# Modeling Market Failures and Regulation in the Changing German Power Market

vorgelegt von
Diplom-Ingenieur
Wolf-Peter Schill

Von der Fakultät VII – Wirtschaft und Management
der Technischen Universität Berlin
zur Erlangung des akademischen Grades
Dr. rer. oec.

genehmigte Dissertation

Promotionsausschuss:

| | |
|---|---|
| Vorsitzender: | Prof. Dr. Georg Meran |
| Gutachter: | Prof. Dr. Christian von Hirschhausen |
| | Prof. Dr. Claudia Kemfert |

Tag der wissenschaftlichen Aussprache: 13.7.2011

Berlin 2011

D 83

*Für Katharina.*

# Abstract

The German power market is shaped by several distinctive trends. These include market restructuring, climate policy measures, renewable energy integration, and electric vehicles. In this thesis, I conduct in-depth model-based analyses of specific economic questions related to the aforementioned developments. More precisely, I examine selected market failures and the need for economic regulation. In doing so, the focus is on imperfect competition, natural monopolies, and $CO_2$ regulation.

The first chapter motivates the research questions and provides an introduction to important power market transformations. Chapter 2 analyzes the strategic utilization of electricity storage in the oligopolistic German power market, and the related implications for market outcomes. Chapter 3 extends this analysis by modeling the interactions of a hypothetical fleet of one million grid-connected electric vehicles with the imperfectly competitive German power market. Chapter 4 provides a comparative analysis of different regulatory approaches for transmission network expansion in the light of fluctuating demand and wind power. Chapter 5 examines the effect of different emission permit allocation schemes on the relative profitability of investments into hard coal and natural gas plants in Germany. The last chapter summarizes and concludes. It also includes a brief discussion of model limitations and perspectives for further research.

This thesis contributes to the literature in several ways. To begin with, it includes an explicit model of the intricate interactions of strategic players' decisions on conventional power generation, storage discharging, and storage loading in an oligopolistic market environment. Likewise, this thesis provides the first analysis of the effects of plug-in electric vehicle fleets on the oligopolistic German power market. Furthermore, the relative performance of a new combined merchant-regulatory mechanism for transmission expansion is modeled with a level of detail that can not be found in the literature. Last, but not least, this thesis presents an innovative methodology for calculating the windfall profits related to emission permit allocation rules in Germany. Drawing on sensitivity analyses, investment distortions related to Germany's first National Allocation Plan are quantified with an accuracy previously not found in the literature.

**Keywords:** Power market modeling, Regulation, Market power, Oligopoly, Storage, Electric vehicles, Transmission expansion, Emission permit allocation.

# Zusammenfassung

Der deutsche Strommarkt ist geprägt von Liberalisierungsprozessen, wachsenden Anforderungen der Klimapolitik, der Integration erneuerbarer Energien und dem Einstieg in die Elektromobilität. In dieser Doktorarbeit untersuche ich anhand detaillierter modellgestützter Analysen spezifische ökonomische Fragestellungen, die mit den genannten Entwicklungen einhergehen. Es werden ausgewählte Fälle von Marktversagen und die Notwendigkeit ökonomischer Regulierung beleuchtet. Dabei liegt der Schwerpunkt auf unvollständigem Wettbewerb, natürlichen Monopolen und der Regulierung von $CO_2$-Emissionen.

In einem einleitenden Kapitel werden die Forschungsfragen eingeführt und wichtige Strommarktentwicklungen vorgestellt. In Kapitel 2 werden die strategische Nutzung von Stromspeichern im oligopolistischen deutschen Strommarkt sowie deren Auswirkungen auf die Marktergebnisse untersucht. Darauf aufbauend analysiert Kapitel 3 die Wechselwirkungen einer hypothetischen Flotte von einer Million Elektrofahrzeugen mit dem Strommarkt. In Kapitel 4 werden verschiedene Ansätze zur Regulierung des Übertragungsnetzausbaus quantitativ verglichen, wobei ein besonderes Augenmerk auf der Abbildung der Variabilität von Stromnachfrage und Windeinspeisung liegt. Kapitel 5 untersucht die Auswirkungen unterschiedlicher Zuteilungsregeln für Emissionsberechtigungen auf die relative Profitabilität von Kohle- und Gaskraftwerken in Deutschland. Das letzte Kapitel enthält eine Zusammenfassung und Schlussfolgerungen, eine Diskussion der Einschränkungen sowie Perspektiven für die weitere Forschung.

Diese Arbeit erweitert die ökonomische Literatur in mehrerlei Hinsicht. So enthält sie ein Modell, mit dem die kombinierten Entscheidungen strategischer Marktakteure hinsichtlich konventioneller Stromerzeugung und dem Betrieb von Speichern in einem nicht perfekt wettbewerblichen Marktumfeld explizit dargestellt werden können. Daneben werden die Auswirkungen einer künftigen Flotte von netzverbundenen Elektrofahrzeugen auf den oligopolistischen deutschen Strommarkt erstmals analysiert. Darüber hinaus wird die Leistungsfähigkeit eines neuen Regulierungsmechanismus mit alternativen Regulierungsansätzen verglichen und mit einem gegenüber bisherigen Analysen höheren Detailgrad quantitativ untersucht. Nicht zuletzt wird eine Methodik zur Berechnung von Windfall Profits vorgestellt, die durch die deutschen Zuteilungsregeln anfallen. Die Verzerrungen der Anreize für Kraftwerksinvestitionen, die mit dem ersten deutschen Allokationsplan einhergehen, werden mit Hilfe umfangreicher Sensitivitätsanalysen mit einer bisher nicht erreichten Genauigkeit quantifiziert.

Schlüsselwörter: Strommarktmodellierung, Regulierung, Marktmacht, Oligopol, Speicher, Elektromobilität, Netzausbau, Allokation von Emissionsrechten.

# Acknowledgements

Trained as an environmental engineer, it was a challenging and exciting endeavor to pursue a doctoral degree in economics. Right at the beginning, Christian von Hirschhausen told me that "the best economists are engineers – but the same is also true for the worst ones". After finishing this thesis, I hope that I have joined the right category of engineers-turned-economists. I would like to seize the opportunity to thank the persons who have accompanied and supported me on this journey.

First of all, I am indebted to my supervisors, Claudia Kemfert and Christian von Hirschhausen, for their continuous support and inspiration, and for introducing me to the power market community. While both of them have helped me to keep on track, they have also granted me the freedom to choose and elaborate the research subjects presented in this thesis, which I appreciate very much. I am also grateful to Georg Meran, without whom I certainly would not have joined the DIW Graduate Center. This program provided me with the financial and institutional resources to write this thesis. I also thank my fellow Graduate Center students for filling our doctoral program with life. In particular, I thank Ludwig Ensthaler for more than three years of microeconomic discussions, some of them in the most improbable places.

Aside from my supervisors, several colleagues have read and discussed various versions of the papers presented in chapters 2-5, most notably Jan Abrell, Frauke G. Braun, Jochen Diekmann, Steven A. Gabriel, Michael Pahle, Thure Traber, and Georg Weizsäcker. I thank all of them for pointing out weaknesses, for insightful discussions, and for valuable input. I also thank my co-authors Jonas Egerer, Lin Fan, Claudia Kemfert, Michael Pahle, and Juan Rosellón for the fruitful cooperation, as well as Frauke G. Braun and Adam Lederer for proof-reading.

I do not want to forget to express my deep-felt gratitude towards my parents for supporting me throughout my studies. And finally, I thank my wonderful wife Katharina. This is for you.

# Rechtliche Erklärung

Hiermit versichere ich, dass ich die vorliegende Dissertation selbstständig und ohne unzulässige Hilfsmittel verfasst habe. Die verwendeten Quellen sind vollständig im Literaturverzeichnis angegeben. Die Arbeit wurde noch keiner Prüfungsbehörde in gleicher oder ähnlicher Form vorgelegt.

Berlin, 9. Juni 2011

Wolf-Peter Schill

*The purpose of computing is insight, not numbers.*

Richard W. Hamming.

# Contents

# List of Tables

# List of Figures

# Nomenclature

**Abbreviations**

| | |
|---|---|
| ACER | Agency for the Cooperation of Energy Regulators |
| BAT | Best Available Technology |
| BDEW | Bundesverband der Energie- und Wasserwirtschaft (German Association of Energy and Water Industries) |
| BMU | Bundesministerium für Umwelt, Naturschutz und Reaktorsicherheit (German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety) |
| BMWi | Bundesministerium für Wirtschaft und Technologie (German Federal Ministry of Economics and Technology) |
| CCGT | Combined Cycle Gas Turbine |
| $CO_2$ | Carbon Dioxide |
| $CO_2$-eq | Carbon Dioxide Equivalents |
| DCF | Discounted Cash Flow |
| DEHSt | Deutsche Emissionshandelsstelle (German Emissions Trading Authority) |
| dena | Deutsche Energie-Agentur (German Energy Agency) |
| DSM | Demand-Side Management |
| EEG | Erneuerbare-Energien-Gesetz (German Renewable Energy Sources Act) |
| EEX | European Energy Exchange |
| ElStorM | Electricity Storage Model |
| EMELIE | Electricity Market Liberalization in Europe |
| ENTSO-E | European Network of Transmission System Operators for Electricity |
| ETS | Emissions Trading System |
| FTR | Financial Transmission Right |
| GAMS | General Algebraic Modeling System |
| GHG | Greenhouse Gas |
| HC | Hard Coal |
| HRV | Hogan-Rosellón-Vogelsang |
| IEA | International Energy Agency |
| IPCC | Intergovernmental Panel on Climate Change |
| ISO | Independent System Operator |
| KKT | Karush-Kuhn-Tucker |

| | |
|---|---|
| LTFTR | Long-Term Financial Transmission Right |
| MCP | Mixed Complementarity Problem |
| MPEC | Mathematical Program with Equilibrium Constraints |
| NAP | National Allocation Plan |
| NG | Natural Gas |
| NPV | Net Present Value |
| PBR | Performance-Based Regulation |
| PIEV | Plug-In Electric Vehicles |
| PJM | A regional transmission organization in the U.S., amongst others serving Pennsylvania, New Jersey, and Maryland |
| PTR | Physical Transmisson Right |
| PV | Photovoltaics |
| RES | Renewable Energy Sources |
| SFE | Supply Function Equilibrium |
| SRU | Sachverständigenrat für Umweltfragen (German Advisory Council on the Environment) |
| Transco | Transmission Company |
| TSO | Transmission System Operator |
| UBA | Umweltbundesamt (German Federal Environment Agency) |
| UCTE | Union for the Coordination of Transmission of Electricity |
| V2G | Vehicle-to-Grid |
| VDEW | Verband der Elektrizitätswirtschaft (German Electricity Association) |
| WEO | World Energy Outlook |

**Units**

| | |
|---|---|
| $kW$ | kilowatt |
| $MW$ | megawatt |
| $GW$ | gigawatt |
| $TW$ | terawatt |
| $kWh$ | kilowatt hour |
| $MWh$ | megawatt hour |
| $GWh$ | gigawatt hour |
| $TWh$ | terawatt hour |
| $ppm$ | parts per million |

# Chapter 1

# Introduction

## 1.1 Motivation and research questions

The German power market is undergoing substantial changes. It is shaped by several distinctive trends that are still evolving, including market restructuring, climate policy measures, renewable energy expansion, and electric vehicles:

- Market restructuring has led to far-reaching transformations of the organization and the structure of power markets. While Anglo-American countries were front-runners of electricity market reform, Germany had a late start. Currently, it is commonly accepted that competition in power markets can improve cost-effectiveness and deliver welfare benefits compared to the "old world" with regulated, monopolistic, state-owned utilities. However, the debate on ideal market design is ongoing.

- Following the 1992 United Nations Conference on Environment and Development in Rio, climate policy has gradually become a top priority for policy makers in many countries of the world. It is widely accepted – at least from a European perspective – that substantial reductions of greenhouse gas emissions must be achieved. This goal has important implications for the power sector, which is a major emitter of carbon dioxide ($CO_2$). In this respect, the introduction of an emissions trading scheme has been a key development in European electricity markets.

- A related trend is the increasing utilization of renewable energy sources (RES). In the future, further large-scale deployment of renewable generation capacity is expected, such that the power sector could be largely based on renewables in the long run. Importantly, technologies like wind power and photovoltaics (PV) show some specific characteristics: These include short-term stochastic generation, a limited correlation of feed-in with demand patterns, longer-term intermittency, and regional disparities of generation and demand. Because of these characteristics, integrating large shares of wind power and PV into networks and markets becomes increasingly challenging. Several strategies have been proposed for dealing with

integration problems, among them electricity storage, demand-side management, the provision of conventional backup capacity, and network extension.

- The aforementioned power market trends started in the 1990s and are still evolving. There is another development which is in its infancy, but is expected to become increasingly important: the advent of plug-in electric vehicles (PIEV). In the future, passenger vehicles traditionally fueled by gasoline or diesel could be powered by electricity. This offers several potential advantages over internal combustion engines, including lower local emissions, greater energy efficiency, and the utilization of electricity instead of oil as primary energy source. Accordingly, the German government aims to have one million electric vehicles on the road by 2020. Future fleets of electric vehicles may have significant implications for the electricity market, as they constitute both additional power demand and potentially also additional grid storage capacity. Aggregated vehicle fleets could thus serve as large-scale flexible power resources in the grid.

To be sure, the transformation processes of the German electricity market outlined above raise a multitude of technical problems that have to be solved by engineers. However, a range of economic research questions also needs to be addressed. Especially, there are unresolved questions of market failure and the need for economic regulation. For example, the electricity market impacts of renewable energy integration measures like electricity storage are not widely studied. In particular, it is not clear how such measures work in liberalized markets, which may be imperfectly competitive. Likewise, researchers have just begun to analyze the need for economic regulation regarding the integration of electric vehicles into power grids. It is also unclear how to regulate transmission expansion in the light of renewable energy integration. To give another example, there is still no complete picture on the impact of emissions trading on liberalized power markets. In this regard, both static and dynamic effects of permit allocations are important, i.e. efficient dispatch of existing power plants, as well as investments into new capacity.

It is not possible to fully cover all mentioned developments in a single research project, let alone in a doctoral thesis. Consequently, I focus on the analysis of market failures and regulation related to four selected topics. These include (1) electricity storage as one of the major strategies for renewable energy integration; (2) plug-in electric vehicles, which constitute both dispatchable power demand and additional storage capacity; (3) regulated transmission network expansion in the light of fluctuating wind power; and (4) incentives for power plant investments under carbon regulation. The focus is mostly on the German power market, whereas the question of transmission expansion can only be analyzed in a meaningful way in a European context. Drawing on four in-depth model-based analyses, I examine the following research questions:

Chapter 2 investigates the utilization of electricity storage by strategic players in an oligopolistic market. Accordingly, this analysis deals with the market failure of imperfect

competition. Do strategic operators underutilize their storage capacity, and what are the effects on social welfare? In particular, how do profit-maximizing firms' decisions on strategic storage interact with their decisions on the dispatch of other generation capacity? These questions are analyzed with a newly developed, game-theoretic model, which is applied to the oligopolistic German power market and pumped hydro storage. Various cases are simulated with competitive and strategic storage operators, which may also own other generation capacity. Drawing on model outcomes, it is also possible to analyze if pumped hydro storage is a potential source of market power in Germany.

In chapter 3, I extend the model developed in chapter 2 in order to examine the interactions between a future fleet of one million plug-in electric vehicles and the oligopolistic German power market. Electric vehicles are assumed to be connected to the power grid during most hours of the day which enables them to bring both additional, dispatchable demand and additional storage capacity to the market. How do different players make use of these resources? And what effects does this have on market prices, social welfare, and electricity generation in the imperfectly competitive power market? Several cases are simulated in which the vehicle fleet is controlled by different players, for example by price-taking car owners or by an oligopolistic generating firm. As in chapter 2, the model provides some insights if electric vehicles could become a relevant source for market power in the German electricity market.

Chapter 4 deals with market failures related to a natural monopoly. It provides an analysis of regulated electricity transmission network expansion in the light of fluctuating demand and wind power. In particular, the performance of a new combined merchant-regulatory approach is examined. How does this mechanism compare to purely merchant and cost-based regulatory alternatives in terms of extension and welfare outcomes? Compared to a simplified analysis with constant power demand, do results change if both a realistic load pattern and fluctuating wind power are considered? These questions are analyzed with a bi-level numerical model, which simultaneously optimizes dispatch of generation and profits of the network operator.

