion management are discussed and solutions to low regional competition are introduced. This competition is important for short-term curative congestion management mechanisms to function properly. However, it does not cure congestion in the long-run and can ultimately result in high welfare losses if congestion is not tackled more fundamentally (De Vries and Hakvoort, 2002). Furthermore, it does not answer the question which short-term congestion is acceptable and which structural congestion needs to be addressed. A long-term strategy for congestion management can be composed of various measures. In this dissertation, two major approaches are discussed: the expansion of transmission grid capacity and the expansion of regional generation or storage capacity. In Part IV, two market mechanisms are presented that can support a long-term strategy against transmission grid congestion. In Chapter 8, a mechanism is introduced that ensures economically efficient expansion of transmission grids and reduces the associated risk borne by the consumers. Furthermore, it ensures that only welfare increasing grid expansion is considered, potentially reducing the public outcry against the unpopular measure. However, the EC has threatened to divide bidding zones if congestion persists. Therefore, Chapter 9 proposes a Multilateral Locational Pricing mechanism, that respects transmission grid constraints at market clearing. Such a mechanism would lead to regional price signals and incentivize spatially beneficial generation and storage expansion. The mechanism is benchmarked against the market results of locational marginal pricing as the assumed welfare optimal market solution with regard to the distribution of welfare and effects on the exercise of market power. In conclusion, this part proposes changes in regulation that incentivize the efficient reduction of transmission grid congestion in the long-run.

CHAPTER 8

MARKETS FOR TRANSMISSION GRID EXPANSION

The previous chapter introduces a way to manage transmission grid congestion using EVs as temporary buffers. However, this is only a short-term solution and cannot reduce systematic congestion. Such congestion can be avoided, among other possibilities, through well designed and operated electricity grids and ultimately transmission grid expansion. However, the necessary dimensions and capacities are hard to determine as grid expansions are expensive, take long to be constructed, and are usually unpopular with the local population (Devine-Wright, 2013). In Germany and most European countries, the operation and expansion of transmission grids are regulated. The German regulation gives incentives to transmission grid operators to favor expansion over other measures such as redispatch (Kemfert et al., 2016; Brunekreeft et al., 2014). As introduced in Section 2.2.1, the profit of TSOs is a fixed return on equity. Therefore, more equity allows for higher profits. A description of the TSO regulation in Germany and an international comparison is provided by Kemfert et al. (2015). However, grid expansions are not always favourable. Notably, in the presence of high shares of intermittent renewable generation a grid expansion up to the infamous last kWh is certainly not efficient (Stoft and Lévêque, 2006). This is a severe issue because alternative mechanisms like redispatch or battery storage (Babrowski et al., 2016) are not considered as alternatives as stated by Kemfert et al. (2016). The authors find that even the currently planned grid expansions might be excessive as the alternatives are not evaluated. Weibelzahl and Märtz (2017) find, for example, how the necessary transmission grid expansion can be reduced through the placement of stationary storage.

Many authors have worked on allowing merchant transmission investment, i.e., the investment of independent parties into transmission capacity (Joskow and Tirole, 2005; Hogan et al., 2010). Such approaches, if well designed, have the benefit that transmission expansion is exposed to efficiency considerations, meaning that the network is only expanded if it is economically the best option. Furthermore, the benefit of grid expansion is greatly determined by the development of the regional generation capacity. The risk of transmission investment is therefore considerable and currently completely borne by consumers in Germany. A merchant approach would be moving this risk to private investors. Due to several reasons, these approaches have not been successful. Some of these reasons can be traced back to mixed incentives of market participants in nodal pricing markets and are presented by Sauma and Oren (2009). Another reason is that these approaches are often applied in nodal pricing market designs where the congestion rent is supposed to recover the total costs. But, as shown by Rubio-Odériz and Perez-Arriaga (2000), congestion rent recovers only about 25% of the investment costs. This can be attributed to the fact that congestion rent is not equivalent to the welfare gain induced through the transmission grid expansion.

However, the cost-based redispatch mechanism with its unique structure allows for an alignment of interests of multiple parties and can be used to incentivize welfare optimal grid expansions. Furthermore, it quantifies the exact welfare loss in each trading period and is therefore a good indicator for the social value of a network expansion. In this chapter, a mechanism to foster this potential is presented and evaluated on synthetic grids and the stylized German transmission grid introduced in the previous chapter. Such a design is also important for the further integration of the European electricity market as potential cross-border interconnector capacity expansions are often neglected because of national interests (Buijs et al., 2007). The next section begins by introducing previous studies on merchant transmission investment.

8.1. Merchant Transmission Expansion

Most studies on merchant transmission expansion focus on the allocation of FTRs (Rosellón and Kristiansen, 2013). These rights entitle their holder to a compensation if the corresponding line is congested and a transmission rent arises. This rent is the difference in payments in the load pocket with higher electricity prices and the generation pocket with lower prices as introduced in Section 3.2.3. One of the first studies on incentive design for transmission expansion is carried out by Bushnell and Stoft (1996). They argue that, under a set of restrictive rules, assigning FTRs to investors should correctly incentivize grid expansion. This is further described in (Bushnell and Stoft, 1997). However, this only holds true under restrictive assumptions as shown by Joskow and Tirole (2005) and can only be applied to markets that implement nodal pricing. Furthermore, several authors have since stated that FTRs alone are not sufficient to recover transmission investment (Cameron, 2001; Brunekreeft et al., 2005). Hogan et al. (2010) therefore combine FTRs with a regulatory approach to allow for merchant transmission investors. The design is tested in several studies such as (Schill et al., 2015). A study of incentive analysis and design is conducted by Sauma and Oren (2009). The authors analyze the incentives for generators to invest in a transmission line between two nodes. They look for Nash equilibria and find that the possibility of exercising market power can lead to inverted incentives. The effect of allocating FTRs is also analyzed. In Kristiansen et al. (2017), the authors consider welfare changes to allocate side payments to different countries in order to reduce opposition to transnational transmission expansion projects. They use the Shapley value to distribute welfare gains fairly. A basic analysis of the welfare effect of transmission expansion is carried out by Léautier (2001). In (Sauma and Oren, 2007), the authors implement a multi-stage optimization problem to analyze strategic responses to transmission expansion. They state that resulting welfare should be distributed among participants but find that severe conflicts of interest remain in the network. They also find that the objectives of reducing market power, maximizing welfare, maximizing consumer surplus and maximizing producers surplus lead to different network topologies. Further work has been conducted by Sauma and Oren (2006), in which the authors consider strategic responses by generators to transmission expansions and find that taking these into account leads to changes in the optimal transmission expansion planning. Studies on merchant transmission expansion in Europe are mostly focused on cross-border transmission expansion such as (Kristiansen and Rosellon, 2010). The authors find that their approach cannot be implemented without additional regulatory oversight. Shrestha and Fonseka (2004) provide a framework for grid expansion driven by congestion. Similarly to the presented approach, they intend to maximize the overall social welfare. However, their framework is intended for a nodal pricing market design with the discussed weaknesses.

8.2. A New Mechanism for Merchant Transmission

In a uniform-price electricity market, transmission expansion has no direct impact on the market clearing price. As the price is determined independently of the grid constraints, it is purely based on the demand and the available generation. Even a wind turbine that is not connected to the grid can sell its generation on the wholesale electricity market. Therefore, there is no immediate impact of the transmission expansion on consumer prices. This might be the reason that literature on merchant transmission expansion is mostly focused on nodal pricing market designs, where a grid expansion directly impacts the price formation. However, merchant transmission designs in nodal pricing markets have three severe drawbacks:

- The congestion rent does not recover the initial investment (Rubio-Odériz and Perez-Arriaga, 2000).
- There are mixed incentives for transmission expansion for different groups of consumers and producers (Sauma and Oren, 2009).
- The payback from transmission rent is not based on the welfare gain caused by the grid expansion, but rather linked to the remaining welfare loss after the expansion (Barmack et al., 2003).

A mechanism based on redispatch expenditures can address all three of these concerns. In the following, the mechanism is introduced before it is demonstrated on different grid topologies.

8.2.1. The Mechanism

The underlying idea of the proposed transmission expansion market design is to compensate transmission expansion based on the congestion management costs it reduces, i.e., if redispatch costs are avoided, the developers of a particular grid expansion should be compensated based on this cost reduction, which represents the exact welfare loss induced by the congestion. In turn, this means that developers also have to compensate the system for inducing additional congestion. This is an important addition as grid expansions can also result in reduced transmission capacity as shown by Hogan (2002). The suggested mechanism works as follows:

1. A new transmission grid expansion project is identified either by the regulator or by an investor.
2. The regulator makes the possible project public. Merchant investors can now evaluate it.
3. The merchant investors place bids in a public auction regarding the **time period** during which they want to receive the reduced congestion management costs as compensation.
4. Using a Vickrey mechanism, it is decided who wins the auction.
5. The transmission project is realized.
6. The need and cost for congestion management is calculated using the old topology of the network and the new topology in each market clearing step. The difference in costs constitutes the payment to (or by) the investor.

The costs are covered by the consumers as part of their grid charges because they would have had to pay for the redispatch costs as well. They profit from the expansion once the compensation period of the merchant investor runs out. Then, only the operation of the infrastructure needs to be covered through grid tariffs. In the process of evaluating the change in congestion cost relief, projects that are still in the compensation period are considered chronologically, i.e., a project is always evaluated based on the system topology that was present when it was realized. This design addresses the issues of merchant transmission in the following way:

- The compensation recovers the investment. If it does not, the welfare gain is not sufficiently high for the expansion investment and the investment should not be pursued.
- The congestion management costs are borne by all consumers. Therefore, they have the same incentives to optimize the grid. This is especially true as grid tariffs are currently being harmonized in Germany (Groebel, 2018). Theoretically, generators should be agnostic to grid expansions in uniform-price electricity markets.
- As the redispatch costs are exactly the welfare loss induced by the congestion, the payback is exactly the welfare gain generated by the transmission grid expansion.

8.2.2. Mechanism Formulation

In this section, the mathematical formulation of the mechanism is introduced as well as the calculation of the optimal benchmark. The problem is described from the perspective of a possible investor, meaning that congestion is considered over a longer time horizon rather than for one specific market clearing. First, the market clearing is formulated. In a uniform-price electricity market without consideration of grid constraints this is a straightforward optimization problem, that minimizes the total generation costs and thereby mimics the Merit Order. Note that for simplification, generation units are assumed to have no ramping constraints, idle times or minimal generation requirements. These assumptions are similarly made in other studies such as Kemfert et al. (2016) or Grimm et al. (2018). The marginal clearing price is then determined by the bid of the marginal unit. The constraints enforce that demand is always met (8.1b), that units cannot generate above their capacity (8.1c) and that no unit can generate a negative amount of energy (8.1d).

$$\min \quad \sum_{t=1}^{T}\sum_{i=1}^{N_b}\sum_{j=1}^{J} p_{i,j} \cdot q_{i,j,t} \tag{8.1a}$$

$$\text{s.t.} \quad \sum_{i=1}^{N_b}\sum_{j=1}^{J} q_{i,j,t} = \sum_{i=1}^{N_b} d_{i,t}, \forall t \in T \tag{8.1b}$$

$$q_{i,j,t} \leq c_{i,j,t}, \forall i \in N_b, \forall j \in J, \forall t \in T \tag{8.1c}$$

$$q_{(i,j,t)} \geq 0, , \forall i \in N_b, \forall j \in J, \forall t \in T \tag{8.1d}$$

$p_{i,j}$ Marginal cost of unit j at node i

$q_{i,j,t}$ Generation at node i of unit j at time t

$c_{i,j,t}$ Capacity of production unit j at node i (at time t for renewables)

$d_{i,t}$ Demand at node i at time t

After market clearing, the congestion management has to be performed. The objective of this step is to minimize the welfare loss that is caused by congestion. In the objective function, a power increase is penalized with the cost of the ramp up and a power decrease is rewarded with the marginal cost of production that is being reimbursed. This objective function implements the mechanism described in Fig. 3.2. In this step, the transmission grid constraints are taken into account in 8.2e. The sum of redispatch always needs to equal zero to ensure the balance (8.2b), and with the redispatch, the generation capacity limits can still not be violated (8.2c and 8.2d).

$$\min \quad \sum_{t=1}^{T}\sum_{i=1}^{N_b}\sum_{j=1}^{J} p_{i,j} \cdot q^{\Delta}_{i,j,t} \tag{8.2a}$$

$$\text{s.t.} \quad \sum_{i=1}^{N_b}\sum_{j=1}^{J} q^{\Delta}_{i,j,t} = 0, \forall t \in T \tag{8.2b}$$

$$q_{i,j,t} + q^{\Delta}_{i,j,t} \leq c_{i,j,t}, \forall i \in N_b, \forall j \in J, \forall t \in T \tag{8.2c}$$

$$q_{(i,j,t)} + q^{\Delta}_{i,j,t} \geq 0, \forall i \in N_b, \forall j \in J, \forall t \in T \tag{8.2d}$$

$$|\sum_{i=1}^{N_b-1} H_{(l,i)} \cdot (\sum_{j=1}^{J}(q_{i,j,t} + q^{\Delta}_{i,j,t}) - d_{i,t}))| \leq \tau_l, \forall t \in T, \forall l \in N_l \tag{8.2e}$$

$q^{\Delta}_{i,j,t}$ Redispatch at node i of unit j at time t

H Matrix of power distribution factors

τ_l Transmission capacity of line l

This optimization formulation calculates the cost of redispatch for the system. Ultimately, this is covered through grid tariffs paid by the consumers. The formulation does not consider the possibility of grid expansion. The following modified formulation minimizes the redispatch over all considered time steps while allowing for grid expansion. It considers the cost for redispatch as well as the cost for grid expansion over an investment horizon:

$$\min \quad \sum_{t=1}^{T}\sum_{i=1}^{N_b}\sum_{j=1}^{J} p_{i,j} \cdot q^{\Delta}_{i,j,t} + \sum_{l=1}^{N_l} \tau_l^{exp} \cdot p_l^{exp} \tag{8.3a}$$

$$\text{s.t.} \quad \sum_{i=1}^{N_b}\sum_{j=1}^{J} q^{\Delta}_{i,j,t} = 0, \forall t \in T \tag{8.3b}$$

$$q_{i,j,t} + q^{\Delta}_{i,j,t} \leq c_{i,j,t}, \forall i \in N_b, \forall j \in J, \forall t \in T \tag{8.3c}$$

$$q_{(i,j,t)} + q^{\Delta}_{i,j,t} \geq 0, \forall i \in N_b, \forall j \in J, \forall t \in T \tag{8.3d}$$

$$|\sum_{i=1}^{N_b-1} H_{(l,i)} \cdot (\sum_{j=1}^{J}(q_{i,j,t} + q^{\Delta}_{i,j,t}) - d_{i,t}))| \leq (\tau_l + \tau_l^{exp}), \forall t \in T, \forall l \in N_l \tag{8.3e}$$

τ_l^{exp} Expansion of line l

p_l^{exp} Cost of expansion of line l per MW and in the considered period

Note that the formulation is the same as for the previous problem with the addition that grid expansions are allowed and the associated costs are added to the objective function. This does of course not include risk considerations or expectations of the future development of generation expansion, electricity price developments or changes in the total demand and temporal demand patterns. Corresponding outlooks would have to be performed by potential investors. However, the optimization problem determines the optimal investment in the transmission capacity given an assumed structure of generation as proposed by Egerer and Schill (2014), for example.

