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1 Introduction

For decades provision of electricity was organized based on vertically integrated geographic monopolies, which operated the entire supply chain from generation, transmission and distribution to retailing of electrical energy. These monopolies were either held by state-owned or regulated private companies. Starting in the 1980s this traditional model of the electricity sector has been liberalized and restructured in many countries.[1] The main goal of these restructuring efforts is to create an institutional framework which enables the efficient allocation of resources based on market mechanisms. To achieve this, the vertically integrated monopolies have been split up and competitively organized markets for generation, wholesale and retail of electricity have been created.[2] The grid infrastructure on the other hand remains a natural monopoly, which is regulated in order to avoid exploitation of market power and to create incentives which align the goals of the regulated monopolists with overall societal preferences and objectives.

In addition to the described reorganization of the electricity sector a second recent fundamental change has been the increased importance of electricity generation based on variable renewable energy sources. Traditionally electricity was mainly generated in large-scale thermal and hydro power plants. However, the potential for hydroelectricity is geographically limited and thermal power plants are largely based on combustion of fossil fuels, which causes negative environmental externalities for example due to carbon emissions. Consequently, as a result of increased global efforts to reduce greenhouse gas emissions and fight anthropogenic climate change, the share of non-hydro renewable electricity generation based on wind and solar energy in global electricity production has increased rapidly over the last years.[3] In light of the recent Paris Agreement to limit the global temperature increase to well below 2 °C this trend is expected to persist.

The integration of large shares of variable renewable electricity generation into liberalized electricity markets creates additional economic and regulatory challenges.

[1] See International Energy Agency (2016b) for an overview of the global status of liberalization.

[2] Note that the question whether the retail sector should be organized competitively is still subject to debate. See Batlle (2013) for a discussion.

[3] Non-hydro renewable energy accounted for 7.5% of total global power production in 2016. In 2000 the share was roughly 1.5%. See BP (2017).

These arise from the specific properties of variable renewable generation technologies, especially wind and solar energy, which differ from conventional thermal power plants. One key difference is that electricity generation based on wind and solar energy is weather dependent and fluctuates over time. As a result, the electricity generation is not perfectly predictable and depends on the specific weather conditions at a given location. The spatial heterogeneity of wind and solar resources also demands for a more decentralized structure of electricity systems, in which individual generation capacities are smaller in scale and more distributed in comparison to centralized structures based on large-scale thermal power plants.

Against the described backdrop, the regulatory challenge is to design a framework, which enables the efficient integration of renewable electricity generation into the competitively organized parts of the electricity sector. Because of the strong implications of high shares of renewable electricity generation on the electricity grid, it is equally important that the regulatory framework incentivizes an efficient and reliable integration of renewable generation capacities into the grid infrastructure. As these challenges have proven to be non-trivial in practice, a vivid debate has been sparked around the efficient integration of renewable energy into liberalized electricity markets in science as well as in the political sphere. The aim of this dissertation is to add new insights to this debate by analyzing different specific issues which arise due to the availability of renewable electricity generation along the unbundled supply chain of the power sector. Building on that, possible improvements of the market design and regulation with respect to the integration of weather-dependent renewable energy are identified. The thesis consists of three main chapters, each based on a single paper:

- Chapter 2: Grid Investment and Support Schemes for Renewable Electricity Generation (based on Wagner (2016), forthcoming in The Energy Journal)
- Chapter 3: Distributed Generation in Unbundled Electricity Markets (based on Wagner (2018))
- Chapter 4: Optimal Allocation of Variable Renewable Energy Considering Contributions to Security of Supply (based on Peter and Wagner (2018), both authors contributed equally)

The remainder of the introduction is structured as follows: Section 1.1 gives an overview of the contents and the focus of each chapter. Building on that, Section 1.2 discusses and compares the different applied methodological approaches and identifies directions for future research.

1.1 Outline

Chapter 2 analyzes coordination problems between investment into grid infrastructure and investment into electricity generation based on weather-dependent renewable energy. These problems emerge because in unbundled electricity systems separate entities such as private generation investors and regulated transmission operators decide on investment into generation and into grid infrastructure. As investments into renewable generation capacities are largely driven by subsidy mechanisms in practice, the chapter focuses on the influence of different subsidy schemes on the locational choice of renewable energy investors and the resulting implications on grid investment. The considered subsidy schemes are feed-in tariffs, feed-in premiums and capacity payments. The analysis is based on a stylized model with two possible locations for renewable generation investment and lumpy transmission investment. Electricity generation at the two locations is stochastic with different total expected generation and imperfectly correlated generation patterns.

Based on the theoretical model it is shown that none of the assessed support mechanisms lead to an efficient allocation of generation capacities. Consequently, a regulatory framework in which grid operators are obliged to connect new generation capacities and therefore follow generation investment can lead to substantial inefficiencies. Instead, a benevolent grid operator can implement the efficient system configuration by anticipatory grid investment, which means that decisions on grid investment precede generation investment. However, imperfect regulation can lead to disincentives if transmission operators are able to invest proactively and maximize profits within the regulatory constraints. Finally it is shown that network charges for renewable power producers which internalize the grid integration costs into investment decisions are also suited to implement the first best solution.

Chapter 3 shifts the focus to the retail part of the supply chain of liberalized electricity systems. More specifically it is analyzed how the availability of distributed generation technologies such as rooftop photovoltaic systems or small-scale wind power plants impacts imperfect retail markets for electricity. As distributed generation is used by end consumers to directly produce electricity it substitutes grid-based electricity purchased via retailers. Consequently, interactions between distributed generation and retailing emerge. To analyze these interactions, a theoretical model based on a spatial competition framework, in which consumers have heterogeneous preferences towards retailers and can choose distributed generation as an alternative to grid-based electricity, is developed. In the model, only a limited share of electricity consumption can be substituted with distributed generation in order to reflect the fact that on the one hand not all consumers are able to use distributed generation, for example because of spatial constraints or financing restrictions, and on the other hand even consumers who use distributed generation typically keep a grid connection as full autarky is very costly with current technologies. Within this model framework, the impact of distributed generation on retailers as well as implications on optimal subsidization of distributed generation are assessed.

The analysis shows, that distributed generation puts competitive pressure on retailers and induces reduced mark-ups. Regulators can exploit this effect by using subsidies to position distributed generation as a competitor to grid-based electricity and shift welfare from producers to consumers. However, if the subsidized cost of distributed generation is sufficiently low there is a point at which retailers discard the substitutable share of electricity demand in order to realize higher margins by supplying only the non-substitutable share of demand. As a result of this effect, increased subsidies for distributed generation can harm consumers and decrease consumer surplus if the increase in subsidization induces retailers to discard the substitutable share of demand. Additionally it is shown that retailers are more reluctant to discard the substitutable share of demand as the substitutable share in electricity consumption increases.

In practice, distributed generation is subsidized indirectly by exempting it from grid fee payments in many jurisdictions. Because of this common regulatory practice, the basic model is extended to analyze interactions of grid fee structures and distributed generation within the presented framework. I find that the optimal regulatory strategy can also be implemented with grid fee exemptions. However, this can only be realized based on a two-part tariff structure in which distributed generation is exempted from variable grid fee payments while a fixed grid fee component ensures recovery of fixed costs for the grid operator. Solely volumetric grid fees are not suited to implement optimal subsidization and lead to inefficient levels of distributed generation.

Chapter 4 focuses on generation investment and the question how electricity generation based on weather-dependent renewable energy sources can contribute to reliability in power systems. The presented analysis contributes to this question by developing a new methodology to endogenously determine the capacity value of generation capacities based on variable renewable energy in large-scale optimization models for electricity markets. After the methodology is introduced, it is applied to simulate an optimal pathway to a decarbonized European electricity system in 2050, which explicitly accounts for the location-dependent contribution of wind power to reliability. The results show that wind power can substantially contribute to reliability despite the weather-induced stochasticity.

Building on this outcome we identify three fundamental drivers for the development of the capacity value of wind power over time. First, the capacity value exhibits decreasing returns to scale which means that the average contribution to reliability decreases as total installed wind power capacity increases. Second, technological innovation increases the capacity value of wind power as current wind power plants are gradually substituted by state of the art wind turbines with higher hub heights and larger rated capacity over time. These plants allow for a more stable electricity production. Third, increasing European market integration due to extended interconnection capacities between countries increases the capacity value of wind power because volatile generation can be backed up by electricity imports instead of additional conventional generation capacities.

We conclude that existing modeling approaches for long-term scenarios in the electricity sector lead to inefficient levels of dispatchable back-up capacities and inefficient spatial distributions of renewable power capacities because the contribution to reliability is not or only crudely accounted for. From a regulatory perspective the results suggest that adequacy studies and capacity mechanisms should consider the contribution of variable renewable energy sources to reliability, for example by allowing renewable generation capacities to participate in capacity markets.

1.2 Methodological approaches and future research

The three chapters address different research questions and therefore apply different methodological approaches. Chapter 2 and 3 use stylized theoretical model frameworks which allow for an analytical solution. Chapter 4 on the other hand applies a numerical solution approach via optimization. Each of the chapters relies on specific assumptions, which on the one hand allow to focus on the respective research question without losing tractability but on the other hand imply a loss in generality. Consequently, understanding the implications of these assumptions is crucial when interpreting the presented results. Relaxing critical assumptions on the other hand opens promising directions for future research. These aspects are discussed in this section.

The analysis in Chapter 2 builds upon a stylized model of grid investment, generation investment and stochastic electricity production from weather-dependent renewable energy sources. While the model captures the fundamental characteristics of these properties in order to derive general theoretical results, its practical applicability to derive specific numerical conclusions for real electricity systems is limited. Consequently, an application of the model to a real-world power system with an explicit representation of grid infrastructure, the conventional power plant fleet as well as real-world statistical properties of variable renewable energy would provide interesting additional insights. Because of the complexity of real-world power systems, this would require numerical methodologies.

More fundamental limitations of the presented model in Chapter 2 are the assumptions of perfect competition, perfect information as well as the lack of endogenous investments into conventional power generation. While perfect competition is a common assumption in the economic literature, in the present context it neglects for example the possibility that individual wind power investors control a large portfolio of assets. In that case there are additional incentives for the locational choice of investments, which arise from the effect of an additional unit of generation capacity on the entire generation portfolio of an investor. Also strategic withholding of capacities could be an issue. Perfect information implies that the regulator is perfectly informed about the quality of different wind locations and can therefore make efficient decisions. In practice there could be substantial informational asymmetries for example because investors have private information on wind conditions at specific sites. As a result, the question arises how a regulatory framework that incentivizes the revelation of private information could be designed. Finally, it is likely that the addition of intermittent wind power capacities induces changes in the structure of the conventional power plant fleet. Including endogenous investment into conventional generation would therefore provide interesting insights into the long term effects of subsidized renewable power production. All these issues could be addressed by extending the presented theoretical model framework.

The analysis in Chapter 3 is also based on a stylized model, which focuses in contrast to Chapter 2 on the retail market. The model is based on a spatial competition framework, which is a widely applied model class in economic literature.[4] It enables the representation of horizontal product differentiation and heterogeneous consumer preferences towards retailers, which are exploited by retailers to exercise market power. As electricity is a homogenous good, the assumption of consumer

[4]See for example Eiselt et al. (2015) for a detailed overview.

preferences might itself be questionable. However, empirical evidence suggests that consumer preferences towards electricity retailers indeed exist.[5] One of the main arguments is that preferences are a result of branding activities which imply heterogeneity.[6] Nevertheless the applied model is only a crude and one-dimensional representation of consumer preferences. Hence a natural extension of the presented framework is the integration of more complex models of consumer choice. One possibility would be the representation of switching costs. Also an extension with multidimensional preferences would be possible, could however yield very complex results.

In addition to a more detailed representation of the demand side there are also potential extensions on the supply side. On the one hand the model assumes fixed locations of the retailers, which means that the degree of horizontal differentiation is exogenous. Consequently, a similar application with endogenous differentiation would be interesting. Also, the model assumes exogenous wholesale prices for electricity. In practice, distributed generation causes a feedback effect on wholesale prices because expensive conventional generation is crowded out of the market. As a result a decreasing effect on wholesale prices emerges. Consequently, the model could be extended to account for this additional complexity. Finally, the theoretically derived propositions on the effect of distributed generation on retail prices could be empirically tested based on econometric methods.

The methodology presented in Chapter 4 builds upon a large-scale investment and dispatch model for electricity markets. To keep these models computationally tractable they typically rely on formulations as linear programs, which minimize total system costs. However, linear cost minimization is only possible under strict economic assumptions such as perfect competition, perfect foresight and inelastic demand. Consequently, the large-scale applicability comes at the cost of simplified market representations. In order to integrate the non-linear contribution of wind power capacities to security of supply in a linear model framework we rely on an iterative solution approach. While this approach enables the successive linearization of the non-linear characteristics of the contribution of weather-dependent renewable energy to security of supply, the non-linearity of the underlying problem remains. As a result, we can only numerically check for existence and uniqueness of a global optimum without formal proof. Hence, further research could focus on formally analyzing the properties of the presented problem.

[5] See for example Kalkbrenner et al. (2017) or Tabi et al. (2014).

[6] Analogous arguments are also made in similar applications for other homogeneous goods such as telecommunication, see for example Laffont et al. (1998).

The large-scale application in Chapter 4 builds upon spatially and temporally high-resoluted data for European wind and solar power production. The data is based on a meteorological re-analysis model. While this methodology enables the generation of consistent high-resolution data on weather-dependent renewable electricity production over a large time frame, it must be kept in mind that the data is itself a model result and is therefore not equivalent to measured wind speed and solar irradiation data. Nevertheless re-analysis data is increasingly used in the scientific literature because consistent measured long-term historical weather data in high spatial resolution for Europe or other relevant regions does not exist. Future research should therefore focus on further validation and calibration of re-analysis data in the context of electricity market models. This is especially crucial in the context of analyses of reliability issues.

2 Grid Investment and Support Schemes for Renewable Electricity Generation

The unbundling of formerly vertically integrated utilities in liberalized electricity markets led to a coordination problem between investments in the regulated electricity grid and investments into new power generation. At the same time investments into generation capacities based on weather-dependent renewable energy sources such as wind and solar energy are increasingly subsidized with different support schemes. Against this backdrop this article analyzes the locational choice of private wind power investors under different support schemes and the implications on grid investments. I find that investors do not choose system optimal locations in feed-in tariff schemes, feed-in premium schemes and subsidy systems with direct capacity payments. Consequently, inefficiencies arise if transmission investment follows wind power investment. A benevolent transmission operator can implement the first-best solution by anticipatory investment behavior, which is however only applicable under perfect regulation. Alternatively a location-dependent network charge for wind power producers can directly influence investment decisions and internalize the grid integration costs of wind power generation.

2.1 Introduction

A large number of electricity systems, for example in the United States or Europe, have been liberalized and restructured over the last decades.[1] A central part of these restructuring efforts is unbundling, which describes the vertical separation of the monopolistic network from the potentially competitive parts of the system, namely generation, wholesale and retail. In unbundled electricity systems, separate entities such as private generation investors and regulated transmission operators make investment decisions based on their individual agenda. Nevertheless, there exist strong interactions between these decisions because of the physical properties

[1] See Joskow (1997) for a general discussion of electricity market liberalization for the US power sector. A similar analysis for European markets can be found in Jamasb and Pollitt (2005). For a retrospective discussion of lessons learned from market liberalization in various countries see Joskow (2008).

of the electricity system, which leads to a coordination problem between generation investment and grid investment. New power plants can for example increase network congestion and therefore force extensions which could be avoided by choosing a different location for the investment.[2]

To address the outlined coordination problem, a proactive approach to transmission planning is increasingly proposed, in which the transmission operator attempts to optimize the aggregated electricity system by taking into account consumer welfare, generation costs and transmission costs. Consequently, the transmission planner explicitly considers the effect of grid extensions on the decision problem of generation investors in order to implement an overall welfare optimal system configuration. Anticipatory planning processes therefore extend the traditional approaches to transmission investment, which focus primarily on reliability issues and technical feasibility instead of an economically optimal total system configuration.

The need for cost effective transmission planning is intensified by the increasing importance of electricity generation from intermittent renewable energy sources such as wind and solar. Because of the weather dependency of these energy sources, the best locations for wind and solar power plants are typically distributed and located away from load centers. As a result, the integration of large amounts of generation capacity based on wind and solar energy into the electricity system requires substantial investments into the electricity grid.[3] Despite these integration challenges, renewable energy investors face favorable regulations regarding grid connection in many countries, which often oblige the grid operator to connect new generation capacities based on renewable energy sources.[4] Consequently, the regulatory framework frequently promotes reactive approaches to transmission planning.

Investment into electricity generation from renewable energy sources is largely driven by support mechanisms such as feed-in tariff systems, feed-in premium sys-

[2] Kunz (2013) finds that investment into coal fired power generation in northern Germany significantly increases congestion costs. Due to lower inland transportation costs for coal, locations at the North Sea coast in northern Germany are more attractive for private generation investors compared to locations in southern Germany if congestion costs are not internalized.

[3] The required grid investments in the European electricity system to reach the European CO_2 reduction and renewable energy targets are analyzed in Fürsch et al. (2013). The results indicate that optimal network extension requires transmission investments of more than 200 billion EUR until 2050. A similar analysis for the United States can be found in National Renewable Energy Laboratory (2012). The required average yearly transmission investment to reach a share of renewable electricity generation of 80% by 2050 is estimated in a range between 6.4 and 8.4 billion USD.

[4] See Swider et al. (2008) for a discussion of the conditions for grid connection of renewable electricity generation in Europe.

tems or capacity subsidies.[5] A crucial difference between these subsidy systems is how producers of renewable electricity are exposed to market signals. Under feed-in tariffs renewable generators receive a fixed payment for every produced kilowatt hour of electrical energy. Consequently, generators are entirely isolated from market signals. With capacity subsidies on the other hand, producers of renewable energy are fully exposed to market signals because they generate revenue only due to electricity sales in the wholesale market. Feed-in premiums combine the described approaches by paying a fixed premium on top of the wholesale electricity price to renewable energy producers.

Against the described backdrop, this paper analyzes the influence of the subsidy scheme for renewable electricity generation on the locational choice of renewable energy investors and the subsequent implications for grid investments. Of particular interest are inefficiencies which arise due to deviations from the socially optimal allocation of renewable generation capacities when transmission investment follows renewable energy investment. Building on that, anticipatory behavior of the transmission operator is assessed as a potential remedy to avoid inefficient system configurations. To analyze these issues a highly stylized model with one demand node, two possible locations for renewable generation investment and lumpy transmission investment is developed. Electricity generation at the two locations is stochastic with different total expected generation and imperfectly correlated generation patterns. Renewable energy investments are subsidized by a feed-in tariff scheme, a feed-in premium system or direct capacity payments in order to reach an exogenous renewable target.[6] The analysis is conducted for wind power, however the results apply for all intermittent and location-dependent renewable energy sources such as solar or marine energy.

The analysis shows, that none of the assessed support mechanisms guarantees an efficient allocation of generation capacities. In a feed-in tariff system, investors develop only the wind location with the highest expected generation because they are isolated from market signals. Consequently, social benefits from developing both locations, which arise because of the imperfect correlation between wind generation at

[5] An overview of support policies for renewable electricity generation in OECD and non-OECD countries is provided in International Energy Agency (2015). The general question of the economic justification of renewable energy support instead of direct CO_2 pricing is not part this paper. The most common argument for renewable energy support policies are market failures due to learning spillovers. See for example Fischer and Newell (2008) or Gerlagh et al. (2009) for an analysis. An extensive review of literature on the rationale of support policies for renewable energies can be found in Fischer (2010).

[6] Note that investment based tax credits or low interest loans are equivalent to direct capacity payments as they reduce the net present value of investment costs.

both sites, are not realized. With capacity payments on the other hand, investors do receive market signals but grid investment costs are external. As a result, investors diversify locations even if the social benefit does not justify the additional grid investment costs, which are necessary to integrate the second wind location into the system. In a feed-in premium system, investors generate revenue from fixed premium payments and from market participation. Hence, investors act either as in a feed-in tariff system or as in a system with capacity payments, depending on which of the two revenue streams dominates. Building on these results I find, that the efficient system configuration can be implemented by anticipatory transmission investment. The results imply, that the locational choice of investors depends on the choice of the subsidy mechanism and that a more active role of the grid operator can help to efficiently integrate renewable energy sources into electricity systems.

The described results are derived in a stylized model framework. Nevertheless, the implications are of high policy relevance. The coordination between investment into generation capacities based on renewable energy sources and investment into transmission lines is a practical issue in a large variety of countries which plan to increase the share of renewable energy in electricity generation. Practical examples for the United States, the European Union, Mexico, Panama, Egypt, Brazil and the Philippines are provided in Madrigal and Stoft (2012). Additionally, numerical studies show that the analyzed inefficiencies are already of relevance in practice. Obermüller (2017) shows that the current regulatory framework in Germany over-incentivizes investment in Northern Germany because transmission bottlenecks are not accounted for. Similarly, Bjørnebye et al. (2018) show for Norway that wind power investment at inefficient locations, which is encouraged by the current regulation, could increase the required grid expansion by 55%. Building on these practical examples, the present paper derives some general conclusions and intends to derive practical implications for policy makers based on theoretical economics.

The paper is mainly related to two literature streams. The first relevant literature stream examines the efficiency of different subsidy schemes for electricity generation from renewable energy sources. Hiroux and Saguan (2010) give an overview of the advantages and disadvantages of different support schemes with respect to the integration of large amounts of wind power into the European electricity system. They argue that support schemes should expose wind power producers to market signals in order to incentivize system optimal choices of wind sites and maintenance planning or to incorporate portfolio effects. Klessmann et al. (2008) on the other hand point out that market exposure increases risk for investors, which leads to a higher required level of financial support in order to stimulate investments. The impact of renewable energy subsidies on the spatial allocation of wind power investments is explicitly studied in Schmidt et al. (2013) and Pechan (2017). Schmidt et al. (2013) analyze the spatial distribution of wind turbines under a feed-in premium and a feed-in tariff scheme based on an empirical model for Austria. They find that the feed-in premium system leads to substantially higher diversification of locations for wind power generation. Pechan (2017) shows in a numerical model, that a feed-in premium system combined with nodal pricing leads to a system friendly allocation of wind power if existing transmission lines are congested. All mentioned papers do not consider capacity payments or the required grid extensions to integrate the wind power capacity into the electricity system.

The second relevant literature stream is focused on the coordination problem between transmission and generation investment in liberalized power markets and the effects of anticipatory transmission investment. Sauma and Oren (2006) and Pozo et al. (2013) show that a proactive transmission planner can induce generation companies to invest in a more socially efficient manner by anticipating investments in generation capacity. Höffler and Wambach (2013) show that generation investment can lead to overinvestment or underinvestment in the electricity grid when private investors do not take the costs and benefits of network extensions into account. They also show that a capacity market can incentivize private investors to make socially efficient locational choices. The implications of renewable subsidies on the coordination problem are not part of the mentioned studies. The interactions of renewable portfolio standards and transmission planning are examined in Munoz et al. (2013). They show that ignoring the lumpy nature of transmission investment when planning the necessary grid extension for the integration of renewable energies can lead to significant inefficiencies in network investments. The effect of different support schemes is not part of the analysis.

In summary the contribution of the paper is threefold. First, the locational choice of renewable energy investors under different support schemes is analyzed in a theoretical framework. Second, interactions between the renewable support scheme and grid investments are analyzed. Third, anticipatory transmission investment is analyzed focusing explicitly on the coordination of subsidized renewable investment and grid investment. Therefore the paper intends to close the gap between the literature streams on support schemes for renewable energy and on the coordination problem between generation investment and grid investment in unbundled electricity systems.

The remainder of the paper is structured as follows. Section 2.2 introduces the model and analyzes the efficient allocation of renewable generation capacities as well as the investment problems for renewable energy investors and grid investments. Building on that, welfare effects are analyzed and a simple numerical example is presented. Section 2.3 introduces asymmetric grid investment costs, imperfect regulation of the transmission operator and network charges for renewable producers as model extensions. Section 2.4 concludes.

2.2 The model

We consider a model with three nodes D, H and L, which are not connected initially. At node D electricity consumption is located with an inelastic demand of quantity d. Additionally, two conventional generation technologies are located at node D. A cheap base-load technology with marginal generation costs c_1 and limited generation capacity $\bar{q}$ as well as a peak-load technology with unlimited generation capacity but higher marginal generation costs $c_2 > c_1$. It is assumed that a political target to reach a generation capacity $K_T < d$ based on renewable energy sources is in place.[7] Additionally it is assumed that $\bar{q} \geq \frac{d}{2}$.[8] The renewable target can be reached by investment into wind generation capacity at nodes H and L. Investment costs for one unit of capacity are I^W.[9] Marginal costs of wind power production are assumed to be zero. Investments are subsidized either by a feed-in tariff system, feed-in premium system or direct capacity payments. To connect the wind power plants at nodes H and L to the demand node D, transmission lines have to be built. Investment into transmission requires investment costs I^G and is modeled as a binary decision. Hence, once an investment is made, the transmission capacity is unlimited, which represents the lumpy character of transmission investments.[10]

The model configuration is depicted in Figure 2.1. Figure 2.1(a) shows the nodes

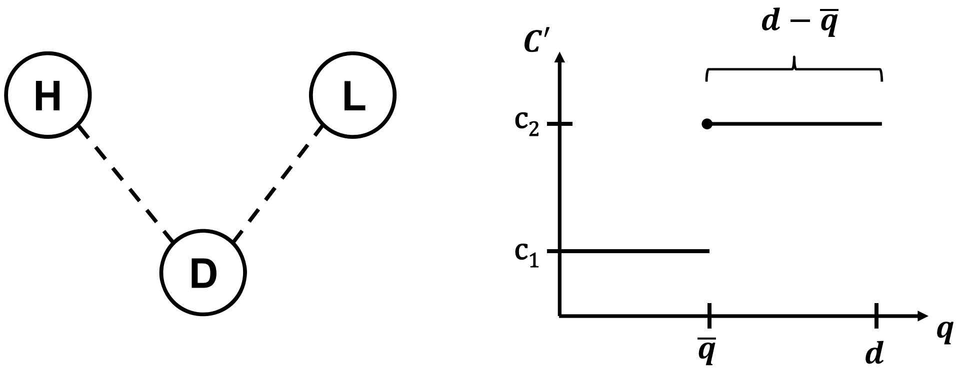
[7]In practice political renewable targets are defined in terms of capacity or electricity generation. However, even in countries with generation targets, for example Germany, the monitoring of target achievement is often undertaken based on installed capacity. See International Renewable Energy Agency (2015) for a discussion.

[8]This assumption is made in order to focus the analysis on the question if and under which conditions the wind locations H and L are developed. Extending the analysis for $\bar{q} < \frac{d}{2}$ is straight forward but requires additional case distinctions which do not provide substantial insights regarding the central questions of the study.

[9]The capacity factor is assumed to be one, which means that the full installed capacity is available for production if wind is present. In reality this factor is smaller than one and depends on the wind speed as well as the technical properties of the wind power plant.

[10]Lumpiness describes the fact that transmission capacity is increased in discrete steps as a result of strong economies of scale, see for example Joskow and Tirole (2005).

of the model as well as the potential network connections represented by dashed lines. Figure 2.1(b) shows the supply curve of conventional generation with different marginal generation costs for the base-load and peak-load technology. The depicted quantity $(d-\bar{q})$ represents the amount of electricity that has to be generated with the costly peak-load technology if no wind power generation is present.



(a) Network configuration (b) Supply curve of conventional generation

Figure 2.1: Basic model setup

Wind generation at nodes H and L is stochastic with three possible states h, l and hl, which occur with probabilities ρ_h, ρ_l and ρ_{hl} $(\rho_h + \rho_l + \rho_{hl} = 1)$. In states h and l only wind power plants at node H or L produce electricity whereas in state hl wind power is produced at both nodes.[11] Additionally it is assumed that $\rho_h > \rho_l$ which means that the expected wind output is higher at node H.

The described configuration accounts for two important properties of wind power generation. The first property is a substantial variation of expected electricity generation between different wind locations. The second property is that wind power generation is imperfectly correlated between different locations as a result of the spatial variation in weather conditions. In the model the correlation between the locations H and L can be modified by the value of ρ_{hl}. If ρ_{hl} equals zero wind output is perfectly negative correlated between the two nodes. The higher ρ_{hl} the higher is the correlation between nodes and the lower is the probability that only one of

[11]A fourth state in which none of the locations produce wind power is not included for reasons of simplification. Such a state could however be included without changing the results of the analysis.

the locations produces wind power.[12] Only two wind locations are chosen for the analysis in order to simplify the model. However, adding additional locations would not change the implications of the paper. Also, in practice there are typically only a limited number of suited geographical areas which have substantially differing wind properties within a country.[13]

The dynamic setting of the model consists of three stages: Transmission investment, wind power investment and cost minimal dispatch. The dispatch takes place in the last stage of the model after the stochastic wind generation is realized. Investment decisions on the other hand are based on the expected wind output. To assess the effects of uncoordinated generation and grid investments as well as anticipatory and reactive behavior of the transmission operator (TSO), three different model configurations are considered:

(i) **Central planner**: The central planner jointly invests into grid and wind power capacities in order to minimize total expected system costs. This model setting represents a vertically integrated electricity system and is considered as a first-best benchmark.

(ii) **Reactive TSO**: Under reactive transmission investment, revenue maximizing investment into wind power with feed-in tariff (FIT), feed-in premium (FIP) or capacity payments (CAP) happens in the first stage followed by transmission investment in the second stage. It is assumed that the TSO has to comply with the renewable target and is therefore obliged to connect all wind power investments from the first stage. Consequently, the TSO solely reacts to wind power investments from the first stage.

(iii) **Anticipatory TSO**: Under anticipatory transmission investment the transmission operator acts first and builds transmission lines to integrate wind power capacities according to the capacity target K_T. In the second stage, wind power investors build generation capacities given the network infrastructure from the first stage. As an additional steering instrument the TSO is able to limit transfer capacities of transmission lines. Hence, the TSO can actively influence wind power investments.

[12] The described representation of stochastic wind power generation is similar to Ambec and Crampes (2012) and Milstein and Tishler (2015). Both papers analyze interactions between investments into dispatchable and intermittent sources of electricity generation. A disadvantage of this simple model of stochasticity is that the variance of wind generation can not be changed independently of the expected wind generation. Note that the model considers only one period of wind generation. However an extension with multiple periods, e.g. for every day in a year, can be realized by repetition, as done for example in Milstein and Tishler (2015).

[13] See Madrigal and Stoft (2012) for a geographical depiction of wind regions in several countries.

In all settings perfect information and risk neutral behavior of investors is assumed. Free market entry is assumed for renewable investors, which means that no market power can be exercised. In the basic model, the TSO is assumed to behave benevolently as a result of perfect regulation. Imperfect regulation is discussed as a model extension in Section 2.3. Figure 2.2 illustrates the dynamics of the model for all considered cases graphically.