Chapter 5 examines the effects of different allocation rules for $CO_2$ emission certificates on thermal power plant investments. This analysis is motivated by the existence of environmental externalities, which provide another instance of market failure, and by specific economic regulation that is intended to internalize these. At the beginning of the first European emissions trading period, how did factual German allocation rules influence investors' technology choices, and what would have been the effect of alternative allocation rules? More precisely, how do different allocation mechanisms change the net present values of hard coal power plants, which tend to be both emission-intensive and inflexible, and natural gas plants, which are both cleaner and more flexible? To answer these questions, it is central to model allocation-related windfall profits, and account for a range of possible fuel and $CO_2$ price paths.

In the following, a background for the research presented in chapters 2-5 is provided. First, I discuss specific characteristics of electric power markets. After that, a literature

overview of the aforementioned electricity market trends is provided. This includes a brief review of the relevant literature in the areas of power market restructuring, climate policy, renewable energy, and electric vehicles. After that, a short overview of electricity market modeling trends is given. Complementary to the general introduction provided here, chapters 2-5 include additional in-depth literature reviews related to the specific research questions.

## 1.2 Specific characteristics of electric power markets

Electric power has some specific properties that distinguish it from other commodities. Accordingly, electricity markets also differ from other markets in several respects. First, electrical energy is closely linked to a physical system consisting of generators, load, as well as transmission and distribution grids. Electric power only flows within this system. Next, large-scale electricity storage is expensive and has a high share of sunk costs.[1] Power supply and demand have to be balanced in the whole grid in real time, i.e. on a second-by-second basis. A failure to maintain this balance can result in system breakdowns that can become extremely costly (Kirschen and Strbac, 2004). Another important feature of electricity refers to the demand side. Demand for electric power is rather inflexible. The short-term price elasticity of electricity demand is very low (Lijesen, 2007, provide a literature survey). In addition, the load shows characteristic daily, weekly, and yearly cyclical variations.

Next, electricity can be generated with a variety of different technologies (see, for example, Erdmann and Zweifel, 2008). Thermal plants draw either on nuclear power or on fossil fuels like lignite, hard coal, or natural gas. They may also use biomass or biogas as fuels. In contrast to thermal plants, electric power can also be generated directly from renewable sources, most notably hydro, wind, solar, and geothermal power. Independent of the generation technology, all electric power is "pooled" within a network. It is thus not possible to direct electricity produced by a specific generator to a specific consumer (Kirschen and Strbac, 2004).

In the light of previously mentioned storage constraints and inelastic demand, real-time-balancing requires the existence of flexible generators that can ramp up and down power output within very short time periods. This is possible with some technologies, particularly with natural gas plants. In contrast, the ramping rates of other generation technologies are restricted (Kirschen and Strbac, 2004). For example, most existing nuclear plants are rather inflexible regarding variations of their output. As starting up and shutting down a thermal plant is not free of costs (partial load inefficiency, wear and tear), such plants generally require a unit commitment planning, i.e. a beforehand

[1] Electricity is often referred to as a non-storable good. In fact, there are many different technologies of storing electricity, for example in the form of chemical, kinetic, or potential energy (see Baker, 2008; Hall and Bain, 2008, and section 1.3.3.3). Yet most of these technologies are expensive compared to the costs of generating electricity, such that large-scale power storage is usually less efficient than adjusting supply or demand. Among different bulk storage technologies, pumped hydro storage has the lowest costs and is thus widely used around the world. Thus, chapter 2 focuses on this technology.

decision on the operating periods (Stoft, 2002).

Another peculiarity relates to power flows in meshed networks. Power does not flow from one node to another in a directed way, but simultaneously over all lines according to Kirchhoff's laws (Schweppe et al., 1988). As a result, there may be network externalities in the sense that actions of a generator or a consumer at a specific network node affect other players at distant nodes. Importantly, the capacity of real-world power lines is often scarce, such that power flows are constrained by physical line limits.

Related to the technical characteristics of electrical power outlined above, electricity markets also show some interesting economic properties, which distinguish them from other markets. From an economic perspective, electricity generally is a homogeneous good, although it can be generated by a variety of different technologies with different marginal costs. For example, a MWh of nuclear power is indistinguishable from a MWh of wind-generated power. Notwithstanding, the output of thermal power plants is generally more predictable than the one of a wind turbine, which is characterized by natural variations and intermittency (see section 1.3.3.3). Typically, there is a single market price, at least during a given hour and at a single node. Yet prices may differ substantially between specific hours of the day, as "electrical energy delivered during one period is not the same commodity as electrical energy delivered during another period" (Kirschen and Strbac, 2004, p. 50). Prices may also vary between different nodes of the transmission network, if the market design properly reflects network constraints (Stoft, 2002, see also section 1.3.1).

The fundamental concept of spot pricing of electricity has first been described by Schweppe et al. (1988). While electricity can generally be traded on markets as a commodity, the previously discussed requirement of real-time balancing necessitates the existence of a "managed spot market", which may also be called "reserve market" or "balancing mechanism" (Kirschen and Strbac, 2004).[2] As a completely free market can not be expected to balance short-term deviations of supply and demand, this task is given to a system operator.[3] Balancing resources can be provided by generators – which may offer to increase or decrease their output – or by consumers, which may offer to adjust demand. An independent system operator (ISO) or transmission system operator (TSO) may acquire these resources in a market-based way, for example by granting generators a certain fee for keeping a specified capacity available. Beyond the provision of balancing power, the system operator is generally also responsible for keeping transmission lines within their physical limits, for voltage and frequency control, for compensating power losses, and for restoring the system after blackouts (Erdmann and Zweifel, 2008).

In contrast to many other markets, electricity markets are prone to market power problems in the sense that some suppliers are able to raise prices above a perfectly com-

[2] In the U.S., only the real-time (intra-day) market is called "spot market" (Stoft, 2002). In Germany, the day-ahead market is also called "spot market" (Ockenfels et al., 2008).

[3] The problem of balancing load and supply is exacerbated by the fact that most consumers receive few price signals. Setting up "smart grids" may change this, and may thus also increase the price elasticity of electricity demand. See also section 6.2.

petitive level. Thermal power generation exhibits economies of scale, which has typically resulted in large company sizes. Large generating firms may exert market power by withholding capacity. This can lead to a price increase, which in turn increases the revenues of all other generation assets of the respective player. Such behavior is very difficult to detect in the light of asymmetric information.[4] The difficulties of monitoring power flows in real-world meshed networks further impede market power detection (Wilson, 2002). Stoft (2002) argues that market power potentials are severely increased by two demand-side flaws: on the one hand, most customers do not have real-time metering or billing. This results in the previously discussed low elasticity of demand. On the other, power withdrawal of specific customers can not be controlled in real-time, or in other words, customers can hardly be cut off the physical power supply. These two demand-side flaws produce "ideal conditions for market power" (Stoft, 2002, p. 15). In addition, there may be considerable entry barriers for new market players, in particular if the transmission network is in the hand of an integrated utility. What is more, transmission and distribution networks generally have a natural monopoly character (Stoft, 2002). Erdmann and Zweifel (2008) point out that a power network is also an indivisible good. Setting up parallel grids operated by different companies would be economically inefficient. Given this natural monopoly, economic regulation is required in order to prevent the transmission owner from extracting monopoly rents. Viscusi et al. (2005) give a detailed introduction to different regulatory approaches, including traditional rate-of return regulation and current incentive regulatory approaches. All things considered, "wholesale markets for electricity are inherently incomplete and imperfectly competitive" (Wilson, 2002, p. 1300). Accordingly, the system operator and the details of market design can play a major role for market power mitigation.

Investments in the power sector typically have long lead times and long lifetimes (Kirschen and Strbac, 2004). Sufficient investment levels are required for ensuring the security of power supply, which has a public good character. As users can hardly be excluded from security of supply their willingness to pay for it is low (Stoft, 2002). Furthermore, electricity is thought to be an "essential good", without which little economic activity would be possible (Erdmann and Zweifel, 2008). There is an ongoing academic debate on the problem of re-financing generation and investments in liberalized electricity markets, sometimes referred to as "missing money" or "resource adequacy" problem (for an introduction, see Cramton and Stoft, 2006). Joskow and Tirole (2007) provide a detailed analysis of investment incentives under different assumptions. They find that market price caps substantially decrease scarcity rents required to finance peaking capacity investments. Furthermore, there may be underinvestment into operating reserves if rationing is not possible and uncertainty is properly reflected. Littlechild (2006) argues that regulatory uncertainty due to repeated market reforms may also lead to insufficient investment levels. Joskow (2005) gives a detailed introduction on transmission invest-

[4]For example, the German competition authority struggled to provide evidence on market power exertion in the wholesale power market in its recent sector inquiry (Bundeskartellamt, 2011).

ments. He argues that standard economic models of transmission investment neglect important technical characteristics. Investment behavior is heavily guided by issues like uncertainty, contingency criteria, and associated engineering reliability rules.

Last, but not least, there are negative environmental externalities of electricity generation. For example, emissions of power generation may negatively affect other economic agents. The power sector is a major emitter of greenhouse gases. In this respect, emissions of carbon dioxide have gained particular interest in recent years.

## 1.3 Review of distinctive power market trends

### 1.3.1 Restructuring and market design

For a large part of the $20^{th}$ century, electricity markets around the world were characterized by large, state-owned utilities and/or regulated, regional monopolies (Sioshansi and Pfaffenberger, 2006a). Electric utilities typically showed a vertical integration of generation, transmission, distribution, and retail activities (Joskow, 2006). Beginning in the early 1990s, many countries started to restructure and liberalize electricity markets with the goal of decreasing costs and improving social welfare by means of competition.[5] Wilson (2002, p. 1299) describes this process as "replacing tight regulation of vertically integrated monopolies with light regulation of functionally specialized firms and supervision of competitive markets".

Joskow (2006) lists the main components of electricity market restructuring, among them privatization of utilities, vertical separation of potentially competitive sectors (generation and retail) and regulated monopoly sectors (networks and system operation), designating an independent system operator responsible for network operations[6], and creating voluntary markets for energy and ancillary services. Together with some other components, these form a "textbook model" of electricity market reform. Joskow (2006) and Littlechild (2006) argue that restructuring was largely successful in delivering cost reductions in those countries that closely followed this "textbook model". However, market reforms failed to deliver benefits and have even resulted in substantial welfare losses in countries that deviated from this approach.[7] Creating well-functioning wholesale markets and securing competition requires constant fine-tuning and remains work in progress in many countries.

[5]Some authors prefer the term "restructuring" while others refer to "deregulation", "liberalization", "electricity market reform", or just to the introduction of "competition" (Stoft, 2002; Sioshansi and Pfaffenberger, 2006b; Kirschen and Strbac, 2004). Joskow (2006) argues that "deregulation" is misleading, as it neglects structural, regulatory, and market design reforms. The ongoing process of adjusting and fine-tuning market reforms has also been called "re-regulation" or "reform of reforms" (Joskow, 2006; Sioshansi, 2008).

[6]The ISO may either be responsible for real-time balancing of supply and demand only; or it may also own and operate the transmission system as a "Transco" (Joskow, 2006).

[7]California provides a much-cited example of how market restructuring can lead to disastrous consequences, if an inappropriate regulatory framework is applied. Following Littlechild (2006), California's main problems included a lack of long-term contracts between retail suppliers and generators and unsuitable retail price caps.

Notwithstanding Joskow's "textbook model" of electricity market reform, many different market designs have evolved in different countries. For example, wholesale power markets differ in the degree of organization, ranging from fully open, bilateral trade to completely centralized pool markets (Stoft, 2002). In contrast to bilateral trading, electricity pools rely on a defined mechanism for determining the equilibrium of supply and demand: generators' and consumers' bids are gathered and aggregated in order to establish a supply and a demand curve, and a corresponding market clearing price (Kirschen and Strbac, 2004). That is, pool markets require the utilization of sophisticated optimization models. Most power markets in the U.S. have adopted the pool model, whereas Germany has decided for an open market, including a power exchange (Ströbele et al., 2010).

Market designs also differ with respect to transmission-congestion management. Brunekreeft et al. (2005) provide a detailed overview of the debate in the Anglo-American world. Erdmann and Zweifel (2008) and Ströbele et al. (2010) focus on the German and European situation. For example, transmission capacity can be allocated by rationing or on a first-come-first-serve basis. Aside from that, there are different market-based allocation mechanisms. These include explicit auctions, in which transmission capacity is auctioned separately from power with an explicit price, and implicit auctions. Implicit auctions, which are sometimes also referred to as "market coupling", rely on a market maker or system operator which collects bids and calculates resulting network flows. The resulting market prices include both the costs of electricity generation and capacity utilization (Ströbele et al., 2010). Electricity trade between European power markets has recently shifted toward implicit auctions (Ockenfels et al., 2008; Weber et al., 2010).

An important distinction relates to the difference between physical transmission rights (PTR) and financial transmission rights (FTR). Acquiring physical rights to use a given transmission line seems to be an intuitive concept. However, it hardly works in practice, as power does not flow from point to point, but over all lines of a meshed network. In addition, PTRs are prone to market power exertion (Joskow and Tirole, 2000). In contrast, FTRs are not attributed to specific lines, but defined from any given point in a network to any other point. By isolating their holders from congestion risks, they serve as a perfect hedge for power trading. Hogan (1992) made the seminal contribution on FTRs, considering loop flows and congestion.

The most coherent approach to transmission-congestion management is nodal pricing.[8] The system operator collects generators' and consumers' bids and calculates prices for each node of the network. These prices inherently reflect transmission constraints (Kirschen and Strbac, 2004). Accordingly, prices differ at each node of the network in case of binding transmission constraints. The system operator collects consumers' payments and pays the generators according to their bids. The remaining surplus constitutes the congestion rent[9] (compare also Stoft, 2002, chapter 5). In contrast to market

[8] Nodal pricing is also called "locational (marginal) pricing" (Stoft, 2002).

[9] Kirschen and Strbac (2004) use the term "merchandising surplus" instead of "congestion rent".

coupling described above, nodal pricing reflects network constraints *within* a market or control area. In other words, market architecture with nodal pricing gives up the "copper plate" assumption of completely unconstrained transmission. Section 1.4 lists several model-based analyses that have indicated welfare gains related to the introduction of nodal pricing in different markets.

Chile, Argentinia, and Great Britain were the first countries to restructure their electricity markets, of which Britain is most often referred to as a model case. Other markets in Anglo-American countries followed suit like Texas, New England, and the regional interconnection PJM (all USA), New Zealand, New South Wales (Australia), and Victoria (Canada) (Sioshansi and Pfaffenberger, 2006b). The Nordic countries were also frontrunners in implementing market reforms. Other European countries have been more hesitant to restructure their electricity markets, although they were forced to do so by EU Directive 96/92/EG, which established common rules for the creation of an internal market in electricity (EU, 1996). Joskow (2006) argues that EU legislation mainly focused on retail competition. Yet opening the retail market hardly improves performance without appropriate wholesale markets, network access, and pricing institutions. Amongst other countries, Belgium, Italy, and France have struggled with creating competitive wholesale markets (Littlechild, 2006).

Similar problems have been observed in Germany. Electricity market reforms started rather late in Germany compared to other industrialized countries. They were triggered by the *Energiewirtschaftsgesetz* (Energy Act) of 1998, which implemented the aforementioned EU Directive (Bundesgesetzblatt, 1998). Yet German policy makers tried to introduce competition with minimal structural or regulatory reforms, as Joskow (2006) concedes. They focused on the retail market, although potential efficiency gains of competition are very low in this market, compared to the wholesale power market (Stoft, 2002). Before restructuring, the market structure in Germany was largely characterized by vertically integrated utilities with regional monopolies (Ströbele et al., 2010). This hardly changed after 1998. In contrast, market concentration regarding generator ownership even increased after a series of mergers, such that the Hirschman Herfindahl Index was pushed to over 2500 by the year 2000 (Brunekreeft and Bauknecht, 2006). By the year 2008, the index was still above 2000 (Bundeskartellamt, 2011). In 2008, the largest four companies RWE, E.ON, Vattenfall, and EnBW together owned 84% of installed generation capacity (Bundeskartellamt, 2011). According to a recent sector inquiry of the German competition authority, this market concentration is a severe obstacle for competitiveness in the wholesale market, as each company is a pivotal supplier in many hours of the year. However, factual market power exertion could not be proven in the years 2007-2008 because of data availability and methodological problems (Bundeskartellamt, 2011).