Finally, to provide the welfare optimal benchmark, the following formulation combines the uniform-price market clearing problem and the redispatch problem into the formulation of a nodal pricing market clearing. The constraints are the same as in the previously described problems, only that now the market is cleared while considering the transmission grid capacity constraints at the same time.

$$
\begin{aligned}
\min \quad & \sum_{t=1}^{T}\sum_{i=1}^{N_b}\sum_{j=1}^{J} p_{i,j} \cdot q_{i,j,t} + \sum_{l=1}^{N_l} \tau_l^{exp} \cdot p_l^{exp} && \text{(8.4a)}\\
\text{s.t.} \quad & \sum_{i=1}^{N_b}\sum_{j=1}^{J} q_{i,j,t} = \sum_{i=1}^{N_b} d_{i,t}, \forall t \in T && \text{(8.4b)}\\
& q_{i,j,t} \leq c_{i,j,t}, \forall i \in N_b, \forall j \in J, \forall t \in T && \text{(8.4c)}\\
& q_{(i,j,t)} \geq 0, \forall i \in N_b, \forall j \in J, \forall t \in T && \text{(8.4d)}\\
& |\sum_{i=1}^{N_b-1} H_{(l,i)} \cdot (\sum_{j=1}^{J}(q_{i,j,t} - d_{i,t}))| \leq (\tau_l + \tau_l^{exp}), \forall t \in T, \forall l \in N_l && \text{(8.4e)}
\end{aligned}
$$

The nodal prices ρ_i can be derived from the optimization problem 8.4 above. They are calculated from the solution of the dual problem and the corresponding Lagrangian multipliers. The dual solution of the balance constraint 8.4b is the marginal price at the slack node. The remaining prices can be calculated in the following way:

$$\rho_i = \rho^{global} + \rho_i^{cong} \tag{8.5}$$

$$\rho^{global} = \lambda \tag{8.6}$$

$$\rho_i^{cong} = \sum_{i=1}^{N_l} H_{(k,i)} \cdot \mu_k \tag{8.7}$$

ρ_i	Marginal price at node i
λ	Dual solution of demand balance constraint 8.4b
ρ_i^{cong}	Marginal price of the network constraints at node i
μ_k	Dual solution of line constraints 8.4e

8.3. Numerical and Simulative Mechanism Evaluation

In this section, the introduced mechanism is applied to a simple 3-node network and to the stylized approximation of the German transmission system from the previous chapter. These examples are intended to first show the operation of the mechanism and second provide an example of the necessary consideration of redispatch besides grid expansion as an integrative part of congestion management in a uniform-price electricity market.

8.3.1. Numerical Example

Consider the grid topology given in Fig. 8.1. The cheapest generation is located at node 1, and the highest demand occurs at node 3, which has the highest generation costs. The total demand is 30. Every node can theoretically supply itself. Using the lossless DC approximation introduced in Chapter 3, the matrix of power distribution factors is as follows:

$$H = \begin{pmatrix} \frac{1}{3} & -\frac{1}{3} \\ \frac{1}{3} & \frac{2}{3} \\ \frac{2}{3} & \frac{1}{3} \end{pmatrix} \tag{8.8}$$

Clearing the market centrally with a uniform-price through a Merit Order dispatch leads to a generation of 20 at node 1 and 10 at node 2 and therefore to a net grid injection of 12 at node 1 and 6 at node 2. This results in the following flows:

$$z = H \cdot (q - d) = H \cdot \begin{pmatrix} 12 \\ 6 \end{pmatrix} = \begin{pmatrix} 2 \\ 8 \\ 10 \end{pmatrix} \tag{8.9}$$

These flows violate the transmission constraints of 1 for each line as shown in Fig. 8.1. Using the redispatch optimization formulation in Equ. 8.2, a feasible result can be calculated. The optimal possible generation pattern is a net injection of 1 at both, nodes 1 and 2. This leads to the following flows and redispatch costs r, which are calculated using Equ. 8.2.

$$z = H \cdot (q - d) = H \cdot \begin{pmatrix} 1 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix} \tag{8.10}$$
$$r = 10 \cdot 6 + 6 \cdot 7 - 10 \cdot 3 - 1 \cdot 2 - 5 \cdot 4 = 50$$

The optimal expansion now depends on the cost for the expansion per individual period. In this example the total redispatch costs per period are 50 and the necessary network expansion to fully eliminate congestion is 17, because expanding line 1-2 by 1, line 2-3 by 7 and line 1-3 by 9 allows for the optimal market solution to be feasible. If the expansion costs p^{exp} per period are below $\frac{50}{17}$ per unit of transmission capacity, it is reasonable to expand the grid to the point of avoiding congestion completely, because the cost per period for the expansion are below the cost per period for redispatch. In the proposed mechanism, these costs would be reimbursed to an investor, who has an incentive to expand the network as long as the payments are above the cost for expansion. However, any higher value of the expansion costs makes it optimal to allow for some congestion in the grid and its short-term management through redispatch. This is automatically warranted for in the proposed mechanism: An investor would not expand a line if the expected revenue is below the cost of expansion per period.

This example is also intended to show that grid expansion cannot occur line by line, but must be performed in projects. If grid expansions would be performed line by line (and the cost of expansion per period are below 6 which is the avoided redispatch by a line expansion of 1) the first addition to the given network would be an expansion of line 3 by 1. This would lead to the following optimal flow and redispatch as calculated by Equ. 8.2:

$$z = H \cdot (q - d) = H \cdot \begin{pmatrix} 3 \\ 0 \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ 2 \end{pmatrix} \leq \tau = \begin{pmatrix} 1 \\ 1 \\ 2 \end{pmatrix} \tag{8.11}$$
$$r = 10 \cdot 6 + 5 \cdot 7 - 9 \cdot 3 - 6 \cdot 4 = 44$$

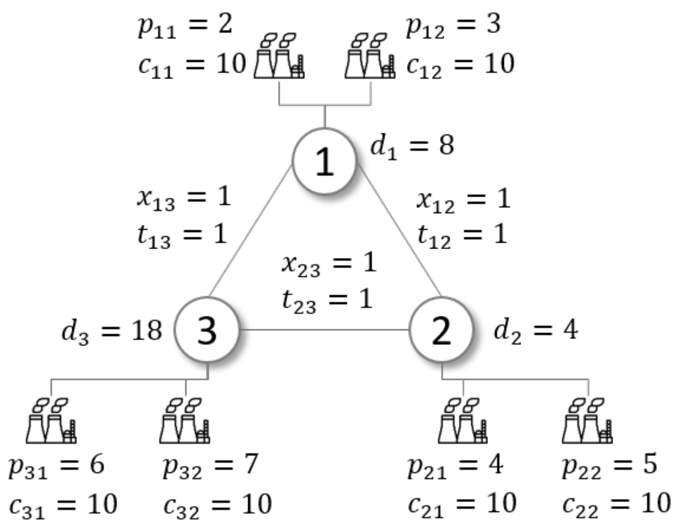


Figure 8.1.: Exemplary grid topology

However, at this point, no individual line expansion would create a benefit even if the cost for an expansion would be close to zero. Therefore, expansion projects often need to consider multiple lines. This holds an important implication for practice: If grid expansion is performed line by line, it is only moving grid congestion along grid areas and it should therefore be considered comprehensively. In the next section, the proposed mechanism is applied to a more practical example.

8.3.2. Application to the German Power System

In this section, the proposed mechanism is applied to the stylized version of the German transmission grid from the previous chapter as shown in Fig. 7.1. This approach is similar to Kemfert et al. (2016), who use a zonal representation of the German grid to assess the current grid expansion plans of the German TSOs. Initially, the situation in 2016 is analyzed. The course of the mechanism is then presented on data from 2016 to 2018. As an additional data point, the situation in 2018 is considered after the nearing nuclear phase-out. As stated by Weibelzahl (2017), network expansion planning can easily become computationally complex as many binary decisions need to be considered. This is also true for the given topology. Therefore, the decisions are reduced to an expansion of existing grid lines instead of a full network expansion. A similar approach is presented by Gunkel and Möst (2014). The authors only allow the additional construction of one particular line along the North-South division. This is redundant in the given case as the North-South connection is represented by a transmission line. The optimal grid expansion for the year 2016 is calculated as well as the costs for consumers, the producer surplus and the redispatch costs. Furthermore, the results are compared to a nodal pricing design. In this case, no redispatch occurs but a congestion rent, which is also calculated. Note, that no strategic behavior of suppliers is assumed, meaning that an optimal cost-based redispatch is performed. As shown in Chapter 4, this is not necessarily the case in practice but is used here as an ideal example. The expansion costs are assumed to be 62,500 Euro per MW of capacity and year of operation. This is based on the values of the SuedOstLink Project, which is currently estimated at 5 billion Euros for 2 GW of capacity and will be written off over 40 years[1]. This is of course only an assumption as the actual cost of expansion differs by length and the particularities of every line. Kemfert et al. (2016) use the midpoints of different zones as the estimation of the length of a line. However, they only consider 380 kV AC lines and no DC transmission and therefore disregard the costs for capacity. Gunkel and Möst (2014) report costs of 1.5 Million Euro per MW of capacity and kilometer of length ($\frac{1500k€}{km \cdot MW}$). However, this would result in costs of more than 1.5 trillion Euros for SuedOstLink (Rippel et al., 2017). Therefore, all possible expansions are assumed to be equally long and only the cost for transmission capacity is considered.

The simulation results are shown in Table 8.1. First of all, as can be seen and as was previously explained, the optimal expansion for redispatch and nodal pricing are the same. This shows, that an expansion policy based on redispatch costs theoretically leads to a welfare optimal grid expansion. If the mechanism leads to a welfare optimal expansion in practice depends on one condition: The investors base their compensation period bid on their expectations of the development of generation capacity and consumption patterns. These expectations need to be correct for a completely welfare optimal grid. However, even if these expectations are off, the risk is borne by the investors.

[1] https://www.tennet.eu/de/news/news/gleichstromverbindungen-suedlink-und-suedostlink-netzbetreiber-starten-ausschreibungen-fuer-erdkabel/

Scenario	Consumer costs	Producer surplus	Cong. rent/ redispatch	Grid exp. (in MW)
Nodal pricing	9,453	4,305	164	592
Redispatch optimal	9,311	4,289	39	592
Redispatch 90%	9,331	4,289	9	1,401
No congestion	10,035	4,289	0	12,806
No expansion	9,329	4,289	95	0

Table 8.1.: Welfare evaluation of different scenarios in million Euro

In the given example, consumers are better off under a uniform-price regime with redispatch than under nodal pricing. This is however dependent on the grid topology and cannot be generalized. As can be seen, a full expansion of the grid with no more congestion is by far the worst outcome for the consumers. It increases their costs by more than 700 million Euros per year as can be deducted from the first column and it leads to a grid expansion that is 20 times as high as in the welfare optimal cases shown in the last column. However, if curing congestion is a more important objective than overall welfare, (for example, due to reasons of competition or future expectations of generation) a reduction of congestion costs by 90% comes at relatively little additional yearly cost. This is a very important finding for practice. As Fig. 8.2 shows, grid expansion especially reduces spikes of congestion costs during the winter months. The results furthermore show that generators should be agnostic to grid expansions in uniform-price electricity markets with redispatch, as their welfare does not change dependent on the grid expansion. This is true as long as they do not profit from wrongly set incentives in the form of payments for required controllable capacity determined by the TSOs (Ocker and Ehrhart, 2017a).