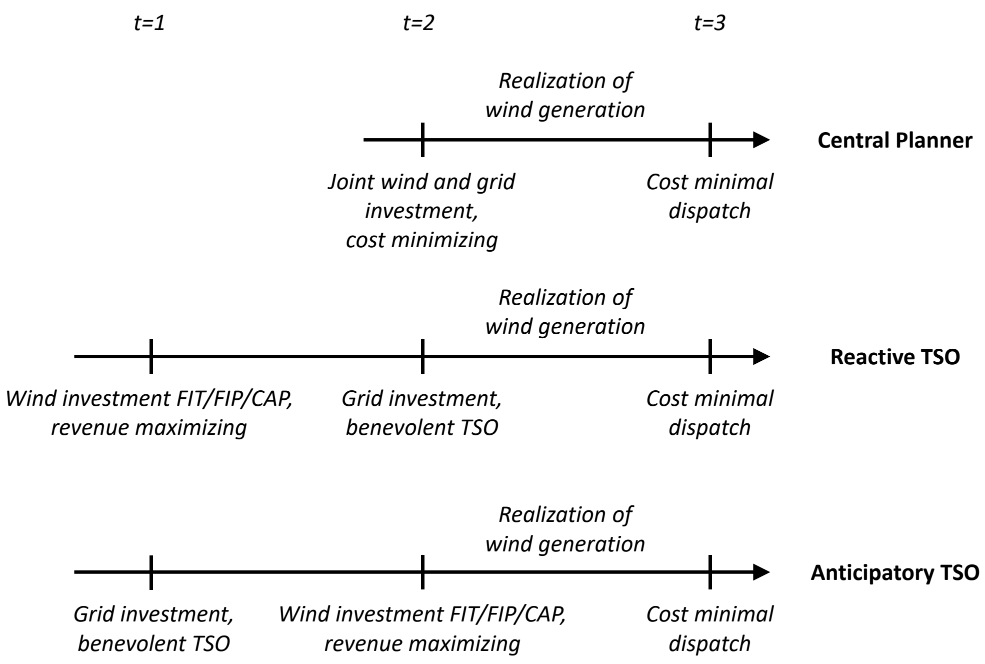


Figure 2.2: Dynamic model settings

The model is solved by backward induction. Therefore the dispatch problem, which is common for all described model settings, is solved first, followed by the renewable and transmission investment problems.

2.2.1 The dispatch problem

In the third stage of the model, the dispatch costs C_D are minimized based on investments in the prior stages and the realization of wind power generation. Consequently, conventional generation capacities at node D are utilized to meet the electricity demand that can not be covered by wind power generation delivered to node D given the grid and wind power investments from the first and second stage. As a result, renewable generation R is exogenous in the third stage and conventional generation q is dispatched according to the problem formulated in Equations (2.1a) and (2.1b).[14]

$$\min_q C_D = \begin{cases} qc_1 & \text{if } q < \bar{q} \\ \bar{q}c_1 + (q - \bar{q})\, c_2 & \text{if } q \geq \bar{q} \end{cases} \tag{2.1a}$$

$$\text{s.t. } d = q + R \tag{2.1b}$$

The cost function (2.1a) represents the two available conventional generation technologies with marginal generation cost equal to c_1 as long as the conventional generation q is smaller than the maximum capacity $\bar{q}$ of the base-load technology. If conventional generation exceeds $\bar{q}$ the marginal generation costs c_2 of the peak-load technology incur. Equation (2.1b) is the balance constraint which ensures that electricity demand d is met. Setting the partial derivatives $\frac{\partial \mathscr{L}}{\partial q}$ and $\frac{\partial \mathscr{L}}{\partial \lambda}$ of the lagrangian $\mathscr{L} = C_D + \lambda\,(d - q - R)$ equal to zero yields the following expressions:

$$\lambda = \begin{cases} c_1 & \text{if } q < \bar{q} \\ c_2 & \text{if } q \geq \bar{q} \end{cases} \tag{2.2a}$$

$$q = d - R \tag{2.2b}$$

Equation (2.2a) expresses that the market price equals marginal generation costs. Equation (2.2b) states that conventional generation equals residual demand. These expressions are a stylized representation of the merit order effect as the market price for electricity drops from c_2 to c_1 if the wind generation delivered to demand node D is higher than $(d - \bar{q})$.[15]

Because of the stochastic nature of wind generation, the investment problems are based on the expected dispatch outcome which depends on the expected value of wind power generation $\mathbf{E}\,(R)$ delivered to node D:

$$\mathbf{E}\,(R) = \rho_h K_H + \rho_l K_L + \rho_{hl}\,(K_H + K_L) \tag{2.3a}$$

$$K_H = Cap_H L_H \tag{2.3b}$$

$$K_L = Cap_L L_L \tag{2.3c}$$

$$L_L, L_H \in \{1, 0\} \tag{2.3d}$$

[14] Curtailment of wind power generation is not considered.

[15] The merit order effect describes the price depressing impact of renewable electricity generation with marginal generation costs close to zero on wholesale prices. See Würzburg et al. (2013) for a review of empirical studies which analyze this effect for different European markets.

$\mathbf{E}(R)$ is a function of the installed wind power capacity at nodes H and L and the probability that these capacities will produce electricity. Additionally, a transmission line between the demand node and the wind site has to be in place in order to use the wind power production to meet electricity demand. This is expressed in Equations (2.3b) and (2.3c) by the product of installed capacities Cap_H, Cap_L and the binary variables L_H, L_L which indicate if a connection between the wind locations and the demand node is in place.

Because of the piecewise linear form of the cost function of conventional power generation, several cases of connected wind power capacity have to be distinguished in order to determine the expected dispatch outcome. Decisive for the case distinction is if the conventional peak load technology is crowded out of the market as result of the realized wind generation in each possible state. Based on this logic, five cases can be distinguished as indicated in Equation (2.4). In the first case the peak load technology is displaced in every possible outcome. In the second and third case the peak load technology is not displaced if states l or h respectively are realized. In the fourth case the peak load technology is only displaced if state hl is realized and in the fifth case the peak load technology is not displaced in all outcomes. The aggregated connected wind power capacity at both wind locations is represented by $K_A = K_H + K_L$.

$$\mathbf{E}(C_D) = \begin{cases} c_1\left(d - \rho_l K_L - \rho_h K_H - \rho_{hl} K_A\right) \\ \qquad\qquad\qquad\qquad \text{if } K_H, K_L > d - \bar{q} \\ c_1\big(\rho_l \bar{q} + \rho_h (d - K_H) + \rho_{hl}(d - K_A)\big) + c_2 \rho_l (d - \bar{q} - K_L) \\ \qquad\qquad\qquad\qquad \text{if } K_H > d - \bar{q},\ K_L \leq d - \bar{q} \\ c_1\big(\rho_h \bar{q} + \rho_l (d - K_L) + \rho_{hl}(d - K_A)\big) + c_2 \rho_h (d - \bar{q} - K_H) \\ \qquad\qquad\qquad\qquad \text{if } K_H \leq d - \bar{q},\ K_L > d - \bar{q} \\ c_1\big((\rho_h + \rho_l)\bar{q} + \rho_{hl}(d - K_A)\big) + c_2\big((\rho_h + \rho_l)(d - \bar{q}) - \rho_h K_H - \rho_l K_L\big) \\ \qquad\qquad\qquad\qquad \text{if } K_H, K_L \leq d - \bar{q},\ K_A > d - \bar{q} \\ c_1 \bar{q} + c_2\left(d - \bar{q} - \rho_l K_L - \rho_h K_H - \rho_{hl} K_A\right) \\ \qquad\qquad\qquad\qquad \text{if } K_H, K_L \leq d - \bar{q},\ K_A \leq d - \bar{q} \end{cases} \tag{2.4}$$

Analogously the expected market price $\mathbf{E}(\lambda)$ can be expressed by the marginal generation costs c_1 and c_2 weighted with the probability that each technology sets the market price in the five distinguished cases.

$$\mathbf{E}(\lambda)=\begin{cases} c_1 & \text{if } K_H, K_L > d-\bar{q} \\ c_1(1-\rho_h)+c_2\rho_h & \text{if } K_H > d-\bar{q},\, K_L \leq d-\bar{q} \\ c_1(1-\rho_l)+c_2\rho_l & \text{if } K_H \leq d-\bar{q},\, K_L > d-\bar{q} \\ c_1\rho_{hl}+c_2(1-\rho_{hl}) & \text{if } K_H, K_L \leq d-\bar{q},\, K_A > d-\bar{q} \\ c_2 & \text{if } K_H, K_L \leq d-\bar{q},\, K_A \leq d-\bar{q} \end{cases} \tag{2.5}$$

Equations (2.4) and (2.5) show that the expected dispatch costs as well as the expected electricity price decrease with increasing connected wind power capacity as a result of the merit order effect. Additionally the effect of imperfect correlation of wind generation between the locations is apparent because the conventional peak load technology is only displaced completely in all states if the installed wind capacity at both locations exceeds $(d-\bar{q})$.

2.2.2 The central planner investment problem

The central planner jointly invests into wind power generation capacity and transmission lines in order to meet the wind power capacity target K_T. The objective of the central planner is to minimize total system costs which include expected dispatch costs and investment costs. With specific investment costs for wind power I^W and grid investment costs I^G this translates into the following minimization problem:

$$\min_{Cap_H, Cap_L, L_H, L_L} C_{Total} = \mathbf{E}(C_D) + I^W(Cap_H + Cap_L) + I^G(L_H + L_L) \tag{2.6a}$$

$$\text{s.t. } K_T = Cap_H L_H + Cap_L L_L \tag{2.6b}$$

$$L_L, L_H \in \{1, 0\} \tag{2.6c}$$

Because of the binary character of grid investments, problem (2.6) can be solved by analyzing optimal wind power investment and the corresponding system costs for all possible network configurations. Consequently, total investment costs with one wind location and both wind locations connected to the demand node D have to be compared. Based on this comparison the following proposition can be derived:

Proposition 2.1. *The central planner diversifies wind locations if the reduction of expected dispatch costs outweighs the required additional grid investment costs. Depending on the target for wind power capacity, two cases can be distinguished:*

(i) For $K_T \leq d-\bar{q}$ diversification is never optimal

(ii) *For $K_T > d - \bar{q}$ diversification is optimal if and only if:*
$(c_2\rho_l - c_1\rho_h)\big(K_T - (d - \bar{q})\big) > I^G$

Proof. See Appendix 2.5.1.

Proposition 2.1 points out that the central planner faces a trade off between reducing expected dispatch cost due to diversification of wind sites and the grid investment costs, which are required to connect the additional location. For renewable targets below $(d - \bar{q})$ it is never optimal to develop both locations because there is no benefit of diversification as long as all the produced wind power at the better wind location H replaces costly conventional peak-load generation.

For renewable targets above $(d - \bar{q})$ the central planner always builds wind power capacity of $(d - \bar{q})$ at node H. The remaining quantity $K_T - (d - \bar{q})$ can either be also built at node H to replace base-load generation with probability $\rho_h + \rho_{hl}$ or alternatively at node L to replace peak-load generation with probability ρ_l and base-load generation with probability ρ_{hl}. Consequently, a prerequisite for developing the low wind location L is that the cost difference between peak-load and base-load generation outweighs the difference in expected wind output between nodes H and L. Formally this means that $c_2\rho_l > c_1\rho_h$ must hold. If this condition is true, the central planner chooses to build a capacity of $(d - \bar{q})$ at the better wind location H and the remaining $K_T - (d - \bar{q})$ at the low wind location L if the achievable reduction in expected dispatch costs outweighs the required investment costs for the additional transmission line to node L. For $K_T > d - \bar{q}$ the potential benefits of developing the second wind location increase with the renewable target. For $K_T = 2(d - \bar{q})$ the maximum potential benefit of diversification is reached, which means that the central planner never chooses to develop both wind locations if the condition $(c_2\rho_l - c_1\rho_h)(d - \bar{q}) > I^G$ is not satisfied.

The described result of Proposition 2.1 is shown graphically in Figure 2.3.[16] Expected dispatch costs when only node H is connected are depicted by the solid line. The reduction of expected dispatch cost for one additional unit of wind power capacity is $c_2(\rho_h + \rho_{hl})$ for $K_T \leq (d - \bar{q})$ and $c_1(\rho_h + \rho_{hl})$ for $K_T > (d - \bar{q})$. Expected dispatch costs with nodes H and L connected are depicted by the dashed line. For $K_T > (d - \bar{q})$ the reduction of expected dispatch costs is $c_2\rho_l + c_1\rho_{hl}$ for every additional unit of wind power generation. The difference between the solid and dashed lines corresponds to the reduction in dispatch costs due to diversification of wind

[16] The depiction in Figure 2.3 assumes that $c_2\rho_l > c_1\rho_h$ is true.

locations. Developing the low wind location L is socially beneficial if this cost reduction exceeds the additional grid investment costs I^G. As indicated in Figure 2.3 this is true for capacity targets for renewable energy above a critical level K_T^*.[17]

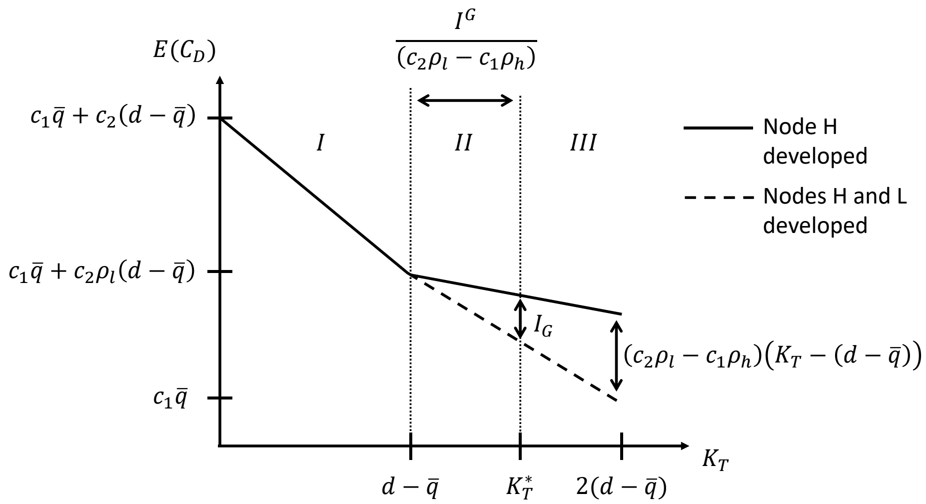


Figure 2.3: Expected dispatch costs in the central planner problem

As a result three areas can be distinguished in Figure 2.3. In area I, investment only at the high wind location is always preferable. In area II, developing the low wind location L is not socially beneficial because the achievable reduction in expected dispatch costs does not outweigh grid investment costs. In area III, developing the low wind location is efficient. The relative size of area II increases with I^G and decreases with $(c_2\rho_l - c_1\rho_h)$. If $(c_2\rho_l - c_1\rho_h)(d-\bar{q}) \leq I^G$ area III does not exist and it is never optimal to develop both locations.

An important result of Proposition 2.1 is that the benefit of wind location diversification increases with ρ_l, c_2 and $\bar{q}$, while it decreases with ρ_h and c_1. Consequently, a lower quality difference between the high wind location H and the low wind location L as well as a steeper merit order of the conventional power plant fleet increases the benefit of developing both wind locations. Additionally, a higher availability of cheap base load technology increases the achievable reduction in expected dispatch costs because less peak load generation can be displaced by wind investments at the better wind location. A higher correlation between wind generation at both wind locations on the other hand decreases the benefit of diversifying wind locations for a given probability ρ_h. The described impact of the correlation between wind generation at nodes H and L shows that not only the total wind generation but also

[17] K_T^* can be directly derived by solving the second part of Proposition 2.1 for K_T.

the difference in generation patterns over time is decisive for optimal wind power investment. It can be socially efficient to develop the location with lower total wind generation because there are situations where the better wind location does not produce electricity while the low wind location does. This is precisely the potential benefit of diversification described in Proposition 2.1.

2.2.3 The renewable energy investment problem

In this section the investment problem for wind power producers in an unbundled electricity system is solved for a feed-in tariff scheme, a feed-in premium system and direct capacity payments. Based on these results the effects of reactive behavior of the transmission operator can be assessed. The central planner problem from the previous section serves as a first-best benchmark to identify inefficiencies.

Feed-in tariff

Under a feed-in tariff scheme, wind power investors receive a fixed payment for every produced kilowatt hour of electrical energy. Consequently, each revenue maximizing investor i faces the optimization problem expressed in Equations (2.7a) and (2.7b). $\mathbf{E}(\pi_i)$ represents the expected revenue and FIT the fixed feed-in tariff.

$$\max_{Cap_{L,i}, Cap_{H,i}} \mathbf{E}(\pi_i) = FIT * \mathbf{E}(R_i) - I^W \left(Cap_{L,i} + Cap_{H,i}\right) \tag{2.7a}$$

$$\text{s.t. } K_T = \sum_i Cap_{H,i} L_H + \sum_i Cap_{L,i} L_L \tag{2.7b}$$

FIT is assumed to be set by the regulator to a level which guarantees non-negative expected profits for all required investments to meet the capacity target K_T. Wind power investors maximize the expected revenue by choosing wind capacities with the highest expected wind generation $\mathbf{E}(R_i)$ for a given FIT. Hence, investors never choose to build capacity at the low wind location L under a feed-in tariff scheme because the market value of the produced electricity is not internalized and $\rho_h > \rho_l$. As a result there is underdiversification of wind locations compared to the first-best solution of the central planner because even if developing both locations is socially beneficial investors do not invest at node L. Consequently, inefficiencies can arise in an unbundled system with a feed-in tariff system if the transmission operator behaves reactively and builds the grid according to the decisions of renewable investors. The results are summarized in the following proposition:

Proposition 2.2a. *In a feed-in tariff system investors always prefer the location with the highest expected wind generation because the market value of electricity is not internalized. As a result, there is underdiversification of wind locations compared to the first-best solution. Overdiversification of wind locations is not possible.*

Proof. See Appendix 2.5.1.

Feed-in premium

In a feed-in premium system, renewable investors sell the produced electrical energy in the spot market and receive an additional fixed premium payment. Hence, investors have to take into account not only the expected wind generation but also the expected market price as well as the correlation between market price and wind generation. Equations (2.8a) and (2.8b) show the resulting maximization problem for each renewable investor i. The covariance term enters in Equation (2.8a) because of the expected market revenue $\mathbf{E}(\lambda * R_i) = \mathbf{E}(\lambda) * \mathbf{E}(R_i) + \mathbf{Cov}(\lambda, R_i)$. FIP represents the fixed premium payment. Again it is assumed, that FIP is set to a level that ensures the realization of the capacity target K_T with non-negative expected profits.

$$\max_{Cap_{L,i}, Cap_{H,i}} \mathbf{E}(\pi_i) = \mathbf{E}(\lambda) * \mathbf{E}(R_i) + \mathbf{Cov}(\lambda, R_i) + FIP * \mathbf{E}(R_i) - I^W \left(Cap_{L,i} + Cap_{H,i} \right) \tag{2.8a}$$

$$\text{s.t. } K_T = \sum_i Cap_{H,i} L_H + \sum_i Cap_{L,i} L_L \tag{2.8b}$$

As indicated by Equation (2.8a), investors receive two different revenue streams in a feed-in premium system. The revenue stream from fixed premium payments is only determined by the expected wind power generation at a given location. The revenue stream from spot market sales however, additionally depends on the realized market price. For low renewable targets $K_T \leq d - \bar{q}$, the market price equals c_2 for all possible states h, l and hl. Consequently, investment is always more profitable at the location with the highest expected wind generation as both revenue streams are higher for investments at node H. For investment levels above $(d - \bar{q})$ it is always preferable to install a capacity of at least $(d - \bar{q})$ at node H because of the higher expected wind output. Above that level an additional unit of wind power capacity at node H earns less revenue in the spot market because prices are depressed to c_1 if states h or hl are realized. However, investors can instead choose to invest at the second wind location, where they still earn the higher market price c_2 when state l is realized and c_1 in state hl. As a result, the expected revenue from spot market sales is higher at node L if $c_2\rho_l > c_1\rho_h$. The premium payment on the other hand depends only on the expected wind power generation and is always higher at node H. Consequently, investors choose to develop the low wind location if the expected additional spot market revenue at node L outweighs the lower expected premium payments:

$$c_2\rho_l - c_1\rho_h > (\rho_h - \rho_l)FIP \tag{2.9}$$

Equation (2.9) implies that the profitability of investing at the low wind location increases with the difference between c_2 and c_1. Hence, comparable to the central planner problem the steepness of the merit order of the conventional power plant fleet is decisive for the profitability of diversifying wind locations. Additionally it can be seen that a higher feed-in premium decreases the profitability of investing at location L, because the share of revenue from the fixed premium payments in relation to the revenue generated from spot market sales increases. A higher quality of the low wind location ρ_l increases the profitability of investments at node L because the expected spot market revenue at the low wind location increases and the difference in fixed premium payments compared to the high wind location decreases. Also, for a given probability ρ_h, a higher correlation between generation at the two wind locations decreases the profitability of diversifying wind locations.

The discussed results show that the grid investment costs which are required to connect the second wind location to node D are external costs for the wind power investor and are therefore not considered in the decision. Consequently, inefficiencies arise in a feed-in premium system if transmission investment follows wind power investors and the optimality conditions in Proposition 2.1 are inconsistent with the behavior of wind power investors formulated in Equation (2.9). Proposition 2.2b summarizes the results for wind power investments in a feed-in premium subsidy scheme.

Proposition 2.2b. *In a feed-in premium system investors develop both locations if the expected additional spot market revenue outweighs the lower premium payments. Investors underdiversify locations if the revenue stream from premium payments dominates. If the revenue stream from market participation dominates, investors overdiversify locations compared to the first best solution.*

Proof. See Appendix 2.5.1.

To further analyze the implications of Proposition 2.2b it is assumed that the feed-in premium equals the efficient level, that sets marginal revenue of wind power investment equal to zero.[18] Plugging this value of FIP into Equation (2.9) yields the following condition for the development of the low wind location L under a feed-in premium scheme with $K_T > (d - \bar{q})$:

$$I^W < \frac{(c_2 - c_1)\left(\rho_l - \rho_l^2\right)}{\rho_h - \rho_l} \tag{2.10}$$

As mentioned above the decision on diversification of wind locations in a feed-in premium scheme depends on the investment costs for wind power plants which determine the required level of subsidies and subsequently the share of revenue from fixed premium payments. Consequently, diversifying wind locations becomes more attractive as the technological maturity of wind power plants increases and less premium payments are necessary to cover investment costs as indicated by the left hand side of Equation (2.10). The right hand side is determined by the steepness of the conventional merit order and the expected wind generation at nodes H and L. It can be seen that a steeper merit order increases the profitability of investing at the low wind location. Additionally, an increase in ρ_l makes investments at node L more attractive as the right hand side of Equation (2.10) is strictly increasing in ρ_l.[19]

Capacity payment

In a subsidy system with direct capacity payments, wind power investors generate revenue only in the spot market. Additionally they receive a fixed subsidy payment *SUB* for every unit of capacity they build, which is equivalent to a reduction of the investment costs. The resulting optimization problem is expressed in Equation (2.11):

$$\max_{Cap_{L,i}, Cap_{H,i}} \mathbf{E}(\pi_i) = \mathbf{E}(\lambda) * \mathbf{E}(R_i) + \mathbf{Cov}(\lambda, R_i) - \left(I^W - SUB\right)\left(Cap_{L,i} + Cap_{H,i}\right) \tag{2.11}$$

With capacity payments renewable investors maximize spot market revenue. For low renewable targets $K_T \leq d - \bar{q}$ the expected spot market revenue is higher at location H because of the higher expected wind generation. Once the installed capacity at the high wind location is equal to $(d - \bar{q})$ an additional unit of wind capacity at node

[18] The mathematical expression for the marginal revenue of wind power investment at nodes H and L is provided in Equations (2.17) and (2.18) in Appendix 2.5.1.

[19] Note that $0 < \rho_l < 0.5$ because of $\rho_h > \rho_l$ so $\rho_l - \rho_l^2$ is strictly increasing in ρ_l.

H generates expected spot market revenue of $c_1(\rho_h + \rho_{hl})$ because the conventional peak-load technology gets crowded out of the market in states h and hl. Investments at node L on the other hand generate expected spot market revenue of $c_2\rho_l + c_1\rho_{hl}$. Consequently, investors always choose to invest at node L if the following condition is true:

$$c_2\rho_l > c_1\rho_h \tag{2.12}$$

Compared to the feed-in premium system, the condition for developing the low wind location is less restrictive. By comparing the results with the central planner solution it can additionally be derived that underdiversification of wind locations is not possible in a subsidy system with capacity payments.[20] Instead, there is overdiversification of wind locations as the market value of wind energy is fully internalized while grid investment costs are external. Proposition 2.2c summarizes the findings.

Proposition 2.2c. *In a system with direct capacity payments investors choose locations where the highest expected spot market revenue can be generated. As a result, there is overdiversiversification of wind locations compared to the first-best solution. Underdiversification of wind locations is not possible.*

Proof. See Appendix 2.5.1.

2.2.4 Anticipatory transmission investment

The results of the previous section show that in an unbundled electricity system inefficiencies can arise due to uncoordinated investment into wind power capacity and into the grid under all considered subsidy schemes. The possible inefficiencies are underdiversification of wind locations, which means that potential reductions in total system costs due to development of additional locations are not used, and overdiversification of wind locations, which means that wind power investments enforce inefficient grid extensions. This section analyzes if a proactive transmission operator can prevent these inefficiencies by anticipating decisions of wind power investors.

It is assumed that the transmission operator is benevolent and minimizes total system costs. Additionally it is assumed that the transmission operator has perfect information and knows all relevant parameters of the electricity system. Consequently,

[20] According to the second part of Proposition 2.1 $c_2\rho_l > c_1\rho_h$ is a necessary but not sufficient condition for the optimality of developing the low wind location L. However, in a subsidy system with capacity payments investors always choose to develop location L if this condition is true.

the transmission operator decides whether to build transmission lines to nodes H and L based on the grid investment costs and the expected dispatch costs, which result from private wind power investments in different network configurations. The objective function of the transmission operator is the same as in the central planner problem because of the assumed benevolence. The difference to problem (2.6) is that the transmission operator can not directly influence installed wind power capacities.

To enable the transmission operator to prevent underdiversification of wind locations it is assumed that he is able to limit the transfer capacity of a transmission line once it is built. For reasons of simplification only the limitation of transfer capacity to the high wind location H is considered.[21] Based on these assumptions the optimization problem of the transmission operator is formulated in Equations (2.13a) to (2.13c). $\overline{L_H}$ represents the limited transfer capacity to node H. $\mathbf{E}\big(C_D\big(\cdot,\ \overline{L_H}\big)\big)$ expresses that the expected dispatch costs are now also influenced by the limited transfer capacity.[22]

$$\min_{L_H, L_L, \overline{L_H}} C_{Total} = \mathbf{E}\left(C_D\left(\cdot,\ \overline{L_H}\right)\right) + I^W\left(Cap_H + Cap_L\right) + I^G\left(L_H + L_L\right) \tag{2.13a}$$

$$\text{s.t. } K_T = Cap_H L_H + Cap_L L_L \tag{2.13b}$$

$$L_L, L_H \in \{1, 0\} \tag{2.13c}$$

As discussed in the previous section, two types of inefficiencies can arise depending on the subsidy scheme for renewable energy, namely underdiversification and overdiversification of wind locations. As the transmission operator has perfect information over the electricity system he can anticipate wind power investments and the resulting inefficiencies. If wind power investors develop too many wind locations, which is possible in a subsidy system with direct capacity payments or in a feed-in premium system under the conditions explained in Sections 2.2 and 2.2, the transmission operator can refuse to connect the low wind location L to the demand node D. This prevents overdiversification as investors have no incentive to invest at location L if they know that no transmission line will be built and they can not generate any revenue at node L. If wind power producers invest only at the high wind location H despite potential social benefits of developing both wind locations, the transmission operator can choose to build both transmission lines and force investors to move to location L by limiting transfer capacity to node H. This prevents

[21] Including the option to limit transfer capacity to node L into the problem would however not change the results

[22] The "·" represents the remaining factors as discussed in Section 2.2.1.

underdiversification because additional investments above the capacity limit will not be able to generate positive expected profits. The optimal capacity limit is equal to $(d - \bar{q})$, which is the social optimal investment level at node H if diversification of wind locations is beneficial. Proposition 2.3 summarizes the results.

Proposition 2.3.

(i) If the subsidy scheme for wind power investment incentivizes overdiversification, the transmission operator chooses not to connect the inferior wind location L.

(ii) If the subsidy scheme for wind power investment incentivizes underdiversification, the transmission operator connects both locations and limits the transfer capacity to the superior wind location to $(d - \bar{q})$, which forces investors to develop both wind locations.

Proof. See Appendix 2.5.1.

2.2.5 Welfare effects and policy implications

Based on the findings described in Propositions 2.1 to 2.3, this section discusses welfare effects and derives policy implications. Figure 2.4 summarizes the previous results graphically. The depiction is analogous to Figure 2.3 and shows expected dispatch costs as a function of the capacity target for renewable electricity generation K_T. Additionally, Figure 2.4 shows the model results and the resulting inefficiencies in an unbundled system with reactive grid investment compared to the central planner solution. K_T^* indicates the capacity target above which the central planner develops the low wind location L.

Figure 2.4 shows that for low renewable targets $K_T \leq (d - \bar{q})$ all support mechanisms lead to the efficient system configuration with only node H developed, which corresponds to area I. For moderate renewable targets $(d - \bar{q}) < K_T \leq K_T^*$ in area II, only the feed-in tariff system guarantees the optimal solution, while capacity payments lead to overdiversification and the feed-in premium system leads to overdiversification if condition (2.10) holds. For high renewable targets $K_T > K_T^*$ in area III on the other hand, only capacity payments guarantee the efficient system configuration, while the feed-in tariff system leads to underdiversification and the feed-in premium system leads to underdiversification if condition (2.10) is violated.

The resulting inefficiencies can be further analyzed by comparing total system costs of the central planner solution to a system with under- or overdiversified wind

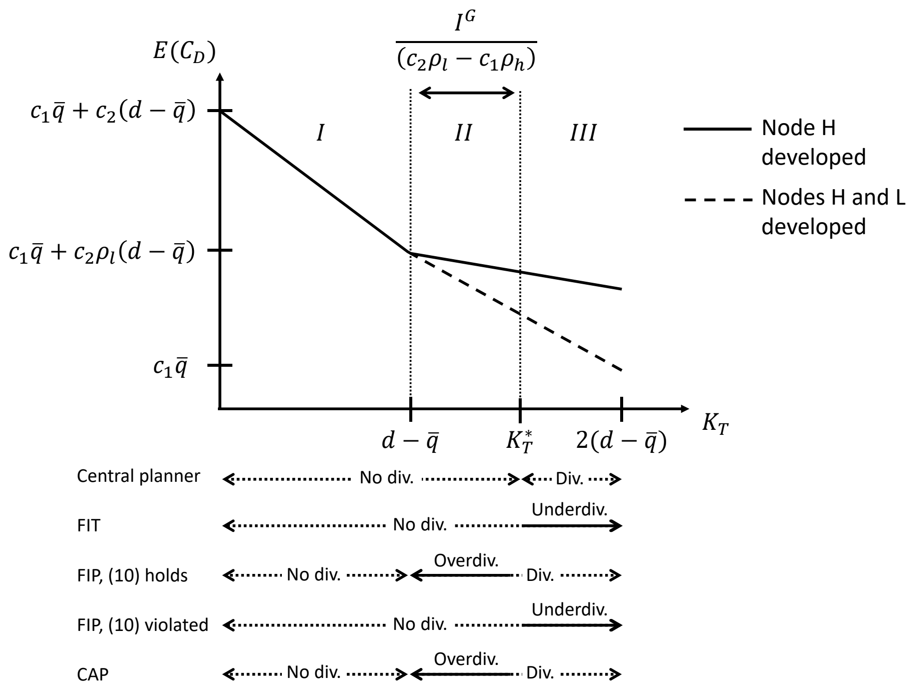


Figure 2.4: Overview of possible inefficiencies under different support schemes

locations. The corresponding welfare effects are described by Equations (2.14a) and (2.14b):

$$\Delta W^{overdiv.} = I^G - (c_2\rho_l - c_1\rho_h)\big(K_T - (d-\bar{q})\big) \qquad \big(\text{for } (d-\bar{q}) < K_T \leq K_T^*\big) \tag{2.14a}$$

$$\Delta W^{underdiv.} = (c_2\rho_l - c_1\rho_h)\big(K_T - (d-\bar{q})\big) - I^G \qquad \big(\text{for } K_T > K_T^*\big) \tag{2.14b}$$

Equation (2.14a) expresses the welfare loss due to overdiversification of wind locations. It can be seen that the welfare loss is decreasing in K_T and increasing in $\bar{q}$. The slope of both effects is higher if the conventional merit order is steep and the quality difference between the wind locations is small. Additionally it can be seen that the welfare loss due to overdiversification is limited to I^G. Equation (2.14b) expresses the corresponding welfare loss due to underdiversification of wind locations, which is increasing in K_T and decreasing in $\bar{q}$. Equivalently, these effects are more pronounced with a steep merit order and a small difference between expected wind generation at the two locations. The possible welfare loss due to underdiversification is theoretically unbounded.