Until 2005, four integrated utilities controlled the German transmission network, which is separated into four control areas.[10] As of 2011, there is still no single independent

[10]The *Energiewirtschaftsgesetz* of 2005 demanded legal unbundling in Germany (Bundesgesetzblatt,

system operator in Germany. What is more, policy makers initially relied on "negotiated third party access" to the transmission system, also called "self-regulation" (Brunekreeft and Bauknecht, 2006). Only in 2005, and pushed by new EU legislation, the new German *Energiewirtschaftsgesetz* established the *Bundesnetzagentur* (Federal Network Agency) as a regulatory body (Bundesgesetzblatt, 2005b). According to the current German market design, the four transmission system operators are responsible for providing real-time balancing energy. Note that there is no nodal pricing in Germany, but a uniform price for the whole market. Wholesale market results thus do not reflect congestion within the transmission network.[11] In case of binding line capacity restrictions, the system operator has to "redispatch" generation, such that no transmission line exceeds its physical limits. This procedure lacks transparency and is unlikely to lead to efficient outcomes (Ströbele et al., 2010, compare). In the light of these facts, and given that "poor market structures poses the greatest threat to the health of the power markets" (Stoft, 2002, p. 74), it is not surprising that market restructuring has delivered disappointing results in Germany.

Market restructuring is not finished in Germany. Compared to other electricity markets – in particular the U.S. –, much has to be done in order to create a competitive wholesale market and reap the full benefits of liberalization (compare Brunekreeft and Bauknecht, 2006). Comparing the German power market design with the ones of several Anglo-Saxon countries, let alone with the academic debate, as for example documented by Stoft (2002), it appears that German policy makers have not noticed the international advances in this field. Having said that, it should be noted that the debate on ideal electricity market reforms and its practical implementation is far from settled. Research on theory and application of appropriate regulation and market design is evolving (compare Hogan, 2002; Sioshansi, 2008).

### 1.3.2 Climate policy

According to the latest Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), the scientific evidence of warming of the global climate system is unequivocal. The average global surface temperature has risen by roughly 0.8°C since pre-industrial times (IPCC, 2007, p. 67). Most of the observed temperature increase is very likely caused by a rise in anthropogenic greenhouse gas (GHG) concentrations. Global GHG emissions from human activities have grown substantially since pre-industrial times, with an increase of around 70% between 1970 and 2004. Carbon dioxide ($CO_2$) is the most important anthropogenic GHG. Its annual emissions have grown by about 80% between 1970 and 2004 (IPCC, 2007). Other important global greenhouse gases are methane ($CH_4$) and nitrous oxide ($N_2O$).

The global surface temperature will continue to increase over the next decades. Even if atmospheric concentrations of carbon dioxide equivalents could be stabilized at around

2005b). E.ON and Vattenfall sold their transmission networks in 2009 and 2010. As of 2011, RWE and EnBW still retain ownership of their transmission grids.

[11] According to the terminology used by Kirschen and Strbac (2004), the German wholesale market leads to economic dispatch, but not to *constrained* economic dispatch.

445-490 parts per million (ppm), the IPCC expects a global average temperature increase of around 2.0-2.4°C above pre-industrial levels. In contrast, stabilizing emissions at 855-1130 ppm $CO_2$-eq would result in a temperature increase of around 4.9-6.1°C (IPCC, 2007). This could induce substantial changes in the global climate system by the end of the century, such as changes in wind patterns, precipitation, weather extremes, and sea ice. According to the IPCC, there is a threat of abrupt or irreversible changes. The IPCC has identified five "reasons for concern", including risks to unique and threatened systems, risks of both more frequent and more violent extreme weather events, the distribution of impacts and vulnerabilities, aggregate impacts, and the risks of large-scale singularities (IPCC, 2007). As a consequence of these changes, global warming could have a major impact on the world economy in the future (Stern, 2006).[12] Some studies indicate that extreme weather events related to climate change have already caused enormous economic damages (for example, see Schmidt et al., 2010).

It should be noted that estimations of future climate change damages and their economic consequences are highly uncertain due to temporal and spatial disparities (Tol, 2002a,b; OECD, 2008). Nevertheless, many scientists propose to follow a precautionary approach of substantially reducing the volume of global GHG emissions. In fact, policy makers around the world have recognized the "two-degree goal", according to which the average global temperature should be prevented from rising by more than 2°C in comparison to pre-industrial times (see also WBGU, 2009). The European Union, the G8 states, and the Major Economies Forum on Energy and Climate have acknowledged this target (EU, 2009b; MEF, 2009).[13]

With current emission trends, however, the "two-degree goal" will not be achieved. In order to limit the rise in average global temperature to two degrees above pre-industrial levels, global emissions of greenhouse gases must reach their peak between 2015 and 2020 and decline afterwards, depending on the climate change scenario (IPCC, 2007). By the year 2050, a 50-85% reduction compared to 2000 emissions levels is necessary. It has been argued that industrialized countries can and must make significantly larger reductions than developing and newly industrialized countries, given their historic emissions and their economic strength (WBGU, 2009). The European Commission aims to cut GHG emissions by 20-30% in 2020 compared to 1990 levels, depending on other countries' efforts (EU, 2008).[14] In the long run, the Council of the European Union even aims to reduce GHG emissions by 80-95% from their 1990 levels by 2050 (EU, 2009b). The German Government aims for GHG emission reductions of 40% by 2020 and 80% by 2050 compared to 1990 levels (BMWi and BMU, 2010).[15]

[12] The methodology used in the Stern Review has met with a lot of criticism. Among others, Dasgupta (2007) and Weitzman (2007) criticize the choice of the discount rate.

[13] Forum members include the G8 states, Australia, Brazil, China, the European Union, India, Indonesia, South Korea, Mexico, and South Africa.

[14] This goal is a part of the EU "20-20-20" targets, which also include the goal of 20% of EU energy consumption to come from renewable resources by 2020, and a 20% reduction in primary energy use.

[15] For the time being, it is highly doubtful if a multi-lateral political agreement can be negotiated that supports such a climate goal. The latest UN Climate Conferences in Copenhagen and Cancún failed to make progress in this direction.

In Germany, $CO_2$ accounted for about 87% of all GHG emissions in 2008, followed by $N_2O$ (6%) and $CH_4$ (5%), according to the National Inventory Report for the German Greenhouse Gas Inventory (UBA, 2010). The energy sector – which includes electricity generation, transport, commercial and residential energy use, and manufacturing according to this classification – was responsible for 81% of all German GHG emissions. Among these segments, electric power generation accounted for the largest share. Accordingly, reducing $CO_2$ emissions in the power sector is key to achieving Germany's climate targets.[16] McKinsey (2007) sorts German GHG abatement potentials for 2020 and 2030 according to marginal abatement costs. Although the methodology neglects dynamic interactions and may thus lead to flawed results, the study finds large abatement potentials in the power sector at moderate costs.[17] A study by WWF presents a very ambitious scenario for reducing German carbon emissions by 95% by 2050 compared to 1990 levels (WWF, 2009). In order to achieve this goal, the power sector must be completely carbon-neutral by 2050. In this regard, massive deployment of renewable energy sources is considered a major strategy.

At the European level, the major policy for achieving GHG emission reductions – not only, but particularly in the power sector – is the European Emissions Trading System (ETS). It was established in 2003 by Directive 2003/78/EC and entered into force in 2005 (EU, 2003). The system comprises a binding cap on overall EU emissions as well as a trading system. In theory, marketable emission permits ensure least-cost emission abatement of a given overall cap (Perman et al., 1999, chapter 12). The first trading phase, which had a trial character, lasted from January 2005 until December 2007. DEHSt (2009) and Ziesing et al. (2007) provide excellent summaries of the EU ETS implementation and the specifics of emission permit allocation in Germany during the first trading phase. Permit allocation in the power sector will be explained in great detail in chapter 5, which analyzes the effect of different allocation rules on power plant investments in Germany. Yet the ETS is not the only strategy for achieving emission reductions in the German power sector. German policy makers have supplemented emissions trading by ambitious policies for supporting the deployment of renewable energy sources. These will be further discussed in the next section.

### 1.3.3 Renewable energy expansion

Another power market trend is the expansion of renewable energy sources (RES) like hydro, wind, solar, and biomass, starting about the mid-1990s. While this trend could be observed in many countries, the development in Germany is particularly remarkable.

[16] The potentials for mitigating emissions of other GHG are not negligible, but clearly limited. For example, $CO_2$ mitigation can be complemented by methane emission abatement to some extent (see Kemfert and Schill, 2010).

[17] In other industrialized countries, the power sector also offers large GHG abatement potentials at relatively low costs (Amann et al., 2009; Akimoto et al., 2010).

#### 1.3.3.1 Strong growth in renewable energy generation

Around the world, the deployment of renewable energy technologies is increasing (IEA, 2010b). For example, the U.S. has seen substantial wind power investments at the beginning of the $21^{st}$ century (Schill et al., 2010). In the European Union, power generation from renewable sources is also growing. The EU aims to increase renewable energy's share in final energy consumption to 20 percent by 2020 (EU, 2008). Since June 2009, a new Directive on the promotion of renewable energy has been in effect, which further specifies this target (EU, 2009a). Given low RES shares in the areas of fuels and heating, it is clear that a substantial fraction of these targets has to be met by renewable electricity generation. Diekmann (2009) gives an overview of EU regulation, individual country's targets and the status quo of renewable power generation in Europe.

In Germany, the share of renewable energy in gross electricity consumption increased substantially from 4.7% in 1998 to 16.8% in 2010 (BMU, 2010b, 2011b). In 1998, hydro power accounted for the largest part of renewable generation (70%). Wind power (17%) and biomass (6%) played minor roles, while photovoltaics were virtually absent (0.1%). This changed dramatically by 2010, with wind power providing 36%, biomass 33%, and hydro power only 19% of renewable power generation. Photovoltaics, which had the largest growth rates, accounted for around 12% in 2010 (based on BMU, 2010b, 2011b). In the future, further large-scale deployment of renewable generation capacity is planned in Germany, such that the power sector could be mainly based on RES in the long run. According to the German government's Energy Concept of 2010, renewables should supply 35% of gross electricity consumption by 2020, 50% by 2030, and 80% by 2050 (BMWi and BMU, 2010). The latest "Lead Study" commissioned by the German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (BMU) foresees a faster path of RES expansion (40% by 2020, 65% by 2030 and 86% by 2050) (BMU, 2010c)). The German Advisory Council on the Environment (SRU) develops scenarios that are even more ambitious, with up to 100% domestic renewable electricity supply by 2050 (SRU, 2011).

#### 1.3.3.2 RES support: rationale and instruments

There are numerous reasons for shifting power generation from nuclear or fossil sources to renewables. These include a decrease in carbon emissions, a potential increase in the security of supply, as well as fostering growth and job creating in sustainable industries. Mitigating $CO_2$ emissions by means of renewable power generation gains importance in the light of developments that have dimmed the prospects of possible low-carbon alternatives like nuclear power and carbon capture and storage (CCS). In particular, the future of nuclear looks bleak after the 2011 Fukushima reactor disaster. Likewise, recent analyses on CCS have indicated that the technology faces higher obstacles than previously thought, for example regarding public acceptance, infrastructure requirements, and profitability (Herold et al., 2010).

Next, renewables have the potential to increase the security of power supply. This may not be true from a short-term dispatch point of view, as the fluctuating generating patterns of some renewable energy technologies can compromise the security of power dispatch (see below). Yet on a longer-term perspective, another RES characteristic comes into play: most renewable energy sources are domestic. In contrast, nuclear and fossil fuels often have to be imported (Büsgen and Dürrschmidt, 2009). Accordingly, renewables can help to lower a country's dependency on energy imports.

Another argument for supporting the deployment of RES technologies is their potential to create new jobs and positive macroeconomic effects. This includes the strengthening of local value chains, increased domestic investment, and higher turnover in "green" industries like manufacturing, operation, and maintenance of RES facilities. Renewables can also improve the trade balance if they lead to decreasing fossil fuel imports and/or exports of RES technology (Büsgen and Dürrschmidt, 2009). However, it should be noted that promoting renewable energy sources can also have negative macroeconomic implications, as they cause additional costs for industry and consumers (Frondel et al., 2010). Accordingly, the economic net effect of promoting renewable energy sources in Germany is ambiguous and subject to ongoing research (compare Hillebrand et al., 2006; BMU, 2010a; Blazejczak et al., 2010).

In general, generating power from renewable energy sources has a different cost structure compared to using conventional technologies like lignite or hard coal. Renewables are typically characterized by high specific investment costs and low variable costs. Pushing renewable energy technologies – aside from well-established hydro power – into the market thus requires financial support. Hydro power provides a notable exception; it has been competitive for decades. Looking at different countries, a broad range of political instruments has been applied, including feed-in tariffs, tender or auctioning models, and renewable quotas in combination with tradable (green) certificates (Meyer, 2003). Menanteau et al. (2003) introduce a more general classification stating that different approaches either focus on prices (feed-in tariffs) or on quantities (quotas, auctions).

The proponents of renewable energy quotas and green certificates argue that this approach delivers the most cost-efficient RES deployment and is also in line with the objectives of market restructuring (Voogt et al., 2000; Morthorst, 2000; Nielsen and Jeppesen, 2003). Söderholm (2008) argues that – in theory – integrated European green certificate markets lead to efficient outcomes. Regarding $CO_2$ abatement, it has been brought forward that even green certificates may be unnecessary; solely relying on a cap and trade system should result in the most cost-efficient emission reduction. In contrast, technology-specific support of RES technologies is criticized as inefficient by advocates of quantity-based instruments, especially if the main goal is reducing $CO_2$ emissions (Frondel and Peistrup, 2009). Yet this is only true in a static perspective, i.e. if the cheapest way of reducing today's emissions is concerned.

In a dynamic context, it is important to consider technology developments that lead to cost decreases. In the literature, this effect is named "learning curves" or "experi-

ence curves".[18] Many renewable generation technologies are rather immature compared to conventional ones. With improving technology and economies of scale in production, RES generation costs are projected to decrease. In contrast, there is less room for technology improvements in well-established conventional generation technologies (Neij, 2008). Rather, the generation costs of conventional power plants are projected to increase over time due to increasing fuel costs and environmental regulation. Given the existence of learning curves, early technology development is required to bring down RES generation costs. Furthermore, it may take considerable lead time to develop renewable energy technologies, appropriate industry structures, and supply chains. Ambitious long-term RES targets might thus require technology-specific support schemes like feed-in tariffs (Meyer, 2003). Simply speaking, one can hardly expect to deploy large amounts of cheap mitigation technologies in the future, if technology and infrastructure developments are not initiated at an early stage. Moreover, the proponents of feed-in tariffs point out potential economic benefits of technology-specific support in the form of "first-mover" advantages (Brandt and Svendsen, 2006; Büsgen and Dürrschmidt, 2009). Following these arguments, it is reasonable to rely not only on emissions trading, but also apply technology-specific instruments (Kemfert and Diekmann, 2009).

Several empirical investigations conclude that feed-in tariffs are both more effective and more efficient in promoting RES deployments than other approaches. In practice, schemes based on green certificates lead to higher RES investor risks, which decreases real-world efficiency (Lemming, 2003). Butler and Neuhoff (2008) compare wind power deployment in Germany and UK and find that the German feed-in tariff reduces consumer costs and increases deployment compared to the UK quota system. Haas et al. (2011) provide a detailed review of RES promotion strategies in different European countries and find that technology-specific support instruments are generally most efficient.