To show a possible development over time, the mechanism is embedded in a simulation of the system over a four year period. The empirical data is based on the model from Chapter 7 and on renewable generation and load data from 2016 to 2018 provided by the European Network of Transmission System Operators (2018). The exact capacities of the network model are given in Fig. A.1 of the Appendix and the conventional generation capacity at each node is provided in Appendix A.7. The renewable generation and load data per node is provided by Bundesnetzagentur

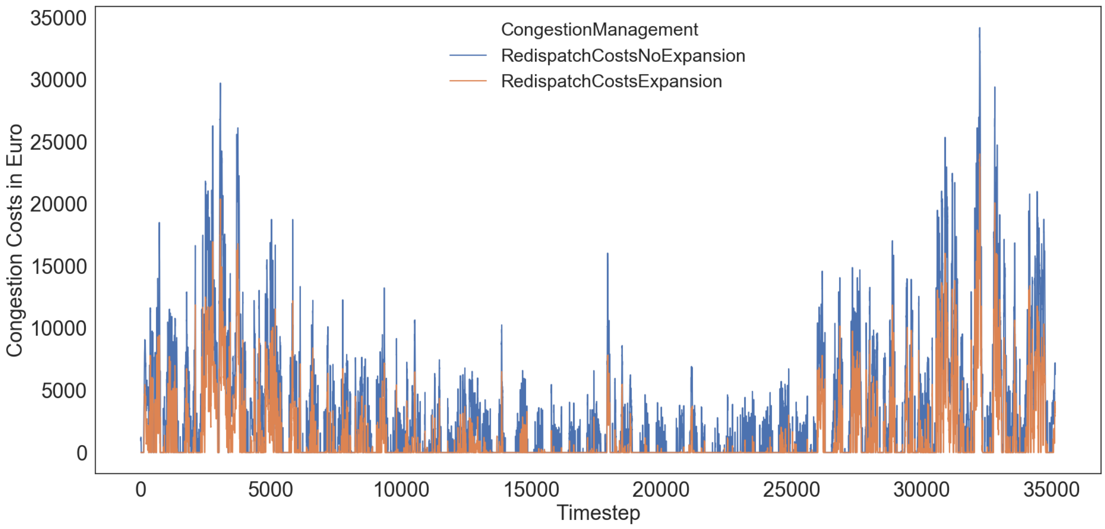


Figure 8.2.: Congestion management costs over the course of 2016

(2019). At this point, it is assumed that investors act without any anticipation of the future generation capacity development. In reality, the future development of the generation infrastructure would be forecasted and the grid development plans would be suggested correspondingly. However, it serves as an illustration to assume that no specific generation investment is anticipated. Furthermore, the immediate realization of projects is assumed. Table 8.2 shows the grid development from 2016 to 2018. The generation and load profile from 2018 without the currently still operational nuclear power plants is used as an additional data point to simulate the situation after the nuclear phase-out in 2022. Over the years, the optimal grid expansion is limited to an expansion of the line between the TenneT North (4) and South (2) zones. This seems reasonable as the North-South division is the main cause for systematic grid congestion in Germany as shown in Chapter 2. For their investment, developers receive an average compensation of 95,000 Euros per MW of installed transmission capacity, which is more than the yearly investment of 65,000 Euros. The exact results are shown in Table 8.2. The values show that redispatch would grow over the considered period without an increase of transmission capacity. It also shows that in each period another expansion is justified by the welfare gains and that correspondingly the investor payments increase. As said, the grid capacity expansions are exclusively performed for line 2-4. In this analysis, the interest

Year	Redispatch costs	Redispatch costs w/o expansion	Optimal expansion (MW)	Payment investors
2016	95	95	592	0
2017	136	187	909	52
2018	126	271	858	145
2018 (w/o Nuc.)	76	317	429	241

Table 8.2.: Grid development and associated costs in million Euro over four year period

rate on investments is assumed to be zero. However, this can easily be added by individual developers if the necessary yearly return on investment is known. The analysis reveals that the designed mechanism with the described assumptions would reduce congestion to about a quarter of its virtual value after four years of operation as shown in the last row of the table.

The proposed mechanism has the potential of greatly reducing consumer payments for congestion management in the long-term, while allowing some short-term congestion to be managed at acceptable costs. In the next section, some necessary practical considerations are discussed.

8.4. Implementability of the Market Design

The proposed mechanism has several advantages over the current regulatory approach for grid expansion. First, under the used assumptions on the development of generation capacity and demand, it leads to a welfare optimal expansion of the grid. The consideration of redispatch as a congestion management approach instead of grid expansion does not have to be performed by state actors but is done by private actors. Furthermore, the risk of expansions is not borne by consumers anymore but by private investors. The implementation can occur as part of the TSO regulation in the sense that grid expansions are no longer compensated based on the equity tied up in the projects but based on its effects on congestion reduction. This is done in a similar fashion for highways or other public projects in the framework of public-private-partnerships (Savas and Savas, 2000). Finally, the incentives are set correctly: Consumers have an interest of a welfare optimal expansion as it reduces their electricity costs. The redispatch payments to the grid developers would have to be paid even without the expansion. Furthermore, developers have no incentive of strategically expanding the grid to inflate theoretical redispatch costs as they would be responsible to compensate the public for additionally incurring costs. And finally, the wholesale market clearing prices do not change as a reaction to the grid expansion. Therefore, there is no market reaction to grid expansion in terms of regional capacity investments as in nodal pricing systems (Pisciella et al., 2016). That makes the anticipation of future capacity expansion easier. The proposed model could also be applied to an improved operation of existing grid resources and reward these in the same way as actual grid expansion. TSOs or service companies can improve the load factor of existing lines through dynamic line rating (Xu et al., 2013). This is the operation of lines depending on ambient conditions, as lower outside temperatures lead to a higher thermal limit of transmission lines. However, due to higher operational costs these solutions are discarded (Matschoss et al., 2019). Using the proposed mechanism, TSOs could be rewarded for searching for low cost alternatives to grid expansion.

However, certain practical considerations need to be discussed before such a market can be implemented. First, if developers propose projects, it needs to be determined in which sequence these projects are accepted as they might be in conflict with each other. This would require a central authority or additional research on the optimal scheduling of expansion projects, for example, by duration or capacity of the suggested projects. Franken et al. (2018) propose an indicator to prioritize projects based on their potential for redispatch reduction. Furthermore, the theoretical calculation of redispatch might be influenced by the shutdown of power plants. For example, it might be possible that after the shutdown of certain power plants, a region might not be able to do a virtual redispatch as they have become so dependent on the expanded grid. In practice, this could mean that a TSO would allow the shutdown of a strategically important power plant because sufficient transmission capacity is available. However, in the calculation of virtual redispatch that is relevant for the compensation of investors, this power plant might be important to avoid very high virtual costs of redispatch. To solve this issue, the TSOs or the government and the transmission grid investors need to agree on a base generation capacity, that is assumed in the future determination of redispatch costs in order to avoid such windfall profits (i.e., "a sudden unexpected profit uncontrolled by the profiting party" (Verbruggen, 2008)). This leads to another question, which is the risk for developers. If the risk is prohibitively high, e.g., due to the uncertainty of the future expansion of the generation capacity, no grid expansion would occur, which would lead to a severe welfare loss in the long-term. This would have to be discussed in consultations with relevant stakeholders. Solutions might be certain guarantees, which need to be carefully considered to avoid a dilution of correct welfare optimal incentives. Furthermore, a clear set of rules regarding the completion of projects needs to be established. If projects cannot be realized in time, this needs to have consequences for the developers, to avoid the strategic blockage of expansion projects. Furthermore, it needs to be discussed how following projects are treated with regard to redispatch payments if other, previously approved projects, are delayed. Finally, the operation of third party grid expansion needs to be discussed. Ideally, these expanded resources would be operated by the respective TSO and the investors would only be compensated for their investment.

8.5. Summary of Chapter 8 and Discussion

CHAPTER 9

MULTILATERAL LOCATIONAL PRICING

The previous chapters evaluate the current congestion management in uniform-price electricity markets and introduce possible improvements. As an alternative approach, this chapter proposes a multilateral market mechanism that is based on minimal oversight and that conserves the freedom of European electricity markets. At the same time, the proposed design discovers the welfare optimal market clearing by considering grid constraints during the clearing process.

The intention of this design is based on a rationale that can be understood using a simple example: Imagine two islands that share a water pipeline which can deliver x liters a day. Due to rough currents, it is not possible to travel between the two islands. Imagine island A had a need for water of $y > x$ liters per day but water is cheaper on island B and the supply is unlimited on both islands. If these islands would employ water supply redispatch, island A would pay island B for y liters every day instead of just x liters while paying again for the remaining $y - x$ liters locally. Such unreasonable economic behavior can be reduced using market designs that explicitly model grid constraints into the market mechanism.

The consideration of these mechanisms is becoming more important in the EU due to two political developments: First, the EC has demanded member states to implement a market-based redispatch (European Commission, 2016). In an ideal environment, local redispatch markets would lead to a nodal dispatch as shown in the previous chapter. However, as discussed in Chapter 4 and Chapter 5 such a design might be sensitive to market power. Secondly, the EC requires member states to open the cross-border interconnectors to at least 75% of its capacity (Bundesregierung, 2018a). This is currently not being achieved in Germany. The EC reserves the right to split bidding zones if the minimal interconnector capacity cannot be made available (Bundesregierung, 2018a).

Both developments make locational market signals more important. This chapter contributes to the discussion by proposing and benchmarking a multilateral locational market mechanism. The multilateral market mechanism is based on the congestion management approach introduced by Wu and Varaiya (1999) that is further developed by Qin et al. (2017). They introduce a System Operator (SO) who is simply in charge of monitoring the trading, curtailing trades that violate transmission grid constraints and communicating the current congestion state of the transmission system. The authors show that their approach theoretically leads to the same efficient market result as nodal pricing. However, no incentive compatible market design respecting individual rationality is presented. Furthermore, they do not compare the welfare distribution in their mechanism to other market designs and do not test the sensitivity of their approach towards market power. They also leave the trade formation to future research. In this chapter, the congestion management approach of Qin et al. (2017) is further developed into a market design and evaluated against a nodal pricing approach.

This is an important contribution as Richstein et al. (2018) state that as "[...] in the long-term all countries will very likely require locational pricing systems to accommodate the increasing share of renewable energy and flexible demand side options, any early national implementation of locational prices offers a learning opportunity and potential blueprint for other countries, but poses the question how such locational marginal pricing (also called nodal pricing) systems will interact within the existing European zonal power market approach".

In conclusion, this chapter introduces a multilateral pricing mechanism based on an existing congestion management approach by Qin et al. (2017) that ensures a feasible market solution through a monitoring of proposed trades. The mechanism is compared to nodal pricing with regard to welfare distribution and market power based on simulations on a range of exemplary networks. Finally, its implementability is discussed with regard to the German electricity market. This chapter is mainly based on (Staudt et al., 2019a).

9.1. Market Design Alternatives

The bilateral-nodal debate has a long history within the field of energy economics (Stoft, 2002). In this context, bilateral usually means that energy is independently and bilaterally traded between a supplier and a consumer. This implies the absence of an intermediary such as an ISO, who collects all supply and demand bids and clears the market centrally. As bilateral might be misleading in the sense that trade can only occur between exactly two parties, such a system is called a multilateral pricing mechanism in this dissertation as the more liberal alternative to the centralized locational marginal pricing. In this section, the underlying mechanisms are introduced.

9.1.1. Locational Marginal Pricing

The general principle of locational marginal pricing is described in Section 3.2.3. In the following, the mathematical formulation of the locational pricing mechanism is briefly introduced. The mechanism that leads to this formulation is illustrated in Section 3.2.3. Assuming an inelastic demand (or at least an inelastic demand in the common price range for electricity), the minimization of the production cost leads to the maximization of social welfare. The distribution of this social welfare on producer, consumer and transmission rent then depends on the market mechanism. In this chapter, the power flow is approximated using the lossless DC power flow approximation introduced in Section 3.2.1. Therefore, the optimal power flow optimization problem can be formulated similar to the optimal grid expansion under nodal pricing in the previous chapter. In this formulation the time and generator dimension are ignored and the optimization is performed only for one time step and one set of operators per node. This leads to the following optimization problem:

$$\min \quad \sum_{i=1}^{N_b} p_i \cdot q_i \tag{9.1a}$$

$$\text{s.t.} \quad \sum_{i=1}^{N_b} q_i = \sum_{i=1}^{N_b} d_i \tag{9.1b}$$

$$\left| \sum_{i=1}^{N_b} H_{(l,i)} \cdot (q_i - d_i) \right| \leq \tau_l, \; \forall l \in N_l \tag{9.1c}$$

$$q_i^{min} \leq q_i \leq q_i^{max}, \; \forall i \in N_b \tag{9.1d}$$

p_i	Generator price at bus i
q_i	Generation at bus i
d_i	Demand at bus i
H	$(N_l \times (N_b - 1))$-dimensional matrix of power distribution factors
τ_l	Transmission capacity of line l
N_l	Number of lines
N_b	Number of buses (nodes)

This formulation finds the welfare optimal dispatch regarding the stated operator prices but not necessarily the actual welfare optimal solution. Therefore, its result is sometimes referred to as the maximization of the stated social welfare (Fernández-Blanco et al., 2014).