In practice, climate policy measures typically include explicit renewable targets as well as reductions of emission intensive, for example coal-fired, base-load capacity.[23] Hence, the model parameters K_T and $\bar{q}$ are typically directly influenced by policy makers. As a result, the following policy implications can be derived based on the discussed welfare effects and the results in Figure 2.4.

First, the choice of the support scheme is uncritical for low renewable targets as all assessed policies yield the efficient solution with only the best wind location developed. Second, overdiversification of locations should be of concern for moderate renewable targets. Consequently a feed-in tariff system may be the best solution. Alternatively the TSO can act proactively, for example by assigning a limited number of good wind locations and commit to not connecting additional sites. Third, market based mechanisms are important for high renewable targets as the value of diversification of wind locations increases. Consequently, capacity subsidies should be implemented. Alternatively a feed-in premium system can be optimal if condition (2.10) is violated. This is however difficult for policy makers to assess in practice as the development of crucial parameters such as marginal conventional generation costs or wind power investment costs is subject to major uncertainty. If high renewable targets are implemented with a feed-in tariff system or a feed-in premium system and condition (2.10) holds, the TSO can only prevent inefficiencies by building transmission lines in advance of generation investment and limiting transmission capacity optimally in order to enforce diversification of wind locations. This is probably difficult to realize in practice as substantial planning efforts are required. Fourth, politically induced reductions of base load capacity decrease the profitability of developing both wind locations as more peak load generation can be displaced by wind power generation from the better wind location. As a result, potential welfare losses due to underdiversification of locations can be dampened. Welfare losses caused by overdiversification on the other hand are increased by reductions in base load capacity.[24]

The discussed policy implications are derived under the assumption of no endogenous changes in conventional power generation capacities. This assumption is uncritical in the short to medium term because wind power investment has sig-

[23]Examples for policy measures that directly influence base load capacity are emission standards, which have been introduced for example in the United States, the European Union, China or India. Additionally, several countries have directly influenced base load generation capacity by shutting down coal-fired generation or putting restrictions on investments into new power generation, see International Energy Agency (2016a). A specific policy that combines the introduction of a feed-in tariff scheme with shut-downs of coal fired power plants is discussed in Stokes (2013) for the case of Ontario, Canada.

[24]Note that regardless of the subsidy mechanism, the expected costs of conventional generation increase due to politically enforced reductions in base load generation capacity.

nificantly lower lead times compared to conventional power plant investments. In the long term however, the addition of intermittent wind power capacities is likely to induce changes in the structure of the conventional power plant fleet, which in turn influences market based investment into wind power. An analysis of these feedback effects is out of the scope of the paper. An extension of the presented model with endogenous investments into conventional power generation is an interesting direction for future research.

2.2.6 Numerical analysis

Based on the analysis in the previous section it can be stated that the two main components that determine the level of inefficiency described by Equations (2.14a) and (2.14b) are the grid investment costs I^G and the benefit of diversifying locations $(c_2\rho_l - c_1\rho_h)\big(K_T - (d - \bar{q})\big)$. Both components can be substantial in practice. An analysis of about 250 transmission projects in Europe in Agency for the Cooperation of Energy Regulators (2015) reports for example median total investment costs of roughly 1 million EUR per kilometer for 2 circuit overhead transmission lines at 380-400 kV voltage. Consequently, overdiversification of wind locations can yield substantial inefficiencies if too many remote wind sites than necessary are developed. For underground cables the equivalent investment costs are almost 6 million EUR per kilometer. In countries where underground cables are increasingly discussed because of public opposition against overhead lines the issue of overdiversification can be therefore even more pressing. A detailed assessment of the benefit of diversification of wind locations in real-world power systems requires detailed statistical analysis and modeling and is therefore out of the scope of this paper. However, a simple estimation based on fuel prices and full load hours of wind power plants in Germany suggests that the potential benefits can be substantial. Methodology and results of the analysis are described in this section.

The marginal generation costs of conventional power plants c_1 and c_2 are assumed to be 30 EUR/MWh and 60 EUR/MWh which roughly corresponds to the marginal costs of a coal-fired power plant and an open cycle gas turbine in Europe. The probabilities for wind power production are determined based on full load hours of modern wind power plants in northern and southern Germany. 2600 full load hours for northern Germany as node H and 2100 full load hours for southern Germany as node L are assumed. The values of ρ_h and ρ_l in Equations (2.14a) and (2.14b) are the probabilities that only one of the two locations produces electricity while the other does not. Consequently, additional assumptions on the correlation of wind power generation at the two locations have to be made. In the model, the correlation is determined by ρ_{hl}, which is the probability that both locations produce at the same time. In the numerical example an additional state 0 with probability ρ_0 and no wind power production is introduced in order to better reflect real-world wind power production.

The relevant probabilities are determined based on a simple logic: When assuming the maximum negative correlation based on the real-world full load hours there are 2600 hours of wind production only at node H and 2100 hours of wind production only at node L while the hours of parallel wind production at both nodes are 0. With 8760 hour per year, the corresponding probabilities are $\rho_h = 0.297$, $\rho_l = 0.24$ and $\rho_{hl} = 0$. If the maximum positive correlation is assumed, there are 2100 hours of parallel production and 500 hours of production only at node H. The corresponding probabilities are $\rho_h = 0.057$, $\rho_l = 0$ and $\rho_{hl} = 0.479$. The probabilities between the two explained extreme cases are scaled linearly based on the ratio between full load hours at nodes H and L. The benefit of diversification is then calculated based on Equations (2.14a) and (2.14b) with $(c_2\rho_l - c_1\rho_h) * 8760$. The result can be interpreted as the yearly benefit of building one MW of wind power capacity at the low wind location L instead of the high wind location H for renewable targets $K_T > d - \bar{q}$. The results are depicted in Figure 2.5 as a function of the correlation coefficient between wind generation at nodes H and L. The correlation coefficient is calculated with the corresponding values for ρ_h, ρ_l and ρ_{hl}.

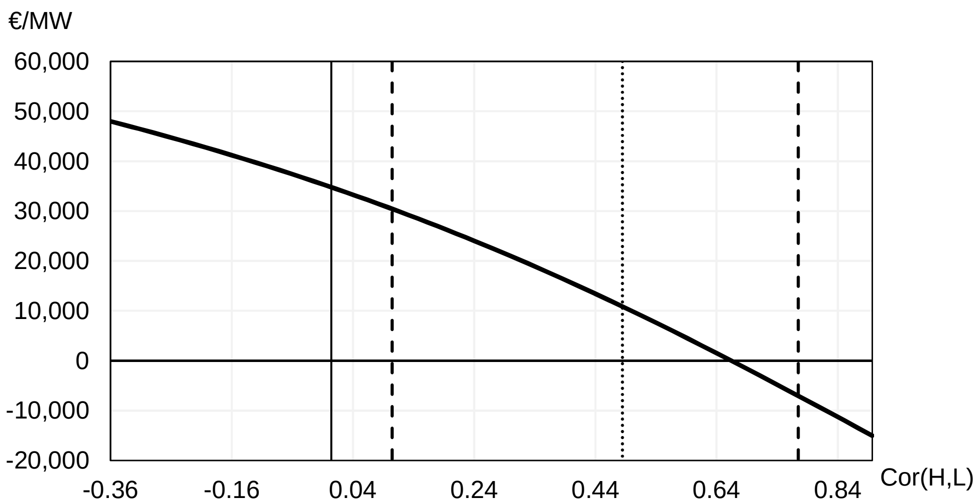


Figure 2.5: Yearly benefit of diversification in the numerical example

Figure 2.5 shows that there is no benefit of diversifying wind locations for high correlations. The break even for diversification is at a correlation of 0.66. For the extreme case of maximum negative correlation the benefit of diversification increases to almost 50000 EUR/MW per year. An analysis of real-world correlation between wind power generation in the different federal states in Germany is conducted in Hagspiel (2018). The analysis shows that the real-world correlation is in a range between 0.1 and 0.77 with a mean of 0.48. The feasible range is indicated by the dashed lines in Figure 2.5. Additionally, the dotted line indicates the mean correlation. It can be seen that the potential yearly benefit of diversification is at roughly 10000 EUR/MW for the mean correlation and 30000 EUR/MW for the minimum correlation. The negative value for the maximum correlation shows that diversification is not necessarily beneficial but depends on the specific wind conditions at the given locations.

The numerical analysis shows, that there can be substantial benefits of diversification in real-world power systems. However, the presented example can only give a first indication. A detailed analysis for real-world power systems with different supply curves of conventional generation and different wind conditions is a promising direction for future research.

2.3 Model extensions

After the basic results and implications of the model have been discussed, this section introduces extensions that give additional insights on the coordination problem between subsidized renewable energy investments and grid investments in unbundled electricity systems.

2.3.1 Asymmetric grid investment costs

Throughout Section 2.2 symmetric investment costs for grid investments are assumed, which means that investments costs for transmission lines to nodes H and node L are equal. In reality, the required costs to integrate different wind location into the electricity system can vary substantially based on factors such as the distance to load centers or effects on bottlenecks within the system. Introducing asymmetric investment costs for grid extensions does not change the dispatch problem nor the investment problem of wind power producers. However, the first-best benchmark solution of the central planner and the transmission investment problem are different. The main difference to the solutions presented in Section 2.2 is that connecting only node L is not dominated by connecting only node H.[25]

As a result, additional inefficiencies can occur when the transmission line to the high wind location H is more costly than the transmission line to the low wind location L. In this case it is preferable to connect only node L if the higher expected wind output at node H does not justify the additional grid investment costs. If wind power investors move first they will however prefer the better wind location H and therefore force the transmission operator to build the more costly transmission line. Analogous to Section 2.2 a perfectly regulated and perfectly informed transmission operator can implement the first best solution by anticipating investment decisions of wind power producers and building the optimal network configuration proactively. The mathematical formulation of the central planner problem with asymmetric grind investment costs is provided in Appendix 2.5.2.

The case of asymmetric grid investment costs has practical relevance because in existing electricity systems there are typically suitable areas for wind power production close to demand centers or existing grid infrastructure which can be integrated at comparably low costs. The areas with the best wind properties on the other hand are often remote and are thus costly to connect to the existing infrastructure. Lamy et al. (2016) show for example that developing the best wind locations in the United States could be inefficient if transmission extensions are included in the assessment. Similarly, Wu et al. (2014) argue that the renewable support mechanism in China incentivized large wind power investments in central China, where the best wind locations are located. However, these areas are far away from the coastal industrial demand centers and therefore costly to connect to the existing grid infrastructure. As a result up to a third of the installed wind power capacity in China is idle and lacks proper grid connection. Against the backdrop of these practical examples the present theoretical analysis underlines the importance of a well designed regulatory framework that coordinates private wind power investment and grid extensions.

2.3.2 Imperfect regulation

The results in Section 2.2 are based on the assumption of benevolent behavior of the transmission operator as a result of perfect regulation. In reality transmission companies are not perfectly regulated and follow their own agenda inside the reg-

[25] Note that a setting with two nodes where demand is located at one node and wind power investment is possible at both nodes can be modeled by setting grid investment costs for the connection to node H or node L to zero. The two node setting is therefore a special case of the three node model with asymmetric grid investment costs.

ulatory constraints. Depending on the regulatory system incentives to overinvest or underinvest compared to the socially optimal network configuration can emerge. Regulatory systems that incentivize overinvestment according to standard economic theory are cost-plus and rate-of-return regulation.[26] Under rate-of-return regulation the transmission operator is allowed to recover investment costs and to earn an additional rate of return which is set by the regulator. In the analyzed model a revenue maximizing transmission operator under rate of return regulation profits from building transmission lines to both wind locations. Hence, given the decision variables from Section 2.2.4, the transmission operator can limit the transfer capacity to node H to a value below the renewable target K_T in order to force wind power investors to develop both locations in all considered subsidy systems.[27] Proactive behavior therefore enables the transmission operator to always build both transmission lines and earn the guaranteed revenue.

An example for a regulatory system that incentivizes underinvestment is price-cap regulation with no adjustments of the cap based on the investment activity of the transmission operator.[28] In such a regulatory system the transmission operator would try to build as little transmission capacities as possible. Assuming that the transmission operator acts proactively and is obliged to enable the realization of the renewable target, it would be optimal to connect only one wind location. With symmetric grid investment costs, the transmission operator is indifferent between locations. With asymmetric investment costs he connects only the location with lower grid investment costs.

The two examples show that imperfect regulation can lead to substantial inefficiencies in grid investment when the transmission operator invests proactively in an unbundled electricity system. A more detailed analysis of the impact of different regulatory regimes on the coordination problem between renewable energy investment and grid investment is left for further research.

[26] See for example Averch and Johnson (1962).

[27] It is assumed that the transmission operator is not able to connect a location where no wind power capacity will be built in the second stage. Therefore he has to limit transfer capacity in order to steer investments.

[28] For a detailed discussion of the effects of price-cap regulation on investment behavior see for example Laffont and Tirole (1993). Modern regulatory systems based on incentive and yardstick regulation can also be seen as a type of price-cap regulation where the price-cap is revised regularly based on industry benchmarks, see Joskow (2014). A comparison of rate-of-return and price-cap regulation can be found in Liston (1993).

2.3.3 G-component

One of the main results of Section 2.2 is that wind power investors do not necessarily choose system optimal locations for their investments. Additionally it has been shown that proactive behavior of a benevolent transmission operator leads to the optimal system configuration, which is however only applicable under perfect regulation. An alternative approach to directly influence the investment behavior of wind power investors is a location-dependent g-component. A g-component is a network charge which is set by the regulator and paid by power generators for the electrical energy they feed into the grid. This section analyzes if such a charge can be set to a level that reflects the impact of investments into new generation capacity on overall system costs, leading to an internalization of the external effects of private investments.

A g-component is not applicable in a feed-in-tariff system because the lack of market signals for investors does not incentivize diversification of locations. Therefore a g-component could only shift investments entirely from the high wind location to the low wind location. In feed-in premium systems however, a g-component can alter the relationship between the revenue generated from spot market sales and fixed premium payments which determines the profitability of diversification for investors. Consequently, a g-component can adjust the investment problem of private investors, formulated in Equation (2.9) in order to harmonize it with Proposition 2.1.

Assuming that developing the low wind location is socially inefficient, the regulator can choose to charge a g-component at location L in order to deincentivize private investments. By introducing the g-component G_L into Equation (2.9) and combining it with Proposition 2.1, the following lower bound for G_L can be derived:

$$G_L \geq \frac{I^G}{\big(K_T-(d-\bar{q})\big)(\rho_l+\rho_{lh})} - \frac{(\rho_h-\rho_l)*FIP}{(\rho_l+\rho_{lh})} \tag{2.15}$$

The first term in Equation (2.15) shows that the g-component introduces the grid investment costs as well as the renewable target K_T into the maximization problem of wind power investors. The minimum value of G_L increases with I^G and decreases with K_T because the social costs of developing the low wind location L are high if the connection is costly and if only small amounts of wind power capacity are built at node L, which still require the full lumpy grid investment. The second term in Equation (2.15) results from the higher fixed premium payments at node H and reduces the lower bound for G_L.

A lower bound for G_H in order to incentivize investments at node L can be derived analogously, the results are provided in Appendix 2.5.2. Similarly to the feed-in premium case, a g-component can be used to steer locational choices of private investors in a subsidy system with direct capacity payments. The resulting lower bound for G_L to prevent potential overdiversification can be obtained by setting FIP to zero in the solution of the feed-in premium case. Underdiversification of wind locations is not possible in a system with direct capacity payments as shown in Section 2.2.

2.4 Conclusion

This article analyzes interactions between the locational choice of private wind power investors in unbundled electricity systems under different subsidy schemes and the required grid investments to integrate the wind power capacity into the system. I find that private investors do not choose system optimal wind locations in feed-in tariff schemes, feed-in premium schemes and subsidy systems with direct capacity payments. In feed-in tariff schemes inefficiencies result from the lack of internalization of the market value of the produced electricity into investment decisions. Under feed-in premium schemes and capacity subsidies the market value is internalized, but the system integration costs are not. Consequently, all three subsidy systems can result in inefficient system configurations if the transmission operator follows wind power investments.

The described inefficiencies can be prevented if a benevolent transmission operator anticipates investment decisions of private investors and steers investment in a system optimal way. Consequently, anticipative transmission investment can help to efficiently integrate generation capacities based on renewable energy sources into electricity systems. However, benevolent behavior is only applicable under perfect regulation. In absence of perfect regulation, incentives to implement the system configuration that maximizes the profit of the transmission operator inside the regulatory constraints arise. A possibility to directly influence investment decisions of private investors by internalizing the system integration costs are location-dependent grid charges for power producers.

The results of the analysis show that support schemes for renewable electricity generation should be designed with awareness for the consequences on the locational choice of investors. In addition, policy makers should assign a more active role to transmission operators, which acknowledges the importance of anticipative investment behavior. However, inefficient steering of renewable investments by transmission companies as a result of imperfect regulation should be of concern. Finally it is shown that power systems which internalize not only the market value of electricity but also the location-dependent integration costs for generation capacities into private investment decisions should be designed.

In future work, the model can be extended with more complex representations of stochastic wind generation. Another possibility for further research is an application of the model with real-world power systems in order to quantify the inefficiencies of uncoordinated renewable energy and grid investments. Also an extension with endogenous investment into conventional generation, multiple renewable technologies or the introduction of incomplete information of the transmission operator regarding the quality of wind locations are promising additions.

2.5 Appendix

2.5.1 Proofs

Proof of Proposition 2.1.
The problem can be solved by comparing the different network configurations. $L_L = 0$ enforces $L_H = 1$ and $Cap_H = K_T$. $L_H = 0$ enforces $L_L = 1$ and $Cap_L = K_T$. If $L_L = 1$ and $L_H = 1$, $Cap_H + Cap_L = K_T$ follows. $L_H = 0$ and $L_L = 0$ can be immediately ruled out because of $K_T > 0$.

For $K_T \leq (d - \bar{q})$, $\frac{\partial \mathbf{E}(C_D)}{\partial Cap_H} < \frac{\partial \mathbf{E}(C_D)}{\partial Cap_L}$ holds because of $\rho_h > \rho_l$. It follows that $L_L = 1$ and $Cap_L > 0$ is never optimal, which is equivalent to the first part of Proposition 2.1.

For $K_T > (d - \bar{q})$ several cases have to be compared. Because $\mathbf{E}(C_D)$ is piecewise linear and strictly decreasing in K_H and K_L the optimal solution must be either $Cap_H = K_T$ and $Cap_L = 0$, $Cap_H = 0$ and $Cap_L = K_T$, $Cap_H = d - \bar{q}$ and $Cap_L = K_T - (d - \bar{q})$ or $Cap_H = K_T - (d - \bar{q})$ and $Cap_L = (d - \bar{q})$. Because of $\rho_h > \rho_l$ the solution $Cap_H = K_T$ and $Cap_L = 0$ dominates $Cap_H = 0$ and $Cap_L = K_T$ and $Cap_H = d - \bar{q}$ and $Cap_L = K_T - (d - \bar{q})$ dominates $Cap_H = K_T - (d - \bar{q})$ and $Cap_L = (d - \bar{q})$ for $K_T \leq 2(d - \bar{q})$. Plugging the remaining candidates for the cost minimum into Equations (2.4) and (2.6a) and comparing the results yields the second part of Proposition 2.1 after some reformulation. □

Proof of Proposition 2.2a.
Plugging Equations (2.3a), (2.3b) and (2.3c) into Equation (2.7a) and taking the first derivative with respect to K_H and K_L yields $\frac{\partial \mathbf{E}(\pi_i)}{\partial K_H} > \frac{\partial \mathbf{E}(\pi_i)}{\partial K_L}$ because of $\rho_h > \rho_l$. $L_H = 1$ and $L_L = 1$ can be assumed for reactive behavior of the transmission operator as transmission lines are built according to wind power investment. □

Proof of Proposition 2.2b.

Equation (2.8a) can be reformulated as follows with $K_{A,i} = K_{H,i} + K_{L,i}$:

$$\mathbf{E}(\pi_i) = \begin{cases} (FIP + c_1)\big(\rho_h K_{H,i} + \rho_l K_{L,i} + \rho_{hl} K_{A,i}\big) - I^W K_{A,i} \\ \qquad \text{if } \sum_i K_{H,i} > d - \bar{q},\ \sum_i K_{L,i} > d - \bar{q} \\ (FIP + c_2)\,\rho_l K_{L,i} + (FIP + c_1)\big(\rho_h K_{H,i} + \rho_{hl} K_{A,i}\big) - I^W K_{A,i} \\ \qquad \text{if } \sum_i K_{H,i} > d - \bar{q},\ \sum_i K_{L,i} \le d - \bar{q} \\ (FIP + c_2)\,\rho_h K_{H,i} + (FIP + c_1)\big(\rho_l K_{L,i} + \rho_{hl} K_{A,i}\big) - I^W K_{A,i} \\ \qquad \text{if } \sum_i K_{H,i} \le d - \bar{q},\ \sum_i K_{L,i} > d - \bar{q} \\ (FIP + c_2)\big(\rho_h K_{H,i} + \rho_l K_{L,i}\big) + (FIP + c_1)\,\rho_{hl} K_{A,i} - I^W K_{A,i} \\ \qquad \text{if } \sum_i K_{H,i} \le d - \bar{q},\ \sum_i K_{L,i} \le d - \bar{q},\ \sum_i K_{A,i} > d - \bar{q} \\ (FIP + c_2)\big(\rho_h K_{H,i} + \rho_l K_{L,i} + \rho_{hl} K_{A,i}\big) - I^W K_{A,i} \\ \qquad \text{if } \sum_i K_{H,i} \le d - \bar{q},\ \sum_i K_{L,i} \le d - \bar{q},\ \sum_i K_{A,i} \le d - \bar{q} \end{cases} \tag{2.16}$$

The partial derivatives with respect to $K_{H,i}$ and $K_{L,i}$ are:

$$\frac{\partial \mathbf{E}(\pi_i)}{\partial K_{H,i}} = \begin{cases} (FIP + c_1)(\rho_h + \rho_{hl}) - I^W & \text{if } \sum_i K_{H,i} > d - \bar{q} \\ (FIP + c_2)\,\rho_h + (FIP + c_1)\,\rho_{hl} - I^W & \text{if } \sum_i K_{H,i} \le d - \bar{q},\ \sum_i K_{A,i} > d - \bar{q} \\ (FIP + c_2)(\rho_h + \rho_{hl}) - I^W & \text{if } \sum_i K_{H,i} \le d - \bar{q},\ \sum_i K_{A,i} \le d - \bar{q} \end{cases} \tag{2.17}$$

$$\frac{\partial \mathbf{E}(\pi_i)}{\partial K_{L,i}} = \begin{cases} (FIP + c_1)(\rho_l + \rho_{hl}) - I^W & \text{if } \sum_i K_{L,i} > d - \bar{q} \\ (FIP + c_2)\,\rho_l + (FIP + c_1)\,\rho_{hl} - I^W & \text{if } \sum_i K_{L,i} \le d - \bar{q},\ \sum_i K_{A,i} > d - \bar{q} \\ (FIP + c_2)(\rho_l + \rho_{hl}) - I^W & \text{if } \sum_i K_{L,i} \le d - \bar{q},\ \sum_i K_{A,i} \le d - \bar{q} \end{cases} \tag{2.18}$$

Because of the assumption of free market entry, investors develop the locations in descending order of marginal revenue. For $K_T \le (d - \bar{q})$, $\frac{\partial \mathbf{E}(\pi_i)}{\partial K_{H,i}} > \frac{\partial \mathbf{E}(\pi_i)}{\partial K_{L,i}}$ holds and $Cap_L > 0$ is never optimal. For $K_T > (d - \bar{q})$, comparing (2.17) and (2.18) yields Equation (2.9). □

Proof of Proposition 2.2c.

The capacity subsidy is equivalent to a reduction of the investment costs for wind power I^W. Consequently, the optimal solution can be derived analogously to Proposition 2.2b with $FIP = 0$. □

Proof of Proposition 2.3.

$L_H = 1$ and $L_L = 0$ implements $Cap_H = K_T$ and $Cap_L = 0$, the first part of Proposition 2.3 follows.

If the transmission operator decides to limit transfer capacity $\overline{L_H}$ two cases can be distinguished. If $Cap_H \leq \overline{L_H}$ the decision problem for renewable investors is unchanged compared to Propositions 2.2a, 2.2b and 2.2c. For $Cap_H > \overline{L_H}$, the marginal revenue $\frac{\partial \mathbf{E}(\pi_i)}{\partial Cap_{H,i}}$ equals $-I^W$, so $Cap_H \leq \overline{L_H}$ in the competitive case. In the monopolistic case, $Cap_{H,i}$ can be substituted by $\overline{L_H}$ in the definition of the five cases in Equation (2.16). Comparing this adjusted Equation (2.16) with $Cap_H = \overline{L_H}$ to $Cap_H > \overline{L_H}$ shows that $\mathbf{E}\big(\pi_i\left(Cap_H = \overline{L_H}\right)\big) > \mathbf{E}\big(\pi_i\left(Cap_H > \overline{L_H}\right)\big)$. Consequently the transmission operator chooses $L_H = 1$, $L_L = 1$ and $\overline{L_H} = (d - \bar{q})$ if it is optimal according to Proposition 2.1. □

2.5.2 Extensions

Asymmetric grid investment costs

Introducing asymmetric investment costs leads to the following expression for total system costs:

$$C_{Total} = \mathbf{E}(C_D) + I^W (Cap_H + Cap_L) + I_H^G * L_H + I_L^G * L_L \tag{2.19}$$

For $K_T \leq d - \bar{q}$ connecting both nodes H and L is dominated by connecting only node H because it is always preferable to build all wind power capacity at the better wind location H when both nodes are connected. Comparing the two possible outcomes for connecting one wind location leads to the condition in Equation (2.20) for developing the low wind location.

$$c_2(\rho_h - \rho_l)K_T > I_H^G - I_L^G \tag{2.20}$$

For renewable targets $K_T > d - \bar{q}$ all three possible network configurations have to be considered. Comparing the outcomes for the configurations with only one of the wind locations connected to the demand node D leads to Equation (2.21a). Equation (2.21b) gives the condition for lower system costs when both wind nodes are connected compared to only node H connected, Equation (2.21c) gives the condition for lower system costs when both wind nodes are connected compared to only node L connected.

$$(\rho_h - \rho_l)\Big(c_1\big(K_T - (d - \bar{q})\big) + c_2\,(d - \bar{q})\Big) > I_H^G - I_L^G \tag{2.21a}$$

$$(c_2\rho_l - c_1\rho_h)\big(K_T - (d - \bar{q})\big) > I_L^G \tag{2.21b}$$

$$(c_2 - c_1)\,\rho_l\big(K_T - (d - \bar{q})\big) + c_2\,(\rho_h - \rho_l)\,(d - \bar{q}) > I_H^G \tag{2.21c}$$

Additional expressions for g-component

Introducing G_H into Equation (2.9) and combining it with Proposition 2.1 yields:

$$G_H \geq \frac{(\rho_h - \rho_l) * FIP}{(\rho_h + \rho_{lh})} - \frac{I^G}{\big(K_T - (d - \bar{q})\big)(\rho_h + \rho_{lh})} \tag{2.22}$$

3 Distributed Generation in Unbundled Electricity Markets

Electricity systems are increasingly characterized by distributed generation technologies, e.g. rooftop photovoltaic systems, which are used by end consumers to directly produce electricity. Additionally, empirical evidence suggests that electricity retailers exercise market power in many unbundled electricity markets. Against this backdrop this articles analyzes the impact of distributed generation on imperfect retail markets for electricity in a spatial competition framework. I find that distributed generation puts competitive pressure on retailers and induces lower retail prices. Therefore even consumers who do not use distributed generation benefit. Based on this effect regulators can shift welfare to consumers by subsidizing distributed generation in order to position it as a competitor to grid-based electricity. However, if only a limited share of demand can be supplied with distributed generation, there is a point at which retailers disregard the substitutable share of demand and focus on the non-substitutable consumption in order to realize higher mark-ups. As a result, increased subsidies for distributed generation can increase retail prices and harm consumers. With optimal subsidies this strategy of retailers is prevented by limiting usage of distributed generation.

3.1 Introduction

Electricity markets are increasingly influenced by distributed generation technologies such as rooftop photovoltaic systems, small-scale combined heat and power plants or wind turbines, which are used by end consumers to directly produce electricity.[1] End consumers use distributed generation to substitute grid-based electricity, which is produced in large-scale power plants and transported to consumers via transmission and distribution infrastructure. This development is also refereed to under the term "prosumage", which indicates that households or businesses are at the same time consumers and producers of electricity. Conceptually the choice

[1] A general discussion of distributed generation in electricity markets is provided in Pepermans et al. (2005).

whether to consume grid-based electricity or produce electricity from distributed generation can be compared to "make-or-buy" or "do-it-yourself" decisions which are present in many markets.[2]

In most cases distributed generation is currently not competitive to centralized large-scale electricity production. However, especially distributed generation technologies based on renewable energy sources often receive financial support either via direct subsides such as feed-in tariffs or via indirect support mechanisms. Indirect subsidization is typically a result of exemption rules which exempt distributed generation from tax or grid fee payments, which both account for a significant share of the total cost of grid-based electricity in practice.[3] Consumers compare the subsidized cost of distributed generation to the price of grid-based electricity when they decide on becoming a "prosumer". Therefore direct subsidy payments, exemption rules and the prices charged by retailers are key drivers for the adoption of distributed generation.