In Germany, a feed-in tariff for renewable energy was first introduced by the *Stromeinspeisungsgesetz*, which entered into force in January 1991 (Bundesgesetzblatt, 1990). It granted priority feed-in for renewable sources and a (modest) guaranteed minimum price. In April 2000, it was replaced by the *Erneuerbare-Energien-Gesetz* (EEG, Renewable Energy Sources Act), which raised the tariff for solar power and biogas, and which also covered geothermal energy (Bundesgesetzblatt, 2000). The differential costs between the feed-in tariff and the market price were apportioned among power consumers. Importantly, the guaranteed tariffs were designed to decrease each year for newly installed generators. This "degression" aims to phase out support over time and to gradually integrate RES generators into the liberalized market. The EEG was subsequently amended in 2004 and 2008 (Bundesgesetzblatt, 2004b, 2008) in order to adjust tariffs to technology developments. Tariffs depend on generation technology and on plant size. In addition, several bonuses are granted, for example for small biomass plants or for wind repowering. In its latest version, the act "aims to increase the share of renewable energy

[18] Söderholm and Sundqvist (2007) and Neij (2008) discuss methodological issues of estimating and using learning curves. Neij (1999) and Junginger et al. (2005) are much-cited references for wind power experience curves.

sources in electricity supply to at least 30 per cent by the year 2020 and to continuously increase that share thereafter" (BMU, 2008, p. 5). As indicated above, the EEG has proved to be very effective regarding RES deployment (compare also BMU, 2010b). Due to its relatively high photovoltaics tariffs, however, the EEG has triggered a boom of PV installations in recent years, which leads to increasing additional costs of the support scheme and has spurred a public debate (BMU, 2010c; Traber et al., 2011).

In the light of growing shares of renewable energy, feed-in tariffs (as well as other existing support schemes) have to be adjusted to better integrate renewable energy into both the electricity system and the power market. With increasing shares of renewables, granting unconditional feed-in priority and fixed minimum prices to RES generators leads to both technical and economic problems. For example, the German feed-in regulation entitles grid operators, by way of exception, to take technical control over RES facilities in order to guarantee the safety and reliability of the power system (Bundesgesetzblatt, 2008, § 11 and 12). In turn, RES generators are compensated for lost tariffs. In 2009, such feed-in management caused overall compensation of only €6 million (Bundesnetzagentur, 2010, p. 29). With very high shares of fluctuating renewables, compensation needs would increase substantially, as there would be more periods during which wind power exceeds demand.

Accordingly, the German feed-in regulation has to be adjusted in the future in order to improve the market and system integration of RES. In particular, economic incentives should be created to better match feed-in to demand and avoid grid congestion (Verbruggen and Lauber, 2009; Langniß et al., 2009). Whereas the specifics are subject to ongoing research, several possible measures are proposed, for example an optional market premium, improved incentives for direct marketing of renewable electricity, and boni for continuous or demand-oriented feed-in (compare BMU, 2011a, section 2). Importantly, such instruments must not endanger long-term renewable targets, i.e. make RES investments unprofitable. In particlar, changes of the German feed-in regulation should not unduly increase investors' risk of recovering costs, as this could severly decrease the incentives to invest in RES technologies (Hiroux and Saguan, 2010).

#### 1.3.3.3 Problems and strategies of RES integration

Some RES technologies fundamentally differ from conventional power plants with regard to generation patterns. The dispatch of nuclear, coal-, or gas-fired plants can be planned well in advance, as they draw on energy stored within their fuels.[19] In contrast, wind power and photovoltaics transform natural energy resources into electricity in real-time. Accordingly, their output varies from one hour to the other with the natural potential. In the literature, wind and solar power have often been described as "intermittent" or "fluctuating". However, these terms are not well-defined. In the following, I define four

[19] It should be noted that this is only true within certain limits. For example, there is the possibility of unscheduled generator outages. Moreover, dispatch of inflexible plants like nuclear or lignite can not be chosen freely from one hour to the other.

specific characteristics of wind power and PV that describe their nature more precisely. It should be noted that the named characteristics overlap to some extent. I also highlight the related consequences for the electricity system in case of growing shares of wind and PV.

1. **Stochastic feed-in**: Actual feed-in patterns of wind and PV regularly differ from the planned dispatch due to unforeseen weather developments. The closer to real-time generation, the better the forecast (Giebel, 2003; Lange et al., 2006). Nonetheless, it is impossible to perfectly predict the actual generation of wind and PV in advance. Growing shares of these technologies thus require having sufficient balancing capacity available.

2. **Limited correlation with the load**: Natural fluctuations of wind and solar power correlate with typical load patterns only to a limited extent (Sinden, 2007). For example, the hours with the highest loads in Germany are typically winter evenings. In these periods, little, if any, PV generation is possible. Growing shares of wind and PV may thus lead to supply problems in some periods and to temporary oversupply in others – even if we completely disregard their stochastic nature.

3. **Intermittency**: High-wind weather fronts may lead to high gradients of wind power feed-in within minutes. Wind turbines generate at full capacity in high-wind hours, but may shut down instantaneously for security reasons if a certain wind speed is exceeded (Tradewind, 2009). In addition, there may be rather long periods with low generation levels. In an extreme case, wind power generation may completely break down for more than a week during large-scale slack periods (VDE, 2008).[20]

4. **Geographical distribution of resources and load**: The geographic correlation of natural RES potentials and load centers is limited both in Germany and – on a larger scale – in Europe. Given present transmission networks, larger RES shares increasingly lead to (temporary) transmission grid congestion (see, for example, dena, 2010). In addition, distributed renewable power generation can lead to bottlenecks in distribution grids.

With increasing shares of wind and solar power in overall electricity generation, the mentioned characteristics make it increasingly difficult to integrate these technologies into power systems and markets. Note that wind power is projected to supply the bulk of future electricity generation in Europe; PV may also play a major role in the longer term (BMU, 2010c). Several strategies for integrating wind power and PV are discussed in the literature, including electricity storage, demand-side measures, the provision of conventional backup capacity, temporary shutting down RES generators, and expanding

[20] In contrast, Sovacool (2009) argues that intermittency of RES generators is not a fundamental technical problem. Rather, renewable energy integration may be exacerbated by institutional barriers and inflexible attitudes of important actors.

transmission and distribution grids.[21] All these strategies aim to increase grid flexibility. In addition, appropriate market design plays an important role. In the following, a brief literature overview of the most important RES integration strategies is provided.

Electricity storage is a much-discussed integration strategy, although it is unclear today how much storage will be required for RES integration. In general, all problems discussed above can by addressed with storage, ranging from short-term stochastic feed-in to longer-term intermittency. However, very large storage capacities would be required for providing back-up for longer-term intermittency, or for balancing seasonal fluctuations (compare VDE, 2008). Benitez et al. (2008) show that storage can decrease wind integration costs by obviating the need for additional peak generation capacity. Storage also allows relieving temporary network congestion (Denholm and Sioshansi, 2009). Yet the main benefit of storage is the possibility of taking up surplus RES generation and releasing it later during periods of lower feed-in. This renders both the shutdown of renewable generators and the provision of conventional backup capacity obsolete.

Baker (2008), Hall and Bain (2008), and Ibrahim et al. (2008) review trends and foreseeable developments of different storage technologies. Electricity may be stored in the form of electrochemical (batteries), kinetic (flywheels), or potential energy (pumped hydro storage and compressed air storage). For decades, pumped hydro storage has been the technology of choice for bulk storage. In general, electricity may also be stored in the form of hydrogen by means of electrolysis (Sherif et al., 2005). It is also possible to generate methane from hydrogen, using an external $CO_2$ source (Sterner, 2009). This strategy would allow utilizing the existing natural gas infrastructure. Storage technologies differ substantially regarding their typical power rating and storage capacity, and also regarding costs. In general, the profitability of storage is unclear in many power markets (BCG, 2011). To give an example, Greenblatt et al. (2007) argue that combining wind and compressed air storage may result in competitive baseload generation; Fertig and Apt (2011) arrive at contrary results. Even with increasing price volatility related to wind power, investors may have very limited incentives to build additional capacity (Loisel et al., 2010). Chapter 2 studies the utilization and the market effects of pumped hydro storage in an imperfectly competitive market.

Measures of demand-side management (DSM), also called "demand response", aim to adjust electricity demand to fluctuating supply of wind and PV (Moura and de Almeida, 2010). On the one hand, DSM measures allow the use of surplus RES generation; on the other, it can reduce the load during times of low RES feed-in. In general, DSM measures could be traded both in the wholesale market and in balancing markets. Yet there are substantial institutional barriers regarding market design, infrastructure, standards, and user behavior (Breukers et al., 2011). Torriti et al. (2010) provide an overview of the current status of demand-side projects in European countries. Generally, DSM has been slow to emerge because of limited knowledge, high costs, and infrastructure

[21] Milligan et al. (2009) provide a short introduction to these strategies. They argue that the problems of integrating wind might be smaller than often conceived. Carrasco et al. (2005) also highlight the importance of power electronics for integrating wind and PV.

issues. The technical and economic demand-side potentials in energy-intensive industries are considered as promising (Paulus and Borggrefe, 2011). In contrast, low-cost DSM potentials in private households are rather limited. In any case, inter-temporal shifting of electricity demand seems to be possible only over the course of several hours, but not over many days, let alone over different seasons. Accordingly, DSM may not be suitable for coping with long-term RES intermittency or seasonal balancing. Demand-side measures appear more promising for addressing stochastic RES feed-in, i.e. the provision of balancing power (Strbac, 2008).

Conventional backup capacity can provide balancing power in order to solve the problems of stochastic RES feed-in. In addition, conventional plants can provide reserve capacity to deal with RES intermittency (Luickx et al., 2008). As of 2011, there is plenty of reserve conventional generation capacity in Germany, which will most likely by available in the longer term (compare, for example, Weigt, 2009). An obvious drawback of this integration strategy is its inconsistency with the long-run goal of a largely renewables-based power system. In addition, the provision of conventional backup capacity does not allow taking up RES surpluses, as opposed to storage and DSM. Milligan et al. (2009) argue that conventional backup is not required at all for wind integration, if forecasts improve and if other integration measures are used.

Another means of integrating large amounts of wind power or PV is to temporarily shut down RES generators during times of excess supply (Fink et al., 2009). This measure can relieve network congestion. It may also decrease integration costs, as the utilization of other integration measures is avoided. Then again, shutting down RES generators means wasting clean electricity that could be put to good use during other periods (compare Denholm and Sioshansi, 2009; Loisel et al., 2010). In addition, shutting renewable generators down in times of potentially high production puts RES investors at substantial risk – or leads to economic inefficiencies, if generators are reimbursed for production losses. Accordingly, this measure should be regarded as a "last resort", if ambitious RES or climate targets are to be reached. Denholm and Hand (2011) argue that shutting down renewable generators can be largely avoided if other integration measures make the power system sufficiently flexible.

Network expansion is another much-cited RES integration strategy. On the one hand, extending transmission grids allows balancing regional disparities between load centers and regions with high renewable potentials. On the other, network expansion allows balancing RES fluctuations over a large geographical area (Denny et al., 2010). For example, northern German regions with large wind power capacity have to be better connected with load centers in the south of the country (Weigt et al., 2010). The German Energy Agency (Deutsche Energie-Agentur, dena) issued two major reports on wind-related network expansion requirements (dena, 2005, 2010). The 2010 report stated that integrating wind power by means of network expansion would require around 3,600 km of new transmission lines before 2020 and investments of nearly €1 billion. Yet both the data and the used model are not publicly available, such that the calculations remain incompre-

hensible. Network expansion may also address the problem of RES intermittency, as reserve capacity located in different areas can be utilized. Drawing on a very ambitious scenario, the "DESERTEC" project may even allow future large-scale imports of solar thermal power from North Africa to Europe, based on high voltage direct current transmission (DLR, 2006). For alternative – and less optimistic – calculations on this "super grid" concept see Egerer et al. (2009). In any case, the project faces enormous political and institutional barriers (compare Werenfels and Westphal, 2010). In general, most transmission network expansion projects are confronted with such obstacles (Buijs et al., 2011). Lengthy authorization procedures and fierce public resistance are common. Chapter 4 deals with regulatory issues of transmission expansion in the light of fluctuating wind power.

In contrast to the aforementioned RES integration strategies, adjusting power market design to RES does not require new technology, but rather improvements in the organizational and institutional setup. Research in this field is its infancy. There is no scientific consensus on how power markets should be best designed in order to efficiently integrate a large amount of renewable sources. Among the existing literature, Newbery (2010) argues that large-scale wind power will result in highly volatile spot prices, low utilization of conventional backup plants, and many periods with zero prices. Accordingly, market reforms are necessary in order to maintain security of supply. Glachant and Finon (2010) state, on the one hand, that wind power producers should be increasingly exposed to market signals; on the other, RES integration may assign new responsibilities to the system operator, for example regarding forecasting or transmission planning. Hiroux and Saguan (2010) also argue that wind power producers should increasingly participate in the market – in particular, in the balancing market. At the same time, RES investors' risk should not be unreasonably increased. They conclude that a "feed-in premium seems to be the best trade-off solution" (Hiroux and Saguan, 2010, p. 3144). Vandezande et al. (2010) also highlight the importance of wind power contributing to system balancing in case of increasing wind penetration. Yet this requires the existence of specifically designed and well-functioning balancing markets. Neuhoff (2011) argues that the application of nodal pricing (compare also section 1.3.1) in European power markets will lead to cost-effective RES integration because of optimal congestion management. However, it should be discussed how nodal pricing can be reconciled with existing RES support schemes, in particular with the German feed-in tariff. Note that nodal prices tend to be low at nodes with ample renewable generation, such that the differential costs for supporting RES generators would even increase compared to the current German market design.[22]

All mentioned RES integration strategies increase the physical and/or organizational flexibility of the power system. Some strategies are complements that could be combined; others should rather be regarded as substitutes. As of today, there is only limited re-

[22]Woo et al. (2011) show that the same argument holds in markets with zonal prices. In the Texas power market, prices in zones with high wind generation (and low load) decrease substantially compared to other zones.

search on the most effective and efficient combinations of RES integration strategies and market design adjustments. For example, Lund (2006), Mathiesen and Lund (2009) and Denholm and Hand (2011) provide some model-based analyses. Different methodological approaches are reviewed by Connolly et al. (2010). Yet there is plenty of room for further research in this area (see also section 6.3).

### 1.3.4 Electric vehicles

Another electricity market trend is an increasing use of electricity for purposes that formerly relied on other primary fuels. For example, electricity-driven heat pumps increasingly substitute oil and natural gas for space heating purposes (DPG, 2010). Yet it is the transportations sector that receives the most public attention in this respect. Electric vehicles promise to substitute oil, which has for decades been the main primary energy source used in this sector, with electricity. Importantly, electricity can be generated from a wide range of different sources, including low-emission renewable energy sources. In addition, electric vehicle drives offer a number of potential advantages over conventional internal combustion engines, for example lower emissions and greater energy efficiency (Samaras and Meisterling, 2008; Bradley and Frank, 2009). In the light of these benefits, the German government aims to have 1 million electric vehicles on the road by the year 2020 (Bundesregierung, 2009). However, there are significant barriers to the rapid adoption of electric cars, including limitations of current batteries, high purchase costs, and infrastructure issues (Schill, 2010a). Institutional and social barriers may also play a major role (Sovacool and Hirsh, 2009). Schill (2010b) provides an overview of potential benefits and barriers of electric vehicles in Germany.

Future plug-in electric vehicles (PIEV) may have significant impacts on both the power system and the electricity market. Parking vehicles could be linked to the grid with a bidirectional connection and the use of intelligent charging infrastructure. This concept is first described by Kempton and Tomic (2005a) and named "Vehicle to Grid" (V2G). They find potentially large synergies between the vehicle fleet and the power system (see also Kempton and Tomic, 2005b). In general, electric vehicle fleets are projected to have high connection power, but low utilization rates; for the conventional power plant fleet, the opposite is true. PIEV fleets could provide a flexible resource that interacts with the power system in several ways. On the one hand, the vehicles imply additional electricity demand, which can be utilized as dispatchable load. Accordingly, electric vehicles could enable additional DSM measures (compare section 1.3.3.3). On the other hand, V2G fleets could also be used as grid storage resources: they could store electricity in times of low demand and feed it back to the grid during times of high demand.[23] Whereas the impacts of future PIEV fleets on power systems have already

[23]Due to their dispatchable load and potential storage capacity, V2G fleets are often depicted as the main component of future "smart grids". However, it should be noted that "smart" recharging infrastructure is urgently required for accommodating large PIEV fleets in the grid, given their large connection power. Thus, the notion may be wrong that electric vehicles are a precondition for the "smart grid"; rather, the opposite seems to be true.

raised scientific interest, the interaction of such vehicles with imperfectly competitive power markets is not analyzed in the literature. The research presented in chapter 3 aims to fill this gap.