9.1.2. Multilateral Locational Pricing

As previously introduced, the ISO is replaced by an SO in the Multilateral Locational Pricing market design. This SO ensures that all trades are feasible with regard to system transmission constraints. Therefore, all agreed trades need to be transmitted to the SO for evaluation. After each trade, the SO checks the feasibility of the set of all submitted trades and the last trade is only accepted as submitted if it does not violate any constraints. If one or more transmission constraints are violated, the SO curtails the last submitted trades uniformly for all participants of the trade. Say a trade is agreed upon at an exchange with multiple buyers and sellers: If this trade is curtailed to α of its original amount, then all buyers receive α of their procured quantity and all sellers sell α of the original amount. This ensures fairness among market participants and does not favor any supplier or consumer. If a trade is curtailed due to a transmission capacity constraint, this constraint is called *activated*. In the following trading round, only trades are allowed that do not further increase the flow with regard to the activated constraint. If a following trade reduces the flow on the line with the active constraint, this constraint gets deactivated. Several constraints can be activated at the same time. They are deactivated as soon as the flow on the respective lines is reduced. They can later be re-activated. Only active constraints need to be considered while trading. Constraints that are not currently activated can be violated through a trade, but this trade is then curtailed to the level where the constraints are respected.

Qin et al. (2017) show that this iterative process leads to the same optimal dispatch as the central nodal optimization of an ISO. This market design allows for more freedom between participants and there is no need for an intrusive centralized ISO (Wu and Varaiya, 1999). The resulting trades and prices are the outcome of a liberalized process between market participants, while respecting transmission grid constraints. The design is based on the idea that a welfare-optimal dispatch can result from an iteration of mutually beneficial bilateral or multilateral trades between consumers and suppliers and mutually beneficial bilateral or multilateral re-trades among suppliers, which are both curtailed if they violate grid constraints.

However, certain sequences of trades might lead to a solution, where some of the demand cannot be covered. A sequence is the order in which bids are accepted. For example, the Merit Order would be the sequence in which generators are dispatched in the order of increasing marginal costs of production. Consider the following simple example: One very cheap supplier can cover the entire demand. However, the generation occurs at a remote location of the system and the transmission system is not sufficiently expanded to transmit all of the generation. In an initial trade all consumers procure their demand from this supplier. The trade is then curtailed. As the supplier has the lowest marginal cost of production in the system, no re-trades between suppliers will occur as no other supplier would generate for the price that the cheap producer received for the generation. Now assume that there is an activated grid constraint for a line for which all nodes have a positive power distribution factor. This means that all remaining demand needs to be covered locally at the nodes as this does not affect the transmission grid. If that is not possible at certain nodes, some load cannot be served.

In their congestion management approach, Qin et al. (2017) formulate the problem such that the SO can curtail even previously approved trades ex-post, without compensating the generators. However, such market interventions are similar to an ISO and should therefore be avoided. The proposed market mechanism is based on individual rationality, i.e., only individually profitable trades are performed. Therefore, the load needs to consider the possibility of not being able to cover the entire demand and if that is not an option as demand is inelastic, procure in a way that such a deadlock is avoided. This is always feasible if a feasible solution exists, as Qin et al. (2017) have shown that the algorithm always converges to the solution of a nodal pricing design. In the proposed mechanism, the load therefore tests all sequences of procurement (i.e., all permutations of the generator sequence are considered) and decides for the cheapest sequence that covers the entire demand. In the following section, the Multilateral Locational Pricing mechanism is introduced.

9.2. Multilateral Market Clearing Algorithm

In the multilateral market mechanism, the generators offer supply contracts to the load. For simplicity, the load is assumed to act as one entity. This assumption is further discussed in Section 9.4. The load chooses from the presented contracts consisting of an ask price and a generation capacity, to maximize the consumer surplus. In order to do so, the load tests all possible sequences before choosing the optimal sequence. As demand is assumed to be inelastic, this is the sequence that covers the entire demand at minimal cost. While there is always a sequence that leads to the welfare optimal solution as shown by Qin et al. (2017), this might not be chosen by the load as it does not necessarily maximize the consumer surplus. The load therefore simulates the market mechanism for each possible sequence and chooses the optimal solution assessing all supplier offers.

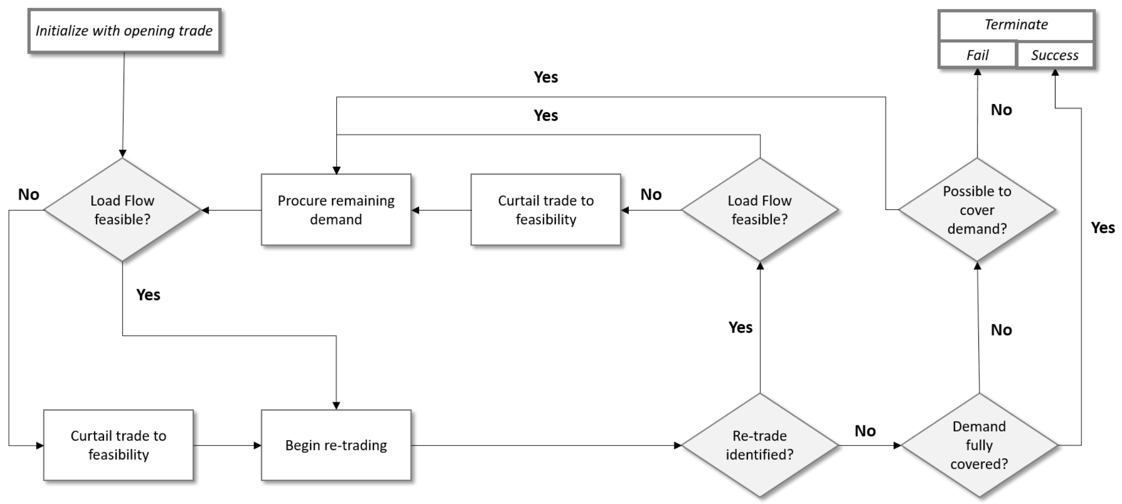


Figure 9.1.: Conceptual diagram of the trading algorithm

The full algorithm of the market clearing is depicted in Fig. 9.1. The market mechanism is composed of procurement and re-trading. During procurement the load intends to cover the remaining demand, and in the re-trade phase the suppliers trade among each other to profit from optimization potential, i.e., more expensive generators, that have sold generation buy their generation back from cheaper generators and can profit off the margin. The procurement is performed according to the defined sequence. This also implies that consumers can choose their suppliers by other factors than the price such as sustainability. Procurement and re-trading are always performed consecutively until the entire load is covered. At that point only re-trades occur until there is no more remaining potential for efficiency improvement. Usually, each procurement round involves multiple parties. The load intends to cover the entire demand according to the chosen sequence. If not all demand can be covered by one supplier, multiple suppliers are involved in the trade. Every individual multilateral trade is priced through a uniform-price approach. This is motivated by the fact that procurement might still occur at exchanges. Therefore, auctions can create a bundle of trades with a uniform market clearing price. However, different trades can have different prices that reflect the regional scarcity of electricity in the system.

A re-trade only occurs between exactly two suppliers who find a mutually beneficial trade. This is the case if one supplier finds another supplier with a cheaper ask price and if that re-trade does not lead to the violation of an active line constraint. Therefore, the price of a re-trade is set to the ask price of the cheaper generator. As the more expensive generator receives a payment of at least his ask price when she sells her capacity, this leads to a profit margin. The re-trade quantity is also fixed at the increment δ^{inc} which needs to be sufficiently small. The rationale is that a re-trade with a large volume might lead to a deadlock if a cheap generator generates sufficient quantity to block the system after a re-trade. Therefore, the volume per re-trade is restricted. The re-trade quantity and the consideration of sequences are the two necessary adaptions to the proposed algorithm by Qin et al. (2017) to create a market mechanism based on their congestion mechanism. This is further discussed in Section 9.4. The suppliers check for re-trades in descending order of their ask prices. If a supplier finds no other supplier with whom she can re-trade respecting the activated constraints, the supplier with the next highest ask price begins the search process.

After each successful procurement or re-trade, trading is interrupted, the SO is notified and checks whether the last performed trade needs to be curtailed. This might have implications for the computational complexity of market clearing, which is left to future research. It is also briefly discussed in Section 9.4. If the new trade violates any grid constraint, the SO finds the minimal necessary curtailment to ensure system stability. If curtailment occurs, at least one capacity constraint becomes active. The system congestion state is then published by the SO correspondingly. Corresponding to the system congestion state, only procurement and re-trades are allowed that respect the active constraints. If there is no curtailment after a trade, all constraints are deactivated. To find the minimal necessary curtailment, the SO solves the following optimization problem:

$$\min \quad \gamma \tag{9.2a}$$

$$\text{s.t.} \quad \sum_{i=1}^{N_b} H_{(L,i)} \cdot \left((q_i^{prev} - d_i^{prev}) + (1-\gamma) \cdot \left(q_i^{\delta} - d_i^{\delta} \right) \right) \leq t_L \tag{9.2b}$$

$$0 \leq \gamma < 1 \tag{9.2c}$$

γ	Curtailment factor
q_i^{prev}	Generation before new trade at node i
d_i^{prev}	Covered demand before new trade at node i
q_i^{δ}	Additionally traded generation at node i
d_i^{δ}	Additionally traded demand at node i
L	Index of active constraint

9.3. Simulating Market Designs

In this section, the two market designs are compared with regard to welfare distribution among consumers, producers and transmission and with regard to market power. For the latter, the same agent-learning approach is used as in Chapter 6. In respect to the classification by Weidlich and Veit (2008a), the study can be categorized as normative agent-based computational economics since the agents are used to evaluate economic design alternatives. The simulation setup is introduced and the results are compared along the considered dimensions.

9.3.1. Analytical Example of Market Mechanisms

To introduce the market mechanism, this section provides a small numerical example as well as an analysis considering welfare distribution and the exercise of market power. The used grid topology is a market with two nodes connected by one transmission line and is adapted from the original paper by Qin et al. (2017). This setup reduces the complexity as no loop flows are possible. The system is shown in Fig. 9.2. As the figure shows, the load L is located on the right node $N2$ with a total

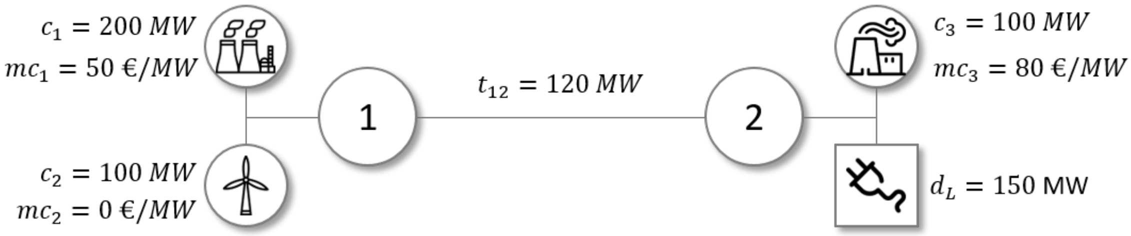


Figure 9.2.: 2-Node network based on Qin et al. (2017)

demand of 150 MWh. One generation unit $G3$ is connected directly to the load, which is the most expensive unit with marginal cost of 80 €/MWh and a capacity of 100 MW. Two other generators are located on the left node $N1$, which is connected to $N2$ through one transmission line with capacity $t_{1,2} = 120MW$. The first, $G2$, is a wind turbine with marginal cost of zero and an assumed power generation of 100 MW and the second, $G1$, is a hard coal power plant with marginal cost of 50 €/MWh and a capacity of 200 MW.

First, the welfare distribution is considered assuming competitive behavior, i.e., marginal cost bidding. Under a nodal pricing market mechanism, the ISO would optimize the system such that the cheapest units generate electricity. This leads to the following revenue outcomes with r_i being the revenue of generator or load i, g_i the corresponding generation and p_j the price at node j in a nodal pricing design or in trade j for the multilateral design:

$$
\begin{aligned}
r_{G1} &= p_{N1} \cdot q_{G1} = 50 \cdot 20 = 1,000 \\
r_{G2} &= p_{N1} \cdot q_{G2} = 50 \cdot 100 = 5,000 \\
r_{G3} &= p_{N2} \cdot q_{G3} = 80 \cdot 30 = 2,400 \\
r_L &= p_{N2} \cdot q_L = 80 \cdot -150 = -12,000
\end{aligned}
\tag{9.3}
$$

The transmission capacity is fully used for the cheap generation capacity from $N1$. As the load demands 30 MW more, the line is congested and there are different prices on $N1$ and $N2$. The load pays the price of $N2$ and there is a congestion rent of 3,600.

Under the multilateral design, the trading occurs in two trading rounds. In the first trade, the load procures its full demand from generators $G1$ and $G2$ at the marginal trade price of 50 €/MWh. This trade is curtailed by the SO to 120 MW. As the activated constraint needs to be respected in the second trading round, the load procures the remaining demand from generator $G3$ at 80 €/MWh. Additionally, as $G1$ and $G2$ are equally curtailed, there is efficiency potential in a third trade between the two generators. This third trade occurs at the marginal cost of $G2$, which is zero. This leads to the following payments.

$$
\begin{aligned}
r_{G1} = p_{T1} \cdot q_{G1_1} + p_{T3} \cdot q_{G1_2} &= 50 \cdot 40 + 0 \cdot -20 = 2,000 \\
r_{G2} = p_{T1} \cdot q_{G2_1} + p_{T3} \cdot q_{G2_2} &= 50 \cdot 80 + 0 \cdot 20 = 4,000 \\
r_{G3} = p_{T2} \cdot q_{G3_1} &= 80 \cdot 30 = 2,400 \\
r_L = p_{T1} \cdot q_{L_1} + p_{T2} \cdot q_{L_2} &= 50 \cdot -120 + 80 \cdot -30 = -8,400
\end{aligned}
\tag{9.4}
$$

The comparison shows that the producer income stays the same but is distributed differently. The consumer costs are decreased by exactly the amount of the transmission rent.