In the course of the liberalization and restructuring of electricity markets over the last decades, many retail markets for electricity in the United States and the European Union have been unbundled and organized competitively.[4] In competitive retail markets, consumers can choose between different retailers depending on their individual preference. Despite this possibility, empirical evidence indicates that only a small share of customers switches retailers in many of the restructured markets and in particular local retailers can realize substantial margins.[5] One possible explanation for these margins are strong consumer preferences towards specific suppliers as a result of risk aversion, imperfect information or advertising activities.[6]

Against the described backdrop this paper analyzes the impact of distributed generation on retail markets for electricity with imperfect competition. Based on this analysis, optimal regulatory strategies with respect to subsidies for distributed generation and grid fees are evaluated. The analysis builds on a standard Hotelling

[2]See for example Sappington (2005).

[3]The average total household electricity price in the European Union consisted of 27% network charges, 25% taxes and 13% charges for renewable energy support. See Agency for the Cooperation of Energy Regulators and Council of European Energy Regulators (2016).

[4]Retail competition is mandatory in the European Union. In the United States roughly half of the states introduced retail competition. See International Energy Agency (2016b) for an overview.

[5]See Agency for the Cooperation of Energy Regulators and Council of European Energy Regulators (2016) for an overview of retail mark-ups in European electricity markets. A similar analysis for Texas can be found in Puller and West (2013).

[6]See Defeuilley (2009) for a discussion of possible drivers of low switching rates and high margins. Empirical analyses can be found for example in Hortaçsu et al. (2017) for Texas, He and Reiner (2017) for Britain, Yang (2014) for Denmark, Duso and Szücs (2017) for Germany, Daglish (2016) for New Zealand or Shin and Managi (2017) for Japan.

spatial competition framework in order to capture market power of retailers as a consequence of heterogeneous consumer preferences.[7] Consumers may choose distributed generation as an alternative to grid-based electricity purchased from retailers. However, only a limited share of total demand can be supplied with distributed generation, which means that some electricity is always received from retailers. This assumption reflects that not every consumer is able to use distributed generation and full autarky from the grid is very costly or even impossible with available technologies.

The analysis shows, that the availability of distributed generation increases competition in the retail market. Hence, as soon as distributed generation is competitive to grid-based electricity, retailers adjust prices and reduce mark-ups. The regulator can exploit this behaviour by subsidizing distributed generation in order to position it as a competitor to grid-based electricity, which reduces market power of retailers and shifts producer rents to consumers. As retail prices are reduced for all consumption, this strategy benefits also consumers who are unable to use distributed generation. However, there is a point where retailers discard the share of electricity consumption which can be substituted with distributed generation and prefer to serve only non-substitutable demand with high mark-ups. As a result, increasing subsidies for distributed generation increases retail prices and therefore harms consumers if retailers discard the substitutable share of demand. Additionally it is shown that optimal subsidization can be realized with grid fee exemptions. However, optimal subsidies can only be implemented with a two-part tariff structure. Grid fee exemptions with volumetric tariffs are not applicable to implement the optimal regulatory strategy.

The paper is mainly related to two literature streams. The first relevant literature stream examines distributed generation technologies in electricity markets. The majority of papers within this stream focuses on numerical simulations or general discussions.[8] Formal analyses of distributed generation are scarce. Brown and Sappington (2017b) build a theoretical model to assess optimal compensation for distributed generation. They find that the optimal policy varies depending on the available instruments and the type of distributed generation technology. However, capacity charges are crucial in order to induce efficient investment into distributed generation. In Brown and Sappington (2017a) this analysis is extended in a very similar model framework in order to analyze net metering policies for small-scale solar power generation. They conclude that the optimal payment for distributed

[7] This model class was first presented in Hotelling (1929).

[8] Simulation studies on the impact of distributed generation can be found for example in Eid et al. (2014), Darghouth et al. (2016) or Munoz-Alvarez et al. (2018).

generation should reflect changes in conventional generation, distribution and network management costs as well as external effects such as environmental benefits. However, a net metering mandate is unlikely to meet these requirements. In both analyses the value chain of electricity supply is assumed to be vertically integrated, which means that unbundling and imperfect retail markets are not considered. Gautier et al. (2018) analyze interactions between distributed generation and grid infrastructure in a theoretical framework. They find that support of distributed generation via net metering overencourages investment into distributed generation and that consumers without access to distributed generation technologies cross subsidize distributed generation investments. The retail market is assumed to be perfectly competitive in their analysis.

The second relevant literature stream consists of applications of spatial competition models. On the one hand the paper is related to models of spatial competition with outside goods, which were first conceptualized in Salop (1979). This model class has been applied for example in Balasubramanian (1998) or Nakayama (2009) to analyze the impact of mail order businesses on traditional retail shops. On the other hand the paper is related to applications of spatial competition frameworks in an energy context. Tode (2016) assesses energy efficiency measures in a model with imperfect competition and imperfect consumer information. Retail markets for electricity with switching costs are analyzed in Ruiz et al. (2015). Distributed generation is not part of the analysis.

In summary the contribution of the paper is threefold. First, distributed generation in unbundled electricity markets is analyzed in a theoretical model with an explicit representation of imperfect competition in the retail market. Second, optimal regulatory strategies and subsidy mechanisms are assessed within this model framework. Third, the impact of distributed generation on recovery of grid costs is evaluated.

The remainder of the paper is structured as follows. Section 3.2 introduces the basic model setup. Section 3.3 analyzes the retail market problem. Building on that, Section 3.4 analyzes optimal subsidies for distributed generation. In Section 3.5, grid fee exemption rules and the impact of the share of electricity demand that can be substituted with distributed generation are discussed as model extensions.

3.2 Model setup

We consider an electricity market with two symmetric retailers R_1 and R_2, who sell electricity to consumers. Two types of consumers are differentiated: a mass α of consumers C_s, who can substitute grid-based electricity consumption with distributed generation and a mass $2-\alpha$ of consumers C_{ns}, who are unable to use distributed generation. This differentiation reflects two practical issues. First, some consumers are unable to use distributed generation for example because of financial, legal or constructional restrictions. Second, even consumers who use distributed generation, typically maintain a grid connection and use both grid-based and self generated electricity. This is especially the case for distributed generation based on weather-dependent renewable energy sources such as wind or solar, where grid-based electricity is used as a back-up when wind and solar generation is unavailable. Consequently α can be interpreted as the share of demand of consumers who are unable to use distributed generation as well as the share of electricity demand that can not be substituted because of unavailability of distributed generation for example during the night. In the basic model, $\alpha = 1$ is assumed. The basic model results are generalized in Section 3.5.2.

Retailers maximize profits by buying electricity in a wholesale market at price w and selling it to consumers at retail prices p_{R1} and p_{R2}. Retailers are assumed to be price takers in the wholesale market. Additionally retailers are horizontally differentiated and consumers have heterogeneous preferences towards retailers. To model consumer preferences and horizontal differentiation a spatial competition framework is applied, where parameter t represents the degree of differentiation. Retailers are not able to discriminate prices. Therefore, they always charge the same retail price for both consumer groups C_s and C_{ns}. The cost of electricity production with distributed generation technologies is c_{DG}.[9] Additionally a subsidy σ is in place that reduces the effective costs of distributed generation for end consumers. The subsidy is set by a benevolent regulator. It is assumed that that $c_{DG} - \sigma \geq w$, which means that the subsidized cost of distributed generation exceeds the wholesale price for electricity.

The dynamic structure of the model consist of three stages. In the first stage, the regulator sets subsidies for distributed generation σ. In the second stage, the

[9]The model considers only one period of electricity production and consumption. A differentiation between fixed and variable costs is not required due to this simplification. Hence, w and c_{DG} can be interpreted as the total specific costs of wholesale electricity and distributed generation over the model period.

two retailers R_1 and R_2 set retail prices in order to maximize profits. In the third stage, consumers choose between retailers and distributed generation. The dynamic structure of the model is depicted graphically in Figure 3.1. The model is solved by backward induction. The retail market is considered first, followed by the regulator problem.

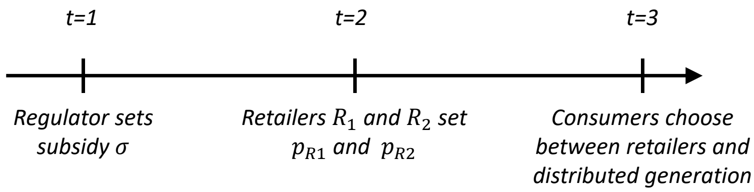


Figure 3.1: Dynamic model setting

3.3 The retail market

3.3.1 Consumer problem

Consumers C_{ns} and C_s are assumed to be uniformly distributed along two separate Hotelling lines with a normalized length of one.[10] The two symmetric retailers R_1 and R_2 are located at the endpoints of both lines. The distance between the retailers represents horizontal differentiation and consumers are located at a location along the line according to their preference towards the retailers. The position of consumers C_{ns} is denoted by $x_{ns} \in [0,1]$ and the position of consumers C_s is denoted by $x_s \in [0,1]$. Every consumer receives a fixed utility v from consuming one unit of electricity. It is assumed that v is sufficiently large such that consumers always choose to consume electricity, which means that total electricity demand is perfectly inelastic. Because of $\alpha = 1$ demand of consumers C_s and C_{ns} is normalized to one in the basic model.

Depending on which retailer consumers choose, they pay a retail price p_{R1} or p_{R2} for electricity consumed from the grid. Additionally, consumers have costs tx for consumption from retailer R_1 and $t(x-1)$ for consumption from retailer R_2 depending on their position $0 \leq x \leq 1$. These costs can be interpreted as a disutility for consumers who cannot choose a retailer that perfectly matches their preferences.

[10] The chosen model structure with two separate Hotelling lines that differentiate two groups of consumers is similar to the model presented in Zēgners and Kretschmer (2016).

Consumers C_s can substitute grid-based electricity with distributed generation. The subsidized cost of distributed generation is $c_{DG} - \sigma$.

Formally the net utility consumers C_{ns} and C_s derive from grid-based electricity consumption purchased via retailer R_i can be described by Equation (3.1a), where x_i represents the position of retailer i.[11] The respective net utility from usage of distributed generation is described by Equation (3.1b):

$$U_{grid} = v - p_{Ri} - t\,|x_i - x| \tag{3.1a}$$

$$U_{DG} = v - (c_{DG} - \sigma) \tag{3.1b}$$

As consumers C_{ns} are unable to use distributed generation, their net utility U_{ns} of grid-based electricity consumption is directly described by Equation (3.1a). Because v is sufficiently large by assumption, this utility is strictly positive and consumers C_{ns} always consume grid-based electricity. Consumers C_s on the other hand compare net utility from grid-based electricity to net utility from distributed generation. The net utility U_s of grid-based electricity consumption for consumers C_s can therefore be determined by the difference between Equations (3.1a) and (3.1b). U_s is only positive if the subsidized cost of distributed generation exceeds the sum of retail price and preference dependent disutility. Otherwise net utility from grid-based consumption is negative and consumers C_s use distributed generation to directly produce electricity. The formal expressions for U_{ns} and U_s are presented in Equations (3.2a) and (3.2b):

$$U_{ns} = v - p_{Ri} - t\,|x_i - x_{ns}| \tag{3.2a}$$

$$U_s = c_{DG} - \sigma - p_{Ri} - t\,|x_i - x_s| \tag{3.2b}$$

Based on Equations (3.2a) and (3.2b) the demand served by each retailer i can be derived by solving for the indifferent consumer between purchasing from retailers R_1 or R_2 and for the indifferent consumer C_s between using grid-based electricity or

[11] In the following $i \in \{1, 2\}$ is used to symbolize retailers 1 and 2 in order to simplify notation. $-i$ stands for the corresponding other retailer.

distributed generation respectively. The following demand function can be derived:

$$q_{Ri} = \begin{cases} \dfrac{t + p_{R-i} - p_{Ri}}{t} & \text{if } p_{R-i} - t \leq p_{Ri} \leq 2(c_{DG} - \sigma) - p_{R-i} - t \\ \dfrac{t + p_{R-i} - p_{Ri}}{2t} + \dfrac{c_{DG} - \sigma - p_{Ri}}{t} & \text{if } 2(c_{DG} - \sigma) - p_{R-i} - t \leq p_{Ri} \leq c_{DG} - \sigma \\ \dfrac{t + p_{R-i} - p_{Ri}}{2t} & \text{if } p_{Ri} > c_{DG} - \sigma \end{cases} \tag{3.3}$$

Equation (3.3) shows that three cases can be distinguished for the demand function. In the first case, distributed generation is not competitive to grid-based consumption for all consumers. As a result, demand from retailers depends only on retail prices and the preference dependent disutility for consumers. The subsidies for distributed generation are irrelevant as all consumption is grid-based. In the second case, distributed generation is used by some consumers C_s. Consequently, retailers compete against distributed generation for the substitutable share of electricity demand. For this share, demand depends on the relationship between the subsidized cost of distributed generation $c_{DG}-\sigma$ and the retail price p_{Ri}. The non-substitutable consumption is still determined by competition between the retailers. In the third case, all substitutable demand is covered with distributed generation and retailers compete for consumers C_{ns}. The subsidized cost of distributed generation $c_{DG} - \sigma$ directly effects the demand function only in the second case. However, changes in $c_{DG} - \sigma$ shift the boundaries between the three cases of the demand functions. An increase in the subsidy for example shifts the boundaries to lower levels and enlarges the relative size of the second case of the demand function. The demand for distributed generation is determined by the residual $q_D = 2 - q_{R1} - q_{R2}$ in all three cases.

3.3.2 Retailer problem

The two retailers buy electricity in the wholesale market at an exogenous wholesale price w. They are located at the endpoints of the Hotelling lines and are assumed to maximize profits π_{R1} and π_{R2}. Retailers set retail prices p_{R1} and p_{R2} according to Problem (3.4). Quantities sold to consumers q_{Ri} are determined by Equation (3.3).

$$\max_{p_{Ri}} \pi_{Ri} = q_{Ri} * (p_{Ri} - w) \tag{3.4}$$

Retailer profits depend on the different cases of the demand function, which means that profits differ if a retailer serves both consumer groups C_{ns} and C_s or if he focuses only on consumption that can not be substituted with distributed generation. Based on the demand function four different cases have to be distinguished in order to solve the retailer problem. These cases are illustrated graphically in Figure 3.2.

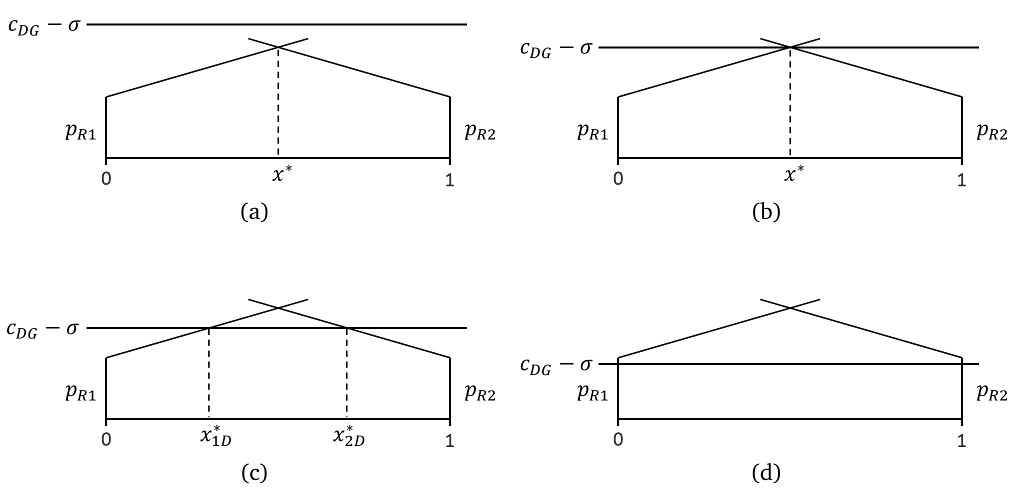


Figure 3.2: Exemplary relations between retail price and cost of distributed generation

Figure 3.2 shows the total cost of grid-based electricity consumption depending on the location x_s of consumers C_s in comparison to the subsidized cost of distributed generation $c_{DG}-\sigma$. In the first case, depicted in Figure 3.2(a), the cost of distributed generation exceeds the sum of retail prices and preference dependent disutility for all x_s. As a result, all consumers use grid-based electricity and choose the retailer which is closest to their preference. Demand is determined by the first case of Equation (3.3). In Figure 3.2(b) distributed generation has reached a cost level at which a marginal reduction would yield it competitive for consumers with the largest preference dependent disutility, which are located in the middle of the Hotelling line. Again all consumers use grid-based electricity, however with a marginal cost reduction, some consumers would start to use it and demand would be determined by the second case of Equation (3.3). In the third case according to Figure 3.2(c), distributed generation is the preferred option for some consumers. Consequently, consumers located between x^*_{1D} and x^*_{2D} avoid grid-based electricity consumption by using distributed generation. Demand is described by the second part of Equation (3.3). In the fourth case, depicted in Figure 3.2(d), distributed generation is cheaper for all consumers and the substitutable electricity consumption is entirely supplied with distributed generation. Usage of grid-based electricity is determined by the third case of Equation (3.3).

Based on the first order conditions derived from Equation (3.4) the following reaction function can be obtained:[12]

$$p_{Ri}(p_{R-i}) = \begin{cases} \dfrac{t+p_{R-i}+w}{2} & \text{if } p_{R-i}-t \leq p_{Ri} \leq 2(c_{DG}-\sigma)-p_{R-i}-t \\ \dfrac{t+p_{R-i}+3w+2(c_{DG}-\sigma)}{6} & \text{if } 2(c_{DG}-\sigma)-p_{R-i}-t \leq p_{Ri} \leq c_{DG}-\sigma \\ \dfrac{t+p_{R-i}+w}{2} & \text{if } p_{Ri} > c_{DG}-\sigma \end{cases} \tag{3.5}$$

Expressing the boundary conditions between the first and the second case of Equation (3.5) in terms of p_{R-i} yields the following equations:

$$p_{R-i} \leq \frac{4(c_{DG}-\sigma)-w-3t}{3} := p'_{R-i} \tag{3.6a}$$

$$p_{R-i} > \frac{10(c_{DG}-\sigma)-3w-7t}{7} := p''_{R-i} \tag{3.6b}$$

Because p''_{R-i} is strictly larger than p'_{R-i} for $c_{DG}-\sigma > w$ there is a region between p'_{R-i} and p''_{R-i} where the best response is not defined by the three cases of Equation (3.5). In this region $\frac{\partial \pi_{Ri}}{\partial p_{Ri}}$ is strictly positive for $p_{Ri} < 2(c_{DG}-\sigma)-p_{R-i}-t$ and strictly negative for $p_{Ri} > 2(c_{DG}-\sigma)-p_{R-i}-t$. As a result, the optimal reaction is $p_{Ri} = 2(c_{DG}-\sigma)-p_{R-i}-t$, which is exactly the boundary between cases 1 and 2 of Equation (3.5).[13]

Expressing the boundary conditions between the second and the third case of Equation (3.5) in terms of p_{R-i} yields the following equations:

$$p_{R-i} \leq 4(c_{DG}-\sigma)-3w-t := p'''_{R-i} \tag{3.7a}$$

$$p_{R-i} > 2(c_{DG}-\sigma)-w-t := p''''_{R-i} \tag{3.7b}$$

Because p''''_{R-i} is strictly smaller than p'''_{R-i} for $c_{DG}-\sigma > w$ the best response can be given by both the second and the third case of Equation (3.5) between p'''_{R-i} and p''''_{R-i}. Substituting both cases into the profit function and comparing the resulting profits yields $\hat{p}_{R-i} := (1+\sqrt{3})(c_{DG}-\sigma)-\sqrt{3}w-t$ as the boundary condition. Based on the

[12] The first order conditions are presented in Equation (3.16) in Appendix 3.7.1.
[13] This case is discussed in detail in Mérel and Sexton (2010).

described results, the reaction function is reformulated in Equation (3.8).

$$p_{Ri}(p_{R-i}) = \begin{cases} \dfrac{t + p_{R-i} + w}{2} & \text{if } p_{R-i} \leq p'_{R-i} \\ 2(c_{DG} - \sigma) - p_{R-i} - t & \text{if } p'_{R-i} < p_{R-i} \leq p''_{R-i} \\ \dfrac{t + p_{R-i} + 3w + 2(c_{DG} - \sigma)}{6} & \text{if } p''_{R-i} < p_{R-i} \leq \hat{p}_{R-i} \\ \dfrac{t + p_{R-i} + w}{2} & \text{if } p_{R-i} > \hat{p}_{R-i} \end{cases} \tag{3.8}$$

The four cases of the reaction function correspond to the four cases depicted in Figure 3.2. In the first case distributed generation is not used. In the second case distributed generation is at the margin to competitiveness. In the third case some consumers C_s use distributed generation and in the fourth case all substitutable consumption is supplied with distributed generation.

Solving the reaction functions for the four possible equilibria and determining the parameter values under which they emerge gives the equilibrium solution of the retailer problem:

Lemma 3.1. *There are four types of symmetric equilibria depending on the relationship between the subsidized costs of distributed generation $c_{DG} - \sigma$, wholesale price w and the degree of horizontal differentiation t:*

$$p_{Ri} = \begin{cases} w + t & \textit{if } c_{DG} - \sigma \geq w + \dfrac{3}{2}t \\ c_{DG} - \sigma - \dfrac{t}{2} & \textit{if } w + \dfrac{7}{6}t \leq c_{DG} - \sigma < w + \dfrac{3}{2}t \\ \dfrac{2(c_{DG} - \sigma) + 3w + t}{5} & \textit{if } w + \dfrac{2\sqrt{3}}{5+\sqrt{3}}t \leq c_{DG} - \sigma < w + \dfrac{7}{6}t \\ w + t & \textit{if } c_{DG} - \sigma < w + \dfrac{2}{1+\sqrt{3}}t \end{cases} \tag{3.9}$$

Proof. See Appendix 3.7.1.

The reaction functions are depicted graphically in Figure 3.3. The decisive model parameter is the effective cost of distributed generation $c_{DG}-\sigma$ because it determines to which extent distributed generation interferes with the strategic interactions of the two retailers. The reaction function described in Equation (3.8) consists of four parts of which the intermediate parts are directly affected by changes in $c_{DG} - \sigma$. Both are shifted downwards as $c_{DG} - \sigma$ decreases which explains the four possible

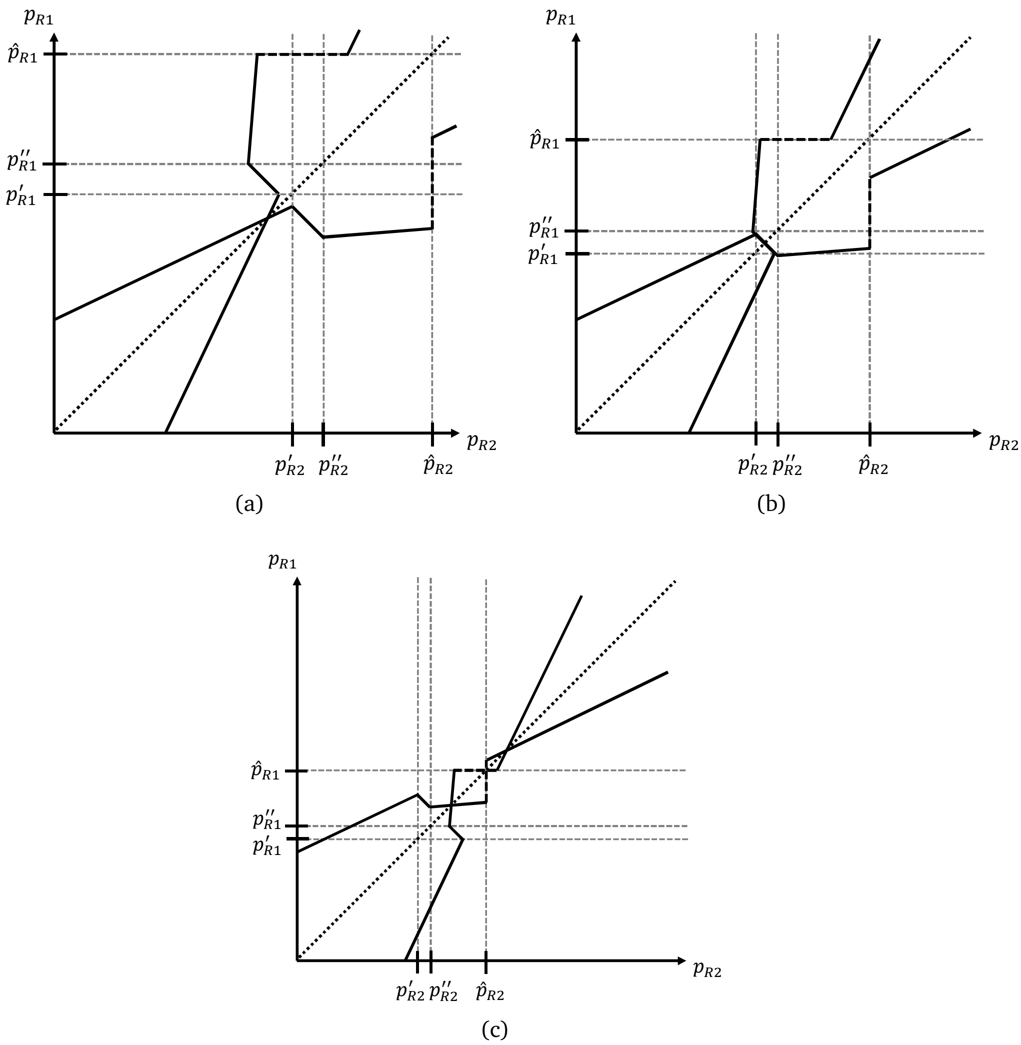


Figure 3.3: Reaction functions and different types of equilibria

equilibrium regions described in Lemma 3.1.

If $c_{DG} - \sigma$ is very large, distributed generation is too expensive to be an alternative to grid-based electricity for all consumers. Consequently, the standard result of spatial competition models applies. This case is depicted in Figure 3.3(a).

As $c_{DG} - \sigma$ decreases, the first consumer is tempted to substitute grid-based electricity with distributed generation. The equilibrium answer of the retailers is to lower prices in order to render distributed generation just unattractive for consumers. As shown in Figure 3.3(b) the reaction functions are downward sloping and overlap for this type of equilibrium. As a result there exist technically an infinite number of asymmetric equilibria. Restricting to symmetric equilibria yields the unique equilibrium described in Lemma 3.1.[14] The reaction functions are downward sloping because distributed generation is at the margin to competitiveness. If one of the retailers increases the price in this situation, consumers located in the middle of the Hotelling line start to use distributed generation. The best response of the corresponding other retailer is then to lower the price in order to gain market share and reestablish the situation in which distributed generation is just unattractive for the consumer with the largest preference dependent disutility.

If $c_{DG} - \sigma$ further decreases, it is no longer worthwhile for the retailers to fully compensate increased competitiveness of distributed generation with price reductions. Instead retailers give up on those customers least attracted to one of the two firms, which are located in the middle of the Hotelling line. Consequently, these consumers start to use distributed generation and avoid grid-based electricity consumption. This equilibrium corresponds to the left intersection of the reaction functions in Figure 3.3(c).

Finally, if distributed generation is very cheap, retailers give up on all substitutable electricity consumption. As a result retailers fully disregard consumers C_s and focus on the non-substitutable share of electricity demand. As indicated by the right intersection of the reaction functions in Figure 3.3(c), retailers return to the high equilibrium price of the first case. As shown in Figure 3.3(c), the reaction functions can intersect twice, which means that serving consumers C_s and C_{ns} as well as as disregarding consumers C_s are equilibrium solutions. From Lemma 3.1 follows that this can only be the case for $w + \frac{2\sqrt{3}}{5+\sqrt{3}}t \leq c_{DG} - \sigma < w + \frac{2}{1+\sqrt{3}}t$. Based on the described equilibria in the retail market Proposition 3.1 is formulated.

Proposition 3.1. *Increasing subsidies for distributed generation can increase the retail price for grid-based electricity.*

Proof. See Appendix 3.7.1.

Figure 3.4 depicts retail prices as a function of the subsidized cost of distributed generation $c_{DG} - \sigma$ in order to clarify the intuition of Proposition 3.1. Figure 3.5 depicts the corresponding retailer profits.[15] Figures 3.4 and 3.5 distinguish five areas, which are discussed from right to left in the following.

[14] As pointed out by Mérel and Sexton (2010), the focus on symmetric equilibria is not too restrictive because introducing even a slight elasticity into consumer demand establishes a unique symmetric equilibrium. Additionally the range of retail prices in the asymmetric equilibria is relatively small.

[15] The mathematical expressions of retailer profits are presented in the appendix.

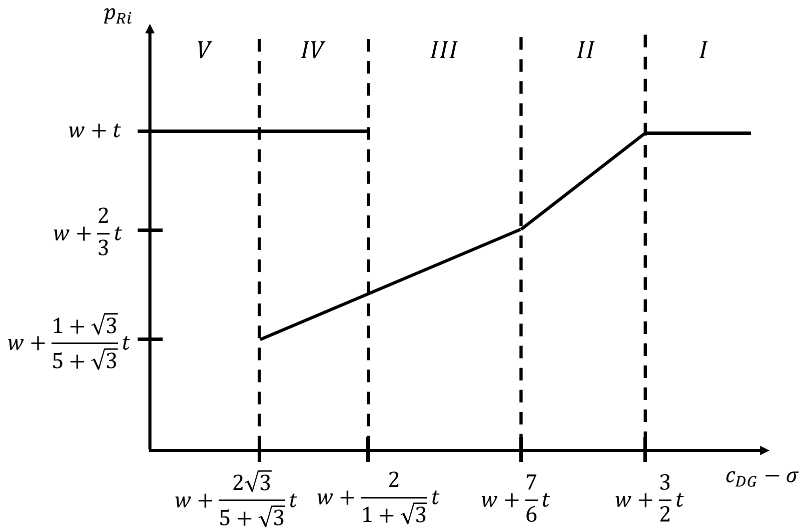


Figure 3.4: Retail prices in equilibrium

In area I, the retail market is not affected by distributed generation and each retailer earns a profit of t by charging a mark-up t on wholesale prices, which corresponds to the first case of Equation (3.9). In area II, retailers adjust retail prices to keep the market fully covered with grid-based electricity as described in the second case of Equation (3.9). Profits linearly decrease with $c_{DG} - \sigma$ because the quantity of sold electricity remains constant. In area III retailers further adjust prices but consumers in the middle of the Hotelling line start to use distributed generation. The slope of the price function in the third case is lower because there are price and quantity adjustments to changes in $c_{DG} - \sigma$. The profit function is quadratic for the same reason.

In area IV there are two possible equilibria which means that the reaction functions intersect in the third and in the fourth case of Equation (3.8). As a result, price adjustments as in area III as well as disregarding consumers C_s in order to serve only non-substitutable electricity consumption with higher mark-ups yield stable symmetric equilibria. Retailer profits are strictly larger in the equilibrium where only consumers C_{ns} are served with grid-based electricity in area IV. Finally in area V there is again only one symmetric equilibrium, in which retailers discard consumers C_s and all substitutable electricity consumption is met with distributed generation.