Electric vehicle fleets could also be used to foster the integration of renewable energy sources. For example, electric vehicles could store excess wind power (Lund and Kempton, 2008) or decrease RES-related ramping of conventional power plants (Göransson et al., 2010). Another approach is the provision of balancing power or other ancillary services by PIEV (Ekman, 2011). Note that the demand for such services will increase with further deployment of fluctuating renewables. The business case for integrating electric vehicles into power grids is subject to ongoing research. It has been found that the provision of ancillary services through V2G would be more profitable than bulk storage and peak shaving (Tomic and Kempton, 2007; Andersson et al., 2010). The analysis presented in chapter 3 comes to similar conclusions.

## 1.4 Electricity market modeling

Chapters 2-5 quantitatively analyze specific aspects of the previously discussed power market trends. In order to do so, the use of appropriate electricity market models is required. A variety of power market models have been developed and applied. In this section, I provide a brief systematic overview of developments in the field of power market modeling.

Following a characterization developed by Ventosa et al. (2005), electricity market models are often grouped into three main categories: single-firm optimization models, simulation models, and equilibrium models. First, there are single-firm optimization models. These draw on a single objective function. In most cases, firms are maximizing profits under various constraints. Prices are either exogenous or dependent on the particular player's decision. Single-firm optimization models allow representing technical restrictions in great detail, for example, complex unit commitment problems (Hobbs et al., 2001). However, these models fail to represent interactions of different agents or market reactions.

A second strand of the modeling literature applies agent-based simulation models. These are usually employed for analyzing longer-term developments and market power issues. Weidlich and Veit (2008) provide an overview of the relevant literature. In contrast to optimization models, simulation models do not draw on formal optimization problems. Rather, different agents' behavior (producers, consumers, or regulators) is simulated with heuristic algorithms that are designed to adapt or "learn" from experience. Agents in the model may, for example, learn to set profit-maximizing bids over time. Krause et al. (2006) show that learning algorithms in agent-based models may converge to analytically derived Nash-equilibrium solutions under certain conditions. As for the German market, Sensfuß et al. (2008) develop the PowerACE model, which is used, for example, for analyses of the impact of wind power feed-in on German spot-market prices. A notable

advantage of simulation models is their capability to model bounded rational actors in complex market systems. On the downside, the lack of micro foundation implies that model results can never be assured to be optimal. In addition, most models neglect transmission constraints and the elasticity of demand (Weidlich and Veit, 2008).

A third strand of the literature comprises market equilibrium models Ventosa et al. (2005). A more precise categorization would be "partial equilibrium models". In general, these focus on the electricity market, but neglect other markets, as opposed to computable general equilibrium models. Partial equilibrium models usually include simultaneous profit maximization (or cost minimization) problems of several players, which are tied together by a market clearing condition. This allows, for example, carrying out market power analyses. To name a drawback, equilibrium models face a range of restrictions regarding their problem structure in order to ensure solvability. Most of the model-based research articles cited in sections 1.3.1-1.3.4 draw on the partial equilibrium approach. Many models use linear programming, as they are most easily solved. Other models require non-linear programs. For example, the models presented in chapters 2 and 3 are non-linear programs because of their iso-elastic demand functions. More complex optimization problems, for example, unit commitment of power plants, require a mixed integer formulation. Such problems include both continuous and integer decision variables and are generally much harder to solve. Yet there are ways of avoiding integer problems. For example, Kuntz and Müsgens (2007) provide a methodology for representing start-up costs in a linear program. A recent trend is the application of bi-level equilibrium problems like mathematical programs with equilibrium constraints (MPEC). These allow tying together two interlinked optimization problems, for example the decisions of a market leader and a follower, or problems of capacity investment and utilization (Hobbs et al., 2000; Gabriel and Leuthold, 2010).

An important subgroup of equilibrium models deals with the strategic interaction of different firms in the power market. Day et al. (2002) provide an excellent overview of different approaches for modeling these interactions. Players may choose their decision variables either simultaneously or sequentially. In addition, strategic decisions may either relate to prices or quantities. Empirical studies have found that setting quantities (Cournot competition) is more applicable to power markets than setting prices (Bertrand competition) (Puller, 2007; Bushnell, 2008). For a detailed introduction to oligopolistic competition see Mas-Colell et al. (1995).

Notwithstanding, several other approaches for modeling imperfect competition are applied aside from Bertrand or Cournot assumptions. For example, the supply function equilibrium (SFE) literature assumes that firms compete both in quantity and prices. Baldick et al. (2004) provide theoretical background on SFE models as well as an exemplary application to the UK power market. Sioshansi and Oren (2007) test the application of an SFE model to the Texas power market. Willems et al. (2009) analyze if Cournot or SFE models fit the oligopolistic German market better. They do not find much of a difference, but suggest using Cournot models for short term analyses, as these are able

to accommodate important market details. To mention an important drawback, SFE models are more difficult to compute compared to Cournot models. Moreover, they may have multiple equilibria and unstable solutions.

Another subgroup of oligopoly models draws on conjectural variations. This approach is introduced by Bresnahan (1981) and Perry (1982). It allows representing different perceptions of the players on how their opponents react to their own decisions. Conjectural variations are sometimes described as useful extension of game-theoretic Cournot models, as they include not only Cournot and Bertrand equilibria, but also perfect competition and monopoly pricing as extreme cases. Song et al. (2003) compare the outcomes of a conjectural variation model to classic ways of modeling strategic interaction, and numerically show that the model includes other game-theoretic approaches as special cases. Day et al. (2002) present a conjectured supply function approach that also includes a power flow model and apply it to the England and Wales market. They find that the approach is more suitable than the Cournot assumption in order to answer policy-relevant questions. Nonetheless, the application of conjectural variations in power market modeling has been limited, maybe due to the problem of choosing the right conjectures of firms on their rival's decisions.

Partial equilibrium models are extensively used in empirical market power analyses by simulating the effects of different, counterfactual institutional arrangements. Green and Newbery (1992) first use such an approach for England and Wales to analyze the welfare effects of imperfect competition.[24] Newbery and Pollitt (1997) use a model-based analysis to analyze the performance of restructuring and privatization in England and Wales and find substantial cost decreases compared to the situation before restructuring. Borenstein et al. (2002) and Joskow and Kohn (2002) analyze the California electricity crisis of 2000-2001 by establishing competitive benchmarks with appropriate models. Additional empirical analyses are discussed in chapter 2.2.

In the light of the literature discussed above, the model ElStorM developed in chapters 2 and 3 draws on a game-theoretic Nash-Cournot approach for analyzing the strategic interaction of power generators, storage owners, and electric vehicle fleet operators. This approach is not only in line with a major strand of the literature, but also ensures solvability. The latter point is particularly important against the backdrop of very large numerical model sizes. It should be noticed that ElStorM is methodologically related to the game-theoretic model EMELIE (Electricity Market Liberalization in Europe), which is designed for market power analyses in European electricity markets (Lise et al., 2006). Traber and Kemfert (2009) use EMELIE to analyze the impacts of German feed-in tariffs on market prices, emissions, and profits. A dynamic model version is used to investigate hypothetical refunding of ETS revenues with the goal of fostering the diffusion of renewable energy technologies (Traber and Kemfert, 2011b). An obvious limitation of EMELIE is its aggregated character that does not allow for the analysis of hourly market

[24] In a critical analysis, Wolfram (1999) finds that the prices predicted by Green and Newbery (1992) and other oligopoly models are higher than in real-world spot markets.

outcomes. Traber and Kemfert (2011a) thus develop a refined version called ESYMMETRY – which includes an hourly time resolution and stylized ramping restrictions – for analyzing the impact of wind power on market prices and plant utilization. The model developed in chapters 2 and 3 further extends this approach by including additional inter-period constraints and power storage.

Aside from the issues discussed above, electricity market models differ with respect to their representation of power flows and transmission constraints. Many models neglect the transmission grid altogether for reasons of simplicity. Others draw on stylized point-to-point transfers of electric power between different countries (for example, Lise et al., 2006). However, such models are criticized for not properly representing important peculiarities of real-world transmission systems like loop flows. Accordingly, a strand of transmission models has evolved. These try to reflect the physical characteristics of power grids with a sufficient level of detail, while still ensuring computability. Yet such transmission-constrained electricity market models are also subject to debate. Neuhoff et al. (2005) test the robustness of three different approaches and find that results are highly sensitive to assumptions on strategic interactions of different players and on the market design, for example the timing of generation and transmission decisions.

Schweppe et al. (1988, Annex D) introduce the so-called "DC load flow" modeling approach. It aims at approximating real-world alternating current networks with a set of linear constraints, which are derived from a range of simplifying assumptions.[25] Following this methodology, Stigler and Todem (2005) introduce an optimization model for the Austrian power market based on nodal pricing. The paper also provides a very accessible derivation of a stylized, lossless DC load flow model from a real-world AC approach. Green (2007) uses a DC load flow model for analyzing the welfare gains of nodal pricing compared to uniform pricing in England and Wales. He finds that nodal pricing leads to (moderate) welfare gains and less vulnerability to market power. However, it also involves "politically sensitive regional gains and losses" (Green, 2007, p. 125). As for Germany, Leuthold et al. (2008b, 2010) introduce the dispatch and generation model ELMOD, also employing a DC load flow approach and a nodal pricing market design, largely following Stigler and Todem (2005). Leuthold et al. (2008a) use this model to analyze efficient pricing for German wind feed-in. Weigt et al. (2010) extend this study by investigating the impacts of large-scale wind deployment in northern Germany on market prices and grid expansion requirements. Weigt and von Hirschhausen (2008) use an ELMOD version that includes unit commitment in order to establish a reference case for analyzing market power in the German wholesale market. In this thesis, the models presented in chapters 2, 3, and 5 neglect transmission constraints in order to reduce complexity and ensure solvability. Chapter 4 includes a transmission model which largely follows the DC load flow approach presented by Leuthold et al. (2008b, 2010).

[25] Note that "DC" does not refer to "direct current", but to a historic algorithm (Schweppe et al., 1988, p. 313).

## 1.5 Overview of the thesis

### 1.5.1 Contributions and publications

The main part of this thesis consists of four original research articles that are presented in chapters 2-5. In each chapter, one of the four research questions outlined in section 1.1 is analyzed. Table 1.1 gives an overview of my contributions to the different chapters and the publication status. I am the main author of chapters 2 and 4, and the sole author of chapter 3. The research in chapter 5 was originally conceived by the main author Michael Pahle. I made substantial contributions regarding model refinements, data collection, and writing of the paper. Chapters 2 and 5 are published in peer-reviewed international journals. As of May 2011, chapter 3 is accepted with minor revisions in *Energy Policy*. The article presented in chapter 4 will be submitted to the *Journal of Environmental Economics and Management (JEEM)* after the 2011 summer conferences.

**Table 1.1:** Contributions and publications for different chapters

| | **Chapter 2**: Modeling strategic electricity storage | **Chapter 3**: Electric vehicles in imperfect electricity markets | **Chapter 4**: Regulated expansion of transmission networks | **Chapter 5**: How emission certificate allocations distort fossil investments |
|---|---|---|---|---|
| **Joint work with** | Claudia Kemfert | - | Juan Rosellón, Jonas Egerer | Michael Pahle, Lin Fan |
| **Contribution** | Main author; main responsibility for modeling and writing. | Independent research by the author. | Main author; responsible for all modeling and most writing (except section 4.2). | Co-author; major contributions: model refinement (5.2), data collection (5.3), interpretation of results (5.4), and conclusions (5.5). |
| **Publications** | Published in *The Energy Journal*, 32(3) 2011, p. 59-87. | DIW Berlin Discussion Paper 1084, Berlin, December 2010. Forthcoming in *Energy Policy*, 2011. | DIW Berlin Discussion Paper 1109, Berlin, March 2011. Submission to *JEEM* planned. | Published in *Energy Policy*, 39(4) 2011, p. 1975-1987. |
| **Notes on versions in this thesis** | Minor adjustments compared to journal article. | Adjusted in order to reduce redundancies with chapter 2. | Minor corrections and adjustments. | Minor adjustments and notational improvements. |

### 1.5.2 Comparison of methods and approaches

Methodologically, the research presented in chapters 2-5 draws on four specifically designed power market models. In general, all models can be attributed to the strand of partial equilibrium models, as categorized in section 1.4, following Ventosa et al. (2005). Having said that, the model in chapter 5 constitutes a special case, as its market clearing

condition is implicit rather than explicit. It could best be characterized as a simulation model with underlying profit maximization problems. Importantly, all models focus on the wholesale power market. As opposed to energy system models, general equilibrium models, or macro-econometric models, markets for other goods are not represented. Ancillary services like balancing power or reactive power are also excluded. Focusing on wholesale electricity may disregard possible interactions with other markets, but it allows analyzing the research questions outlined in section 1.1 in great detail, while at the same time ensuring solvability and traceability.

The models share several common features. For example, all draw on exogenous generation capacity and exogenous costs parameters. Likewise, hourly dispatch of power generation and market results are endogenous variables in all models. The models differ, however, regarding overall focus, problem formulation, level of detail, time horizon, and the inclusion of specific technologies. Table 1.2 provides an overview of the major features, similarities, and differences between the models.

**Table 1.2:** Overview of model features

| | **Chapter 2** | **Chapter 3** | **Chapter 4** | **Chapter 5** |
|---|---|---|---|---|
| **Type of model** | Game-theoretic partial equilibrium model (MCP) | Game-theoretic partial equilibrium model (MCP) | Optimization model with partial equilibrium constraints (MPEC) | Simulation model with underlying optimization problems |
| **Objective function** | Firms maximize profits | Players maximize profits and minimize loading costs | Upper-level: Transco maximizes profit; Lower-level: welfare-maximizing dispatch of generation | Firms maximize profits |
| **Decision variables** | Dispatch of generation, loading and discharging of pumped hydro storage | Dispatch of generation, timing of vehicle recharging, loading and discharging of batteries and pumped hydro storage | Transco: Location, timing, and level of network extensions; ISO: dispatch of generation | Dispatch of generation, technology of thermal power plant investment (hard coal or natural gas) |
| **Other endogenous variables** | Prices, profits, social welfare | Prices, profits, social welfare | Prices, power flows, profits, social welfare | Prices, profits, NPV of thermal investments |
| **Endogenous investments** | - | - | Transmission | Generation |
| **Representation of competition** | Cournot oligopoly | Cournot oligopoly | Natural monopoly for transmisson; perfect competition for generation | Perfect competition |

Continued on next page

**Table 1.2:** Overview of model features – continued from previous page

| | **Chapter 2** | **Chapter 3** | **Chapter 4** | **Chapter 5** |
|---|---|---|---|---|
| **Representation of wholesale power demand** | Iso-elastic, elasticity -0.45 | Iso-elastic, elasticity -0.45; Electric vehicles: inelastic | Linear, elasticity at reference point -0.25 | Inelastic |
| **Representation of inter-temporal contraints** | Ramping of thermal generation, storage inflows and outflows | Ramping of thermal generation, storage inflows and outflows, daily vehicle recharging | Transmission constraints, inter-temporal optimization | Intertemporal calculation of NPV of thermal investments |
| **Transmission representation** | - | - | DC load flow model | - |
| **Modeled generation technologies** | Nuclear, lignite, hard coal, natural gas, oil, hydro | Nuclear, lignite, hard coal, natural gas, oil, hydro, wind | Nuclear, lignite, hard coal, combined cycle gas turbine, gas turbine, oil, hydro, wind | Implicit: renewable sources, nuclear; explicit: hard coal, natural gas, peaker technology |
| **Modeling of wind power fluctuations** | - | Historic feed-in data | Fluctuating, drawing on yearly distribution | Yearly average (merit order effect) |
| **Modeled storage technologies** | Pumped hydro storage | Pumped hydro storage, excess vehicle batteries | - | - |
| **Time resolution** | Hourly | Hourly | Hourly | Hourly |
| **Time horizon** | 13 exemplary days | 14 exemplary days | 6 representative days; 6-11 years | 365 days; 20 years |
| **Reference year** | 2009 | 2009 | 2009 | 2005 |
| **Countries covered** | Germany | Germany | Germany, France, Belgium, The Netherlands | Germany |
| **Special features** | Pumped hydro storage is controlled by various players that may also be oligopolistic generators | Pumped hydro storage and grid-connected vehicle batteries are controlled by various players that may also be oligopolistic generators | Bi-level programming: Transco maximizes profits by deciding on network extension, given welfare-maximizing dispatch | Detailed representation of allocation rules and generation cost components; extensive sensitivity analyses |
| **Implementation** | GAMS, 32bit PC | GAMS, 32bit PC | GAMS, 64bit Linux | Matlab, 32bit PC |
| **Solver** | PATH | PATH | CONOPT | - |

Chapters 2 and 3 apply a game theoretic modeling approach, implemented as a mixed complementarity problem (MCP). Oligopolistic firms maximize profits by endogenously deciding on generation of different technologies and storage utilization (chapters 2 and

3), as well as on electric vehicle recharging (chapter 3 only). The strategic interaction between the firms is modeled as a Cournot oligopoly. That is, players anticipate the market's reaction to their choice of decision variables (see section 1.4). The model solution represents a Cournot-Nash equilibrium. That is, no player can increase its profits by deviating from its decisions, given all rivals' decisions. In contrast, electricity generation in chapters 4 and 5 is modeled under the assumption of perfectly competitive, profit-maximizing dispatch. However, the model used in chapter 4 includes another dimension of market power: the firm that owns the network (called Transco) is assumed to have a natural monopoly on transmission lines. The Transco decides on network extension in a strategic way, i.e. anticipates the market's reactions to its decisions on line upgrades. Accordingly, the model of chapter 4 entails bi-level programming. The upper level problem constitutes the Transco's profit-maximizing transmission investments; on the lower level, welfare-maximizing dispatch of electricity generation is represented. Whereas all models feature endogenous determination of dispatch, chapter 5 also includes investments into generation capacity. The model evaluates the net present value (NPV) of hard coal and natural gas investments by means of a discounted cash flow (DCF) analysis.