Now, strategic agent behavior is introduced. In order to assess the effects of market power, a market-cap of 1,000 €/MWh is introduced to cap the bid of pivotal suppliers. Furthermore, generators are now aware of their position and the next more expensive competitor. For the nodal design, this leads to the following market result:

$$
\begin{aligned}
r_{G1} &= p_{N1} \cdot q_{G1} = 80 \cdot 20 = 1,600 \\
r_{G2} &= p_{N1} \cdot q_{G2} = 80 \cdot 100 = 8,000 \\
r_{G3} &= p_{N2} \cdot q_{G3} = 1000 \cdot 30 = 30,000 \\
r_L &= p_{N2} \cdot q_L = 1000 \cdot -150 = -150,000
\end{aligned}
\tag{9.5}
$$

$G1$ bids 80 €/MWh as this is the next more expensive supplier. $G2$ bids the marginal cost of $G1$, which is not important for the market result as $G1$ sets the price. $G3$ is aware of being the pivotal supplier and bids the market-cap. The load pays the price of $N2$, which leads to a transmission rent of 110,400. In the multilateral design the trading course is the same as in the welfare example.

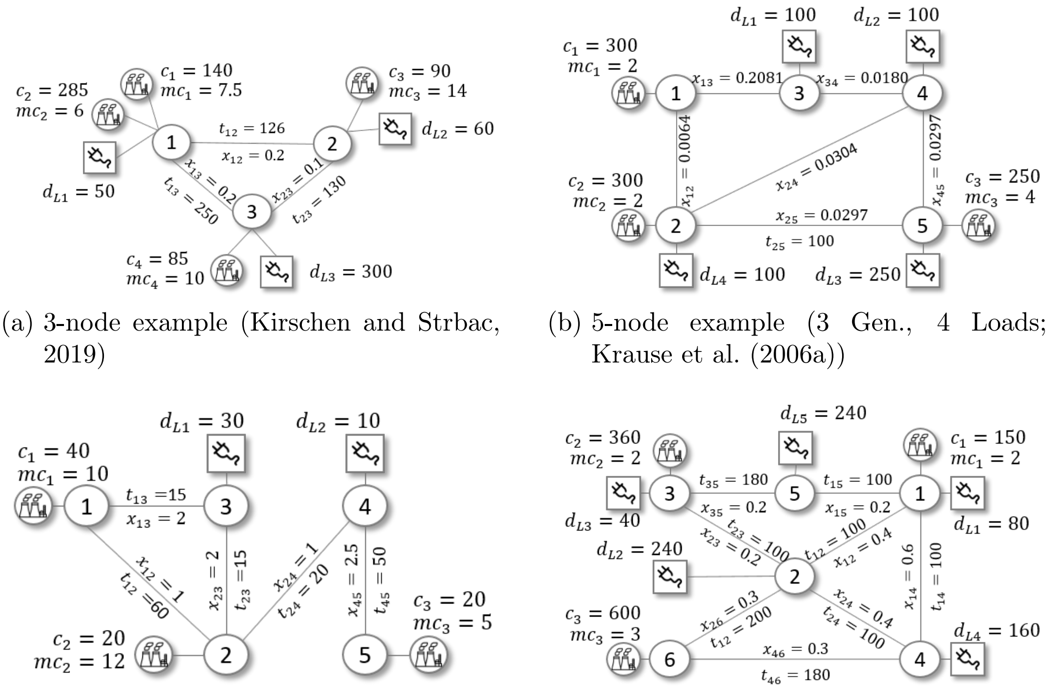
$$
\begin{aligned}
r_{G1} &= p_{T1} \cdot q_{G1_1} + p_{T3} \cdot q_{G1_2} = 80 \cdot 40 + 50 \cdot -20 = 2,200 \\
r_{G2} &= p_{T1} \cdot q_{G2_1} + p_{T3} \cdot q_{G2_2} = 80 \cdot 80 + 50 \cdot 20 = 7,400 \\
r_{G3} &= p_{T2} \cdot q_{G3_1} = 1000 \cdot 30 = 30,000 \\
r_L &= p_{T1} \cdot q_{L_1} + p_{T2} \cdot q_{L_2} = 80 \cdot -120 + 1000 \cdot -30 = -39,600
\end{aligned}
\tag{9.6}
$$

The results show that the effects of market power on the load are greatly reduced through the multilateral design. However, the individual behavior does not change considerably. This example serves as an illustration of the market mechanism. In the next sections, the design's effects are analyzed for more sophisticated grid topologies, generation and load distributions.

9.3.2. Simulation Setup

The simulation is performed on a variety of test grids that are taken from the literature. A visual overview of the displayable grids is given in Fig. 9.3. Additionally, the simulation is run on a 56-bus example from Peng and Low (2013). As previously stated, the load is considered as one single entity that has the priority of covering the entire demand at the minimal possible cost. For the nodal pricing simulation, mandatory spot market participation is assumed. Each supplier always asks exactly one marginal price for its generation. No out-of-market trading is permitted. For the assessment of welfare distribution, perfect competition is assumed. This means that all suppliers ask their marginal cost and in the nodal pricing case, market clearing results in the welfare optimal solution (Krause et al., 2006b). For the multilateral pricing design, suppliers can only submit one ask price and cannot adjust it after the initial submission. This is intended to reduce the exercise of market power: A high price might lead to less sold quantity in the initial trading rounds and might therefore be unattractive. Furthermore, bidding above marginal cost might lead to re-trades that are not necessarily profitable if the provided ask price does not correspond to the actual marginal cost of production.

The agent-learning algorithm for the assessment of market power is the same as in Chapter 6. Each supplier is modelled as an agent and uses a variation of the



(a) 3-node example (Kirschen and Strbac, 2019)

(b) 5-node example (3 Gen., 4 Loads; Krause et al. (2006a))

(c) 5-node example (3 Gen., 2 Loads; own variation)

(d) 6-node example (R. Romero et al., 2002)

Figure 9.3.: Reference networks

Probe and Adjust algorithm developed by Kimbrough (2011) to adjust the ask prices. Each market is being given a market-cap such that the ask prices of an individual supplier can vary between the marginal cost of production and the market-cap. The algorithm is chosen as in Chapter 6 because of its favorable characteristic that the action space does not have to be discretized. The agents place their bids and process the feedback from the achieved revenue. The base bid is initialized as the marginal cost of production and the algorithm performs a heuristic neighborhood search over the course of an epoch. After an epoch, the agents adjust their base bid to the mean of the best performing 50% of the probed bids. The exploration parameter δ around the base bid is set to 1 and the epoch size is 50.

	Pricing Scheme	Consumer Payments	Producer Revenue	Congestion Rent
3-bus example	**Nodal Pricing**	4050	3262	788
	Multilateral Pricing	3272	3272	0
	Difference	*-778*	*10*	*-788*
5-bus example (3 Gen., 4 Loads)	**Nodal Pricing**	1841	1689	152
	Multilateral Pricing	1772	1772	0
	Difference	*-69*	*83*	*-152*
5-bus example (3 Gen., 2 Loads)	**Nodal Pricing**	658	464	193
	Multilateral Pricing	480	480	0
	Difference	*-178*	*16*	*-193*
6-bus example	**Nodal Pricing**	2052	1914	138
	Multilateral Pricing	1988	1988	0
	Difference	*-64*	*74*	*-138*
56-bus example	**Nodal Pricing**	839	755	84
	Multilateral Pricing	827	827	0
	Difference	*-12*	*72*	*-84*

Table 9.1.: Welfare distribution in simulated grids under perfect competition

9.3.3. Welfare Distribution

As previously stated, perfect competition is assumed for the initial welfare analysis. This implies that all suppliers bid their marginal cost of production. The intention is to initially understand the changes in welfare distribution that result from the new market design. The welfare is therefore split up into consumer and producer surplus and congestion rent. In all tested grids, the consumers choose a sequence of generators for procurement that leads to the optimal nodal dispatch. This means that the overall welfare remains constant and only changes in distribution need to be considered. The results are displayed in Table 9.1. The consumer surplus increases in all considered test grids. This is due to a redistribution of the transmission rent, which is not being paid in the Multilateral Locational Pricing design as opposed to nodal pricing. The division of the congestion rent among consumers and producers varies for the different test grids. It is noteworthy that in the considered test grids no welfare is shifted between consumers and producers beyond the payments that arise from the congestion rent for each group.

In order to explain the division of the transmission rent, a more detailed analysis of the procedure of the trading algorithm is performed. Table 9.2 gives information on the course of the algorithm in each simulation. There is no obvious connection between the course of the algorithm and the results of the simulation. Therefore, it is concluded that the market results do not depend on the technical procedure of the algorithm but on the grid topology and the distribution of generation and

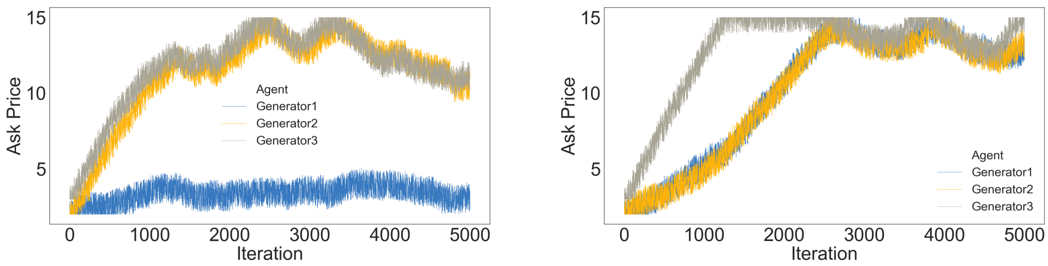
	Initial trade feasible	Number of re-procurements	Number of re-trades	Share of solvable sequences
3-bus example	No	1	100	24/24
5-bus example (3 Gen., 4 Loads)	No	140	352	6/6
5-bus example (3 Gen., 2 Loads)	No	15	17	2/6
6-bus example	No	20	82	2/6
56-bus example	No	688	789	720/720

Table 9.2.: Course of the algorithm for different test grids

load. Another finding from the technical analysis is that the most complex 56-bus grid clears the market for all 720 sequences. This raises the suspicion that a more complex grid might provide more alternatives and the sequencing of procurement might not be necessary. This analysis shows that the two designs do not lead to an unexpected redistribution of welfare in any direction. Therefore, with regard to welfare distribution, both options are equally well suited as electricity market designs.

9.3.4. Exercise of Market Power

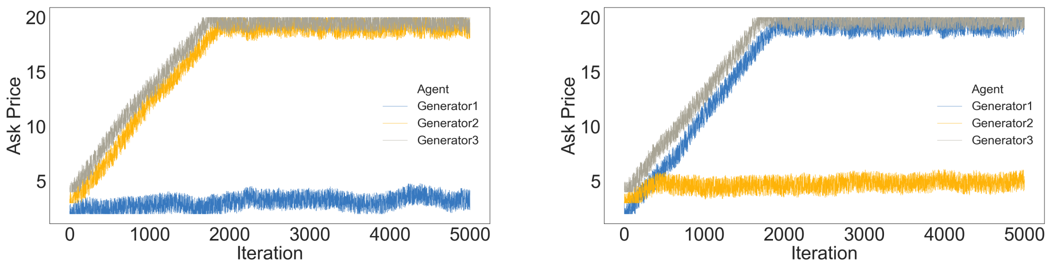
As discussed in Part III, electricity markets are often exposed to market power as they used to be natural monopolies and because entry barriers are high. In this section, the two market designs are compared with regard to their containment of market power. To this end, supply agents are enabled to bid strategically. After 4000 rounds of training the market results and bidding strategies of agents are evaluated for the 1000 consecutive rounds. The designs are evaluated on all test grids except the 56 bus example as it is computationally too expensive to be simulated for a large number of simulation runs (using the provided mechanism, the calculation time for the 56-bus grid (Peng and Low, 2013) is 851 seconds per round on a machine with 2.8 GHz and 8 GB RAM). The market results for the final 1000 rounds are displayed in Table 9.3 and the strategic bidding behavior of the last 1000 rounds is shown in Table 9.4. In 3 out of 4 cases the consumers pay slightly more under the multilateral market design. However, the differences are small and the general trend is the same for both market designs. The 6-bus test grid exhibits the largest difference. On closer examination of the evolution of the ask prices for the two designs in Fig. 9.4, it can be seen that the evolution of prices is similar. In the 5-bus test grid with



(a) Behavior under nodal pricing

(b) Behavior under multilateral pricing

Figure 9.4.: Ask prices of the of 6-bus example



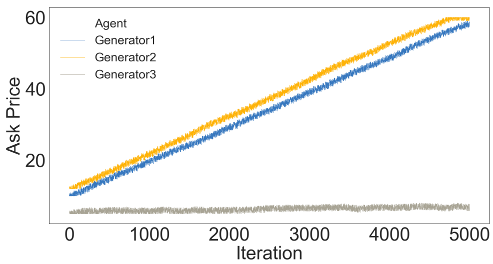
(a) Behavior under nodal pricing

(b) Behavior under multilateral pricing

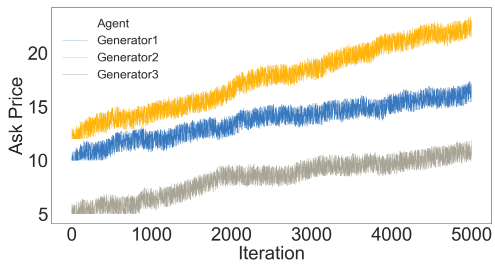
Figure 9.5.: Ask prices of the of 5-bus (3 Gen., 4 Loads) example

less consumer payments in the multilateral case, the examination of the ask price development shows that the ask prices are constantly rising but not at the rate of the nodal case (see Fig. 9.5). That means that they will eventually reach the price cap and that market power is not contained. Especially in the 3-bus case, competitive behavior can be observed. This is similar for both market designs even though the individual strategies are different. This is due to the fact that the individual payments are more dependent on the individual behavior in the multilateral market design. However, as individual trades are cleared with a uniform-price, the behavior is sometimes equivalently profitable under nodal pricing and multilateral pricing.