With respect to the level of subsidization for distributed generation Figure 3.4 shows that an increase in subsidies lowers retail prices as long as both consumer groups C_{ns} and C_s are served by retailers because distributed generation puts com-

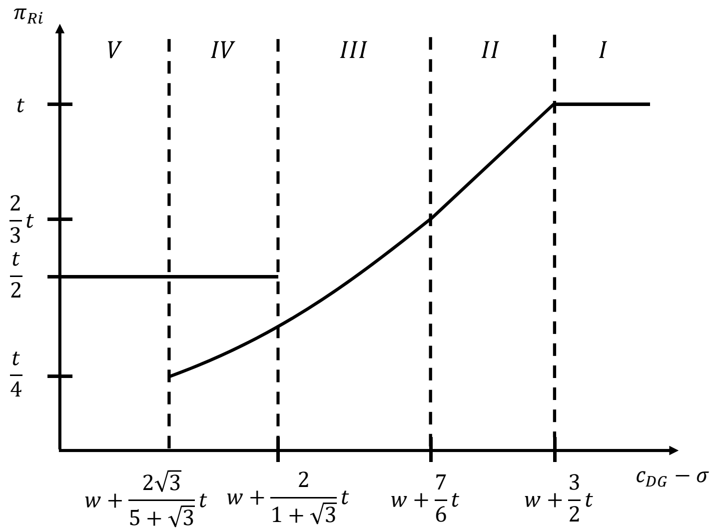


Figure 3.5: Retailer profits in equilibrium

petitive pressure on retailers. However, if $c_{DG} - \sigma$ is already sufficiently low, an increase in subsidization can shift the equilibrium from a situation in which both consumer groups C_{ns} and C_s are served to an equilibrium in which only consumers C_{ns} are served by retailers. If this is the case, the increased subsidization increases retail prices as stated in Proposition 3.1.

3.3.3 Welfare effects

This section assesses the implications of the presented results on welfare. First the effect on consumer surplus is discussed, followed by a discussion of total welfare effects.

Consumer surplus

Consumer surplus consists of surplus of consumers C_s and C_{ns}, which differs depending on the retail market outcome. Both surplus functions can be determined by substituting the results of Lemma 3.1 into the utility functions and integrating over the consumer taste parameter x. The resulting total consumer surplus function is presented in Lemma 3.2.

Lemma 3.2. *Consumer surplus in equilibrium is described by the following equation:*

$$CS = \begin{cases} 2v - 2w - \frac{5}{2}t & \text{if } c_{DG} - \sigma \geq w + \frac{3}{2}t \\ 2v - 2(c_{DG} - \sigma) + \frac{t}{2} & \text{if } w + \frac{7}{6}t \leq c_{DG} - \sigma < w + \frac{3}{2}t \\ 2v - 2(c_{DG} - \sigma) + \frac{9(c_{DG} - \sigma - w + \frac{t}{2})^2}{25t} - \frac{t}{2} & \\ & \text{if } w + \frac{2\sqrt{3}}{5+\sqrt{3}}t \leq c_{DG} - \sigma < w + \frac{7}{6}t \\ 2v - w - (c_{DG} - \sigma) - \frac{5}{4}t & \text{if } c_{DG} - \sigma < w + \frac{2}{1+\sqrt{3}}t \end{cases} \tag{3.10}$$

Proof. See Appendix 3.7.1.

The consumer surplus function consists of four parts, analogously to the four types of retail market equilibria. The subsidized cost of distributed generation $c_{DG} - \sigma$ determines the retail market outcome and the subsequent level of consumer surplus. The main result with respect to the influence of subsidization of distributed generation on consumer surplus is described in Proposition 3.2.

Proposition 3.2. *Increasing subsidies for distributed generation can reduce consumer surplus even if consumers do not contribute to financing the subsidy payments.*

Proof. See Appendix 3.7.1.

To clarify the implications of Proposition 3.2, Figure 3.6 depicts the net effect of distributed generation on consumer surplus ΔCS as a function of $c_{DG} - \sigma$.[16] Analogously to Figure 3.4 five areas are distinguished. In area I the retail market is unaffected by distributed generation. In area II, retailers adjust prices in order to keep the entire market covered with grid-based electricity. As a result, consumer surplus increases as $c_{DG} - \sigma$ decreases. Both consumer groups benefit from lower prices for distributed generation because prices are adjusted for all consumers. In area III, consumers start to use distributed generation. Again, both consumer groups benefit from price adjustments as $c_{DG} - \sigma$ decreases. Additionally consumer group C_s avoids costs due to taste mismatch by using distributed generation. Therefore, the surplus of consumers C_s in area III is strictly above surplus of consumers C_{ns} and the

[16] Formally the net effect of distributed generation on consumer surplus is defined as $\Delta CS = CS - (2v - 2w - \frac{5}{2}t)$.

consumer surplus function is quadratic. In area IV there exist two equilibria, one in which both consumer groups C_{ns} and C_s are served and one in which consumers C_s are disregarded by retailers. In area V, there is again a unique equilibrium in which only consumers C_{ns} are served by retailers. If only consumers C_{ns} are served by retailers, consumer surplus increases as $c_{DG} - \sigma$ decreases because consumers C_s benefit from lower costs of distributed generation.

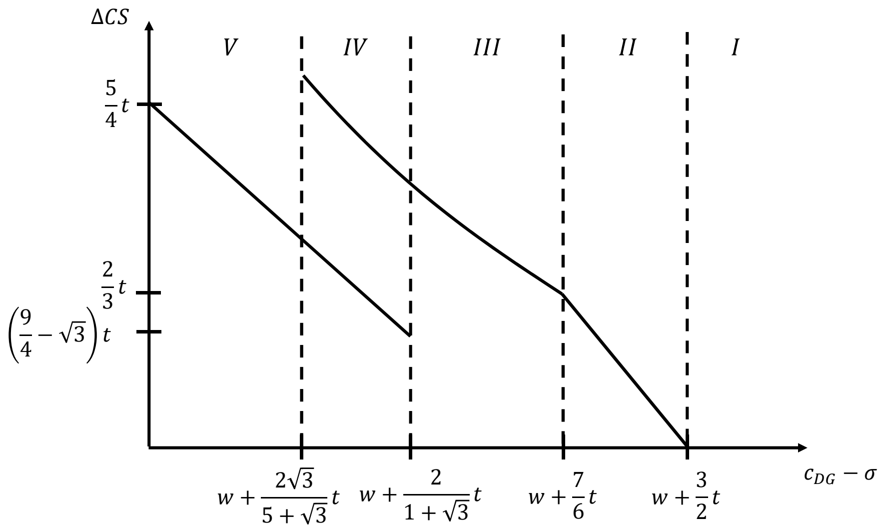


Figure 3.6: Effect of distributed generation on consumer surplus

As shown in Figure 3.6 there is a discontinuity in the consumer surplus function when consumers C_s are discarded by retailers. This discontinuity results of two effects. First, consumer group C_{ns} is charged a higher retail price $p_{Ri} = w+t$. Because of the higher retail price, surplus of consumers C_{ns} is strictly below the surplus of consumers C_s if consumer group C_s is discarded by retailers. Second, all consumers C_s are pushed into usage of distributed generation when retailers raise prices to $p_{Ri} = w + t$. A direct result from these two effects is that an increase in subsidy payments can decrease consumer surplus if the increased subsidy payments induce retailers to discard substitutable electricity demand in order to focus on the non-substitutable share of demand. This holds true even if the subsidy comes at no costs for consumers, which is assumed in this section.

Total surplus

Total welfare can be determined as the sum of retailer profits and consumer surplus. The aggregated welfare effects are described in Lemma 3.3.

Lemma 3.3. *Total surplus in equilibrium is described by the following equation:*

$$TS = \begin{cases} 2v - 2w - \dfrac{t}{2} & \text{if } c_{DG} - \sigma > w + \dfrac{7}{6}t \\ 2v - 2(c_{DG} - \sigma) + \dfrac{84(c_{DG} - \sigma - w + \frac{t}{2})^2}{100t} - \dfrac{t}{2} & \\ & \text{if } w + \dfrac{2\sqrt{3}}{5+\sqrt{3}}t \leq c_{DG} - \sigma < w + \dfrac{7}{6}t \\ 2v - w - (c_{DG} - \sigma) - \dfrac{t}{4} & \text{if } c_{DG} - \sigma < w + \dfrac{2}{1+\sqrt{3}}t \end{cases} \tag{3.11}$$

Proof. See Appendix 3.7.1.

Because of the assumed inelastic electricity demand, total welfare changes are limited to two effects. First, consumers avoid costs due to taste mismatch when they use distributed generation. Second, distributed generation is more costly than the wholesale price for electricity. Consequently consumers avoid paying rents to retailers by using an outside option that would not be competitive without the mark-ups charged by retailers. Based on the effect of subsidies for distributed generation on total surplus, Proposition 3.3 is formulated.

Proposition 3.3. *Usage of distributed generation increases total surplus if and only if* $c_{DG} - \sigma < w + \frac{1}{4}t$.

Proof. See Appendix 3.7.1.

To illustrate the intuition behind Proposition 3.3, Figure 3.7 depicts the net effect of distributed generation on total surplus ΔTS.[17] Again five areas are distinguished in Figure 3.7. In area I, the retail market is unaffected by distributed generation. In area II, retailers adjust prices to keep the market fully covered with grid-based electricity. However, total surplus remains unchanged because welfare is shifted from retailers to consumers without a net effect on total surplus. In area III distributed

[17] Formally the net effect of distributed generation on total surplus is defined as $\Delta TS = TS - (2v - 2w - \frac{t}{2})$.

generation enters the market and consumers avoid paying rents to retailers by directly producing electricity. However, distributed generation is still costly compared to the wholesale price of electricity when it enters the market because of the mark-up charged by retailers. As a result, the decrease in retailer profits outweighs the increase in consumer surplus and total surplus decreases as consumers start to adopt distributed generation.

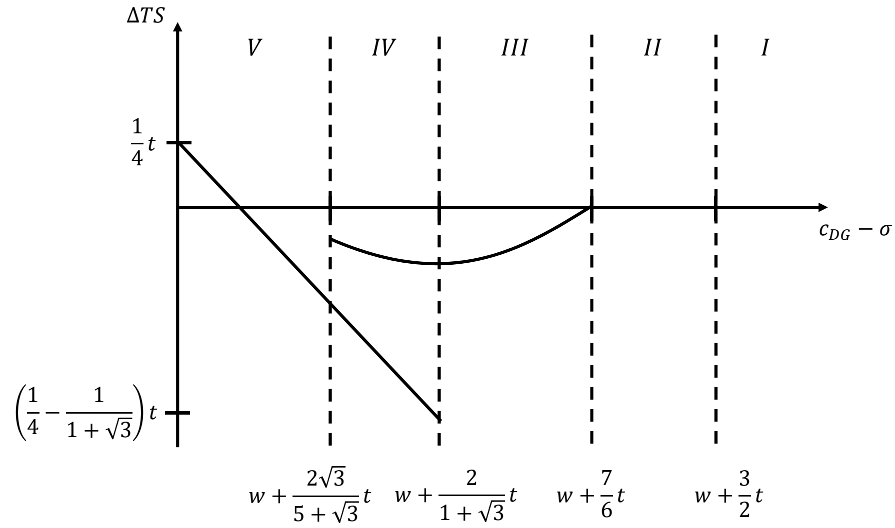


Figure 3.7: Effect of distributed generation on total surplus

In area IV further price adjustments as well as discarding consumers C_s are equilibrium solutions. A switch to an equilibrium, in which consumers C_s are discarded by retailers always decreases total surplus in area IV because all consumers C_s are pushed into usage of distributed generation. In area V, only discarding consumers C_s is an equilibrium solution. For low values of $c_{DG}-\sigma$ in area V total surplus is higher compared to a situation without usage of distributed generation. This increase in total surplus emerges because all consumers C_s use distributed generation and therefore avoid costs due to taste mismatch. Consequently, total surplus increases if the avoided costs due to taste mismatch exceed the difference between the subsidized costs of distributed generation $c_{DG}-\sigma$ and the wholesale price w.

3.4 Regulator problem

In the first stage of the model, the regulator decides on the subsidy for distributed generation. In this section, the optimal regulatory strategy is derived. In contrast to the welfare effects discussed in the previous section, the cost of the subsidy payments are accounted for in the regulator problem. It is assumed that the regulator maximizes consumer welfare. Hence, a consumer surplus standard is applied in the model. Applying a consumer surplus standard instead of a total surplus standard in competition policy is controversial in economic literature. However it seems appropriate in the present context for two reasons. First, retail markets for electricity are still highly concentrated in many countries, which makes reducing market power of suppliers one of the main regulatory concerns in practice. Second, unbalanced powers between consumers and producers as a result of information asymmetries and lobbying activities, which is one of the main arguments in favor of a consumer surplus standard, seem to be an issue in the electricity industry.[18]

The regulator maximizes consumer surplus while taking into account the costs of the subsidy. Subsidy payments are assumed to be refinanced by end consumers on a per capita basis, which means that consumers can not avoid contributing to subsidy financing.[19] The resulting maximization problem for the regulator is formulated in Equation (3.12).

$$\max_{\sigma}\ CS - \sigma * q_D \tag{3.12}$$

The regulator maximizes the difference between consumer surplus CS and subsidy payments which are determined by the product of the level of subsidization σ and the usage of distributed generation q_D. The regulator problem is solved by substituting the consumer surplus function formulated in Lemma 3.2 into Equation (3.12).

An important issue is that the regulator faces the possibility of multiple equilibria in the retail market, which means that the regulator can not anticipate with certainty the resulting equilibrium for some levels of subsidization.[20] Two different types of equilibria can emerge, in which retailers either choose to serve both consumer groups C_s and C_{ns} or choose to discard consumers C_s and serve only consumers C_{ns} in order to realize higher margins. The second type of equilibrium leads to strictly lower consumer surplus when multiple equilibria are possible.[21] Because of this relation, it is assumed that the regulator does not risk the realization of the consumer harming equilibrium. This assumption can be interpreted as risk averse

[18] For a general discussion of consumer surplus vs total surplus standard, see Motta (2004). A discussion of market concentration in retail markets for electricity in the United States and the European Union is provided in Morey and Kirsch (2016). Kang (2015) empirically analyzes lobby activity of the energy and electric utility industry in the United States

[19] See Section 3.5.1 for a discussion of a setting where consumers can avoid contributing to subsidy financing by using distributed generation.

[20] See Lemma 3.2.

[21] See Figure 3.6.

behavior of the regulator. Based on the described assumptions the optimal subsidy policy is summarized in Lemma 3.4.

Lemma 3.4. *Depending on the relationship between the cost of distributed generation and the wholesale price of electricity, the regulator chooses the following subsidies:*

(i) For $c_{DG} - w > \frac{11}{6}t$, the regulator positions distributed generation as a competitor to grid-based electricity with $\sigma = c_{DG} - w - \frac{7}{6}t$. There is no usage of distributed generation.

(ii) For $\frac{11}{6}t \geq c_{DG} - w \geq \frac{15+\sqrt{3}}{5+5\sqrt{3}}t$, the regulator implements the optimal amount of distributed generation with $\sigma = \frac{1}{7}(2(c_{DG} - w) + t)$.

(iii) For $c_{DG} - w < \frac{15+\sqrt{3}}{5+5\sqrt{3}}t$, the regulator avoids additional distributed generation in order to prevent retailers from charging the full mark-up while discarding consumers C_s with $\sigma = c_{DG} - w - \frac{2}{1+\sqrt{3}}t$.

Proof. See Appendix 3.7.1.

The implications of Lemma 3.4 are best understood with the depiction of the consumer surplus function in Figure 3.6. As discussed in Section 3.3.3, consumers can benefit from distributed generation even if it is not used because retailers adjust prices in order keep the market fully covered with grid-based electricity. This can be exploited by the regulator to reduce market power of retailers and shift welfare from producers to consumers. Consequently, the regulator subsidizes distributed generation even if the usage is inefficient in order to position it as a competitor to grid-based electricity which is described in the first part of Lemma 3.4. This redistribution of welfare is without a cost because no distributed generation is used and no subsidy payments have to be made. In the second case of Lemma 3.4, distributed generation is adopted by some consumers. The regulator chooses optimal subsidies in order to internalize the competitive effect of distributed generation into consumer decisions.

With increased adoption of distributed generation, retailers discard the substitutable share of electricity demand in order to charge higher mark-ups on the non-substitutable demand, which leads to a decrease in consumer surplus. In the third case of Lemma 3.4, the regulator avoids this pricing strategy by setting the subsidy to a level, which ensures that retailers always choose to serve both consumer groups. Hence, the regulator avoids additional distributed generation in order to prevent retailers from raising prices. The regulator therefore never chooses a subsidy level that leads to full substitution of demand of consumers C_s with distributed generation. This result is independent of the assumed risk averseness of the regulator. Under a different assumption, the regulator would risk the realization of the equilibrium where consumers C_{ns} are discarded. However the regulator would still strictly prefer the retail equilibrium in which both consumer groups are served. The results are summarized in Proposition 3.4.

Proposition 3.4. *If the cost of subsidy payments is accounted for, maximal usage of distributed generation is never welfare optimal for consumers.*

Proof. See Appendix 3.7.1.

To give additional intuition for Proposition 3.4, Figure 3.8 shows the solution of the regulator problem as a function of c_{DG}. The depiction additionally differentiates between the two consumer groups C_s and C_{ns}. In area I, no distributed generation is used but the regulator sets subsidies in order to position distributed generation as a competitor to grid-based electricity which induces positive welfare effects for both consumer groups. In area II, distributed generation enters the market. Both consumer groups benefit as retail prices are further reduced. Consumers C_s additionally avoid costs caused by taste mismatch which leads to a level of surplus strictly above the surplus of consumers C_{ns} for $c_{DG} < w + \frac{11}{6}t$. In area III the amount of distributed generation used by consumers C_s is constant because the regulator avoids additional usage in order to protect consumers from higher retail prices. Nevertheless surplus for both consumer groups further increases with decreasing costs of distributed generation because the required subsidy payments decrease if distributed generation becomes more competitive.

3.5 Extensions

This section presents two extensions of the basic model framework. Section 3.5.1 analyzes interactions between distributed generation and grid fees. Section 3.5.2 discusses the impact of the share of electricity demand that can be substituted with distributed generation.

3.5.1 Distributed generation and grid fees

In practice distributed generation is often subsidized indirectly with exemption rules. In many countries distributed generation is exempted from grid fee payments. In

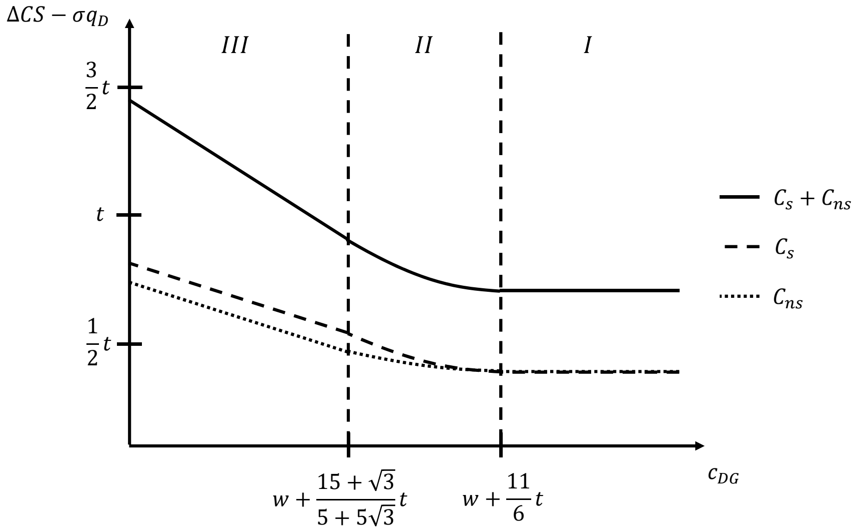


Figure 3.8: Solution of the regulator problem

order to asses this within the presented model framework it is assumed that the electricity purchased from retailers has to be transported to consumers via a grid infrastructure, which causes fixed costs $fixc > 0$. Grid costs have to be recovered by charging grid fees. It is assumed that a benevolent grid operator sets grid fees in order to maximize consumer welfare analogously to the regulator in Section 3.4. Two model settings are considered. In the first setting, the grid operator sets a two-part tariff consisting of an avoidable variable component p_G and a fixed component f. This configuration is comparable to a network tariff regime with a volumetric component charged based on consumption from the grid and a fixed component charged based on the capacity of the grid connection. In the second setting, the grid operator can only set an avoidable variable component p_G, which corresponds to volumetric tariff structures in practice.

In the first analyzed model setting consumers can avoid the variable grid fee component by using distributed generation, while the fixed component f can not be avoided. The exemption from grid fee payments is modeled by setting $\sigma = p_G$. The resulting problem of the grid operator is formulated in Equations (3.13a) and (3.13b). Consumer surplus CS is determined by the surplus function presented in Lemma 3.3 with $\sigma = p_G$. Additionally, grid fee payments are added to the surplus function and the cost recovery constraint in Equation (3.13b) is introduced.

$$\max_{p_G, f} CS \tag{3.13a}$$

$$\text{s.t. } p_G * (q_{R1} + q_{R2}) + 2 * f \geq fixc \tag{3.13b}$$

As there are no direct subsidy costs in the case of grid fee exemptions, the objective function (3.13a) consists only of consumer surplus. The solution of Problem (3.13) is presented in Lemma 3.5.

Lemma 3.5. *Depending on the relationship between the cost of distributed generation and the wholesale price of electricity the grid operator chooses the following tariff structures:*

(i) For $c_{DG} - w > \frac{11}{6}t$, the grid operator positions distributed generation as a competitor to grid-based electricity with $p_G = c_{DG} - w - \frac{7}{6}t$. There is no usage of distributed generation and $f = \frac{fixc}{2} - p_G$ ensures recovery of grid costs.

(ii) For $\frac{11}{6}t \geq c_{DG} - w \geq \frac{15+\sqrt{3}}{5+5\sqrt{3}}t$, the grid operator implements the optimal amount of distributed generation with:

$$p_G = \frac{1}{7}\big(2(c_{DG} - w) + t\big) \tag{3.14a}$$

$$f = \frac{fixc}{2} - \frac{6}{49t}\left(c_{DG} - w + \frac{t}{2}\right)^2 \tag{3.14b}$$

(iii) For $c_{DG} - w < \frac{15+\sqrt{3}}{5+5\sqrt{3}}t$, the grid operator avoids additional distributed generation in order to prevent retailers from charging the full mark-up while disregarding consumers C_s. Grid fees are set to $p_G = c_{DG} - w - \frac{2}{1+\sqrt{3}}t$ and $f = \frac{fixc}{2} - (q_{R1} + q_{R2})\frac{p_G}{2}$.

Proof. See Appendix 3.7.1.

Lemma 3.5 shows, that the optimal subsidy policy can be implemented with grid fee exemption rules. However, the optimal strategy can only be realized with a two-part tariff structure. In that case the grid operator can use the variable grid fee to incentivize optimal usage of distributed generation and adjust the fixed tariff accordingly in order to ensure recovery of grid costs. The fixed fee f could even be negative if the required subsides for distributed generation are large. Because of the two-part tariff structure it is ensured that all consumers contribute to financing fixed grid costs. Consequently, costs are allocated in accordance with the cost causation principle as distributed generation typically does not change fixed network costs in the short to medium term, especially if consumers keep a grid connection.[22]

In practice, grid fees often consist only of volumetric tariffs charged based on the amount of electrical energy withdrawn from the grid. The main difference in a system with volumetric tariffs compared to a two-part tariff structure is that fixed grid costs have to be recovered with variable grid fees. This causes additional incentives to use distributed generation if decentralized production is exempted from grid fee payments because consumers can avoid contributing to fixed cost financing by using distributed generation. Within the presented model framework this leads to the following reformulation of Problem (3.13):

$$\max_{p_G} CS \tag{3.15a}$$

$$\text{s.t. } p_G * (q_{R1} + q_{R2}) \geq fixc \tag{3.15b}$$

In the adjusted grid operator problem, there is only one decision variable p_G. A direct result of this limitation is that the regulator is unable to position distributed generation as a competitor to grid-based electricity because high variable grid fees directly reduce consumer surplus and a compensation via the fixed fee is not possible. Additionally, as distributed generation is adopted and consumers start to avoid grid fees by using distributed generation, the fixed grid costs have to be burdened on a smaller consumer base, which incentivizes additional usage of distributed generation. Because of this effect a stable solution where only a share of substitutable electricity demand is supplied with distributed generation exists only under strict conditions. If fixed grid costs are high compared to the other cost components of the electricity systems a spiral effect is induced and all substitutable demand is met with distributed generation as soon as it is the cheaper option for the first consumer.[23] Consequently, a volumetric grid fee structure leads to inefficient levels of distributed generation within the presented model. The results are summarized in Proposition 3.5. The detailed solution of Problem (3.15) is presented in Appendix 3.7.1.

Proposition 3.5. *Optimal subsidization of distributed generation can be implemented based on grid fee exemptions only with a two-part tariff structure.*

Proof. See Appendix 3.7.1.

[22]The issue of fixed cost recovery in the electricity system is discussed in detail in Borenstein (2016).

[23]This effect is sometimes refereed to as the death spiral of public utilities, see Castaneda et al. (2017) for a discussion.

3.5.2 The share of substitutable electricity demand

In the basic model $\alpha = 1$ is assumed. Consequently, the electricity demand that can be substituted with distributed generation equals the non-substitutable electricity demand. In reality the substitutable share of demand varies depending on a variety of factors such as technological constraints, geographical conditions, weather conditions or consumer characteristics. To analyze the impact of the share of substitutable electricity demand, this section generalizes the presented model by varying parameter α, while total electricity demand is kept unchanged. Hence, a share α of total demand can be substituted with distributed generation while the remaining $2 - \alpha$ can be supplied only with grid-based electricity.

The solution of the generalized model follows the same logic as the presented solution of the basic model. The detailed derivation is presented in Appendix 3.7.2. Interestingly, varying the share of substitutable demand shifts the solution space but the main implications of the model remain. To illustrate the generalized model results, Figure 3.9 depicts retail prices, retailer profits, consumer surplus and total surplus for different shares of substitutable electricity demand. As additional references, model results for $\alpha = 0$, which means that no distributed generation is available, and for $\alpha = 2$, which means that that electricity demand can be entirely supplied with distributed generation, are depicted in Figure 3.9.

Figure 3.9(a) depicts the mark-up charged by retailers. It is evident that the basic intuition described in Lemma 3.1 and Proposition 3.1 is independent of the value of α. However, the higher the share of substitutable demand, the more retailers are willing to reduce the mark-up in order to compete against distributed generation. The reason is that the remaining demand they can cover if the substitutable share of demand is discarded, decreases as α increases. The corresponding effects on retailer profits are depicted in Figure 3.9(b). The decrease in retailer profits is more pronounced the higher the share of substitutable demand. If only a small share of demand can be substituted with distributed generation, retailers choose earlier to supply only the non-substitutable share which stabilizes profits on a higher level.

The described dependency of retailer mark-ups on the level of α also shift the consumer surplus function as shown in Figure 3.9(c). Again, the basic shape of the function described in Lemma 3.2 remains. However, the potential gains in consumer surplus are higher, if a large share of demand can be supplied with distributed generation. Additionally, the drop in consumer surplus when retailers discard the substitutable share of demand, is smaller for large and small values of α and has a

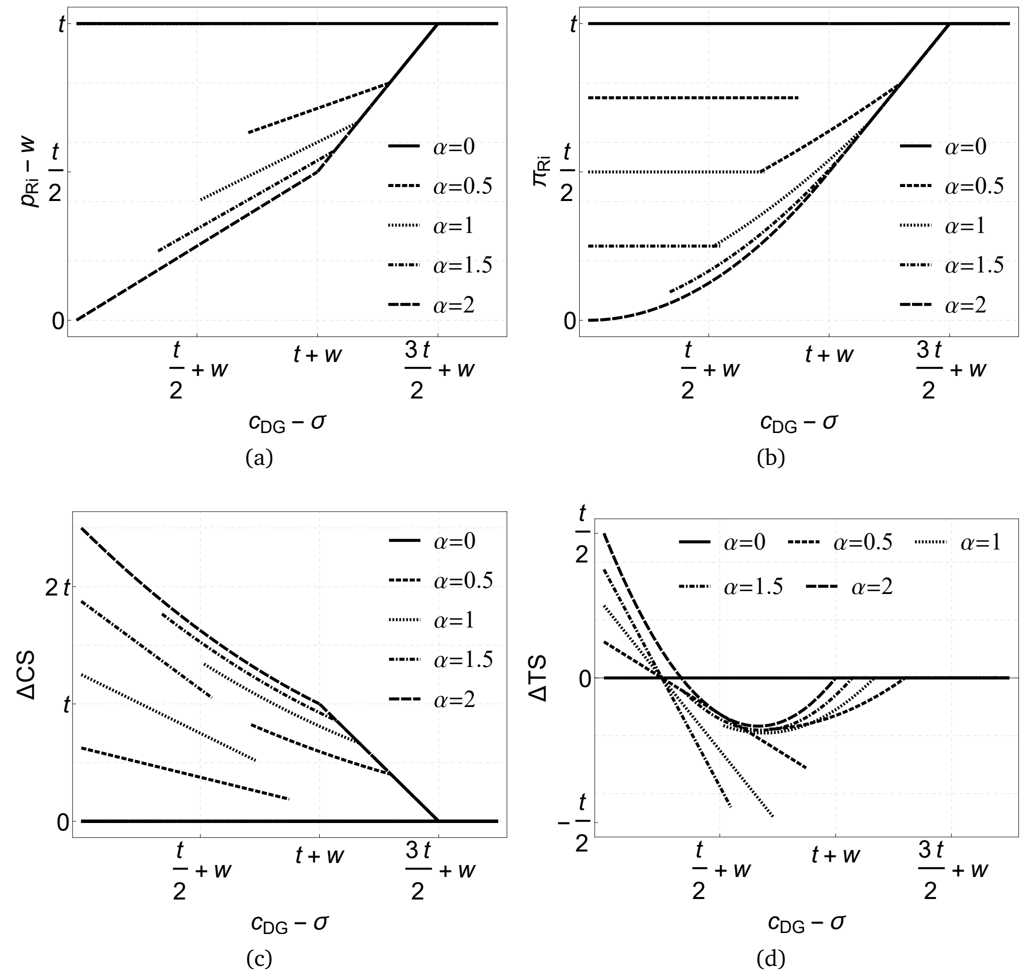


Figure 3.9: Retailer mark-up (a), retailer profits (b), consumer surplus (c) and total surplus (d) for different levels of α

maximum for medium values. The reason for this is that as α increases, a smaller share of the consumers is affected when retailers raise prices. As α decreases on the other hand, retailers are less willing to adjust prices to distributed generation and discard the substitutable share of demand earlier, which leads to a less pronounced discontinuity.

The discussed effects also transfer to the shape of the total surplus function depicted in Figure 3.9(d). It can be seen that total surplus always decreases as consumers start to adopt distributed generation. The reason is that consumers avoid paying rents to retailers, which those generate by exercising market power. However, distributed generation is still more costly compared to the wholesale price for electricity when the first consumers start to use it, which leads to the decrease in total surplus. The breakeven point for total surplus is at $c_{DG} - \sigma = w + \frac{t}{4}$ for most possible values of α, which is consistent with Proposition 3.3. Only for high values of α above 1.6, there are potentially positive welfare effects when both consumer groups are served by retailers which leads to a break-even point at slightly higher levels of $c_{DG} - \sigma$.[24]

The dependency of consumer surplus on α also shapes the optimal regulatory strategy for subsidizing distributed generation. Nevertheless, the key properties of Lemma 3.4 remain. It is always beneficial for consumers if the regulator positions distributed generation as a competitor to grid-based electricity. However for low values of α, retailers are more reluctant to reduce prices as a response to the outside competition because the share of non-substitutable demand is high. Consequently, the potential gains in consumer surplus due to subsidization of distributed generation are lower for low values of α.[25] For the same reason, retailers discard the substitutable share of demand at higher levels of $c_{DG} - \sigma$. In the basic model it is never optimal for the regulator to allow usage of distributed generation for all consumers C_s as shown in Proposition 3.4. In the generalized model this result remains true for a wide range of α. Only for high shares of substitutable electricity demand full substitution with distributed generation can become welfare optimal for consumers. This result is summarized in Proposition 3.6. The full generalized solution of the regulator problem is presented in Appendix 3.7.2.