Regarding the representation of electricity demand, the models make different assumptions. The game-theoretic approaches in chapters 2 and 3 assume iso-elastic wholesale power demand. In chapter 3, the additional load of electric vehicles is considered to be inelastic. The same is true for wholesale power demand in chapter 5. In contrast, chapter 4 employs a linear demand function. These different representations of demand are chosen in order to take account of specific characteristics of different research questions, in particular regarding the representation of competition, and different time horizons. While all models feature an hourly time resolution, chapters 2 and 3 examine the hourly market outcomes of 13 or 14 specific days, respectively. Chapter 4 draws on six days that are assumed to be representative for the whole year. These include both a weekday and a weekend day for different seasons (summer, winter, and a transitory season). Drawing on these representative days, an intertemporal analysis is conducted over 6-11 years.[26] In contrast, the model used in chapter 5 explicitly includes all 8760 hours of the year, and intertemporally optimizes for 20 years.

Table 1.2 shows that the models also differ with respect to the inclusion of intertemporal constraints. The models in chapters 2 and 3 have the strongest "bottom-up" character as they include inter-period constraints on the ramping of thermal generation technologies, as well as on storage loading and discharging. Including such constraints is essential for analyzing the market effects of storage and electric vehicle fleets. In chapter 4, such details are disregarded, as the focus is on transmission. Accordingly, chapter 4 includes a power flow model of transmission, following the DC load flow approach discussed in section 1.4. The transmission model reflects Kirchhoff's current law, according to which the sum of currents flowing into a given node equals the sum of currents flowing

[26] As discussed in section 4.5.4.1, including more years leads to much-increased execution time without changing the main results.

out of this node. Chapter 5 neither features transmission nor ramping constraints. The model rather focuses on an inter-temporal optimization with a very detailed representation of generation costs and emission permit allocation rules, as these characteristics are essential for the analysis. Regarding the inclusion of different conventional generation technologies, there are only small differences. Wind power is explicitly included in all models except for chapter 2. While chapter 3 makes use of historic hourly feed-in data, chapter 4 draws on the historic distribution of wind power feed-in over 8760 hours of the year. In chapter 5, an average yearly capacity factor of wind power is used for constructing the merit order of power plants.

Methodically, the models in chapters 2-4 are implemented with the General Algebraic Modeling System (GAMS) and solved numerically. In contrast, chapter 5 is implemented in Matlab. Amongst all models, the bi-level program in chapter 4 is computationally most demanding. It is thus solved on a high-performance 64bit Linux system. The source code of all models is included in the Appendix.

Geographically, there is a focus on the German electricity market. However, chapter 4 also includes France, Belgium, and the Netherlands in order to analyze cross-border transmission expansion. Notwithstanding, the results are applicable to other power markets in the world that are characterized by imperfect competition (chapters 2 and 3) or face transmission congestion (chapter 4). Moreover, conclusions drawn in this thesis are also valid for other storage technologies than pumped hydro (chapter 2) and other dispatchable load resources than electric vehicles (chapter 3). Likewise, the implications of different emission permit allocations for power plant investment incentives (chapter 5) are also applicable to other European countries.

# Chapter 2

# Modeling strategic electricity storage: the case of pumped hydro storage in Germany

## 2.1 Introduction

Interest in electricity storage is increasing. Grid storage capacity is expected to grow in many countries. This development is mainly driven by the need to integrate large amounts of fluctuating renewable energy into electricity systems. Bulk electricity storage is primarily achieved through pumped hydro storage. However, other storage technologies might be increasingly used in the future.

Yet economic research on electricity storage is limited, especially regarding storage utilization in the light of market failures. In particular, energy economists pay little attention to the strategic operation of storage facilities. While the strategic dispatch of self-replenishing hydro reservoirs is studied to some extent, there is a research gap on the strategic utilization of storage facilities which can be actively charged and discharged, in the form of, for example, pumped hydro plants. In addition, the interrelation of storage operations with strategic conventional electricity generation scheduling is not yet studied.

In this chapter, we examine the issue of strategic storage utilization with a model-based analysis, applied to the German power market and the case of pumped hydro storage. We develop the game-theoretic electricity market model ElStorM (Electricity Storage Model), which allows analyzing strategic storage utilization in an oligopolistic market environment with imperfectly competitive generators. The strategic interaction between the firms is modeled as a Cournot oligopoly. Our analysis illustrates the dynamic interaction of profit-maximizing firms' decisions on strategic storage and the dispatch of other generation capacity. More specifically, we study the impacts of different storage operators on both storage utilization and welfare outcomes by drawing on various cases in which storage is assigned to different players. Storage players may either be merchant storage operators without involvement in conventional generation, or they may hold

other generation capacity, as well. They may also differ in their ability to exert market power both regarding storage and conventional generation, i.e. to anticipate the effect of production decisions on market outcomes. Furthermore, the remaining generators in the market may be perfectly competitive or oligopolistic.

Our main finding is that storage utilization and storage-related welfare effects depend on the storage owner and its ability to exert market power. Strategic storage operators generally under-utilize their capacity. Regarding welfare, storage has two important effects. On the one hand, it generates arbitrage profits for the storage operator. On the other, it has a smoothing effect on market prices, which may decrease generators' surpluses and increase consumer rents. As a result, we find that the introduction of storage decreases total producer surplus. Yet an increase in consumer surplus outbalances the decrease in producer surplus. Overall welfare thus increases in all modeled cases, although the magnitude of the effect depends on storage ownership. Welfare gains from storage in an oligopolistic market environment are lowest if the total storage capacity is controlled by a single strategic generator. The most realistic cases shows that, currently, strategic pumped hydro storage utilization is unlikely to be a relevant source of market power in Germany.

The chapter is structured as follows. First, we discuss the relevant literature. Section 2.3 introduces the model ElStorM. Section 2.4 provides data and lists the different cases of storage operation by various strategic and non-strategic players. Section 2.5.1 analyzes the general effects of electricity storage on market outcomes. In 2.5.2, we analyze how storage utilization depends on different players. Section 2.5.3 studies welfare effects in detail. The last section summarizes and concludes.

## 2.2 Literature

Green and Newbery (1992) made a seminal contribution with their case study of the British market. They found that the Nash equilibrium in supply schedules of two dominant generators might imply high markups on marginal costs and substantial deadweight losses. Several more recent articles empirically test different theories of oligopolistic firm behavior by competitive benchmark analyses. For example, Borenstein et al. (2002) perform such an analysis for the Californian power market from 1998 to 2000 and find substantial mark-ups on wholesale electricity prices in high demand periods due to market power exertion. Puller (2007) extends this analysis by studying different types of oligopoly pricing. Hortaçsu and Puller (2008) perform a comparable analysis for the bidders in the Texas hourly balancing market. Mansur (2008) develops an alternative econometric approach which accounts for intertemporal production constraints like start-up costs. An application to the American PJM market indicates that historic prices have exceeded competitive benchmarks, but not as much as other methods suggests. Weigt and von Hirschhausen (2008) develop a competitive benchmark model for Germany that also includes start-up constraints and find that market prices in 2006 were above com-

petitive levels.

Beyond retrospective empirical analyses, market power also plays an important role in bottom-up numerical electricity market modeling. Ventosa et al. (2005) review and classify various electricity market model types and show that partial equilibrium models are most suitable for market power analyses as these are able to deal with simultaneous profit maximization problems of all players in the market. These are either based on Cournot or Bertrand competition (quantity or price competition), or apply the supply function equilibrium approach (firms compete both in quantity and prices). Klemperer and Meyer (1989) show that, drawing on some assumptions, supply function equilibria are bound by Cournot and Bertrand outcomes. Bolle (1992) analyzes how producers make use of supply functions in spot power markets and finds opportunities for tacit collusion. Puller (2007) and Bushnell (2008) provide empirical support that Cournot pricing may be the most reasonable assumption for electricity market modeling. Andersson and Bergman (1995) are among the first to implement the Cournot approach in a numerical model of the Swedish market. Borenstein and Bushnell (1999) perform a Cournot analysis for the Californian market, assuming three Cournot competitors and a competitive Fringe. Lise et al. (2006) apply a similar model to the Northwestern European electricity market and quantify how market power exertion by large producers harms consumers in different scenarios. Lise et al. (2008) find that scarce European cross-border transmission capacity and dry weather lead to additional market power exertion potentials. As for Germany, Traber and Kemfert (2009 and 2011a) use game-theoretic Cournot models to study the impact of German support for renewable electricity generation on prices, emissions, and profits as well as the impact of wind power on incentives for investments in thermal power plants. Our model implements strategic Cournot pricing in a numerical, game-theoretic partial equilibrium framework and thus follows the strand of literature mentioned above. We extend the methodological scope of the cited models by including both an hourly time resolution and intertemporal constraints.

The research reviewed so far does not include storage. Interest in modeling storage and its strategic interaction with conventional generation has recently increased. However, the strand of literature largely deals with hydro reservoirs only and not with pumped storage. There is a substantial difference between the two technologies. Hydro reservoirs are self-replenishing because of natural inflows. As opposed to thermal generation, a strategic dispatch of hydro reservoirs is not related to withholding capacity as such, but rather to strategically allocating hydro resources over different time periods. In contrast, pumped hydro storage operators may not only strategically decide on storage outputs, but also on *inputs*. This may complicate strategic decision-making and may also lead to additional market power potentials.

Rangel (2008) provides a literature review dealing with strategic scheduling of hydro reservoirs. He shows that players in hydro-dominated markets, like New Zealand, Norway and some South American countries, may exploit market power potentials related to hydrological conditions, reservoir levels and inflow probabilities. Scott and Read

(1996) were among the first to study gaming by mixed hydro-thermal firms by applying a Cournot duopoly model to the New Zealand market. Borenstein and Bushnell (1999) use a Cournot oligopoly model to analyze the potential for market power exertion in the Californian power market before deregulation. They find that the availability of hydro power is an important factor in determining the extent of market power. Johnsen (2001) further explores this issue with a stylized two-period model. He finds that a monopolist generates too much electricity from hydro resources in the first period compared to the competitive solution, which leads to welfare losses. Garcia et al. (2001) develop a simplified oligopoly model with dynamic Bertrand competition of hydro generators and find welfare losses from reservoir-related market power exertion. Bushnell (2003) develops a multi-period Cournot model of hydrothermal coordination in the Western United States in a mixed complementarity framework. He finds that strategic firms increase profits compared to competitive ones by shifting more hydro production toward off-peak periods. The model developed in this paper can be interpreted as an extension of Bushnell's approach to pumped hydro storage.

In contrast to the aforementioned hydro reservoir literature, other studies explicitly deal with pumped hydro or comparable large-scale storage technologies. Yet these largely neglect market power issues. For example, Crampes and Moreaux (2010) theoretically analyze how firms' combined decisions on pumped hydro storage and thermal plants can lead to cost savings and net social welfare gains under the assumption of perfect competition. Sioshansi et al. (2009) analyze arbitrage profits to be captured by the owner of a price-taking storage device in the PJM market between 2002 and 2007 with an optimization model. As storage decreases peak prices and increases off-peak prices, they find that consumers benefit from storage while producers lose. In section 2.5, we show that these findings also apply in an oligopolistic market. Sioshansi (2010) models the strategic utilization of large-scale storage facilities by different owners and the effects on storage utilization and welfare. While consumers overuse their storage capacity, merchant storage operators and generators tend to underuse it. The author finds that private incentives for storage operation might not be aligned to the social optimum and that merchant storage operators should be encouraged from a welfare perspective. The model developed in this chapter shows some similarities to Sioshansi (2010), but is more refined due to the inclusion of intertemporal constraints. Even more importantly, we are able to explicitly model the interaction of strategic storage and thermal generation decisions in an oligopolistic market structure.

The model and its application to the case of pumped hydro storage in Germany contribute to the literature in several ways. First, it increases the understanding of strategic storage utilization as it not only deals with the strategic allocation of self-replenishing hydro resources, but also with firms' strategic decisions on storage loading. We furthermore model the interaction of different players' combined decisions on thermal generation, storage loading, and discharging. We explicitly consider the price-smoothing effects of storage and related welfare impacts. Finally, we are able to compare the potential for exerting

market power that is associated with pumped hydro storage operations to the market power potentials related to conventional generation. The chapter thus complements the literature that deals with market power exertion in electricity markets.

## 2.3 The model

We introduce the game-theoretic electricity market model, ElStorM. Following the categorization presented in section 1.4, it can be characterized as a game-theoretic partial equilibrium model. Firms maximize profits by deciding on hourly electricity generation levels of different conventional technologies as well as on hourly pumped hydro storage loading and discharging. In doing so, players face a range of technical constraints. The model formulation allows us to include strategic players that exert market power. The solution represents a Cournot-Nash equilibrium. In contrast to earlier Cournot models, ElStorM includes not only electricity storage, but also an hourly time resolution and intertemporal constraints for both conventional generation technologies and pumped storage. These features are essential for analyzing strategic storage operation. Table 2.7 in the Appendix lists all model sets, indices, parameters, and variables.

In each time period $t \in T$, profit-maximizing firms $f \in F$ supply electricity by deciding on generation levels $x_{f,i,t}$ of different conventional technologies $i \in I$, for example, coal or natural gas. Firms also decide on hourly loading $stin_{f,t}$ and discharging $stout_{f,t}$ of pumped hydro storage. Each player faces the following constrained maximization problem. Player's indices $f$ are omitted in order to improve readability.

$$\max_{\substack{x_{i,t}\\ stin_t\\ stout_t}} \sum_{t\in T}\left[p_t\left(\sum_{i\in I} x_{i,t} + stout_t - stin_t\right) - \sum_{i\in I} vgc_i x_{i,t} - vstc\cdot stout_t\right] \tag{2.1a}$$

$$s.t. \quad x_{i,t} - \overline{x}_i \leq 0,\ \forall i,t\ (\lambda^{gen}_{i,t}) \tag{2.1b}$$

$$x_{i,t} - x_{i,t-1} - \xi^{up}_i \overline{x}_i \leq 0,\ \forall i,t\ (\lambda^{rup}_{i,t}) \tag{2.1c}$$

$$x_{i,t-1} - x_{i,t} - \xi^{down}_i \overline{x}_i \leq 0,\ \forall i,t\ (\lambda^{rdo}_{i,t}) \tag{2.1d}$$

$$stout_t - \overline{st}^{out} \leq 0,\ \forall t\ (\lambda^{stout}_t) \tag{2.1e}$$

$$stin_t - \overline{st}^{in} \leq 0,\ \forall t\ (\lambda^{stin}_t) \tag{2.1f}$$

$$\sum_{\tau=1}^{t} stout_\tau - \sum_{\tau=1}^{t-1} stin_\tau \eta_{st} \leq 0,\ \forall, t\ (\lambda^{stlo}_t) \tag{2.1g}$$

$$\sum_{\tau=1}^{t} stin_\tau \eta_{st} - \sum_{\tau=1}^{t-1} stout_\tau - \overline{st}^{cap} \leq 0,\ \forall t\ (\lambda^{stup}_t) \tag{2.1h}$$

$$x_{i,t} \geq 0,\ \forall i,t \tag{2.1i}$$

$$stin_t, stout_t \geq 0,\ \forall t \tag{2.1j}$$

The objective function (2.1a) represents player f's profit function. It adds up revenues from selling electricity generated by conventional technologies $\sum_{i\in I} p_t x_{i,t}$ and by pumped

storage $p_t stout_t$ for each period $t$. As usual in electricity markets, there is one market price independent of the generation technology. Note that in the case of market power, the market price, $p_t$, depends on a firm's decisions on conventional output, storage loading, and storage discharging. On the cost side, (2.1a) includes technology-specific variable generation costs, $\sum_{i \in I} vgc_i x_{i,t}$, which represent fuel prices, emission prices, technology-specific generation efficiency and other variable costs. For reasons of consistency, variable costs of storage operation $vstc \cdot stout_t$ are also included, which are assigned to storage loading and assumed to be constant for every unit of electricity generated.[27] Furthermore, (2.1a) includes the costs $p_t stin_t$, reflecting the fact that electricity stored at period $t$ had to be bought or could have been sold on the market at the price $p_t$. Firms thus face costs equal to the market price $p_t$ for each unit of electricity stored at time $t$.