Increasing competition In order to assess the effect of increased competition, the supplier at node 6 is divided into two suppliers in the 6-bus test grid and the supplier at node 5 is divided into two suppliers in the 5-bus test grid with 4 loads. No

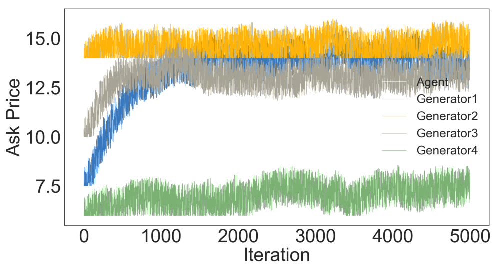


(a) Behavior under nodal pricing

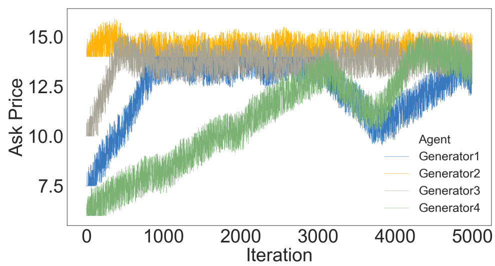


(b) Behavior under multilateral pricing

Figure 9.6.: Ask prices of the of 5-bus (3 Gen., 2 Loads) example



(a) Behavior under nodal pricing



(b) Behavior under multilateral pricing

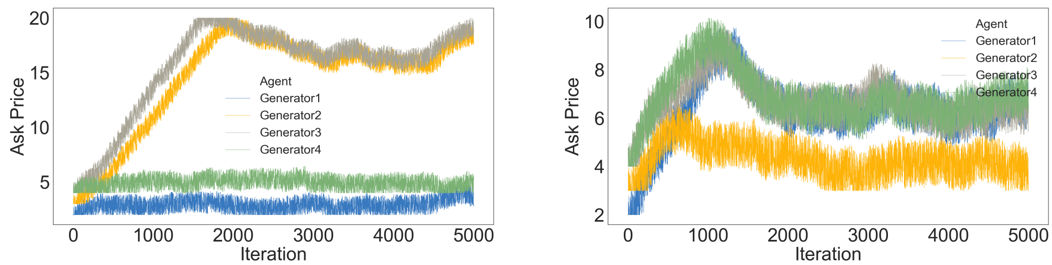
Figure 9.7.: Ask prices of the of 3-bus example

		Mean of last 1000 simulation rounds		
	Pricing Scheme	**Consumer Payments**	**Producer Revenue**	**Congestion Rent**
3-bus example	**Nodal Pricing**	5703	5671	32
	Multilateral Pricing	5714	5714	0
	Difference	*11*	*43*	*-32*
5-bus example (3 Gen., 4 Loads)	**Nodal Pricing**	9663	9578	85
	Multilateral Pricing	9685	9685	0
	Difference	*22*	*107*	*-85*
5-bus example (3 Gen., 2 Loads)	**Nodal Pricing**	2482	2233	249
	Multilateral Pricing	866	866	0
	Difference	*-1616*	*-1367*	*-249*
6-bus example	**Nodal Pricing**	9027	8787	240
	Multilateral Pricing	10412	10412	0
	Difference	1385	1625	-240

Table 9.3.: Simulation results for strategically acting agents

	Pricing Scheme	Mean ask prices of last 1000 simulation rounds Generator 1	Generator 2	Generator 3	Generator 4	*Price Cap*
3-bus example	***Marginal Cost***	*7.50*	*14.00*	*10.00*	*6.00*	*70.00*
	Nodal Pricing	13.88	14.75	13.20	7.38	
	Multilateral Pricing	12.37	14.42	13.93	13.84	
5-bus example (3 Gen., 4 Loads)	***Marginal Cost***	*2.00*	*3.00*	*4.00*	-	*20.00*
	Nodal Pricing	3.46	19.08	19.50	-	
	Multilateral Pricing	19.20	4.89	19.61	-	
5-bus example (3 Gen., 2 Loads)	***Marginal Cost***	*10.00*	*12.00*	*5.00*	-	*60.00*
	Nodal Pricing	53.75	57.07	6.90	-	
	Multilateral Pricing	15.75	21.66	10.27	-	
6-bus example	***Marginal Cost***	*2.00*	*2.00*	*3.00*	-	*15.00*
	Nodal Pricing	3.40	11.59	11.49	-	
	Multilateral Pricing	12.88	12.87	13.50	-	

Table 9.4.: Agent behavior under imperfect competition



(a) Behavior under nodal pricing

(b) Behavior under multilateral pricing

Figure 9.8.: Ask prices of the of 5-bus example with increased competition

changes can be observed for the 6-bus grid. However, for the 5-bus grid the bidding behavior is now much more competitive under Multilateral Locational Pricing than under nodal pricing as can be seen in Fig. 9.8. The consumer payments in the last 1000 rounds are 62% lower under locational marginal pricing.

It has to be concluded that the effects of market design on the competitive agent behavior are unclear. However, there is no indication that market power might increase under Multilateral Locational Pricing as compared to nodal pricing. On the contrary, one example shows that the multilateral market design can have a diminishing effect on the exercise of market power. Therefore, the results of this section show that Multilateral Locational Pricing performs at least as good as nodal pricing with regard to the containment of market power.

9.4. Implementability of the Design

The presented multilateral market pricing design is a more liberalized version of the locational marginal pricing approach that requires an ISO to run the system. It is hard to imagine that such an ISO would be implemented in the European electricity grid, which has many TSOs and stakeholders (Schmitz and Weber, 2013). The German system alone is operated by four TSOs meaning that their interests would have to be aligned. Therefore, the presented approach could help the market to self-regulate instead of imposing a centralized entity. However, some assumptions of the given analysis need to be discussed.

The main assumptions that had to be introduced to transition the design of Qin et al. (2017) to an actual market design beyond the sheer steering of the system through an SO, are (1) the test of generator sequences by the load and (2) the restriction of re-trades to a small enough increment. Small enough means that the increment should be of the magnitude, so that a deviation by this amount does not pose a threat for system stability because it represents by how much the final solution can be away from the optimal power flow. Furthermore, the load is pooled and assumed to act as one entity (3).

Pooling the load is necessary to avoid diverging interests, e.g., one consumer could try to trade with a supplier that would block a certain transmission line for other consumers. This is closely connected to the sequence approach that makes sure that the load has the overall objective to cover the entire demand before supplying certain consumers with cheaper generation. The approach chosen in the simulation cannot be translated into actual market regulation as this would greatly reduce the liberal spirit of the market design. The design is still useful as it can help the market to self-regulate. Both issues can be addressed at the same time. In such a design, redispatch would not be completely abolished. However, it would only be employed if the system ends up in a deadlock and cannot be optimized through further trading rounds. If this is the case, the TSOs attribute the costs of this redispatch according to previously specified rules to the loads that are responsible for the deadlock. One possibility is to use the power distribution factors of each node to calculate the influence of that node's behavior on the congestion. This allows to attribute the costs to each node. They can then be further broken down to individual market agents by the demand at each node. This way the awareness of consumers towards grid constraints is increased and they are held accountable for grid congesting trades.

Such a design can be incorporated into the current design as even a few of the trading rounds might already reduce the most severe congestion. The remainder might still be cured through socialized redispatch. One could think of an initial forward auction a month before delivery with an initial curtailable auction that is updated daily. Such a design would also greatly decrease the computational complexity. Furthermore, it introduces a combinatorial character into the power auction as it might become important to procure bundles of supply from generators that are beneficial from a grid perspective. This opens interesting areas of future research.

The other assumption that needs to be addressed, is limiting generator re-trades to an increment to avoid a deadlock. This can be cured in a similar fashion as for the consumers. Generators can be held accountable for necessary redispatch that becomes necessary due to their trading behavior, which would incentivize grid friendly trading. These results open an interesting field of future research that could be addressed for example through behavioral experiments.

Finally, the German government is dedicated to the single price zone such that any regional price components are undesirable. This would make the presented approach obsolete. However, the German government might be forced by the EC to reconsider the national bidding zone (European Commission, 2016). This opens an interesting controversy: Is it fair to charge more for electricity at certain points in the network even though investment decisions, such as constructing a production facility, were made under the assumption of a uniform electricity price in the German system. It is not within the responsibility of this production facility operator to improve the transmission grid design. In fact, Article 72 of the German constitution states that the social and living conditions need to be the same everywhere in Germany. The German government has recently passed legislation to protect the uniform-price bidding zone. In §3 of the *StromNZV* it is stated that the TSOs are responsible to

uphold the single bidding zone as long as possible. However, one possibility of implementing spatially differentiated prices is the use of transfer payments that ensure a uniform consumer price everywhere in Germany. This would however dilute possible coordinating price effects on consumption. The discussion on a compromise between the objective of a welfare optimal electricity system and the uniform-price for all consumers will likely continue in the near future as the German government has recently published a study on the comparison of different locational market mechanisms (Maurer et al., 2018).
While Multilateral Locational Pricing has the potential of increasing the social welfare in the electricity system in the long-term, it might create unwanted effects for the economy. Overall, regional price components would set incentives for regional capacity development and therefore help in reducing congestion in the long-run. The political implications and the political will for such a step remain in question.

9.5. Summary of Chapter 9 and Discussion

This chapter proposes and evaluates a new market mechanism that considers transmission grid constraints at market clearing. It is referred to as Multilateral Locational Pricing and it is based on the congestion management approach introduced by Qin et al. (2017). This design is chosen as it is more liberal than other locational pricing methods in its market design and can be implemented without an ISO, which makes it the better fit for the European electricity market. The design of the mechanism is presented and it is evaluated against locational marginal pricing (also known as nodal pricing). The intention of this analysis is to find changes in the welfare distribution and the effects on the exercise of market power in the more liberal design. The results show that the mechanism performs equally well as nodal pricing and in certain cases even better with regard to market power. The welfare distribution is contained to the redistribution of congestion rent. The exact values depend on the grid topology and the distribution of generators and load. The market power analysis is based on an agent-learning algorithm that performs well on related tasks. Finally, a critical appraisal of the implementability of the design is provided. The additional assumptions of the market design are discussed and alternatives are provided that would incentivize self-regulation of consumers and suppliers in terms of transmission grid congestion. The design is therefore a building block of a more congestion aware electricity system. It cannot be the single solution to resolve congestion but it can induce a grid friendly trading behavior and send long-term regional investment signals that reduce congestion. Finally, a well designed congestion management approach has to be a combination of different mechanisms and designs both short-term and long-term that can tackle congestion from different perspectives as proposed in this and the previous chapters.

Part V.

Finale

CHAPTER 10

CONCLUSION

This dissertation contributes to the short- and long-term solution of the increasing problem of transmission grid congestion caused by intermittent and regionally clustered renewable generation and the integration of the European electricity market. The German government expects the cost for congestion management, that has reached a record high in 2017, to increase to about 4 billion Euros in 2023 (Bundesregierung, 2016). This shows that the field is of growing importance and that solutions need to be developed. Regulatory developments in the European Union, which require the implementation of regional redispatch markets and an increased cross-border trade, as well as the nuclear and coal phase-out in Germany intensify the problem. While congestion always leads to a welfare loss, the presented approaches are intended to reduce this welfare loss to an economically efficient minimum. It is especially important to introduce regional incentives through market mechanisms that foster investments in generation, storage and transmission capacity, which reduce the systematic long-term grid congestion. This includes a critical appraisal of the current mechanisms and the current regulation, an analysis of possible adverse effects of alternative mechanisms, and the proposal of new market designs.

10.1. Summary and Implications

The development of congestion in the German transmission grid and the associated costs require new solutions and mechanisms to manage congestion efficiently. The current design of the transmission grid and the handling of congestion was optimized for a time when controllable generation units, with long construction lead times, dominated the energy supply. Especially, the intermittency of renewable generation requires a flexible approach that can efficiently cure short-term congestion and sends appropriate long-term investment signals. In the following, the findings of this dissertation are summarized along the research questions and structure introduced in Chapter 1. To allow for an understanding of the origin of congestion and the congestion management mechanisms in the German electricity system, Chapter 2 and Chapter 3 introduce the recent evolution of power system regulation, associated objectives and different congestion management approaches. This includes a general analysis of electricity market engineering and design alternatives. The introduction is followed by the three main contributions of this dissertation.