Proposition 3.6. *If the subsidy costs are accounted for, full substitution of substitutable electricity demand with distributed generation can be optimal for consumers if and only if* $\alpha \gtrsim 1.7$.

Proof. See Appendix 3.7.2.

3.6 Conclusion

This article analyzes the impact of distributed generation technologies on retail markets for electricity. A spatial competition framework is applied in order to account for horizontal product differentiation and heterogeneous consumer preferences with regard to electricity retailers. I find that distributed generation puts competitive pressure on retailers and induces lower retail prices. Therefore even consumers who

[24]The exact value is $c_{DG} - \sigma - w = 0.2679t$. The calculation is based on the surplus function provided in Appendix 3.7.2.

[25]see Figure 3.9(c).

do not use distributed generation benefit. Regulators can subsidize distributed generation in order to exploit this competitive effect and increase consumer surplus. However, if the cost of distributed generation is low and only a limited share of demand can be substituted with distributed generation, there is point at which retailers disregard the substitutable share of demand and focus on the non-substitutable consumption in order to realize higher mark-ups. As a result, increased subsidies for distributed generation can increase retail prices and harm consumers. In the optimal regulatory strategy this behaviour of retailers is therefore prevented by limiting usage of distributed generation.

The results of the analysis show that subsidies for distributed generation can be a regulatory tool to increase competition in retail markets for electricity. Hence, policy makers should design subsidy mechanisms for distributed generation with awareness for the competitive effects. In addition the analysis shows that grid fee exemptions, which are widely used in practice, are only suitable to implement the optimal regulatory strategy if a two-part-tariff structure is in place. Exemption rules with volumetric grid fees lead to inefficient levels of distributed generation.

The analysis is conducted for distributed generation in electricity markets. However, the results can be also applied for the heating sector. Consumers can avoid gas consumption for heating by using alternative heating technologies based on renewable energy, for example solar thermal technologies. If gas is delivered to end consumers via a grid infrastructure, the discussed effects on refinancing of grid costs also apply for operators of gas grids. In further research the presented theoretical framework could be extended to more complex representations of retail competition, for example by integrating switching costs into consumer decisions. Additionally, the wholesale market could be modeled in more detail by accounting for feedback effects of distributed generation on wholesale prices. Finally, an empirical evaluation of the presented propositions would be an important contribution to the understanding of the economics of distributed generation.

3.7 Appendix

3.7.1 Proofs

Proof of Lemma 3.1.
Based on Equation (3.4) the following first order conditions can be derived:

$$\frac{\partial \pi_{Ri}}{\partial p_{Ri}} = \begin{cases} \dfrac{p_{R-i} - p_{Ri} + w}{t} & \text{if } p_{R-i} - t \leq p_{Ri} \leq 2(c_{DG} - \sigma) - p_{R-i} - t \\ \dfrac{t + p_{R-i} - 6p_{Ri} + 3w + 2(c_{DG} - \sigma)}{2t} & \\ & \text{if } 2(c_{DG} - \sigma) - p_{R-i} - t \leq p_{Ri} \leq c_{DG} - \sigma \\ \dfrac{p_{R-i} - p_{Ri} + w}{2t} & \text{if } p_{Ri} > c_{DG} - \sigma \end{cases} \tag{3.16}$$

Setting $\frac{\partial \pi_{Ri}}{\partial p_{Ri}} = 0$ and some reformulation yields Equation (3.5). The four symmetric equilibria follow from the reformulations of the reaction function discussed in Section 3.3.2. Despite the discontinuity and the non-monotonicity of the reaction function (see Equation (3.8)), existence of symmetric pure strategy equilibria is guaranteed because the game is symmetric with a one-dimensional strategy space and all jumps in the best reply function are upwards (See theorem 2.6 in Vives (2001)). For the second case of Lemma 3.1, symmetry is assumed. □

Proof of Proposition 3.1.
Distributed generation is competitive to grid-based electricity if $c_{DG} - \sigma < w + \frac{3}{2}t$. For $w + \frac{7}{6}t \leq c_{DG} - \sigma < w + \frac{3}{2}t$ increased subsidies decrease retail prices as $\frac{\partial p_{Ri}}{\partial \sigma} = -1$. For $w + \frac{2\sqrt{3}}{5+\sqrt{3}}t \leq c_{DG} - \sigma < w + \frac{7}{6}t$, $\frac{\partial p_{Ri}}{\partial \sigma} = -\frac{2}{5}$. Consequently, increased subsidies decrease retail prices as long as both consumer groups are served by retailers. If retailers discard consumers C_s the retail price is $w + t$, which is strictly larger than $\frac{2(c_{DG}-\sigma)+3w+t}{5}$ for $c_{DG} - \sigma < w + 2t$. Consequently increased subsidies increase retail prices if the solution is shifted from an equilibrium where both consumer groups C_s and C_{ns} are served by retailers and $c_{DG} - \sigma < w + \frac{3}{2}t$ to a solution where retailers discard consumers C_s. □

Proof of Lemma 3.2.
Consumer surplus is calculated by integrating over the utility function of consumers.

Consumer surplus for consumers C_{ns} is determined by Equation (3.17).

$$CS_{ns} = 2 * \int_0^{\frac{1}{2}} (v - p_{Ri} - tx)dx \tag{3.17}$$

Consumer surplus for consumers C_s is determined by the sum of surplus resulting from grid-based electricity and distributed generation, where q_{Ris} stands for electricity sold by retailer i to consumers C_s and q_D stands for distributed generation:

$$CS_s = 2 * \int_0^{q_{Ris}} (v - p_{Ri} - tx)dx + \int_0^{q_D} \big(v - (c_{DG} - \sigma)\big)dx \tag{3.18}$$

Substituting the results of Lemma 3.1 into Equations (3.17) and (3.18) and summing $CS = CS_{ns} + CS_s$ yields Lemma 3.2 after some reformulation. □

Proof of Proposition 3.2.
For $c_{DG} - \sigma < w + \frac{3}{2}t$, consumer surplus is strictly increasing in subsidies as long as both consumer groups C_s and C_{ns} are served by retailers. For $w + \frac{7}{6}t \leq c_{DG} - \sigma < w + \frac{3}{2}t$, $\frac{\partial CS}{\partial \sigma} = 2$ and for $w + \frac{2\sqrt{3}}{5+\sqrt{3}}t \leq c_{DG} - \sigma < w + \frac{7}{6}t$, $\frac{\partial CS}{\partial \sigma} = \frac{18(-c_{DG}+w+\sigma)+31t}{25t}$, which is strictly positive for $c_{DG} - \sigma < w$. If retailers discard consumers C_s, consumer surplus is determined by $CS' = 2v - w - (c_{DG} - \sigma) - \frac{5}{4}t$. If both consumer groups are served and $c_{DG} - \sigma < w + \frac{7}{6}t$, $CS'' = 2v - 2(c_{DG} - \sigma) + \frac{9(c_{DG}-\sigma-w+\frac{t}{2})^2}{25t}$. Because of $CS' < CS''$ for $t > 0$, increased subsidies decrease consumer surplus if the solution is shifted from an equilibrium in which both consumer groups are served, to an equilibrium in which consumers C_s are discarded by retailers. □

Proof of Lemma 3.3.
Total surplus is determined by $TS = CS + 2 * \pi_{Ri}$. π_{Ri} is determined by substituting the results of Lemma 3.1 into Equation (3.4). The following expression can be derived:

$$\pi_{Ri} = \begin{cases} t & \text{if } c_{DG} - w - \sigma > \dfrac{3}{2}t \\ c_{DG} - w - \sigma - \dfrac{t}{2} & \text{if } \dfrac{7}{6}t \leq c_{DG} - w - \sigma \leq \dfrac{3}{2}t \\ \dfrac{6(c_{DG} - w - \sigma + \frac{t}{2})^2}{25t} & \text{if } w + \dfrac{2\sqrt{3}}{5+\sqrt{3}}t \leq c_{DG} - \sigma < w + \dfrac{7}{6}t \\ \dfrac{t}{2} & \text{if } c_{DG} - \sigma < w + \dfrac{2}{1+\sqrt{3}}t \end{cases} \tag{3.19}$$

With Equation (3.19), the results of Lemma 3.2 and $TS = CS + 2 * \pi_{Ri}$, Lemma 3.3

follows after some reformulation. □

Proof of Proposition 3.3.
If distributed generation is not used, total surplus is determined by $TS' = 2v - 2w - \frac{t}{2}$. If only a share of consumers C_s uses distributed generation, total surplus is determined by $TS'' = 2v - 2(c_{DG} - \sigma) + \frac{84(c_{DG} - \sigma - w + \frac{t}{2})^2}{100t} - \frac{t}{2}$. Because $TS'' < TS'$ for $w + \frac{2\sqrt{3}}{5+\sqrt{3}}t \leq c_{DG} - \sigma < w + \frac{7}{6}t$, total surplus is strictly smaller in the second case. If all consumers C_s use distributed generation, total surplus is determined by $TS''' = 2v - w - (c_{DG} - \sigma) - \frac{t}{4}$. Because of $TS''' > TS'$ for $c_{DG} - \sigma < w + \frac{1}{4}t$, Proposition 3.3 follows. □

Proof of Lemma 3.4.
Equation (3.12) is strictly increasing in σ for $c_{DG} - \sigma \geq w + \frac{7}{6}t$ because $q_D = 0$.

For $c_{DG} - \sigma > w + \frac{7}{6}t$ distributed generation is used by consumers. The first order condition of Equation (3.12) with respect to subsidy σ and $CS_{Reg} = CS - \sigma * q_D$ is:

$$\frac{\partial CS_{Reg}}{\partial \sigma} = \frac{6(2(c_{DG} - w) + t - 7\sigma)}{25t} \tag{3.20}$$

Based on $\frac{\partial CS_{Reg}}{\partial \sigma} = 0$, $\sigma = \frac{1}{7}(2(c_{DG} - w) + t)$ can be derived. The second order condition $\frac{\partial^2 CS_{Reg}}{\partial \sigma^2} = -\frac{42}{25t}$ is strictly negative for $t > 0$, which proves a maximum. The solution is however only valid as long as the optimal subsidy level guarantees an equilibrium where both consumer groups C_s and C_{ns} are served by retailers. The threshold value can be determined with Lemma 3.1:

$$\frac{1}{7}(2(c_{DG} - w) + t) \leq c_{DG} - w - \frac{2}{1+\sqrt{3}}t \tag{3.21}$$

Reformulating Equation (3.21) yields $c_{DG} - w \geq \frac{15+\sqrt{3}}{5+5\sqrt{3}}$. If this condition is not true, the optimal subsidy can lead to an equilibrium where retailers discard consumers C_s and raise prices. The regulator avoids this by setting the subsidy at the boundary of the fourth case of Lemma 3.1, $\sigma = c_{DG} - w - \frac{2}{1+\sqrt{3}}t$. The last step is to check, if there is a value of $c_{DG} - w$, where an equilibrium with maximum possible usage of distributed generation is welfare optimal. This can be verified by substituting the corresponding solutions for σ into the objective function and comparing the results. $\sigma = c_{DG} - w - \frac{2}{1+\sqrt{3}}t$ yields the solution:

$$CS_{Reg1} = 2v - 2c_{DG} + (6\sqrt{3} - 3)(c_{DG} - w) - (353 - 144\sqrt{3})t \tag{3.22}$$

The regulator objective function with maximum distributed generation $q_D = 1$ yields:

$$CS_{Reg2} = 2v - c_{DG} - w - \frac{5}{4}t \tag{3.23}$$

Comparing Equation (3.22) with Equation (3.23) yields $CS_{Reg1} > CS_{Reg2}$ for $c_{DG} > 0, w > 0, c_{DG} > w$ and $t > 0$ which is true by assumption. As a result maximum usage of distributed generation is never optimal and Lemma 3.4 follows. □

Proof of Proposition 3.4.
Proposition 3.4 follows directly from Lemma 3.4. □

Proof of Lemma 3.5.
Grid fees are integrated into consumer utility by changing Equations (3.1a) and (3.1b) to:

$$U_{grid} = v - f - p_G - p_{Ri} - t\,|x_i - x| \tag{3.24a}$$

$$U_{DG} = v - f - p_G - (c_{DG} - \sigma) \tag{3.24b}$$

Setting $\sigma = p_G$ exempts distributed generation from variable grid fee payments. The consumer surplus function changes accordingly. Based on Problem (3.13) the following lagrangian function is derived, with λ as the dual variable of the cost recovery constraint:

$$\mathscr{L} = CS + \lambda\left(2f - fixc + p_G\frac{3\big(2(c_{DG} - p_G - w) + t\big)}{5t}\right) \tag{3.25}$$

$\frac{\partial \mathscr{L}}{\partial p_G} = 0$, $\frac{\partial \mathscr{L}}{\partial f} = 0$ and $\frac{\partial \mathscr{L}}{\partial \lambda} = 0$ yields:

$$p_G = \frac{1}{7}\big(2(c_{DG} - w) + t\big) \tag{3.26a}$$

$$f = \frac{fixc}{2} - \frac{6}{49t}\left(c_{DG} - w + \frac{t}{2}\right)^2 \tag{3.26b}$$

$$\lambda = 1 \tag{3.26c}$$

The remainder follows exactly the same logic as the proof of Proposition 3.4 and is thus omitted. □

Proof of Proposition 3.5.
The first part of Proposition 3.5 follows from Problem (3.15) because increased grid

fees directly reduce consumer surplus if compensation via the fixed component is not possible. Positioning distributed generation as a competitor to grid-based electricity for $c_{DG} - w + intc > \frac{11}{6}t$ is therefore not possible.

For the second part of Proposition 3.5 Problem (3.15) is solved with the lagrangian:

$$\mathscr{L} = CS + \lambda\left(-fixc + p_G \frac{3\big(2(c_{DG} - p_G - w) + t\big)}{5t} \right) \tag{3.27}$$

$\frac{\partial \mathscr{L}}{\partial p_G} = 0$ and $\frac{\partial \mathscr{L}}{\partial \lambda} = 0$ yields:

$$p_G = \frac{1}{2}\big(c_{DG} - w + \frac{t}{2}\big) - \frac{\sqrt{3}}{12}\sqrt{-40fixc * t + 3\big(2(c_{DG} - w) + t\big)^2} \tag{3.28a}$$

$$\lambda = \frac{3}{10}\left(1 + \frac{\sqrt{3}(2(c_{DG} - w) + t)}{\sqrt{-40fixc * t + 3\big(2(c_{DG} - w) + t\big)^2}}\right) \tag{3.28b}$$

Based on Equations 3.28a and 3.28b it follows that there exists a real solution only if:

$$fixc > \frac{3\big(2(c_{DG} - w) + t\big)^2}{40t} \tag{3.29}$$

Substituting the results into the objective function shows that welfare with volumetric tariffs is strictly lower compared to the two-part tariff case unless:

$$fixc = \frac{3\big(2(c_{DG} - w) + t\big)^2}{49t} \tag{3.30}$$

If condition (3.30) is true, the resulting welfare is the same in both cases. □

3.7.2 Substitutable share of demand

Varying the share of substitutable electricity demand changes the demand function from the basic model to:

$$q_{Ri} = \begin{cases} \frac{t + p_{R-i} - p_{Ri}}{t} & \text{if } p_{R-i} - t \leq p_{Ri} \leq 2c_{DG} - 2\sigma - p_{R-i} - t \\ (2-\alpha)\frac{t + p_{R-i} - p_{Ri}}{2t} + \alpha * \frac{c_{DG} - \sigma - p_{Ri}}{t} & \\ & \text{if } 2c_{DG} - 2\sigma - p_{R-i} - t \leq p_{Ri} \leq c_{DG} - \sigma \\ (2-\alpha)\frac{t + p_{R-i} - p_{Ri}}{2t} & \text{if } p_{Ri} > c_{DG} - \sigma \end{cases} \tag{3.31}$$

Following the same steps as described in Section 3.3.2, the retailer problem can be solved to derive the following retail prices:

$$p_{Ri} = \begin{cases} w+t & \text{if } c_{DG}-\sigma-w > \frac{3}{2}t \\ c_{DG}-\sigma-\frac{t}{2} & \text{if } \frac{3}{2}t \geq c_{DG}-\sigma-w \geq \frac{6+\alpha}{4+2\alpha}t \\ \frac{\alpha\big(2(c_{DG}-\sigma)-t+w\big)+2(t+w)}{2+3\alpha} & \\ \qquad \text{if } \frac{6+\alpha}{4+2\alpha}t \geq c_{DG}-\sigma-w \geq \frac{(2+3\alpha)\sqrt{4-\alpha^2}-4+\alpha^2}{\alpha(6+5\alpha)}t & \\ w+t & \text{if } c_{DG}-\sigma-w < \frac{\sqrt{4-\alpha^2}-2+\alpha}{\alpha} \end{cases} \tag{3.32}$$

Substituting retail prices into the profit equation yields:

$$\pi_{Ri} = \begin{cases} t & \text{if } c_{DG}-w-\sigma > \frac{3}{2}t \\ c_{DG}-w-\sigma-\frac{t}{2} & \text{if } \frac{3}{2}t \geq c_{DG}-\sigma-w \geq \frac{6+\alpha}{4+2\alpha}t \\ \frac{(2+\alpha)\big(2t+2\alpha(c_{DG}-\sigma-w-\frac{t}{2})\big)^2}{2(2+3\alpha)^2 t} & \\ \qquad \text{if } \frac{6+\alpha}{4+2\alpha}t \geq c_{DG}-\sigma-w \geq \frac{(2+3\alpha)\sqrt{4-\alpha^2}-4+\alpha^2}{\alpha(6+5\alpha)}t & \\ \frac{t}{2}\big(2-\alpha\big) & \text{if } c_{DG}-\sigma-w < \frac{\sqrt{4-\alpha^2}-2+\alpha}{\alpha} \end{cases} \tag{3.33}$$

To determine consumer surplus, transport costs for consumers C_s and C_{ns} are normalized to the corresponding total electricity consumption. The resulting expressions for consumer surplus are:

$$CS_{ns} = 2 * \int_0^{\frac{1}{2}} \big(v - p_{Ri} - \frac{t}{2-\alpha}x\big)dx \tag{3.34a}$$

$$CS_s = 2 * \int_0^{q_{Ris}} \big(v - p_{Ri} - \frac{t}{\alpha}x\big)dx + \int_0^{q_D} \big(v-(c_{DG}-\sigma)\big)dx \tag{3.34b}$$

With retail prices from Equation (3.32) and $A = (2c_{DG} - 2\sigma - 2w - 5t)$, $B = (2c_{DG} - 2\sigma - 2w - t)$ consumer surplus $CS = CS_{ns} + CS_s$ can be reformulated to:

$$CS = \begin{cases} 2v - 2w - \frac{5}{2}t & \text{if } c_{DG} - w - \sigma > \frac{3}{2}t \\ 2v - 2c_{DG} + 2\sigma + \frac{t}{2} & \text{if } \frac{3}{2}t \geq c_{DG} - \sigma - w \geq \frac{6+\alpha}{4+2\alpha}t \\ 2v - 2w + \frac{1}{4(2+3\alpha)^2 t}\big(4\alpha(A^2 - 30t^2) + 2\alpha^2(2A^2 - 41t^2) + \alpha^3 B^2 - 40t^2\big) & \\ \qquad \text{if } \frac{6+\alpha}{4+2\alpha}t \geq c_{DG} - \sigma - w \geq \frac{(2+3\alpha)\sqrt{4-\alpha^2} - 4 + \alpha^2}{\alpha(6+5\alpha)}t & \\ 2v - 2w - \alpha\big(c_{DG} - \sigma - w - \frac{5}{4}t\big) - \frac{5}{2}t & \text{if } c_{DG} - \sigma - w < \frac{\sqrt{4-\alpha^2} - 2 + \alpha}{\alpha} \end{cases} \tag{3.35}$$

Summing retailer profits and consumer surplus yields total surplus with $B = (2c_{DG} - 2\sigma - 2w - t)$, $C = (2c_{DG} - 2\sigma - 2w - \frac{5}{3}t)$:

$$TS = \begin{cases} 2v - 2w - \frac{t}{2} & \text{if } c_{DG} - w - \frac{6+\alpha}{4+2\alpha}t \\ 2v - 2w + \frac{1}{4(2+3\alpha)^2 t}\big(4\alpha(B^2 - 10t^2) + 2\alpha^2\big(6C^2 - \frac{35}{3}t^2\big) + 5\alpha^3 B^2 - 8t^2\big) & \\ \qquad \text{if } \frac{6+\alpha}{4+2\alpha}t \geq c_{DG} - \sigma - w \geq \frac{(2+3\alpha)\sqrt{4-\alpha^2} - 4 + \alpha^2}{\alpha(6+5\alpha)}t & \\ 2v - 2w - \alpha\big(c_{DG} - \sigma - w - \frac{t}{4}\big) - \frac{t}{2} & \text{if } c_{DG} - \sigma - w < \frac{\sqrt{4-\alpha^2} - 2 + \alpha}{\alpha} \end{cases} \tag{3.36}$$

Following exactly the same logic as in the proof of Lemma 3.4 the following optimal regulatory strategy can be determined for $\alpha \lesssim 1.7$:

(i) For $c_{DG} - w > \frac{10+\alpha}{2(2+\alpha)}t$, $\sigma = c_{DG} - w - \frac{6+\alpha}{4+2\alpha}t$.

(ii) For $\frac{10+\alpha}{2(2+\alpha)}t \geq c_{DG} - w \geq \frac{1}{\alpha(2+3\alpha)}\big(2(\alpha-2)(2\alpha+1) + (2+5\alpha)\sqrt{4-\alpha^2}$, $\sigma = \frac{2\alpha(c_{DG}-w)+(2-\alpha)t}{2+5\alpha}$

(iii) For $c_{DG} - w < \frac{1}{\alpha(2+3\alpha)}\big(2(\alpha-2)(2\alpha+1) + (2+5\alpha)\sqrt{4-\alpha^2}$, $\sigma = c_{DG} - w - \frac{\sqrt{4-\alpha^2}-2+\alpha}{\alpha}$

Proof of Proposition 3.6.

If all substitutable electricity demand is supplied with distributed generation, the following solution for the regulator problem can be derived:

$$CS - \sigma * q_D = 2v - 2w - \frac{5}{2}t + \alpha(w - c_{DG} + \frac{5}{4}t) \tag{3.37}$$

Comparing Equation (3.37) with the result of the regulator problem for $\sigma = c_{DG} - w - \frac{\sqrt{4-\alpha^2}-2+\alpha}{\alpha}$ yields that maximum usage of distributed generation can be welfare optimal for $\alpha \gtrsim 1.6985$ $\square$

4 Optimal Allocation of Variable Renewable Energy Considering Contributions to Security of Supply

Electricity markets are increasingly influenced by variable renewable energy such as wind and solar power with a pronounced weather-induced variability and imperfect predictability. As a result, the evaluation of the capacity value of variable renewable energy, i.e. its contribution to security of supply, gains importance. This paper develops a new methodology to endogenously determine the capacity value in large-scale investment and dispatch models for electricity markets. The framework allows to account for balancing effects due to the spatial distribution of generation capacities and interconnectors. The practical applicability of the methodology is shown with an application for wind power in Europe. We find that wind power can substantially contribute to security of supply in a decarbonized European electricity system in 2050, with regional capacity values ranging from 1 - 40 %. Analyses, which do not account for the temporal and spatial heterogeneity of the contribution of wind power to security of supply therefore lead to inefficient levels of dispatchable back-up capacity. Applying a fixed wind power capacity value of 5 % results in an overestimation of firm capacity requirements in Europe by 66 GW in 2050. This translates to additional firm capacity provision costs of 3.8 bn EUR per year in 2050, which represents an increase of 7 %.

4.1 Introduction

The Paris climate agreement aims at holding global warming to well below 2 degrees Celsius (United Nations (2015)), creating the need for a deep decarbonization of the global electricity sector. Recent cost reductions suggest that the optimal pathway will to a substantial part be based on variable renewable energy sources (VRE). As a consequence, global electricity markets are increasingly influenced by generation technologies based on VRE such as wind and solar energy. Electricity generation from VRE differs from dispatchable power generation in its pronounced dependency on weather conditions. These weather-induced variations show spatial variance and are not perfectly predictable. Accordingly, there arise important implications for reliability of supply in power systems as electricity is only storable at comparatively high cost and the supply-demand balance has to be maintained at all times in order to prevent outages.

Reliability of supply has always been a major concern in electricity systems as outages incur high economic losses. With increasing shares of VRE, reliability issues gain further importance due to the variability, spatial dependency and imperfect predictability of electricity generation based on VRE and the resulting risk of unavailability during times of stress (e.g. Cramton et al. (2013)). VRE resources are typically less correlated on a wider geographical scope, which enables balancing effects because of imperfectly correlated generation patterns at different locations. Hence, markets can benefit from these balancing effects via interconnections and cross-border cooperation. Envisaged reliability levels can thereby be reached at lower costs compared to reliability measures restricted to national borders (e.g., Cepeda et al. (2009) and Hagspiel (2017)). Against this background, the following research question arises: What is the optimal mix and allocation of VRE capacity in order to benefit from balancing effects both in generation and contribution to security of supply to reach an envisaged reliability target?

Assessing the contribution of VRE to security of supply is complex, because of the stochasticity of electricity generation based on weather-dependent resources. The ability of an additional VRE generation unit to provide secure capacity depends on the correlation of its electricity generation with electricity demand and with electricity generation from other units. To give intuition for this dependency, consider a simple example for wind energy: An electricity system has an off-peak demand of one and a peak demand of two with off-peak periods being more frequent compared to peak demand situations. Additionally, there are two possible sites A and B for investment into wind capacities. Wind generation at site A is perfectly correlated with off-peak demand and wind generation at site B is perfectly correlated with peak demand hours. In this setting, wind capacities at site A generate more electrical energy because off-peak situations are more frequent. Nevertheless, wind investments at site B can be preferable because wind generation capacities at site B generate electricity in the critical peak demand situations. Thus, one unit of wind capacity at site B reduces the need for one unit of dispatchable capacity and therefore contributes to security of supply. Now consider the situation where there is already one unit of wind capacity in place at site B, which generates one unit of electricity in peak demand hours. The remaining residual demand, which must be supplied by dispatchable generation capacity, is one in off-peak and one in peak demand periods. As a result, installing one additional unit of wind capacity at site B cannot contribute to security of supply because firm capacity is still required in the off-peak demand period and thus cannot be substituted. However, if there were wind capacities of one unit installed at both sites, investing in one additional unit of wind capacity at site B would indeed contribute to security of supply.

The highly stylized example clarifies that the marginal contribution to security of supply from additional generation capacities based on VRE depends on all existing installed capacities within the system, because these capacities and their weather-dependent generation determine the critical residual demand situations. Typically, generation patterns of wind and solar power plants at different locations are positively correlated. Therefore, the ability of one unit of VRE generation capacity to substitute firm capacity, which is referred to as its capacity value (or capacity credit)[1], declines as the share of VRE in total generation increases.[2] Nevertheless, economic long-term simulation models for electricity markets, which are widely used in scientific and political practice, often assign fixed exogenous capacity values to wind and solar generation and neglect cross-border effects for reasons of simplification and computational tractability. Similarly, adequacy studies and capacity mechanisms often do not or only crudely allow for participation of VRE and are often confined to national borders.[3]

Against the described backdrop, this paper develops a new methodology to endogenously determine the contribution of VRE to security of supply in a long-term partial equilibrium model for electricity markets. The proposed methodology builds on an iterative approach, which captures the non-linear dependency of the capacity value of VRE on installed capacity and its spatial distribution considering cross-border cooperation via interconnectors. The methodology therefore determines cost-minimal investment into power plants taking into account electricity generation as well as provision of security of supply of VRE, while keeping computational tractability in a large-scale application. After introducing our methodology, we apply it in a

[1]In literature, capacity value and capacity credit are used as synonyms. Throughout this paper we will stick to the term capacity value. It is important not to confuse a technology's capacity value with its capacity factor describing its yearly average capacity utilization.

[2]See International Renewable Energy Agency (2017) for an overview of empirical studies showing this decreasing return to scale effect.

[3]See e.g. Cepeda et al. (2009) and Hobbs and Bothwell (2017) for a discussion. An overview on how U.S. and European capacity mechanisms credit VRE contributions to reliability is given in Byers et al. (2018) and European Commission (2016a). Furthermore, there are efforts to coordinate European adequacy assessments and foster cross-border cooperation (European Commission (2016b)).

first step to a simple two-country example. Building on that, we extend it to the European electricity system to determine an optimal decarbonization pathway until the year 2050, starting from the existing power plant fleet. Our analysis focuses on wind power, however the presented approach can be applied to all VRE technologies. We build the analysis on a new dataset, which is based on meteorological reanalysis data featuring a high spatial and temporal resolution. The data is therefore well suited to optimally capture the stochastic properties of wind generation and the resulting contribution to security of supply.

We show that the proposed methodology is capable to endogenously determine the capacity value of wind power in large-scale investment and dispatch models for electricity markets. The results of the large-scale application imply that wind power can substantially contribute to security of supply in a decarbonized European electricity system cooperating with respect to reliability, with an average wind power capacity value of 13 % in 2050. Additionally the results show that the capacity value of wind power is heterogeneous across different regions and years, which is a result of varying wind conditions as well as increasing total installed capacities and technological innovation over time. Existing modeling approaches, which typically assign constant exogenous capacity values for wind power, therefore result in inefficient levels of dispatchable capacities, which are required to guarantee security of supply in electricity systems with high shares of VRE. In our application for the European electricity system, the additional yearly costs for firm capacity provision[4] when applying exogenous fixed wind power capacity values of 5 % compared to endogenous capacity values amount to 1.5 and 3.8 bn EUR in 2030 and 2050, respectively, which represents additional costs of 3 % and 7 %. Finally our results suggest that European market integration can substantially improve the contribution of wind power to security of supply due to cross-border balancing effects.

Our paper is mainly related to two streams of literature. The first relevant stream examines system adequacy and reliability of supply in electricity systems. Reliability of supply in electricity systems has been subject to extensive scientific research effort, both from a technical as well as an economic point of view.[5] In particular, the contribution of individual technologies to system adequacy, i.e. the capacity value, has been a focus of interest. The probability theory of the capacity value of additional generation for the cases of statistical independence and dependence is presented in

[4]The yearly costs to provide firm capacity are calculated by summing the annuitized investment costs and the fixed operation and maintenance costs of all dispatchable power plants. Thereby, the fixed costs to hold available dispatchable capacity are represented.

[5]Early contributions in the two fields include e.g. Billinton (1970) and Telson (1975).