Condition (2.1b) represents maximum generation capacity restrictions. For each conventional technology $i$, a firm's actual power generation can not exceed its installed capacity. (2.1c) and (2.1d) are intertemporal constraints on conventional generation, depending on technology-specific parameters $\xi_i^{up}$ and $\xi_i^{down}$, and on the total installed capacity. $\xi_i^{up}$ and $\xi_i^{down}$ take on values between 0 and 1. For example, both are relatively small for inflexible nuclear power, but assume the value 1 for perfectly flexible technologies. (2.1c) is a ramping up restriction: between two subsequent hours, electricity generation of a particular technology can only be increased to a certain degree. Likewise, condition (2.1d) represents technology-specific ramping down restrictions. Note that we draw on a stylized concept of ramping constraints in this context. Here, the term "ramping" does not refer to individual power plants, but to a firm's total capacity of a given technology. In the real world, thermal power plants face both start-up and ramping constraints. They can not start up or shut down instantaneously due to thermal restrictions on minimum on- and off-times. For example, it takes several hours to get a coal plant fully operational. Once a plant is started up, there are still ramping constraints in the sense that output can not instantly change. From a modeling perspective, it would be challenging to fully represent these constraints. A detailed bottom-up approach would require to model individual power plants and include binary on/off variables, start-up and ramping restrictions for each single plant (compare Abrell et al., 2008). The resulting mixed-integer unit commitment problem would invalidate the Karush-Kuhn-Tucker conditions for each player's optimization problem. Solving the resulting Nash-equilibrium problem would be very hard, if not impossible. We thus refrain from modeling individual power plants and rather focus on a firm's cumulative installed capacity of a given technology. Start-up and ramping constraints are represented by an aggregated ramping restriction that is not applied to single power plants, but to the whole capacity of a player's generation technology.

Conditions (2.1e) to (2.1h) constrain pumped hydro storage decisions.[28] (2.1e) resem-

[27] It does not matter if variable storage costs are assigned to storage loading or discharging.

[28] Note that pumped hydro storage facilities do not directly store electricity, but rather the potential energy of water by pumping water through a pipe into an uphill reservoir. Later on, the stored energy can be retrieved by letting the water run downhill again, where it drives a generator that produces

bles (2.1b) and states that the power generated from pumped storage can not exceed the installed generating capacity in any period $t$. Likewise, condition (2.1f) constrains the amount of electricity that can be loaded into the storage facility in any period $t$. In other words, the conditions represent limited generation and pumping capacity of pumped hydro plants. (2.1g) and (2.1h) represent reservoir restrictions, i.e. energy storage capacity. (2.1g) ensures that generation from storage stops once the reservoir is empty. The amount of electricity generated from pumped hydro storage in any period $t$ thus can not exceed the net of previous inflows and outflows.[29] Condition (2.1h) represents the upper storage capacity constraint. For each period, $t$, the amount that can be loaded into the storage facility can not exceed the total reservoir capacity, given the history of inflows and outflows up to this period. This restriction makes sure that reservoirs never overflow. Conditions (2.1g) and (2.1h) include efficiency losses. As pumped storage facilities are not perfectly efficient, only a share $\eta_{st}$ of stored electricity can be recovered. There is no ramping constraint for pumped storage, because it is by design a very flexible technology. Conditions (2.1i) and (2.1j) ensure non-negativity of the variables $x_{i,t}$, $stin_t$ and $stout_t$.

Equation (2.2) defines total electricity supply $X_t$ as the total amount of electricity generated by all firms by conventional technologies, plus generation from pumped storage, minus storage loading. The market clearing condition (2.3) makes sure that total supply equals demand in every period. Demand is represented by an iso-elastic function, drawing on exogenous hourly reference demands $d0_t$ and prices $p0_t$. $\sigma$ is the price elasticity of demand, which is assumed to be time-invariant.

$$X_t = \sum_{f \in F} \Big[ \sum_{i \in I} x_{f,i,t} + stout_{f,t} - stin_{f,t} \Big], \ \forall t \tag{2.2}$$

$$X_t = d0_t \left( \frac{p_t}{p0_t} \right)^{-\sigma}, \ \forall t \tag{2.3}$$

Equations (2.1a-2.1j) have to be solved for all players, whereas (2.3) links the problems of the individual players together. We formulate the optimization program as a mixed complementarity problem (MCP), which is the suitable formulation for this type of problem. The definition of an MCP, its application to economic analyses and its implementation in GAMS is described by Rutherford (1995) and Ferris and Munson (2000). Consisting of a square system of equations, an MCP problem is a generalization of special cases like nonlinear equation systems or complementarity problems. Mixed complementarity problems incorporate both equalities and inequalities and can thus be used for modeling Karush-Kuhn-Tucker (KKT) optimality conditions. With a convex underlying optimization problem, as (2.1a-2.1j), the KKT approach leads to a globally optimal solution. We combine the market clearing condition (2.3) with (2.2), solve for $p_t$ and insert the expression into (2.1a). We then derive the KKT optimality conditions

electricity. This process is characterized by mechanical and electrical losses, which lead to round-trip efficiencies of around 0.75 for average pumped hydro storage plants. That is, for each MWh of electricity used for pumping water into the reservoir, only 0.75 MWh can be retrieved again later.

[29] The model could be extended by including additional natural inflows to the reservoir.

2.5a-2.5k), which are listed in the Appendix. The KKT conditions form our nonlinear mixed complementarity equation system. It consists of more than 80,000 variables and equations in our application. It is implemented in the General Algebraic Modeling System (GAMS), including real data on generation capacity, costs and demand from the German electricity market (Section 2.4). The problem is solved numerically with the solver PATH, which represents a generalization of Newton's method, including a path search (Ferris and Munson, 2000).

After solving the complementarity problem, consumer rent and producer rent are calculated. Consumer rent of period $t$ is determined according to equation (2.4a) by integrating the demand function from 0 up to the the actual quantity and subtracting the amount actually paid.[30] Producer rent for each player is calculated according to equation (2.4b) by summing up revenues and subtracting costs.

$$crent_t = \int_0^{X_t} p0_t \left(\frac{x}{d0_t}\right)^{-\frac{1}{\sigma}} dx - p_t X_t, \ \forall t \tag{2.4a}$$

$$\begin{aligned} prent_{f,t} = &\sum_{i \in I} x_{f,i,t}(p_t - vgc_i) \\ &+ stout_{f,t}(p_t - vstc) - stin_{f,t}p_t, \ \forall f, t \end{aligned} \tag{2.4b}$$

## 2.4 Model application

We apply the model to the German electricity market during a typical winter week. A winter week is most suitable for analyzing storage in the German electricity market, as we find the highest peak loads and the highest prices in this season. We include three additional days both before and after the week in order to establish meaningful storage patterns that take into account the lower demand levels around the weekends. Thus, we model 13 days or 312 consecutive hours. Hourly data on German reference demand $d0$ and reference prices $p0$ is taken from the European Energy Exchange (EEX) for 16 January to 28 January 2009. We assume a price elasticity of demand of $\sigma = -0.45$. Calibrating the model with this value allows to replicate the reference demand and price levels very well. The value is also in line with other models (Borenstein and Bushnell, 1999; Traber and Kemfert, 2009). For reasons of simplicity and traceability, $\sigma$ is assumed to be time-invariant. We perform sensitivity analyses for alternative assumptions on $\sigma$ of $-0.3$ and $-0.6$.

We include six players, among them the four large strategic firms E.ON, RWE, Vattenfall, and EnBW. Combined, these firms hold more than 80% of total German generation capacity. The remaining generation capacity is assigned to a competitive generation firm named "Fringe". In addition, we include a merchant storage player "NoGen" without any conventional generation capacity, which only engages in storage operations. As

[30] In the numerical application, $x = 1$ is used as the lower integration limit for reasons of solvability. $x = 0$ would result in a division by zero. Other non-zero values are possible, as well. However, the choice of the lower integration limit is irrelevant as we do not look at absolute levels of consumer rent, but only at rent changes between different scenarios.

**Table 2.1:** Generation and pumped hydro storage capacity

| | EnBW | E.ON | RWE | Vattenfall | Fringe | NoGen |
|---|---|---|---|---|---|---|
| Available conventional generation capacity in MW: | | | | | | |
| Nuclear | 3,974 | 7,553 | 3,496 | 1,402 | 946 | 0 |
| Lignite | 398 | 1,302 | 8,494 | 7,201 | 403 | 0 |
| Hard coal | 1,570 | 5,833 | 2,615 | 979 | 3,604 | 0 |
| Natural gas | 686 | 2,543 | 1,959 | 1,382 | 4,302 | 0 |
| Oil | 103 | 348 | 5 | 152 | 127 | 0 |
| Hydro | 299 | 1,055 | 447 | 0 | 625 | 0 |
| Installed pumped hydro storage capacity: | | | | | | |
| Loading/discharging rate in MW | 1,006 | 1,017 | 1,023 | 2,893 | 456 | 0 |
| Capacity in MWh | 7,200 | 6,790 | 6,959 | 17,141 | 2,202 | 0 |

for conventional generation technologies, we include nuclear, lignite, hard coal, natural gas, oil, and hydro power. Natural gas includes combined cycle, steam and gas turbines. Hydro power includes run-of-river and other hydroelectric plants, but excludes pumped storage. Table 2.1 lists the conventional generation capacity available to different players. Data is derived from the database used by Traber and Kemfert (2009). It is adjusted with technology-specific plant availabilities in order to reflect regular maintenance and outages. We exclude other renewable technologies like wind power since its generation in Germany is currently not driven by wholesale market prices, but by technology-specific feed-in tariffs. Accordingly, it is only indirectly related to the price formation at EEX.

Table 2.1 also includes the pumped hydro storage capacity currently installed in Germany.[31] The total pumped hydro generation capacity amounts to around 6.4 GW. A literature survey shows that most pumped storage plants have roughly the same capacity for loading and discharging. We thus assume $\overline{st}_f^{out} = \overline{st}_f^{in}$. Note that these values refer to the power of turbines and pumps, and are accordingly measured in MW. In contrast, the installed storage capacity, $\overline{st}_f^{cap}$, refers to the volumes of the storage reservoirs and is thus measured in MWh. We assume that only 80% of the capacity shown in Table 2.1 is available for arbitrage purposes. In doing so, we reflect outages and regular maintenance, as well as the fact that some storage capacity is reserved for backup and black start purposes.

Table 2.2 lists ramping parameters and variable generation costs for conventional generation technologies. As explained in Section 2.3, the ramping parameters do not refer to single power plants, but to a player's overall capacity of the respective technology. Since bottom-up data on such aggregated ramping constraints does not exist, we draw on effective generation as reported to EEX over the course of a whole year. For a

[31] Sources include Tiedemann et al. (2008) and company information provided by EnBW, E.ON, RWE, Vattenfall and Schluchseewerk. In addition to the domestic capacity listed in Table 2.1, German grid operators also utilize pumped hydro storage plants in neighboring countries to some extent. Yet for reasons of traceability and consistency, we only draw on domestic capacity. Note that "Schluchseewerk" is a large German pumped hydro storage operator that is owned jointly by EnBW and RWE, each with a 50% share. An interview with a company representative showed that 50% of the company's storage capacity is operated for EnBW and another 50% for RWE. Accordingly, the total "Schluchseewerk" capacity is assigned to EnBW and RWE with 50% each.

**Table 2.2:** Parameters for conventional generation technologies

| | **Nuclear** | **Lignite** | **Hard Coal** | **Natural Gas** | **Oil** | **Hydro** |
|---|---|---|---|---|---|---|
| Ramping parameters | | | | | | |
| $\xi_i^{up}$ | 0.05 | 0.07 | 0.22 | 0.28 | 0.68 | 0.22 |
| $\xi_i^{down}$ | 0.10 | 0.06 | 0.18 | 0.26 | 0.72 | 0.19 |
| Variable generation costs $vgc_i$ in €/MWh | 10 | 25 | 30 | 40 | 50 | 10 |

representative sample of weeks, we determine the maximum output changes between two consecutive hours for each technology and relate this value to the overall installed capacity of the respective technology. This results in the values listed in the table. For example, the data shows that the nuclear power plant fleet is usually ramped up only 5% of the total capacity within one hour and 10% down. While it may be technically feasible to achieve higher ramping rates in case of extreme events, our empirically founded ramping parameters represent the technology-specific generation flexibility for respective technologies very well.[32]

Table 2.2 also lists variable generation costs, which reflect fuel and other operational costs as well as emission costs. These are estimated drawing on dena (2005), Wissel et al. (2008), as well as data provided by EEX and the International Energy Agency. The costs of operating pumped hydro storage mainly consist of opportunity costs, $p_t stin_t$ and efficiency losses. We assume an average round-trip storage efficiency of $\eta_{st} = 0.75$ (Tiedemann et al., 2008). That is, for each MWh that is loaded into pumped storage facilities, only 0.75 MWh can be retrieved again later. Because of a lack of reliable data, we neglect variable storage operation costs $vstc$. This simplifying assumption is not important as the variable costs of operating a pumped hydro storage plant (other than $p_t stin_t$) may indeed be close to zero. Nonetheless, this assumption might lead to slightly over-optimistic arbitrage profits.

Overall, we study 20 different cases, which are listed in Table 2.3. All cases draw on the same distribution of conventional generation capacity among the market players, as shown in Table 2.1. In contrast, the scenarios vary with respect to the existence and distribution of pumped hydro storage capacity among different players, which may or may not own other generation capacity. For example, in the counterfactual PC1 case, the total pumped hydro storage installed in Germany is completely assigned to the operator NoGen, which does not own any other generation assets. In PC4, the total storage capacity is distributed among the German generators in a realistic way according to Table 2.1. In other words, cases 1-3 and 5-7 (both PC and IC) have a counterfactual character as the total storage capacity is concentrated in the hand of a single player. Note that all cases (except the baselines) assume the same overall storage capacity, but

[32]In the first period, we relax the ramping restrictions on conventional generation in order to avoid distortions. We furthermore assume that the storage facilities are empty in period 1. We do not restrict storage levels in the final period, which in an optimal solution will result in an empty reservoir in the last period.