First, the current redispatch regulation and a market-based alternative are evaluated along empirical congestion data from the German transmission grid. Before alternative approaches for congestion management are developed, the cost-based redispatch mechanism is analyzed in Chapter 4. The chapter focuses on the operation of the cost-based redispatch mechanism, its environmental impact, strategies to profit from the mechanism and how these strategies influence the wholesale market overall. This analysis reveals that corresponding strategies are dependent on an accurate anticipation of congestion management deployment. To this end, a model is developed to forecast redispatch deployment of individual generation units, using day-ahead forecast data. The results show that many operators can anticipate their redispatch deployment accurately and especially with a high certainty if the deployment is forecasted. This finding requires regulators to observe the behavior of power plant operators more closely. However, the cost-based redispatch mechanism has another fundamental flaw: Regional grid friendly generation expansion is not incentivized. Therefore, there is no economic signal that would reduce systematic congestion in the long-run. One such approach is market-based redispatch. The implementation of this mechanism is demanded by the European Commission. However, Chapter 5 shows that such a design may lead to even higher grid congestion and associated costs if congestion can be anticipated and regional market power is high. This would lead to strategic behavior of market participants. Therefore, the ability to anticipate load and generation pockets is assessed. Using appropriate models and input data, the chapter shows that congestion can indeed be well anticipated, especially on certain lines. Generators who are aware of their specific power distribution factor for congested lines, can act strategically if competition is small and the risk of strategic gaming due to generation and demand uncertainty is limited. This needs to be considered by regulators when implementing such designs.

The following part builds on these findings and proposes mechanisms to measure if regional competition is sufficient for the implementation of regional market-based redispatch. The impact of competition on redispatch markets makes it important to assess regional market power. To this end, Chapter 6 introduces an agent-based analysis tool that helps to identify the expected non-competitive markup in an electricity market. The tool is based on computational agents, which are trained using a tested reinforcement learning approach. It also includes the consideration of tacit collusion as a strategy to increase electricity prices. The tool is validated on a case study that simulates a regional market of private consumers that is disconnected from the external grid. The results show that peak load competition is an important factor when assessing market power and that a diverse portfolio of generation units with varying marginal generation costs helps in reducing non-competitive markups. Furthermore, a mechanism to increase competition and reduce the welfare loss of congestion is proposed that is based on vehicle-to-grid technology. Chapter 7 proposes a design to include electric vehicles as a buffer for congestion into the electricity system. A mechanism is developed that is computationally cheaper than a full network optimization and can be applied as an online algorithm. The design is evaluated on a stylized zonal representation of the German electricity grid. A simulation using one year of empirical data shows that electric vehicles can greatly contribute to congestion management if a sufficient number of participants can be acquired and that the imbalance in the planned state of charge can mostly be settled quickly. Furthermore, the possible compensation of a cost-neutral mechanism is calculated.

However, the mechanism does not provide incentives or gives indications for the necessary long-term reduction of congestion. Consequently, the third main contribution of this dissertation is the proposition of mechanisms to eliminate long-term congestion through market-based approaches. To this end, a mechanism is introduced to expand the transmission grid based on redispatch costs. This is especially important as redispatch needs to be considered as a viable congestion management alternative in the presence of extensive intermittent generation capacity. Only systematic congestion needs to be cured through measures of additional infrastructure such as grid or generation capacity expansion. Grid regulation currently creates incentives for transmission system operators to favor grid expansion over other short- and long-term congestion management alternatives. However, redispatch actually provides well-designed incentives to align the interests of different parties for grid expansion. Therefore, Chapter 8 shows how redispatch can be used to achieve a welfare optimal grid expansion. To this end, it is benchmarked with a nodal pricing design and the optimization formulations are compared with regard to their results. The mechanism is tested over a period of four years on a stylized zonal representation of the German transmission grid. The calculations include the compensation for potential investors. Besides the advantage of incentivizing a welfare optimal expansion instead of an inflated transmission grid, it shifts the risk of the future system development from consumers to private investors. However, even grid expansion has certain limits. To efficiently send signals for regional generation expansion, locational price components need to be developed. To this end, Chapter 9 proposes the Multilateral Locational Market mechanism that conserves the liberal European market design but leads to the same welfare optimal dispatch results as the centralized nodal pricing approach. A first analysis of the design is intended to evaluate the mechanism's welfare distribution among market parties. Secondly, it is analyzed whether the mechanism leads to a greater exercise of market power. The results show that welfare is similarly distributed as under a nodal pricing design and that market power can be exercised equally or less. The implementation of the design in the German system is discussed and possible contributions to congestion management are discussed.

The described results indicate that the discussion on congestion management needs to be broadened. The currently suggested grid expansion is one but certainly not the only viable long-term option to relieve the transmission grid of congestion. Smart grid alternatives need to be discussed and the regulation needs to be adapted to improve the efficiency of short-term congestion management. The current regulation was designed for a different power system, where congestion was a rare event. The intermittency of renewable generation forces us to develop a market design that is robust towards short-term congestion while optimizing the overall system including its emissions. Furthermore, the long-term management of congestion should be considered from different angles and grid expansions should only be considered if they are economically without reasonable alternative. Therefore, this dissertation can help regulators and politicians to improve the transmission congestion management in Germany and Europe, both, in the short- and long-run.

The suggestions and results of this dissertation can be used to design a market for congestion management that is efficient and sends the correct investment signals. A combination of the provided solutions can lead to a balance between the short-term welfare optimal treatment of congestion and a long-term strategy to reduce systematic grid congestion. However, this leaves a variety of future research directions and open questions, which are discussed in the following section.

10.2. Outlook

This dissertation contributes to the current discussion on congestion and congestion management in the German electricity system and provides solutions to reduce its anticipated increase. The ongoing expansion of renewables and the gradual phase-out from emission intensive fossil generation cause new challenges for the transmission system that have to be addressed. The presented results give impulses to new directions of congestion management and efficient short- and long-term solutions. This is achieved by providing regional investment signals for both transmission and generation expansion and an improvement of the current redispatch mechanism. However, several important directions of future research remain.

Firstly, the behavior of power plants under the current redispatch regulation needs to be monitored more closely. The ENTSO-E provide a detailed generation schedule for large power plants. This can be used to identify possible effects of power plant strategies especially if this data is combined with price and redispatch data using artificial intelligence. This might reveal the current abuse of the mechanism. Furthermore, it should be evaluated whether environmental considerations should play a role in the redispatch mechanism. This could incentivize an environmentally friendly behavior (e.g., the abandonment of partial load operation) and favor low emission technology such as stationary storage in combination with renewable generation capacity.

Furthermore, a comprehensive study on market-based redispatch is necessary. Regional market power needs to be evaluated using the presented tool. This can be complemented by agent-based models that use sophisticated training methods. In this context, artificial intelligence is a promising avenue to learn strategies that allow to identify market shortcomings that can then be addressed. Market-based redispatch should only be introduced in regions, where competition is sufficiently high and where no adverse strategies of the developed agents can be identified. It should be noted that the coal phase-out will likely create more regional market power. Therefore, a complete shift to a market-based redispatch approach should be carefully and holistically reviewed. Additionally, the role of distribution and transmission system operators in future congestion management needs to be further defined. This includes especially the question whether they should be allowed to own and operate storage or similar technology to ensure system stability.

Alternative approaches based on vehicle-to-grid technology need to be evaluated regarding the necessary compensation that suffices to incentivize owners to participate in such a mechanism. Such a study would help to find the overall potential of curing congestion using electric vehicles. To do so, more knowledge on the cyclic aging of vehicle batteries is needed. It also needs to be shown how the electric vehicle charging gap develops with the future change in the generation portfolio through the coal phase-out. The acceptance of such an approach has not only monetary but also temporal limits. Finally, other alternative buffer approaches to an active redispatch need to be evaluated and benchmarked against each other such as power-to-gas, stationary storage or other demand side management measures. This includes a comprehensive view of energy intensive sectors to investigate if sector coupling (the linkage of the power, heat and mobility sector) can have an effect on congestion management.

From a grid perspective, the effect of the current expansion projects needs to be evaluated more carefully. It should be investigated if the current expansion plans only move congestion through the grid instead of reducing congestion. This is especially important in the context of a stronger integration of the European electricity market. Furthermore, the risk of the presented market-based transmission grid expansion mechanism needs to be evaluated to find if private investors would be willing to invest under such a design. This also includes studies on the treatment of disappearing conventional generation within the mechanism to avoid windfall payments. Finally, a long-term study needs to be performed including scenario paths for the expansion of renewable generation and the decrease of conventional controllable generation capacity.

Regarding the presented multilateral pricing mechanism, a market platform needs to be developed that allows regional trading. Furthermore, it should be investigated to what extend a few rounds of the presented mechanism can reduce the redispatch needs. In regard to these findings, it will be important to reduce the computational complexity through appropriate heuristics. Furthermore, the combinatorial spirit of the design needs to be evaluated and combined with innovative tariff design. If consumers are made responsible to procure their energy such that it can be transmitted through the system, this becomes an additional attribute of the product electrical energy and procurement auctions might become combinatorial. This opens the possibility to include other attributes of power such as its sustainability and its origin. These attributes can then be marketed to consumers through innovative tariffs that include more time-varying charges based on the congestion state of the system.

Finally, a regulatory framework including all presented approaches needs to be developed. By definition, congestion leads to a loss of welfare. However, the efficient short- and long-term management of congestion should limit this welfare loss to a minimum. All mechanisms in this dissertation can contribute to this objective but they need to be appropriately combined. Therefore, a critical discussion of the future role of distribution and transmission system operators is necessary with regard to their responsibilities and mandate. This includes the redispatch itself, the operation of system stability equipment other than grids, the grid expansion and a possible mediating role in market clearing.

Appendices

APPENDIX A

Power Plant	Recall ANN	Precision ANN	Recall ExtraTree	Precision ExtraTree
Vorarlberger Illwerke AG	0.68	0.69	0.49	0.86
Gebersdorf 2	0.83	0.84	0.67	0.94
Heizkraftwerk Heilbronn	0.83	0.87	0.72	0.96
Staudinger 5	0.83	0.86	0.70	0.92
Rheinhafen-Dampfkraftwerk	0.84	0.87	0.69	0.95
Heizkraftwerk Altbach_Deizisau	0.71	0.78	0.56	0.94
Heyden	0.87	0.90	0.75	0.91
Zolling 5	0.80	0.85	0.61	0.94
Irsching 5	0.84	0.90	0.70	0.95
Grosskraftwerk MXTreeheim	0.75	0.79	0.54	0.95
Ingolstadt	0.85	0.91	0.60	0.97
Reservekraftwerk Heilbronn	0.88	0.95	0.74	0.99
Reservekraftwerk Irsching	0.84	0.89	0.59	0.98
Emsland	0.82	0.89	0.59	0.98
Weiher	0.82	0.85	0.51	0.96
Reservekraftwerk Walheim	0.86	0.91	0.72	0.99
Reservekraftwerk Staudinger 4	0.83	0.92	0.70	0.96
Bexbach	0.84	0.91	0.61	0.96
Netzreservekraftwerk KMW 2	0.94	0.94	0.83	0.96
Hamm Uentrop	0.81	0.84	0.49	0.95
Erzhausen	0.41	0.52	0.21	0.82
Kraftwerk Walheim	0.57	0.66	0.26	0.88
Kraftwerk Mainz Wiesbaden	0.81	0.88	0.54	0.99
Wilhelmshaven (Uniper)	0.86	0.92	0.50	0.98
Herne	0.72	0.88	0.45	0.95
Average	0.79	0.85	0.59	0.95

Table A.1.: Cross-validation results of the redispatch forecast for a power increase

Power Plant	Recall ANN	Precision ANN	Recall ExtraTree	Precision ExtraTree
EPH_Braunkohle	0.86	0.87	0.75	0.93
Vattenfall_Braunkohle	0.70	0.78	0.58	0.89
Neurath	0.89	0.90	0.74	0.95
Brokdorf	0.78	0.81	0.67	0.91
Vattenfall_Schkopau	0.78	0.80	0.57	0.94
Wilhelmshaven (ENGIE)	0.77	0.83	0.53	0.93
Mehrum	0.72	0.80	0.48	0.93
Niederaussem	0.89	0.88	0.75	0.93
Knapsack	0.80	0.88	0.61	0.94
Wilhelmshaven (Uniper)	0.73	0.77	0.42	0.91
Vattenfall_Rostock	0.69	0.79	0.45	0.91
Vattenfall_Moorburg, Schkopau	0.86	0.87	0.59	0.96
EPH_Braunkohle, Schkopau	0.90	0.93	0.57	0.97
Kiel	0.61	0.74	0.32	0.92
Zolling 5	0.74	0.81	0.40	0.94
Heyden	0.69	0.80	0.44	0.93
Farge	0.65	0.79	0.39	0.92
Heizkraftwerk Altbach_Deizisau	0.77	0.84	0.38	0.96
Grohnde	0.77	0.86	0.45	0.95
Rostock	0.54	0.66	0.27	0.88
Waldeck	0.58	0.64	0.30	0.81
Lippendorf EnBW	0.74	0.84	0.47	0.95
EPH_Lippendorf EnBW, Schkopau	0.85	0.93	0.58	0.98
Hamm Uentrop	0.71	0.80	0.39	0.92
Schkopau	0.62	0.72	0.35	0.92
Average	0.75	0.81	0.50	0.93

Table A.2.: Cross-validation results of the redispatch forecast for a power decrease

APPENDIX B

For the proposed neural network, several similar setups are tested with an epochs size ranging from 50 to 200, a batch size between 25 and 50 and two hidden layers with 100 neurons in the first, 50 in the second and 25 in the third layer. Note that mini-batch sizes in the chosen range can lead to adverse convergence of the neural network. The chosen value of 25 is already below the proposed minimum of 50 (Ruder, 2016). The final setup represents the best working configuration considering the validation results. It is shown in Table A.3. The table also displays the distance from the best result for other configurations.