Zachary and Dent (2012). Based on these theories, various contributions investigate empirical methods to evaluate the capacity value of wind power in electricity systems.[6] Cepeda et al. (2009) investigate the positive implications of connecting different electricity systems on reliability and ways to internalize cross-border effects in a two-zone model. Hagspiel et al. (2018) introduce a comprehensive framework to investigate reliability in power systems consisting of multiple technologies and interconnected regions. All the mentioned studies focus on static analyses for given power systems. Consequently, the capacity value is not evaluated within a dynamic model, which determines the optimal future structure of an electricity system.

The second relevant literature stream focuses on the analysis of electricity systems with high shares of VRE based on long-term dynamic partial equilibrium models. Typical research questions within this literature are optimal decarbonization pathways for electricity systems or optimal allocation of renewable generation capacites. However, the contribution of VRE to security of supply is often only crudely accounted for by assigning fixed exogenous capacity values.[7] Grave et al. (2012) address this issue by varying the capacity value of wind power exogenously in order to determine sensitivities in the resulting amount of required dispatchable back-up capacity. The endogenous dependency of the capacity value on total installed capacity of VRE and the impact of interconnections are not accounted for. Welsch et al. (2015) integrate a stepwise linear function for the capacity value into an optimization model. As a result, the capacity value declines endogenously. However, balancing effects of imperfectly correlated wind power generation in different geographical areas and technological innovation over time are not captured by this approach. Hobbs and Bothwell (2017) use a market equilibrium model for the ERCOT system to endogenously assess the capacity value of wind and solar power. However, they apply a greenfield approach with a limited regional representation of wind and solar power generation. The scalability of the applied methodology to more complex models with various years and a higher geographical resolution is computationally limited.

In summary, our contribution with respect to the above mentioned literature is to (i) endogenously evaluate the capacity value of wind power within a dynamic investment and dispatch model for electricity markets, while (ii) accounting for the statistical properties of wind power in interconnected systems and (iii) keeping com-

[6] See e.g. Keane et al. (2011) for a discussion of different methodologies including capacity value approximation techniques and Milligan et al. (2017) for a recent review of research on the capacity value of wind power.

[7] See for example Hagspiel et al. (2014) or Fürsch et al. (2013).

putational tractability in a large-scale application.

The remainder of the paper is structured as follows. Section 4.2 introduces our methodology. Section 4.3 illustrates the proposed approach based on a simple example with two countries. Section 4.4 discusses a large-scale application for the European electricity system. Section 4.5 concludes.

4.2 Methodology

In order to develop a consistent economic framework to investigate the system adequacy of future electricity systems and the contribution of VRE generation to reliability, we will start with a brief revision of the reliability metrics, in particular the well-known loss of load expectation, expected energy unserved and equivalent firm capacity measures, and a definition of the capacity value (Section 4.2.1). We will then describe a framework to calculate the contribution of a single supplier to reliability, i.e. its capacity value, based on an optimization framework (Section 4.2.2). Subsequently, we will revisit the optimization problem for planning and operation of power systems in order to show how the capacity value of individual technologies is typically accounted for in long-term investment and dispatch models (Section 4.2.3). Finally, we will discuss how the two economic modeling frameworks are linked by means of an iteration procedure developed in this work (Section 4.2.4).

We will use the notation as listed in Table 4.1. Unless noted differently, we will use capital letters for random variables, bold capital letters for sets, lower case letters for parameters and bold lower case letters for optimization variables.

4.2.1 Reliability metrics

Different methodologies have been proposed to determine generation adequacy and the capacity value of individual technologies. Hereby, the two measures loss of load expectation ($LOLE$) and expected energy unserved (EEU) are often applied to depict the ability of a system to cover expected load levels (Allan and Billinton (1996)). The contribution of individual technologies to system adequacy, i.e. its capacity value, has been investigated using different approaches, whereof the most commonly used are the effective load carrying capability ($ELCC$) and the equivalent firm capacity (EFC) approaches (Keane et al. (2011), Madaeni et al. (2013), Zachary and Dent (2012)). Following Hagspiel et al. (2018), we apply the EFC

Table 4.1: Model sets, parameters and variables

Sets	
$i \in \mathbf{I}$	Generation technologies
$m, n \in \mathbf{M}$	Markets
$t \in \mathbf{T}, \mathscr{T}$	Time (**T**: complete data set, $\mathscr{T}$: time slices)
Random variables	
L	Load
X	Availability of existing capacity
Y	Availability of extra capacity
K	Availability of import capacity
Parameters	
$LOLP$	Loss of load probability
$LOLE$	Loss of load expectation
EEU	Expected energy unserved
EFC	Equivalent firm capacity
$\bar{x}$	Nominal capacity of existing generator
x	Availability of existing generator
$\bar{y}$	Nominal capacity of extra generator
v	Capacity value of extra capacity $\bar{y}$
$\bar{k}$	Transmission capacity
η	Transmission efficiency
l	Load
l_{peak}	Peak demand
δ	Fixed costs
γ	Variable costs electricity generation
Optimization variables	
$\mathbf{z}$	Overall equivalent firm capacity needed
$\mathbf{z}^y$	Equivalent firm capacity of extra capacity $\bar{y}$
$\mathbf{u}$	Load curtailment
$\mathbf{k}$	Capacity / electricity transmission between markets
$\bar{\mathbf{x}}$	Generation capacity
$\mathbf{g}$	Electricity generation

approach.[8] Note that the EFC approach provides consistent results with the $ELCC$ approach (Amelin (2009)).

In the following, we will briefly revisit the derivation of the well-known $LOLE$ and EEU measures. We define the loss of load probability ($LOLP$) at a specific instant in time t as

$$LOLP_t = P(X_t < L_t), \tag{4.1}$$

i.e., as the probability that the available existing capacity X_t is smaller than load

[8] Amelin (2009) define the equivalent firm capacity of a generating unit as the capacity of a fictitious 100 % reliable unit, which results in the same loss of load probability decrease as the respective unit.

L_t (Allan and Billinton (1996)).[9]

The well-known reliability level measure loss of load expectation is then derived by summing up probabilities over some time-period T:

$$LOLE = \sum_{t \in \mathbf{T}} LOLP_t. \tag{4.2}$$

To calculate the expected energy unserved EEU, the $LOLPs$ are weighted with the expected load level that cannot be served:

$$EEU = \sum_{t \in \mathbf{T}} E(L_t - X_t) * LOLP_t. \tag{4.3}$$

The contribution of individual technologies is then determined by applying the EFC approach. Our focus of interest is the amount of equivalent firm capacity $\mathbf{z}^y$ by which the available existing capacity X_t can be reduced when installing some new capacity $\bar{y}$ with availability $Y_t \in [0,1]$, such that the initial (target) reliability level EEU is achieved. Thus, by replacing X_t by its equivalent $(X_t + \bar{y}Y_t - \mathbf{z}^y)$ and applying Equation (4.1), the modified equation that needs to be solved for $\mathbf{z}^y$ then writes as

$$EEU = \sum_{t \in \mathbf{T}} E(L_t - (X_t + \bar{y}Y_t - \mathbf{z}^y)) * P(X_t + \bar{y}Y_t - \mathbf{z}^y < L_t). \tag{4.4}$$

Based on the resulting $\mathbf{z}^y$, the capacity value v of a technology with capacity $\bar{y}$ can be calculated according to

$$v = \frac{\mathbf{z}^y}{\bar{y}} \tag{4.5}$$

with $0 \leq v \leq 1$.

In practice, Equation 4.4 is typically solved by means of numerical iteration: after $\bar{y}$ has been added to the system, in each iteration step $\mathbf{z}^y$ is increased by some small amount until the reliability target EEU is reached.

The above equations describe a self-contained system without interconnections to neighboring systems. In interconnected systems, the $LOLP$ and $LOLE$ depend on the statistical characteristics of the random variables involved, i.e. their joint distributions. If we consider dependent stochastic variables such as load and wind

[9] Note that in Equation (4.1), we implicitly assume that load is inelastic with no adjustment when capacity is scarce, e.g., due to the lack of real-time pricing.

profiles in neighboring countries, the problem becomes analytically highly complex and thus not tractable in a large-scale application.[10] Thus we apply a framework that endogenously determines the level of equivalent firm capacity by means of numerical optimization, as described in the following section.

4.2.2 A framework for endogenous equivalent firm capacity in multiple interconnected markets

In contrast to the above introduced reliability metrics, which typically build upon *exogenously* given existing capacities X_t and demand levels L_t, the framework at hand *endogenizes* the level of equivalent firm capacity by minimizing the firm capacity $\mathbf{z}$ that needs to be available in the system to achieve the target reliability level EEU. Following Hagspiel et al. (2018), we formulate the deterministic equivalent of the probabilistic problem by replacing probabilities and random variables by their deterministic counterpart based on data covering a large range of possible outcomes, which is typically referred to as hindcast approach in the literature. Hereby, the probability measure P models the distributions of the random variables, approximated via sums over historic time series. The validity of the hindcast approach may be justified by the central limit theorem (Zachary and Dent (2012)).

The general idea of the optimization framework is the following: A central authority (social planner) minimizes the required firm capacity over all markets to reach a certain market-specific target reliability level EEU, taking into consideration load, solar and wind characteristics as well as interconnection constraints.[11] Alternatively, the social planner problem can be interpreted as a representation of multiple interconnected markets, which perfectly cooperate with respect to reliability. The resulting planning problem can then be formulated as the integrated optimization problem (4.6).[12]

The objective function (4.6a) minimizes the sum of firm capacity $\mathbf{z}_m$ over all markets, subject to four constraints: The adequacy constraint (4.6b) states that the

[10] See Zachary and Dent (2012) for a thorough discussion of the probability theory of the capacity value of additional generation considering independent and dependent variables.

[11] It is straightforward to reformulate the problem for reliability targets based on the $LOLE$ measure instead of EEU (see Hagspiel et al. (2018)). Note however, that, as this approach includes binary load shedding variables, the problem becomes a mixed integer optimization problem as opposed to the linear program optimization at hand.

[12] The reader is referred to Hagspiel et al. (2018) for a comprehensive derivation of the methodology. Note that for notational simplicity, the capacity additions $\bar{y}$ in Equation (4.4) were dropped and all capacities exogenously given to the system were aggregated by their nominal capacities $\bar{x}_i$ and their capacity availabilities $x_{i,t}$.

required firm capacity has to be greater or equal to the market-specific and time-varying load $l_{m,t}$ minus the load curtailment variable $\mathbf{u}_{m,t}$, minus the sum of the available generation capacity, plus the sum over electricity exchanges $\mathbf{k}_{m,n,t}$ and $\mathbf{k}_{n,m,t}$ between market m and market n at every instant of time t. Thereby, we charge electricity imports with an efficiency loss $\eta_{m,n}$ in order to account for transmission losses. The reliability constraint (4.6c) requires the sum of load curtailment activities $\mathbf{u}_t$ not to exceed a certain reliability target, specified as expected energy unserved EEU within the considered period of time T. Hence, the load curtailment variable $\mathbf{u}_t$ allows for a relaxation of the load serving requirement (Equation (4.6b)) by shaving off load peaks until the reliability level EEU is reached. And finally, the electricity exchange constraint (4.6d) limits $\mathbf{k}_{m,n,t}$ to the installed transmission capacity $\bar{k}_{m,n}$.

$$\min \sum_m \mathbf{z}_m \tag{4.6a}$$

$$\text{s.t.} \quad \mathbf{z}_m \geq l_{m,t} - \mathbf{u}_{m,t} - \sum_{i \in \mathbf{I}} \bar{x}_{i,m} x_{i,m,t} + \sum_{n \in \mathbf{M}} \mathbf{k}_{m,n,t} - \sum_{n \in \mathbf{M}} \eta_{m,n} \mathbf{k}_{n,m,t} \qquad \forall m, t, m \neq n \tag{4.6b}$$

$$\sum_t \mathbf{u}_{m,t} \leq EEU_m \qquad \forall m \tag{4.6c}$$

$$\mathbf{k}_{m,n,t} \leq \bar{k}_{m,n} \qquad \forall m, n, t, m \neq n \tag{4.6d}$$

for $i \in \mathbf{I}, m, n \in \mathbf{M}, t \in \mathbf{T}$.

Solving Problem (4.6) yields the required firm capacity in each market $\mathbf{z}_m^+$ to reach the specified level of reliability, assuming cooperation with respect to reliability. In order to determine the capacity value of technology i in market n under perfect cooperation, we set the corresponding capacity $\bar{x}_{i,n}$ to zero and resolve the model, which yields $\mathbf{z}_{i,n,m}^-$.

Based on the result we then calculate the technology- and region-specific capacity value under perfect cooperation according to

$$v_{i,n,m} = \frac{\mathbf{z}_{i,n,m}^- - \mathbf{z}_m^+}{\bar{x}_{i,n}} \qquad \forall i, m, n. \tag{4.7}$$

This framework can be applied to derive the local capacity value $v_{i,m,m}$ of technology i with capacity $\bar{x}_{i,m}$ with respect to market m where the technology is located

$(n = m)$, but also to derive the cross-border capacity value $v_{i,n,m}$ of a technology $\bar{x}_{i,n}$ located in market n with respect to a neighboring market m.

Note that in this formulation, the capacity value represents the marginal contribution of a technology to reliability, given the contribution of all other technologies. Or, framed as a coalition game, it depicts the marginal contribution of a single coalition member to the total coalition of suppliers, e.g. wind and solar generators.[13] Additionally, note that each market m can consist of more than one region for solar and wind generation to account for their spatial heterogeneity. Thereby, we implicitly assume no internal network constraints inside a market.[14]

4.2.3 Accounting for the contribution to reliability in an investment and dispatch model

To pursue our objective of investigating allocational effects of different ways to account for contributions to reliability, we apply an investment and dispatch model based on optimization problem (4.8). The problem at hand is similar to the integrated problem for investment and operation as formulated e.g. in Turvey and Anderson (1977). By assuming inelastic demand, e.g. due to the lack of real-time pricing, and market clearing under perfect competition - which is common in electricity market modeling literature - we are able to treat the problem as a cost minimization problem. It can be interpreted as a social planner problem where a social planner with perfect foresight minimizes total system costs for investment in gener-

[13] Such a coalition game, namely the allocation of the joint contribution of a set of multiple interdependent suppliers to reliability has been analysed by Hagspiel (2018). He finds that the Shapley value represents a unique additive consistent allocation rule. While the Shapley value represents the average marginal contribution of a single supplier over all possible permutations to form a coalition, our approach captures the marginal contribution of the analyzed supplier to the full coalition (see Equation (4.7)). Because of the decreasing returns to scale of the capacity value with respect to total installed capacity, our approach can be interpreted as a conservative estimate in comparison to the Shapley value.

[14] Our approach generally allows for consideration of internal network constraints. It could be extended in this direction, e.g. by applying a load flow approach with multiple nodes per market.

ation capacity and the operation of generation and transmission between markets.

$$\min \quad TC = \sum_{i,m} \delta_{i,m}\bar{\mathbf{x}}_{i,m} + \sum_{i,m,t} \gamma_{i,m,t}\mathbf{g}_{i,m,t} \tag{4.8a}$$

$$\text{s.t.} \quad l_{m,t} = \sum_{i} \mathbf{g}_{i,m,t} + \sum_{n} \mathbf{k}_{n,m,t} \qquad \forall m,t,m \neq n \tag{4.8b}$$

$$\mathbf{g}_{i,m,t} \leq x_{i,m,t}\bar{\mathbf{x}}_{i,m} \qquad \forall i,m,t \tag{4.8c}$$

$$|\mathbf{k}_{m,n,t}| \leq \bar{k}_{m,n} \qquad \forall m,n,t,m \neq n \tag{4.8d}$$

$$\mathbf{k}_{m,n,t} = -\mathbf{k}_{n,m,t} \qquad \forall m,n,t,m \neq n \tag{4.8e}$$

$$l_{m,peak} \leq \sum_{i,n} \nu_{i,n,m}\bar{\mathbf{x}}_{i,n} \qquad \forall m \tag{4.8f}$$

for $i \in \mathbf{I}, m,n \in \mathbf{M}, t \in \mathscr{T}$.

The objective function (4.8a) minimizes total system costs over all markets m, technologies i and time steps t. It consists of a fixed costs term and a variable costs term. Generation capacity $\bar{\mathbf{x}}$, electricity generation $\mathbf{g}$ and transmission between markets $\mathbf{k}$ are optimization variables. Additional generation capacities can be installed at the costs of $\delta_{i,m}$ and electricity generation incurs variable costs of $\gamma_{i,m,t}$. The cost minimizing objective function is subject to various constraints: The equilibrium constraint (4.8b) states that the load level $l_{m,t}$ has to be satisfied at all times by the sum of generation in market m and electricity exchanges between markets m and n. Constraints (4.8c) and (4.8d) mirror that generation and transmission are restricted by installed generation and transmission capacities.[15] Furthermore, electricity trades from market m to market n are necessarily equal to negative trades from market n to market m (Equation (4.8e)). Finally, the peak capacity constraint (4.8f) requires the sum of generation capacities $\bar{\mathbf{x}}_{\mathbf{i,n}}$ weighted with their capacity values $\nu_{i,n,m}$ to be greater or equal than the market-specific annual peak load $l_{m,peak}$. Note that both local capacity ($n = m$) as well as capacity from a neighboring market n can contribute to the peak constraint in market m. The peak constraint is typically introduced in models that apply a time slices approach in order to represent the full variability of demand and VRE supply, as well as unavailabilities of dispatchable generation.

The investment and dispatch model (4.8) is formulated as a linear program. However, as discussed above, the capacity value $\nu_{i,n,m}$ is a function of generation capacity

[15]Note that in this formulation, we neglect a market's internal transmission constraints. Like in the capacity value framework introduced above, the model at hand could be extended to account for internal transmission constraints, e.g. by applying a load flow approach with multiple nodes per market.

$\bar{x}$. Hence, if the capacity value in the peak capacity constraint (4.8f) would be formulated as a function of generation capacity $\bar{\mathbf{x}}_{i,m}$, e.g. by applying the analytical expression introduced by Voorspools and D'haeseleer (2006) for the capacity value of wind, the problem would become non-linear. While solution algorithms exist to solve non-linear problems, the applicability of non-linear problems in real-world, large-scale electricity market applications often suffers from prohibitively high solving times. Alternatively, piece-wise linearization would represent a way to deal with non-linear analytical expressions in linear problems. However, analytical expressions so far only exist for systems without interconnections and are thus not suited to address our research question. Against this background, we solve the non-linear problem by means of iteration, as discussed in the following section.

4.2.4 A framework to endogenize the capacity value in a large-scale electricity market model

In order to endogenize the capacity value of VRE in a large-scale electricity market model, we introduce the iteration algorithm depicted in Figure 4.1 and discuss its application for the example of wind power: after running the investment and dispatch model (4.8) with exogenous start values for the region-specific capacity values of wind generation, the capacity value framework (4.6) is applied based on the resulting optimal region-specific wind generation capacities. In the next iteration step, the updated capacity values $v_{i,n,m}$ calculated in Equation (4.7) are passed to the peak capacity constraint (4.8f) of the investment and dispatch problem. Subsequently, updated capacity values are calculated considering the new wind capacities. This iteration algorithm is continued until convergence is reached.

Note that the investment model is solved based on a dataset with reduced temporal resolution (time slices) in order to keep the model computationally tractable. We apply a two-stage spatial and temporal clustering algorithm in order to derive a reduced dataset, which captures the relevant properties of wind and solar generation as well as load.[16] The capacity value on the other hand is calculated based on the full temporal resolution in order to allow for a correct evaluation of security of supply.

The procedure depicted in Figure 4.1 successively linearizes the non-linear properties of the capacity value by iteratively solving two corresponding linear problems. Hence, this novel framework allows to endogenously account for the non-linear de-

[16]See Section 4.4.2 and Appendix 4.6.2 for a description of the comprehensive high-resolution data set and the clustering algorithm.

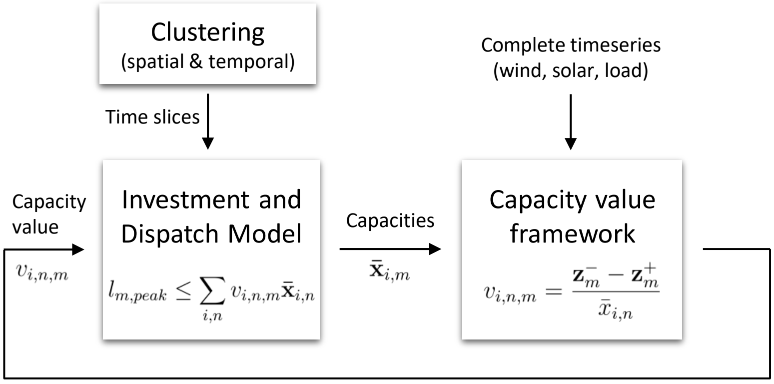


Figure 4.1: Iteration algorithm

pendency of the capacity value of wind power on the amount and spatial distribution of installed wind capacity, as well as resulting system effects via interconnectors. Building on that, effects on system costs and optimal allocation of capacities resulting from different ways of crediting the contribution of wind power to reliability can be quantified. Despite the iterative linearization, the non-linearity of the problem remains. As a result, existence and uniqueness of a global optimum can not generally be guaranteed.[17] In order to address this issue, we numerically test optimality by comparing model runs for a wide range of start values.[18]

From a practical perspective, the social planner in the capacity value framework can be interpreted as a central authority, e.g. the European Commission, which assesses the required firm capacity in each market in order to reach market-specific target reliability levels, taking into consideration load, solar and wind characteristics as well as interconnection constraints. This centralized assessment of market-specific required dispatchable capacity is then taken as a basis for the amount of capacity procurement in each market. Consequently, the capacity value framework determines the required quantity of dispatchable generation capacity, while the specific cost-minimal structure of back-up capacities to meet this requirement is determined in the investment and dispatch model.

In the following, we apply the presented methodology to a simple two-country system for illustrative purposes (Section 4.3), followed by a large-scale application covering the European electricity system (Section 4.4).

[17]Global unique optima can be guaranteed for convex minimization problems. A formal proof of the convexity of the problem is out of the scope of the paper. Nevertheless the decreasing returns to scale of the capacity value with respect to installed capacity, which is observed in empirical studies, suggest convexity.

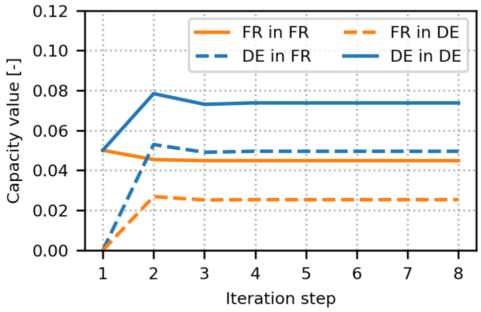
[18]See Sections 4.3 and 4.4.

4.3 Illustrative example: Two-country system

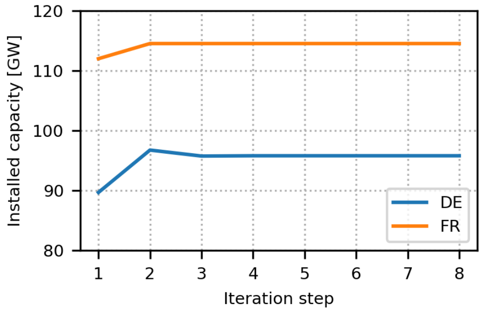
In order to illustrate the basic functioning of the proposed methodology, this section presents an application to a simple case with only two countries, namely France and Germany. The example follows a greenfield approach, which optimizes the system configuration in both countries for the year 2030. For reasons of simplification, only investments into gas-fired power plants, battery storage and onshore wind power capacities are allowed with each country consisting of only one wind region. The interconnection between both countries is assumed to have a capacity of 5 GW. The remaining data assumptions for example on costs, electricity demand and CO_2 reduction targets are equivalent to the large-scale application and are described in detail in Section 4.4.2.

By solving the integrated problem (4.6), it is assumed that the two countries perfectly cooperate with respect to reliability. As such, they take full advantage of balancing effects in capacity supply and demand. In this illustrative example, for simplification, the reliability target expected energy unserved is set to perfect reliability ($EEU = 0$) in both countries, which means that load must be fully served in all hours as no peak shaving is allowed. Thus, the problem reduces to the analysis of the hour with peak residual load in each country and derives the minimally required firm capacity, considering capacity exchanges via the interconnector. The resulting firm capacity requirement is then applied as minimal capacity procurement level in the electricity market investment and dispatch model (4.8).

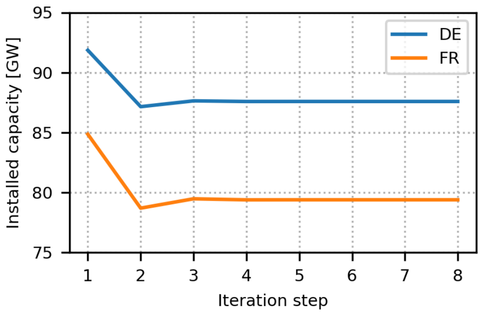
We start the iteration by running the investment and dispatch model with a start value of 5 % for the local capacity value of wind power and 0 % for cross-border contributions of wind to security of supply. The resulting capacity values, installed capacities for wind power and required firm capacity as well as total system costs are depicted in Figure 4.2 for the first eight steps of the iteration. Figure 4.2(a) shows the local capacity value of wind power (e.g. 'FR in FR' for the capacity value of French wind power in France) as well as the cross-border capacity value via the interconnector from France to Germany ('FR in DE') and vice versa. In the first iteration step, the electricity market model determines the optimal wind power capacities based on the start values for the wind power capacity values. The resulting wind power capacities are then used in the capacity value framework to calculate capacity values based on actual wind infeed and load time series. As shown in Figure 4.2(a), the local capacity value of wind in Germany increases in the second iteration step, while the French capacity value slightly decreases. Moreover, the cross-border capacity values both increase to non-zero values.



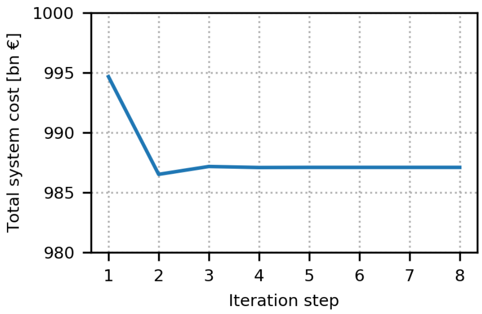
(a) Capacity value of wind power in FR and DE (national and cross-border)



(b) Installed wind power capacity in FR and DE



(c) Required firm capacity in FR and DE



(d) Total system costs for two-country system

Figure 4.2: Iteration results for the illustrative two-country system FR-DE

Based on the updated capacity values the electricity market model determines new optimal wind power investment, taking into consideration the adjusted contribution to security of supply from wind power. As shown in Figure 4.2(b), optimal wind power capacities increase in the second iteration step because of the higher capacity value. The corresponding required firm capacity to reach the reliability target decreases, as shown in Figure 4.2(c). Consequently, the required firm capacity provided by dispatchable capacities is reduced as the contribution of wind power to security of supply is increased. In the third iteration, the capacity values are slightly reduced because increased wind capacities decrease the relative contribution to security of supply. After the fifth iteration, convergence is reached and the model results remain constant in the following iterations.[19]

The two country case shows the basic interactions of the key model variables throughout the iteration process. In the following section, the methodology will

[19]In order to test for robustness, the calculations were conducted for a wide range of start values.

be applied to a real-world large-scale application. The basic logic of the model interactions is identical to the discussion in this section.

4.4 Large-scale application: European electricity market

This section presents an application and extension of the previously developed methodology to the European electricity system. A large-scale investment and dispatch model for the European electricity market is applied in order to determine the optimal pathway to a low-carbon electricity system in 2050. Based on the presented methodology, the development of regional capacity values of wind power over time and the corresponding implications on optimal allocation of wind power capacities are assessed.

The analysis is structured as follows: Sections 4.4.1 and 4.4.2 give a brief description of the applied electricity market model as well as assumptions and data sources. Section 4.4.3 presents the model results.

4.4.1 Electricity market model and scenario definition

The applied model is a partial equilibrium model that determines the cost minimal configuration of the European electricity system, considering investment decisions as well as dispatch of power plants. Cost minimization over several years reflects perfect competition and the absence of market distortions as well as perfect foresight as fundamental model assumptions. The model is an extended version of the linear large-scale investment and dispatch model presented in Richter (2011), which has been applied for example in Bertsch et al. (2016) and Knaut et al. (2016). The basic model structure follows the same logic as in Problem (4.8), however additional constraints are included in order to improve the representation of politically implied restrictions and technical properties of electricity systems. These constraints include for example ramping or storage constraints as well as politically imposed CO_2 reduction targets to decarbonize the power sector.[20]

The model represents a total of 27 European countries.[21] Transmission between

[20] See Richter (2011) for a detailed description of the model.

[21] Austria (AT), Belgium (BE), Bulgaria (BG), Switzerland (CH), Czech Republic (CZ), Germany (DE), Denmark (DK), Estonia (EE), Spain (ES), Finland (FI), France (FR), Great Britain (GB), Greece (GR), Croatia (HR), Hungary (HU), Ireland (IE), Italy (IT), Lithuania (LT), Latvia (LV), Netherlands (NL), Norway (NO), Poland (PL), Portugal (PT), Romania (RO), Sweden (SE), Slovenia (SI), Slovakia (SK)

countries is represented by net transfer capacities (NTC), which are assumed to be extended according to the ENTSO-E Ten-Year Network Development Plan 2018 (ENTSO-E (2018)). The starting year of the model is 2015. Existing capacities in 2015 are based on a detailed database developed at the Institute of Energy Economics at the University of Cologne, which is mainly based on the Platts WEPP Database (Platts (2016)) and constantly updated. Based on these start values, the model optimizes the electricity system until the year 2050. The European CO_2 reduction targets are implemented as yearly CO_2 quotas, which impose a reduction of emissions by 95 % in 2050 compared to 1990 levels. Additional reduction targets for the intermediate years are implemented with 21 % reduction in 2020 compared to 2005 and 43 % in 2030 compared to 2005. All values are based on official reduction targets formulated by the European Commission.[22] Investment into nuclear power is only allowed for countries with no existing nuclear phase-out policies. Fuel costs and investment costs for new generation capacities are based on the World Energy Outlook 2017 (International Energy Agency (2017)). Yearly national electricity consumption is assumed to develop according to the ENTSO-E Ten-Year Network Development Plan 2018 (ENTSO-E (2018)). The detailed numerical assumptions are presented in Appendix 4.6.3.

The country-specific reliability target in the capacity value framework of the large-scale application is set to an EEU, which corresponds to a loss of load expectation of 3 hours per year in every modeled country. This value is often applied in theory (e.g., Keane et al. (2011)) as well as in practice (e.g., in the capacity markets in Great Britain or by the ISO New England).[23]

4.4.2 Input data for variable renewable electricity generation and load

In addition to the assumptions described in the previous section, detailed data on weather-dependent renewable energy sources are required in order to assess contributions to security of supply of wind power generation and to generate robust estimates for the capacity value. We apply a novel dataset for wind and solar power

[22] See https://ec.europa.eu/clima/policies/strategies for detailed explanations.