Parameter	Model 1	Model 2	Model 3	Model 4
Batch size	25	25	25	25
Epochs	100	100	100	100
Neurons in first hidden layer	100	100	100	100
Neurons in second hidden layer	50	50	25	0
Neurons in third hidden layer	25	0	0	0
Distance from best result	best	0.4 %	3.6 %	23.4 %

Table A.3.: Excerpt of the engineering process of the ANN in Chapter 5

APPENDIX C

The average standard deviation of the cross validation results is 0.10 for precision and 0.11 for recall. A more detailed analysis of 15 exemplary lines with regards to precision and recall is provided in the following table. The last two columns show the standard deviation of the values over all folds and the mean relative to the standard devation.

Line / Fold	1	2	3	4	5	6	7	8	9	10	StD	$\frac{StD}{Mean}$
Prec._26	0.81	0.65	0.93	0.80	0.77	0.63	0.89	0.91	0.78	0.74	0.09	0.12
Recall_26	0.72	0.59	0.86	0.83	0.79	0.83	0.55	0.69	0.64	0.61	0.11	0.16
Prec._30	0.50	0.00	0.00	0.67	0.40	0.00	0.33	0.00	0.25	0.67	0.27	0.98
Recall_30	0.80	0.00	0.00	0.40	0.80	0.00	0.40	0.00	0.25	0.50	0.32	1.02
Prec._39	0.79	0.74	0.78	0.88	0.75	0.74	0.89	0.89	0.87	0.91	0.07	0.08
Recall_39	0.88	0.77	0.90	0.73	0.73	0.74	0.61	0.71	0.79	0.79	0.08	0.11
Prec._41	0.89	0.76	0.94	0.88	0.57	0.75	0.94	0.93	0.67	0.91	0.13	0.16
Recall_41	0.77	0.73	0.73	0.68	0.59	0.68	0.81	0.62	0.86	0.48	0.11	0.16
Prec._45	0.86	0.83	0.81	0.75	0.80	0.81	0.81	0.80	0.85	0.77	0.03	0.04
Recall_45	0.68	0.72	0.72	0.75	0.71	0.72	0.70	0.65	0.65	0.75	0.04	0.05
Prec._47	1.00	0.90	0.93	0.86	1.00	0.96	0.83	0.93	0.93	0.90	0.05	0.06
Recall_47	1.00	1.00	0.93	0.89	0.96	0.88	0.96	1.00	1.00	1.00	0.05	0.05
Prec._48	0.83	0.76	0.94	0.73	0.76	0.82	0.71	1.00	0.88	1.00	0.11	0.13
Recall_48	0.65	0.70	0.70	0.86	0.59	0.82	0.77	0.77	0.64	0.59	0.09	0.13
Prec._49	0.53	0.84	0.87	0.68	0.75	0.70	1.00	0.56	0.93	0.83	0.15	0.20
Recall_49	0.90	0.72	0.69	0.45	0.83	0.72	0.55	0.76	0.50	0.71	0.14	0.21
Prec._50	0.84	0.83	0.88	0.84	0.80	0.92	0.88	0.83	0.76	0.85	0.04	0.05
Recall_50	0.76	0.92	0.74	0.75	0.92	0.73	0.81	0.86	0.87	0.86	0.07	0.09
Prec._53	0.74	0.79	0.65	0.81	0.70	0.73	0.83	0.52	0.65	0.86	0.10	0.14
Prec._53	0.74	0.53	0.68	0.51	0.56	0.66	0.58	0.70	0.67	0.41	0.10	0.17
Prec._54	0.77	0.84	0.85	0.82	0.83	0.85	0.80	0.78	0.80	0.87	0.03	0.04
Recall_54	0.71	0.72	0.88	0.55	0.59	0.86	0.86	0.81	0.89	0.72	0.12	0.16
Prec._55	0.89	0.77	1.00	0.81	0.89	0.84	0.84	0.77	0.73	0.85	0.08	0.09
Recall_55	0.57	0.68	0.72	0.91	0.74	0.74	0.63	0.70	0.70	0.51	0.11	0.16
Prec._56	0.82	0.90	0.93	0.79	0.83	0.71	0.91	0.88	0.81	0.82	0.06	0.08
Recall_56	0.86	0.86	0.86	0.72	0.77	0.81	0.49	0.84	0.79	0.63	0.12	0.16
Prec._62	1.00	1.00	0.83	1.00	0.80	1.00	1.00	0.83	1.00	1.00	0.09	0.09
Recall_62	1.00	1.00	1.00	1.00	0.80	0.80	0.80	1.00	1.00	1.00	0.10	0.10
Prec._66	0.83	0.60	0.83	1.00	1.00	0.57	0.80	1.00	1.00	0.60	0.18	0.22
Recall_66	1.00	0.60	1.00	1.00	0.80	0.80	0.80	0.80	1.00	0.75	0.14	0.16

Table A.4.: Evaluation of the presented ANN using 10-fold cross-validation

APPENDIX D

beta (average)	β (avg.)	p (avg.)	β (221)	p (221)	β (49)	p (49)
Intercept	-8.55	0.13	-11.62	1.00	-5.06	0.00
Load Forecast 50Hertz	2.28	0.05	-15.15	0.06	-0.40	0.59
Load Forecast Ger	-1.20	0.13	-3.36	0.65	1.82	0.00
Net input	1.50	0.13	53.98	0.00	0.23	0.71
Solar	-0.71	0.21	-9.23	0.36	1.92	0.00
Wind	1.65	0.13	-19.99	0.11	4.06	0.00
ImpExp_DECZ	0.28	0.09	40.93	0.00	-0.90	0.06
ImpExp_DEDK	-0.68	0.13	-14.35	0.01	-0.56	0.01
ImpExp_DEPL	0.44	0.13	-6.66	0.15	-0.63	0.23
Scheduled Gen 50Hertz	-0.77	0.15	-12.63	0.41	-7.71	0.00
Market Price	-0.98	0.15	-45.25	0.00	4.59	0.00
Season	-0.12	0.09	-16.43	0.99	0.24	0.00
Weekday/WE	-0.90	0.28	-22.21	0.99	-0.06	0.72
Pseudo R^2		0.28		0.85		0.04

Table A.5.: Average (over all lines), best (line 221) and worst (line 49) result of the logistic regression in regard to McFadden Pseudo R^2

APPENDIX E

Federal state	Conventional capacity							Renewable capacity					
	Lignite	Coal	Natural gas	Nuclear	Pumped storage	Oil	Others	Biomass	Hydro	Wind offshore	Wind onshore	PV	Others
BW	0	19.5	4.1	25.1	29.5	18.1	1.4	11.1	22.3	0	1.8	13.0	5.8
BY	0	3.0	17.6	36.9	8.5	25.1	3.9	20.6	55.0	0	4.4	28.8	24.5
BE	0.8	2.7	3.7	0	0	8.5	0.5	0.6	0	0	0	0.2	1.3
BB	21.1	0	2.9	0	0	8.6	5.2	6.2	0.1	0	14.1	7.6	6.7
HB	0	3.2	0.7	0	0	2.3	5.8	0.1	0.3	0	0.4	0.1	3.5
HH	0	6.3	0.6	0	0	1.0	0.3	0.6	0	0	0.2	0.1	0.9
HE	0.2	2.7	6.3	0	9.8	0.6	2.3	3.5	1.8	0	3.1	4.6	8.1
MV	0	1.8	1.2	0	0	0	0.3	5.0	0.1	0	6.9	3.6	1.5
NI	1.7	10.3	16.1	25.0	3.5	1.5	9.3	19.4	1.7	0	20.5	9.1	4.6
NW	50.0	40.1	31.2	0	4.8	13.0	57.4	10.6	4.2	0	9.8	11.1	24.4
RP	0	0	7.5	0	0	0	3.0	2.4	6.4	0	7.1	4.9	5.1
SL	0	7.8	0.4	0	0	0	4.4	0.3	0.3	0	0.7	1.1	1.0
SN	20.7	0	2.6	0	17.1	0.4	0.2	4.2	6.0	0	2.8	4.1	1.4
ST	5.5	0	3.0	0	1.3	6.0	3.8	6.0	0.7	0	11.1	5.0	8.1
SH	0	2.6	0.1	13.1	1.9	14.9	2.0	5.9	0.1	0	13.9	3.8	2.2
TH	0	0	1.9	0	23.7	0	0.2	3.6	0.9	0	3.1	3.0	0.9
North sea	0	0	0	0	0	0	0	0	0	90.2	0	0	0
Baltic sea	0	0	0	0	0	0	0	0	0	9.8	0	0	0
Total	100	100	100	100	100	100	100	100	100	100	100	100	100

Table A.6.: Share of generation capacity by federal state in 2016

APPENDIX F

Techn./Node	1	2	3	4	5	Total
Hydro	780	2,175	396	74	276	3,700
Nuclear	2,712	3,982	-	-	-	6,694
Lignite	-	-	7,439	4,106	9,510	21,055
Hard Coal	4,872	510	11,192	5,523	1,078	23,175
Pumped Storage	1,873	1,006	303	339	2,674	6,195
Others	874	2,410	7,843	1,502	2,286	14,914
Natural Gas	1,308	4,250	7,982	5,095	4,581	23,215
Oil	206	221	231	719	890	2,267
Total	12,624	14,554	35,386	17,357	21,295	101,216

Table A.7.: Conventional capacities in MW in the German transmission grid based on (Bundesnetzagentur, 2017b)

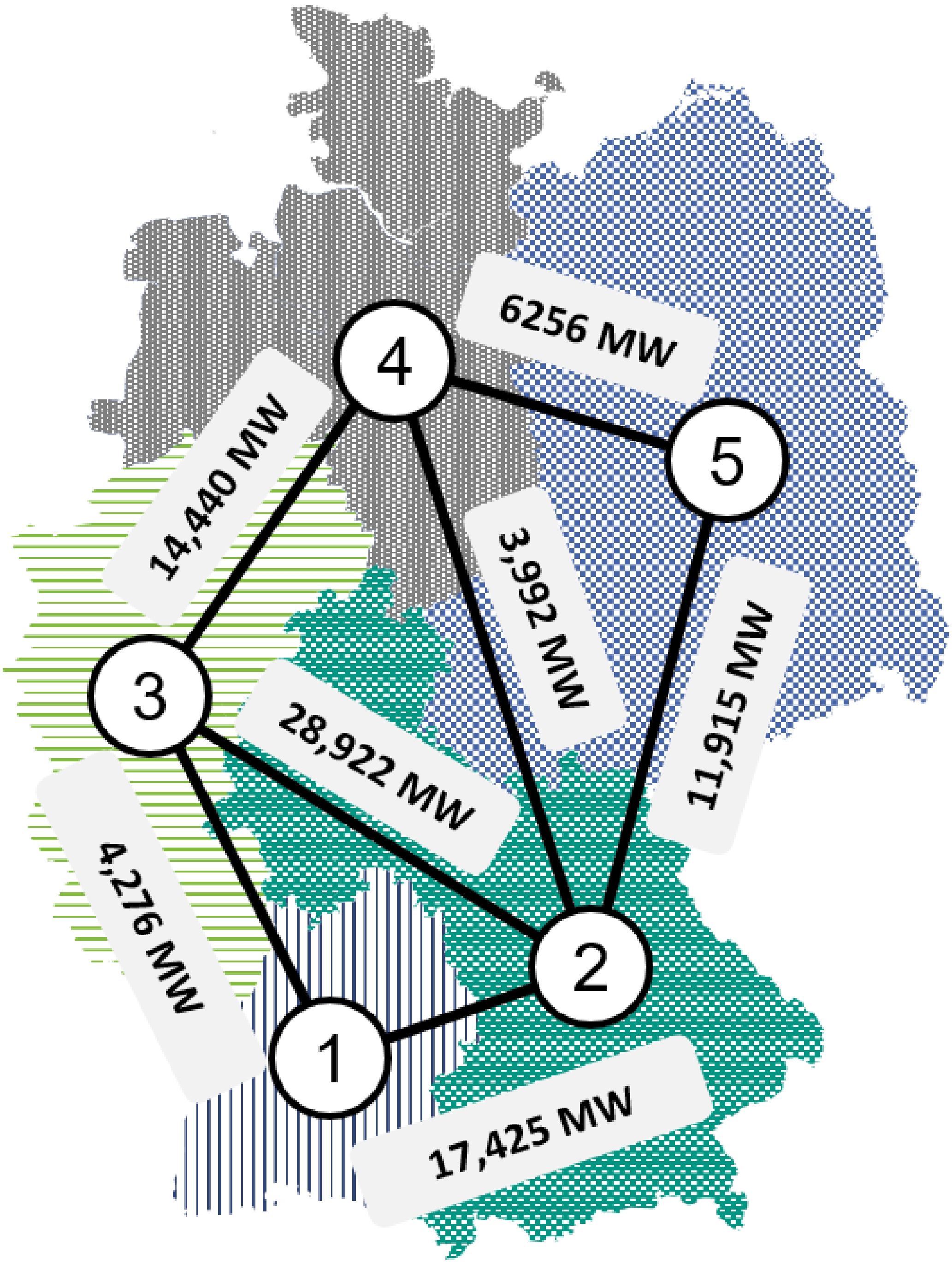


Figure A.1.: Abstracted model of the German transmission grid with capacities in MW based on the static network models of the TSOs

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EIDESSTATTLICHE ERKLÄRUNG

Ich versichere wahrheitsgemäß die Dissertation bis auf die in der Abhandlung angegebene Hilfe selbständig angefertigt, alle benutzten Hilfsmittel vollständig und genau angegeben und genau kenntlich gemacht zu haben, was aus Arbeiten anderer und aus eigenen Veröffentlichungen unverändert oder mit Abänderungen entnommen wurde.

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(Philipp Staudt)