[23] In European countries, reliability targets measured in $LOLE$ generally range from 3 to 8 hours per year (Table 6 in European Commission (2016a)). Note that in case of a loss of load event, the system operator typically still has a number of options before finally resorting to selective disconnections, amongst others asking generators to exceed their rated capacity, invoking demand side balancing reserves or reducing voltage levels (Newbery (2016)). We estimate the EEU corresponding to $LOLE = 3$ in each country based on the historical ordered residual load curve in each modeled country. The resulting EEU for all markets are listed as shares of yearly demand in Table 4.4 in Appendix 4.6.3.

generation based on the meteorological weather model COSMO-REA6. The data for wind power generation from existing capacities is based on Henckes et al. (2018b). The wind speed data derived from the weather model is combined with a detailed dataset of European wind parks, which includes location, installed capacity, hub-height and turbine data in order to generate a consistent hourly time series of wind power generation over 20 years (1995-2014).

The same methodology is extended in our application for potential future generation capacities. We assume power curves based on state-of-the-art onshore and offshore wind power plants for new capacity investment.[24] These plants are assumed to be distributed on a 24x24 km grid over whole Europe in order to determine wind generation data for potential new generation investment. Again, a consistent hourly 20 year time series of wind power generation is generated.

Even though solar power generation is not the focus of the present analysis we also use high resolution hourly time series for solar power. The data is generated based on solar irradiance data of COSMO-REA6 for the same 24x24 km grid over Europe as for wind power generation. The methodology is described in detail in Frank et al. (2018) and Henckes et al. (2018a).

In order to keep the large-scale investment and dispatch model computationally tractable, the spatial and temporal resolution of wind and solar power generation data has to be reduced. We apply a two-step clustering approach in order to accomplish this. In a first step the spatial resolution is reduced by clustering the high resolution data into representative wind and solar regions. The number of regions for onshore wind and solar is chosen based on the surface area of each country. Additionally one offshore wind region with water depths smaller than 50 m for bottom-fixed offshore wind turbines and one region with water depths between 50 m and 150 m for floating offshore wind turbines are considered. In total the model consists of 54 representative regions both for onshore wind and solar power and 41 representative regions for offshore wind in Europe (see Table 4.6 in Appendix 4.6.3). A detailed description of the spatial clustering methodology is presented in Appendix 4.6.2.

Based on the spatially reduced data a temporal clustering is performed in order to identify time slices, which allow to reduce the temporal resolution without losing the statistical properties of weather-dependent wind and solar power generation and

[24]The considered wind turbines are Enercon E-126 EP4 for onshore wind and Vestas V164 for offshore wind. Power curves for both turbines were determined based on technical data on the manufacturer websites.

load. Load data is based on hourly national vertical load[25] data for all considered countries for the years 2011-2015 taken from ENTSO-E (2016). Note that these historical measurements - being the result of a functioning electricity market - may include some price responsiveness of consumers or load shedding. However, historical load represents the best approximation available for the variable electricity demand over time. Additionally, price responsiveness during times of scarcity is low (Lijesen (2007)), which justifies the assumption of inelastic load. The historical load data is normalized and scaled based on the assumptions for total yearly future electricity demand development in order to generate consistent time series.[26] Each of the five years is then combined with the 20 years of renewable energy generation data in order to get a good representation of the joint probability space, resulting in 100 synthetic years of hourly load and renewable energy data. Hereby, we assume stochastic independence between load and wind.

Based on this dataset and the temporal clustering approach presented in Nahmmacher et al. (2016), we generate 16 typical days for the time slices used in the investment and dispatch model.[27] As depicted in Figure 4.1, these typical days are used as input data only for the electricity market model while the capacity value calculations are based on the full temporal resolution of the data set.

4.4.3 Results and discussion

This section presents the model results, which are determined based on the described methodology and assumptions in an application for wind power. Section 4.4.3 presents the resulting contribution of wind power to security of supply. Based on these results Section 4.4.3 discusses differences between the proposed optimization methodology and existing modeling approaches, which do not account for the endogeneity of the capacity value of wind power generation.

The applied iteration algorithm converges also in the large-scale application after only a few iterations (see Figure 4.8 in Appendix 4.6.1). In order to check the presented results for robustness we ran the model with a wide range of start values for the capacity value. All robustness checks showed quick convergence and merely identical results.

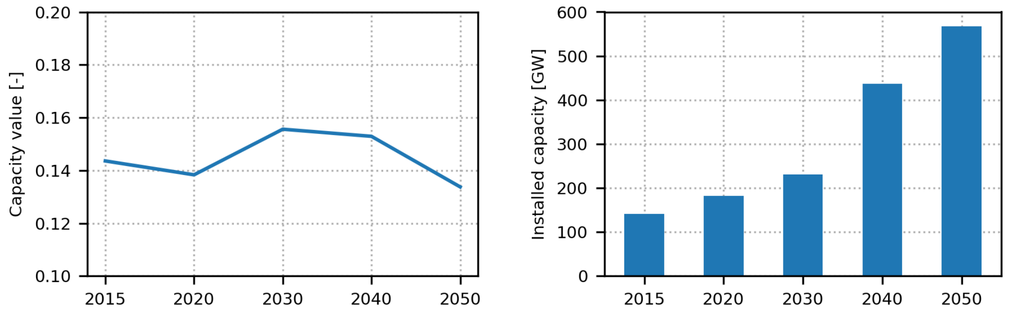
[25] i.e., national net electricity consumption plus network losses.

[26] Scaling historical load time series implies that the temporal structure of electricity demand does not change in the future. Consequently, possible changes in the demand structure as a result of increasing electrification in the mobility or heating sector are not accounted for.

[27] Nahmmacher et al. (2016) show that, in investment models for electricity markets, even less than 10 typical days are sufficient to obtain similar results to model runs with high temporal resolution.

Contribution of wind power to security of supply

The main novelty of the presented methodology is the explicit endogenous representation of the contribution of wind power generation to security of supply in a large-scale model for electricity markets. Figure 4.3 shows the resulting aggregated average national capacity value of European wind power plants together with total installed wind power capacity in Europe for the simulated years. The presented values can be interpreted as the average share of wind power capacity in Europe that can be considered as firm capacity in the respective year, assuming cooperation with respect to reliability by means of an efficient usage of interconnectors.



(a) Aggregated average capacity value of wind power in Europe

(b) Aggregated installed wind capacity in Europe

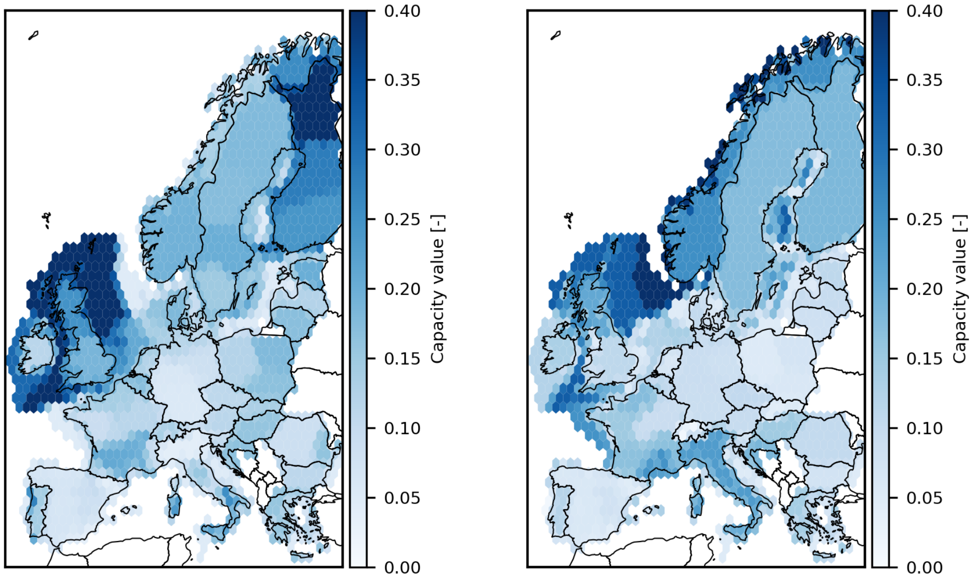
Figure 4.3: Average contribution of wind power to security of supply in Europe

The depicted results show that the contribution of wind power to security of supply is above 10 % in all considered model years. In 2015 the capacity value of wind amounts to roughly 14 % on average. Until 2020 this value only slightly decreases despite capacity additions. The reason is that interconnections between European countries are extended according to the Ten-Year Network Development Plan 2018 of ENTSO-E. As a result the decline in average capacity value, which results from additional generation capacities and decreasing returns to scale, is dampened by additional interconnectors. This dampening effect emerges because we calculate the capacity value based on the ability of wind power to provide secure capacity given the availability of interconnections to neighboring countries. Consequently, as interconnector capacities increase, the ability of wind power to provide secure capacity in combination with interconnectors also increases.

Remarkably, between 2020 and 2030 the average capacity value of European wind power increases despite continued capacity additions. This effect can be explained by technological innovation as a large share of the existing wind power plants reach the end of their technical lifetime during this time span. Consequently, many old wind power plants with relatively low rated capacities and hub heights are substituted by state-of-the-art wind turbines, which enable more stable and reliable wind power generation on average. As a result the capacity value increasing effect of technological innovation in combination with continued increased market integration outweighs the decreasing effect of decreasing returns to scale. After 2030, the two increasing effects are less pronounced because the wind power plant fleet is already to a large part renewed and the extension of interconnectors is less pronounced. Additionally total installed wind power capacity more than doubles from roughly 230 GW in 2030 to over 560 GW in 2050. Accordingly, the average capacity value of wind power decreases between 2030 and 2050.

In addition to the described average effects in Europe, the model results show a strong heterogeneity across different regions. To illustrate this, Figure 4.4 shows the regional capacity value in 2030 and 2050, based on color-coded maps. It is shown that the capacity credit varies between 1 % and 40 % across countries and declines in most regions between 2030 and 2050. Interestingly this is not the case for all regions, for example in some regions in France and Italy as well as some offshore regions in France and Norway, the capacity value remains constant or even increases. In all mentioned regions, this can be explained by small installed wind power capacities in 2030 and no or relatively small capacity additions between 2030 and 2050. Thus, no decreasing return to scale effect arises, which would reduce the capacity value. At the same time, the temporal structure of residual load in neighboring regions changes due to wind and solar capacity additions, increasing the value of the temporal wind structure in the mentioned regions. It can be concluded that the differing temporal patterns of wind power generation as well as the differing total installed capacities, technology mixes and interconnection capacities lead to heterogeneous contributions of wind power to security of supply across countries.

Based on the market-specific capacity values the equivalent firm capacity of wind power can be calculated. The results for all considered countries in 2050 are shown in Figure 4.5. It differentiates between firm capacity that is provided by wind power plants within the respective country and firm capacity that is provided cross-border via interconnections to neighboring markets, given they cooperate with respect to reliability. Again it is apparent that the contribution of wind power to security of supply varies substantially between countries depending on the capacity value and the installed capacities. In comparatively large countries such as Germany, France or



(a) Capacity value of wind power in 2030 (b) Capacity value of wind power in 2050

Figure 4.4: Regional capacity values of wind power in the European electricity system

Great Britain the national equivalent firm capacity of wind power amounts to more than 10 GW. Additionally, it is shown that substantial cross-border contributions are present in many countries. In Switzerland, for example, the equivalent firm capacity provided by wind in neighboring countries amounts to more than 5 GW. This is a result of increasing Swiss market integration and large installed wind power capacities in neighboring countries, especially Germany and France.

Implications on electricity system configuration

As shown in the previous section, the contribution of wind power capacities to security of supply can be substantial. Additionally the results show that the capacity value of wind power is heterogeneous across countries and varies over time depending on the installed capacity of wind power, the available transmission capacities between countries and technological innovations. In practice however, long-term scenarios of the electricity system are typically based on the assumption of a fixed exogenous capacity value (e.g. 5 % in Jägemann et al. (2013)). Because of these modeling practices we analyze in this section how the results of our proposed methodology differ from existing modeling approaches with fixed capacity values for wind power. We thereby compare our model results to equivalent model runs with fixed capacity

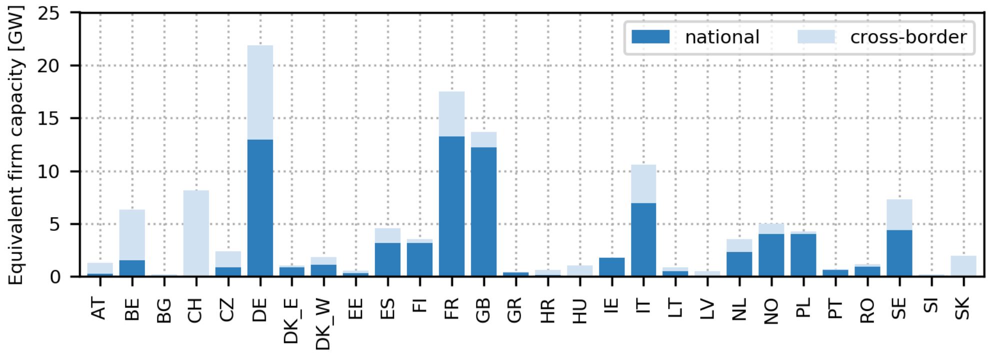


Figure 4.5: National and cross-border equivalent firm capacity provision of wind power in European countries in 2050

values for wind ranging from 0 % to 20 %.

Figure 4.6 shows the difference in firm capacity requirements for European countries in 2050 for simulations based on exogenous wind power capacity values compared to simulations applying endogenous capacity values, which account for their temporal and spatial heterogeneity. Positive values imply additional firm capacity requirements with exogenous capacity values. It is evident that fixed exogenous wind capacity values result in inefficient amounts of firm capacity provision. Applying wind capacity values below 10 % leads to an overestimation of firm capacity requirements for most countries. In addition, the heterogeneity of the capacity value across different countries implies that country- or even region-specific evaluations of the capacity value are necessary in order to correctly estimate the required dispatchable firm capacity.

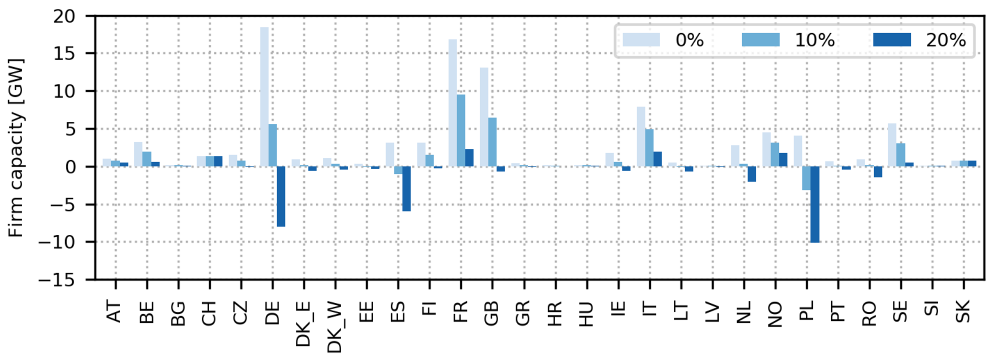


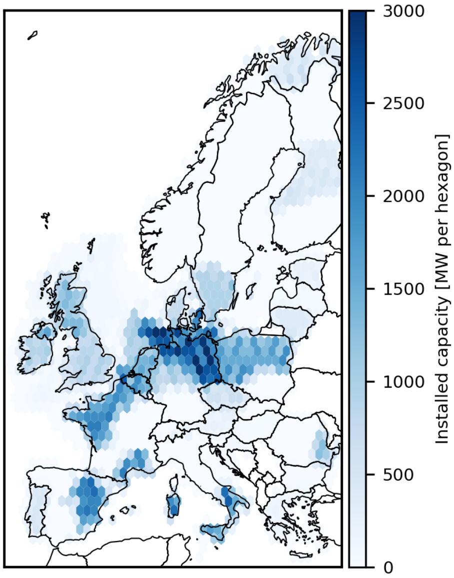
Figure 4.6: Difference in firm capacity requirements in 2050: Endogenous wind power capacity values vs. exogenous capacity values

The requirement for additional firm capacity translates into additional yearly costs for its provision, i.e. annuitized investment costs as well as fixed operation and maintenance costs. Typically, such additional dispatchable back-up capacity is provided by low-cost open-cycle gas turbines. The additional yearly costs for firm capacity provision when applying exogenous fixed wind power capacity values of 5 % compared to endogenous capacity values amount to 1.5 and 3.8 bn EUR in 2030 and 2050, respectively, which represents additional costs of 3 % and 7 %.

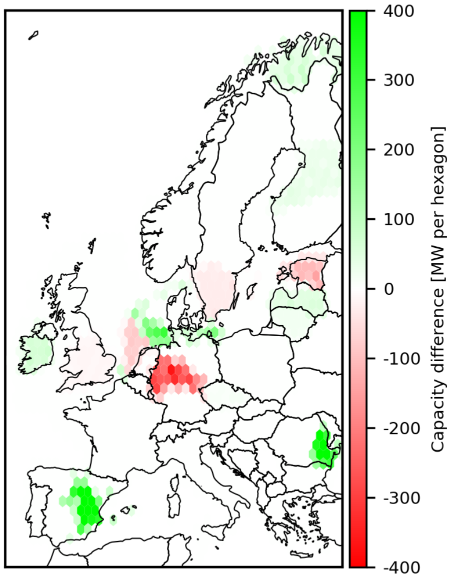
In addition to cost differences the results of our modeling approach also differ in comparison to existing approaches with respect to the geographical distribution of the installed wind power capacity. This is a result of the marginal local contribution of wind power to security of supply, which is reflected in our modeling approach and is often neglected in existing methodologies. To analyze the impact of this effect, Figure 4.7(a) shows the geographically differentiated installed wind capacities in 2050 based on endogenous capacity value calculations. Figure 4.7(b) displays the regional differences in installed capacities compared to an equivalent model run with fixed wind power capacity values of 5 %. Green areas on the map in Figure 4.7(b) indicate that more wind power capacities are installed when endogenously calculating the contribution to reliability, red areas on the other hand indicate that less wind power capacities are installed in the respective area.

The results illustrate that there are substantial regional differences between a model run with a constant capacity value of 5 % and our methodology. The reason for the regional shifts in wind power capacity is that when the contribution to security of supply is accounted for, it can be cost optimal to prefer locations with relatively lower total wind power generation, which instead have a higher capacity value. Consequently, there is a trade-off between electricity generation and contribution to security of supply of one unit of wind power capacity. Because of the weather dependency of wind power generation this trade-off depends on the wind conditions in a specific region and the correlations with demand and wind power generation at other sites.

It can be seen from Figure 4.7 that there is for example a shift of offshore wind power capacity from the Netherlands to German and Belgian offshore wind regions if the contribution to security of supply is endogenously accounted for. Additionally, the results show that there is less onshore wind power capacity installed in central Germany. Instead more capacity is installed for example in Spain, Romania, Finland and Norway. Consequently, the results suggest that wind power generation is shifted from Germany to other countries in order to spread wind power plants over a wider



(a) Installed wind power capacity in 2050 based on endogenous capacity value calculations



(b) Difference in optimal wind power capacity in 2050: Endogenous capacity values vs exogenous capacity values of 5%

Figure 4.7: Allocational effects of endogenizing the capacity value of wind power in investment and dispatch models for the European electricity market

area, and take advantage of differing wind conditions on a wider geographical scope.

More generally it can be concluded that there are regional as well as technological differences regarding offshore and onshore wind power plants between our methodological approach and existing modeling approaches. Hence, our results suggest that the contribution to security of supply should be considered in studies that analyze optimal locations of wind power generation in electricity systems based on long-term investment models.

4.5 Conclusion

This article analyzes the contribution of wind power generation to security of supply in electricity systems and develops a new methodology to endogenously determine the capacity value of generation capacities based on variable renewable energy sources in large-scale optimization models. Our novel framework allows to account for the non-linear dependency of the capacity value of wind power on the amount and spatial distribution of installed wind capacity, considering cross-border cooperation via interconnectors. Building on that, we quantify differences in system costs and wind power capacity allocation in comparison to existing modeling approaches, which typically assign fixed exogenous capacity values for wind power.

We find, based on a large-scale application of the proposed methodology, that wind power substantially contributes to security of supply in a decarbonized European electricity system with capacity values between 1 % and 40 %. The regional capacity value of wind power depends on the region-specific wind conditions, its correlation to other regions, as well as on the installed wind power capacity and the capacity of interconnections to neighboring markets. Assigning fixed and invariable capacity values therefore results in inefficient levels of required back-up capacities in electricity systems with high shares of variable renewable energy. We find that, for the European electricity system, the additional yearly costs for firm capacity provision when applying exogenous fixed wind power capacity values of 5 % compared to endogenous capacity values amount to 1.5 and 3.8 bn EUR in 2030 and 2050, respectively, which represents additional costs of 3 % and 7 %.

Our results imply that long-term scenarios for electricity systems should account for the contribution of variable renewable energy sources to security of supply. Additionally our results suggest that capacity mechanisms, which are being implemented in many countries should allow for participation of generation capacities based on variable renewable energy sources as well as cross-border contributions. However, the assigned capacity values should be determined based on careful assessments of the statistical properties of the variable renewable energy generation and need to be regularly updated in order to account for changes in the system configuration. Finally, our results show that market integration by increasing interconnections between different countries increases the potential of variable renewable energy sources to contribute to security of supply.

In future work our developed methodological approach could be extended to account for the electrical properties of transmission lines by integrating a load flow model. Thereby, internal transmission constraints could be accounted for. Additionally, other metrics for reliability of supply could be integrated in our model. Finally, an application of our approach to solar power generation would be a substantial contribution to the understanding of security of supply in electricity systems with high shares of generation based on variable renewable energy sources.

4.6 Appendix

4.6.1 Convergence

Figure 4.8 shows total system costs for each step of the iteration for different start values for the capacity value. It can be seen that total system costs converge quickly to very similar values independently of the start value. It is also apparent that changes in total system costs are negligible after the third iteration. We abort the iteration after the tenth step. The relative change in total system costs between the ninth and the tenth iteration is less than 0.1 %. The results for other start values within the depicted range were merely identical and are therefore omitted in Figure 4.8.

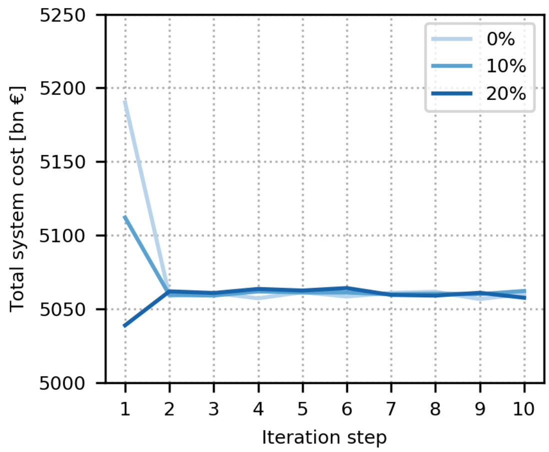


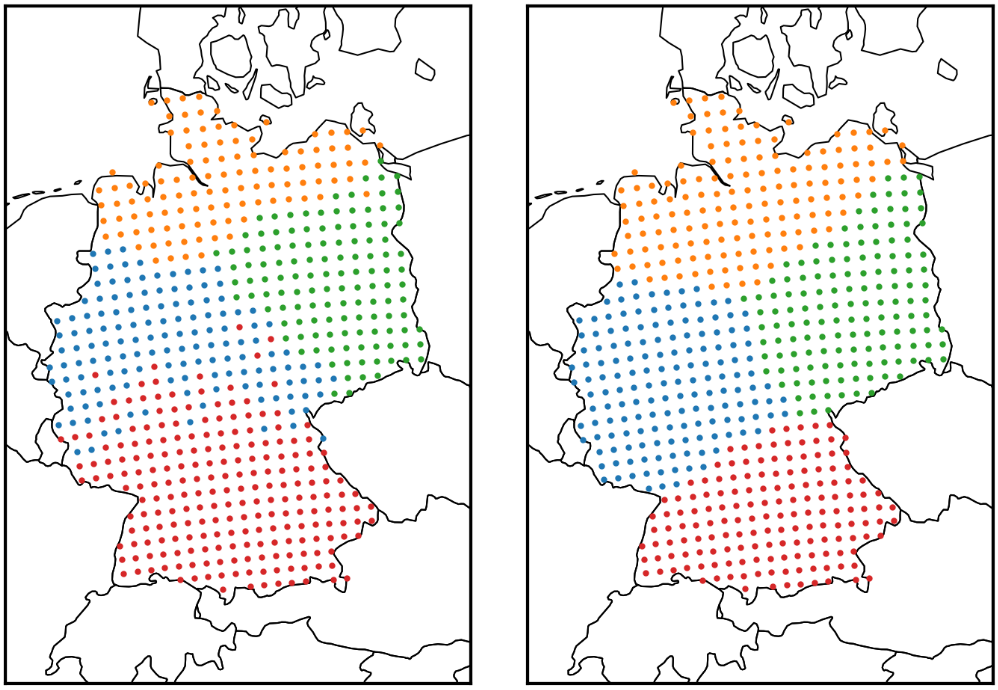
Figure 4.8: Convergence of total system costs in large-scale application for different starting values

4.6.2 Spatial clustering methodology

The input data for wind and solar power generation is derived from the meteorological reanalyis dataset COSMO-REA6. The data has a high spatial resolution with data points on a 24x24 km grid over whole Europe. In order to keep the electricity market model computationally tractable the spatial resolution has to be reduced. We apply a spatial clustering methodology in order to construct representative regions, which optimally reduce the spatial resolution. Our methodology consists of three basic steps:

1. Derive number of clusters per market and energy source

2. Apply the clustering algorithm
3. Determine regional potential for wind and solar power capacities



(a) Wind onshore (b) Solar

Figure 4.9: Exemplary results of spatial clustering for onshore wind power (a) and solar power (b) in Germany

In the first step we choose the number of clusters. We use a simple heuristic approach based on the surface area of a country to determine the number of clusters for onshore wind and solar power. The total surface are of each market is divided by 100'000 km^2 and the resulting number is rounded to determine the number of clusters. For offshore wind we choose only one region per market for water depths below 50 m and one region for water depths between 50 m and 150 m. The results are presented in Table 4.6.

In the second step we apply a k-means clustering algorithm in order to cluster the data points into the number of chosen regions. Wind power and solar power are clustered independently in order to capture the spatial properties of both energy sources. Based on the clustered data points the energy output of one representative region is calculated by averaging over all data points in a cluster. Figure 4.9 shows exemplary the clustering results for onshore wind and solar power in Germany. Each data point is represented by a dot, while the color coding differentiates the resulting clusters.

In the third step the potential for installed capacity in each region is calculated for wind and solar power. The calculation is based on the country-level area potentials in Schmidt et al. (2016). Based on the total area potentials we calculate the regional area potentials with the ratio between the number of data points per region and the total data points in the corresponding country, assuming an equal distribution.

4.6.3 Numerical assumptions

Table 4.2: Assumptions on generation technology investment costs (EUR/kW)

Technology	2015	2020	2030	2040	2050
Wind onshore	1656	1602	1548	1512	1476
Wind offshore (bottom-fixed, <50 m depth)	3493	3168	2473	2236	2061
Wind offshore (floating, >50 m depth)	3749	3460	2581	2300	2099
Photovoltaics (roof)	1440	1152	972	882	792
Photovoltaics (ground)	1188	936	774	702	630
Biomass (solid)	3298	3297	3295	3293	3287
Biomass (gas)	2826	2826	2826	2826	2826
Geothermal	12752	10504	9500	9035	9026
Hydro (river)	5000	5000	5000	5000	5000
Compressed air storage	1100	1100	1100	1100	1100
Pump storage	2336	1237	1237	1237	1237
Battery	1000	1000	750	650	550
Nuclear	6253	5684	4832	4263	4263
OCGT	464	464	464	464	464
CCGT	1063	928	928	928	928
IGCC	2350	2350	2350	2300	2300
Coal	1957	1957	1957	1957	1957
Coal (advanced)	2152	2152	2152	2152	2152
Lignite	1596	1596	1596	1596	1596

Table 4.3: Assumptions on techno-economic parameters of electricity generators

Technology	**FOM costs (EUR/kW/a)**	**Net efficiency (-)**	**Technical lifetime (a)**
Wind onshore	13	1	25
Wind offshore (bottom-fixed, <50 m depth)	93	1	25
Wind offshore (floating, >50 m depth)	93	1	25
Photovoltaics (roof)	17	1	25
Photovoltaics (ground)	15	1	25
Biomass (solid)	120	0.30	30
Biomass (gas)	165	0.40	30
Geothermal	300	0.23	30
Hydro (river)	12	1	60
Compressed air storage	9	0.70	40
Pump storage	12	0.76	60
Battery	10	0.90	20
Nuclear	101-156	0.33	60
OCGT	19	0.28-0.40	25
CCGT	24-29	0.39-0.60	30
IGCC	44-80	0.46-0.50	30
Coal	44-60	0.37-0.46	45
Coal (advanced)	64	0.49	45
Lignite	46-53	0.32-0.46	45

Table 4.4: Assumptions on the future development of net electricity demand including network losses (TWh) and the reliability target expected energy unserved *EEU* as share of yearly demand (‰)

Country	**2015**	**2020**	**2030**	**2040**	**2050**	*EEU* **(‰)**
AT	70	73	77	80	80	0,005
BE	85	87	89	90	90	0,008
BG	33	41	42	44	44	0,011
CH	63	62	58	56	56	0,006
CZ	63	69	71	74	74	0,007
DE	521	565	547	552	552	0,007
DK_E	13	15	17	18	18	0,014
DK_W	20	26	30	32	32	0,014
EE	8	9	10	11	11	0,015
ES	263	268	282	283	283	0,010
FI	82	90	94	96	96	0,007
FR	475	481	467	447	447	0,013
GB	333	328	322	313	313	0,010
GR	51	57	63	70	70	0,013
HR	17	19	22	24	24	0,010
HU	41	43	47	52	52	0,002
IE	27	31	36	38	38	0,010
IT	314	326	362	400	400	0,007
LT	11	12	13	15	15	0,006
LV	7	8	8	9	9	0,008
NL	113	115	119	122	122	0,006
NO	128	136	150	143	143	0,019
PL	151	163	207	253	253	0,006
PT	49	51	53	56	56	0,009
RO	55	58	64	70	70	0,007
SE	136	142	143	142	142	0,008
SI	14	13	17	20	20	0,007
SK	27	29	33	36	36	0,004

Table 4.5: Assumptions on gross fuel prices (EUR/MWh_{th})

Fuel type	**2015**	**2020**	**2030**	**2040**	**2050**
Nuclear	3	3	3	3	3
Lignite	2	3	3	3	3
Coal	9	10	11	11	11
Oil	22	33	49	58	58
Natural gas	15	19	25	28	28

Table 4.6: Number of spatial clusters for VRE per country

	Number of clusters			
Country	**Wind onshore**	**Wind offshore (<50 m depth)**	**Wind offshore (>50 m depth)**	**Solar**
AT	1	0	0	1
BE	1	1	0	1
BG	1	1	1	1
CH	1	0	0	1
CZ	1	0	0	1
DE	4	1	0	4
DK_E	1	1	1	1
DK_W	1	1	1	1
EE	1	1	1	1
ES	5	1	1	5
FI	3	1	1	3
FR	6	1	1	6
GB	2	1	1	2
GR	1	1	1	1
HR	1	1	1	1
HU	1	0	0	1
IE	1	1	1	1
IT	3	1	1	3
LT	1	1	1	1
LV	1	1	1	1
NL	1	1	0	1
NO	4	1	1	4
PL	3	1	1	3
PT	1	1	1	1
RO	2	1	1	2
SE	4	1	1	4
SI	1	0	0	1
SK	1	0	0	1

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