**Table 2.3:** Overview of scenarios

| Case | Conventional generation | Storage assigned to | Storage operation |
|---|---|---|---|
| PCBase | Perfect competition | - | - |
| PC1 | Perfect competition | NoGen only | Non-strategic |
| PC2 | Perfect competition | Fringe only | Non-strategic |
| PC3 | Perfect competition | E.ON only | Non-strategic |
| PC4 | Perfect competition | Real-world distribution | All non-strategic |
| PC5 | Perfect competition | NoGen only | Strategic |
| PC6 | Perfect competition | Fringe only | Strategic |
| PC7 | Perfect competition | E.ON only | Strategic |
| PC8 | Perfect competition | Real-world distribution | All strategic |
| ICBase | Imperfect competition | - | - |
| IC1 | Imperfect competition | NoGen only | Non-strategic |
| IC2 | Imperfect competition | Fringe only | Non-strategic |
| IC3 | Imperfect competition | E.ON only | Non-strategic |
| IC4 | Imperfect competition | Real-world distribution | All non-strategic |
| IC5 | Imperfect competition | NoGen only | Strategic |
| IC6 | Imperfect competition | Fringe only | Strategic |
| IC7 | Imperfect competition | E.ON only | Strategic |
| IC8 | Imperfect competition | Real-world distribution | EnBW, E.ON, RWE and Vattenfall strategic, Fringe non-strategic |
| EONBase | E.ON strategic | - | - |
| EON7 | E.ON strategic | E.ON only | Strategic |

differ with respect to its distribution among firms.

The cases further differ with respect to market power assumptions. Storage operators may decide on storage loading and discharging in a strategic or in a non-strategic way. This means that $\theta_f^{st} = 1$ *or* $0$ $\forall t$ in the first order conditions (Appendix). Moreover, we make different assumptions on the general structure of the German electricity market. It may either be perfectly competitive (PC1-8) or an imperfectly competitive oligopoly with four strategic generators (IC1-8). That is, $\theta_{gen,f,t} = 0$ $\forall f, t$ for the IC cases, but $\theta_{gen,f,t} = 1$ $\forall t$ for the four largest generators in the PC cases. For illustrative purposes, we also include two additional counterfactual cases in which only the largest generating firm, E.ON, has market power regarding conventional generation. We then assign the storage capacity exclusively to E.ON, assuming that the player also utilizes it in a strategic way. For reasons of consistency, we label these cases EONBase and EON7. Table 2.4 summarizes the market power parameters $\theta_f^{gen}$ and $\theta_f^{st}$ for all scenarios.

The different cases allow us to analyze the interrelation of storage and other generation decisions in a competitive or an oligopolistic market environment in depth. The most realistic case may be IC8, if one assumes oligopoly pricing on the German generation market. Other cases are less realistic, but interesting from an analytical point of view. For example, oligopolistic generating firms anticipate the price reactions of their conventional generation decisions in IC4, but not of their storage decisions. This may not be realistic, but the results are illustrative.

**Table 2.4:** Market power parameters in different scenarios. Note that the parameters hold for all technologies $i$ and hours $t$.

| Case | Conventional generation | Storage |
|---|---|---|
| PCBase | | - |
| PC1, PC2, PC3, PC4 | $\theta_f^{gen} = 0 \; \forall f$ | $\theta_{st,f,i,t} = 0 \; \forall f$ |
| PC5, PC6, PC7, PC8 | | $\theta_{st,f,i,t} = 1 \; \forall f$ |
| ICBase | | - |
| IC1, IC2, IC3, IC4 | $\theta_f^{gen} = 1 \; for \; f = EnBW, E.ON, RWE, Vattenfall$ | $\theta_{st,f,i,t} = 0 \; \forall f$ |
| IC5, IC6, IC7, IC8 | $\theta_f^{gen} = 0 \; for \; f = Fringe$ | $\theta_{st,f,i,t} = 1 \; \forall f$ |
| EONBase | $\theta_f^{gen} = 1 \; for \; f = E.ON$ | - |
| EON7 | $\theta_f^{gen} = 0 \; for \; f = EnBW, RWE, Vattenfall, Fringe$ | $\theta_{st,f,i,t} = 1 \; \forall f$ |

## 2.5 Results

### 2.5.1 General effects of introducing storage

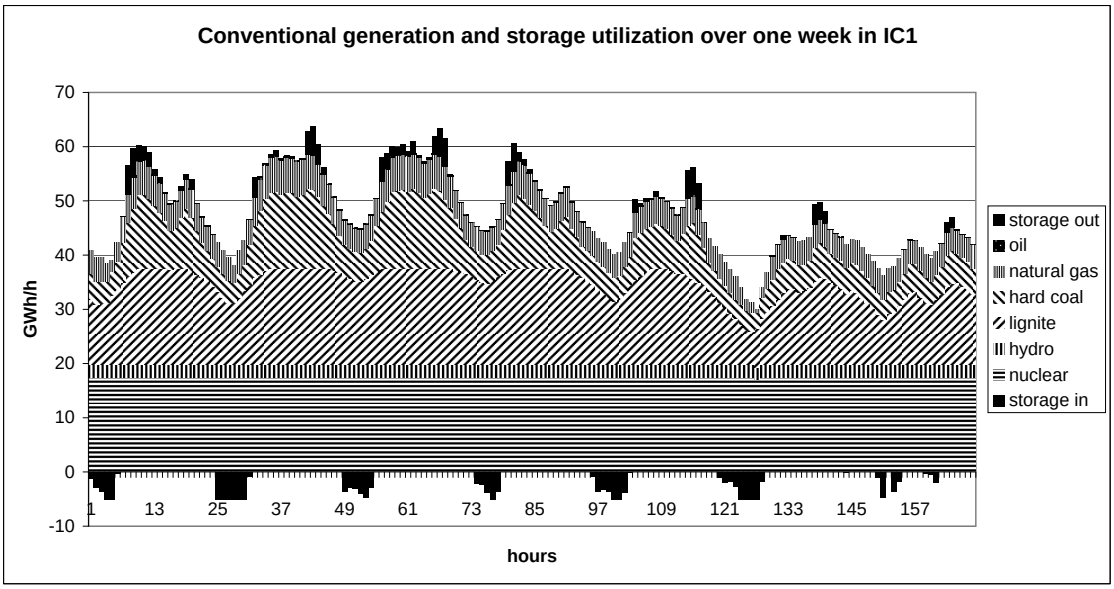


**Figure 2.1:** Conventional generation and storage utilization over one week in IC1

We illustrate the general effects of introducing storage to the German market by looking at the stylized IC1 case, which assumes an oligopolistic generation market. However, we make the counterfactual assumption that all German storage capacity is in the hands of one or several merchant storage operators that carry out storage operations in a non-strategic way. As the merchant storage player's decisions are not distorted by any involvement in the conventional generation business, this case lends itself to illustrative purposes. Figure 2.1 shows the storage operation pattern in IC1 in the context of overall generation for a whole week (the 7 days in the middle of the 13 days modeled). A characteristic pattern of daily load peaks and nightly off-peak periods is visible. Nuclear and run-of-river hydro power are always generating due to low marginal costs. Lignite generation is principally running during weekdays and is, to some extent, ramped down

during off-peak periods. Hard coal and natural gas provide medium and peak load, whereas oil serves peak loads only. Looking at pumped hydro storage, we find that a profit-maximizing storage operator loads storage during the night and discharges it during the daily peak hours. As a result, conventional generation is smoother than in the baseline without storage. This fact is reflected by the number of binding ramping constraints, which decreases from 1071 in ICBase to 945 in the IC7 case.

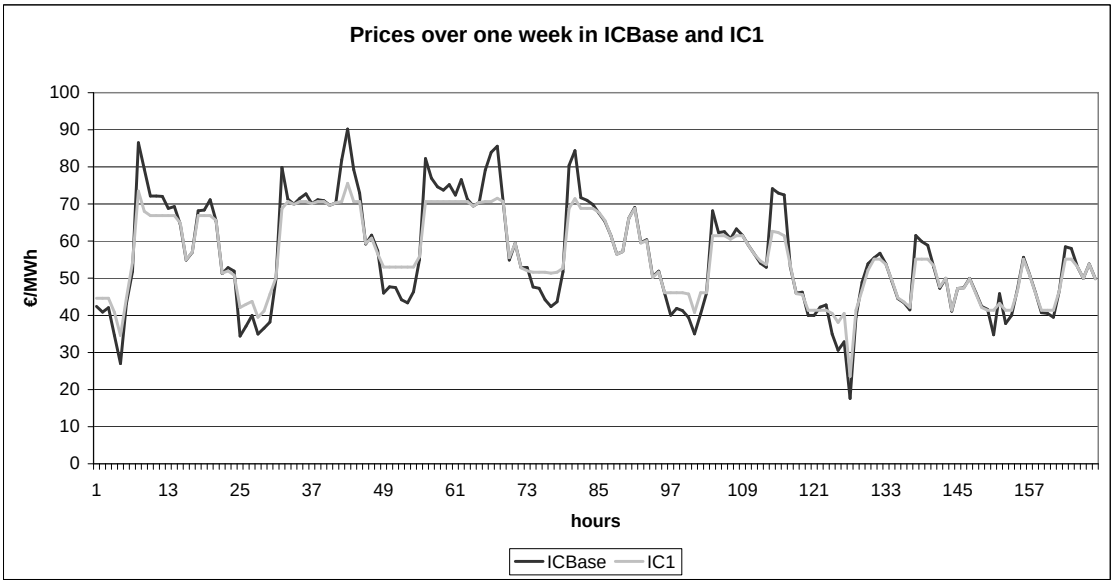


**Figure 2.2:** Prices over one week in ICBase and IC1

Buying electricity during inexpensive off-peak periods and selling it again during high-price peak periods allows the merchant storage operator to make arbitrage profits of around €2 million over 13 days. Extrapolating this value results in a yearly profit of around €58 million. Yet the introduction of storage smoothes electricity prices compared to the baseline due to additional demand in off-peak periods and additional supply in peak periods. Figure 2.2 shows that off-peak prices increase, while peak load prices decrease. This price-smoothing effect of storage negatively affects the producer rents of electricity generating firms, which benefit from peak prices. We find that generators' losses outweigh the merchant storage operator's profits. Overall producer surplus thus declines. For consumers, the opposite is true: their surplus increases because consumers benefit more from lower peak prices than they are harmed by higher off-peak prices. As the increase in consumer rent outweighs the decrease in producer rent, overall welfare increases.[33] Additional details on welfare results are provided below.

### 2.5.2 Storage utilization of different players

Figure 2.3 shows that storage utilization is highest in the PC1-4 cases among all model runs. Perfect competition for both storage utilization and conventional generation thus

[33]The results are in line with the findings by Sioshansi et al. (2009), which apply a strategic optimization model to the PJM market.

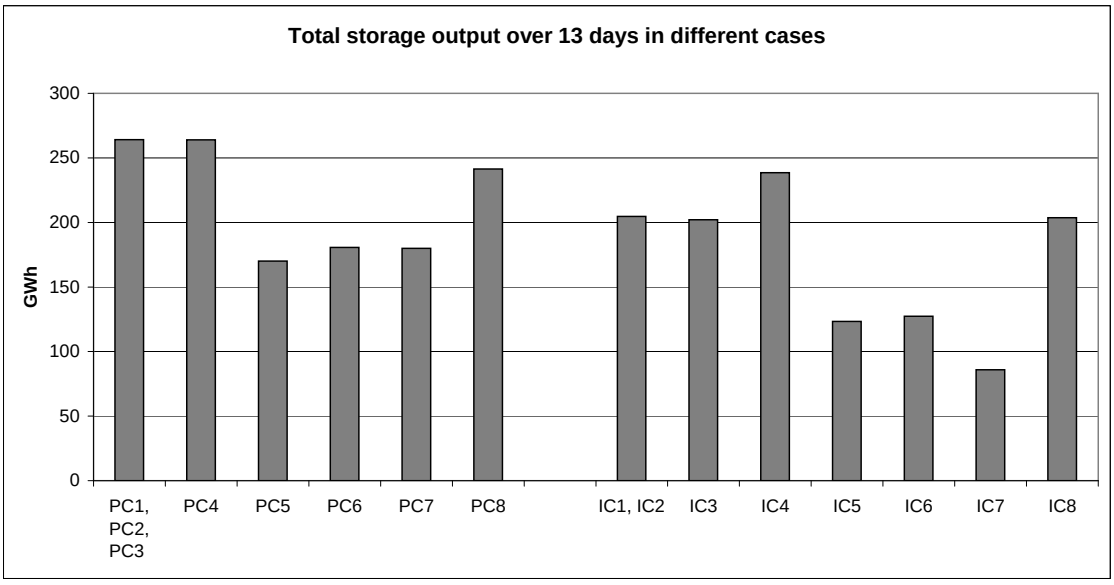


**Figure 2.3:** Total storage output over 13 days in different cases

leads to the highest possible utilization of existing storage capacity. Among the cases with perfectly competitive generators (PC1-8), storage utilization is low in the strategic storage cases PC5-7, in which all storage capacity is in the hands of a single strategic operator. In these cases, the players strategically under-utilize the storage capacity in order not to excessively smooth prices, which results in higher arbitrage gains. The strategic case PC8 provides an exception to this finding. In this case, storage is distributed among several strategic operators, which makes it difficult for a single operator to withhold storage capacity. Storage utilization is thus nearly as high as in the non-strategic cases.

Looking at the cases that assume oligopolistic generators, we find that storage utilization is always lower than in the respective cases with perfectly competitive generators. Storage utilization is highest in the IC4 case, in which storage is distributed among the generators and operated in a non-strategic way. Storage utilization in the non-strategic IC1-3 and the strategic IC8 cases is nearly equal. As in the PC cases, we find that the distribution of the total storage capacity among several strategic operators (IC8) leads to storage utilization comparable to the non-strategic cases. If the storage capacity is in the hands of a single strategic operator (IC5-7), storage utilization is substantially lower. This effect is much more pronounced than in the previously discussed PC5-7 cases. In particular, concentrating the total storage capacity in the hand of a strategic operator, which also holds large strategic conventional generation capacity leads to a substantial under-utilization (IC7). Summing up, independent of our assumptions on the market power of generators, strategic storage operation always results in a lower use of the storage capacity than non-strategic operation. The under-utilization of storage capacity is more pronounced in an oligopolistic generation market and particularly high if the total storage capacity is concentrated with a single strategic generator.

### 2.5.3 Welfare results

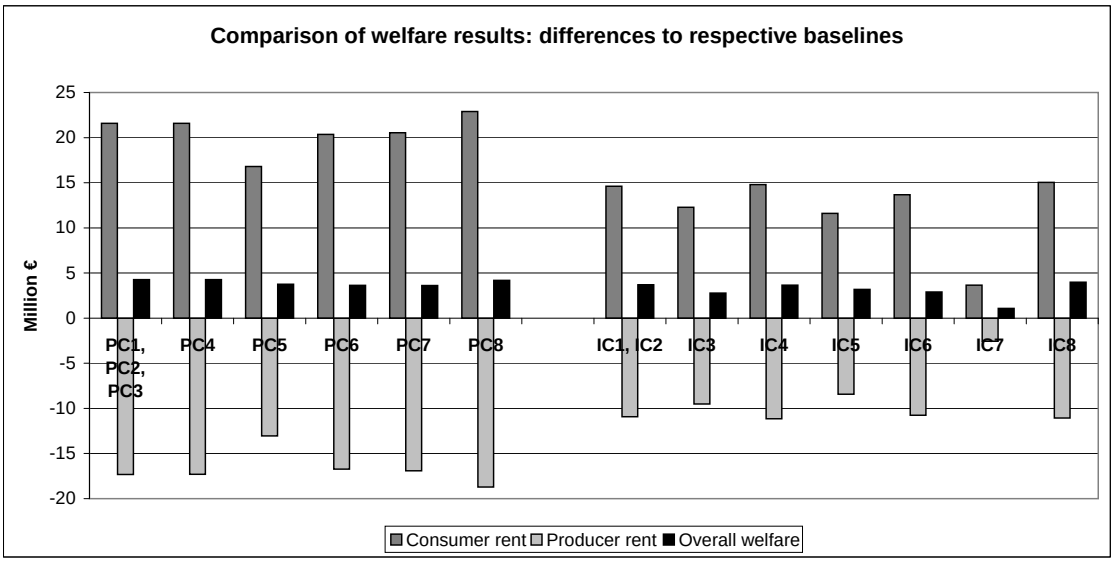


**Figure 2.4:** Comparison of welfare results: differences to respective baselines over 13 days

Figure 2.4 shows storage-related welfare effects over the 13 modeled days. It indicates the differences between the respective storage case and the baseline runs without storage. In all cases, storage increases overall welfare and consumer rents, whereas total producer rent decreases. Results for PC1, PC2, and PC3 are jointly shown as these lead exactly to the same overall welfare outcomes. The same is true for cases IC1 and IC2. In contrast, individual producer rents differ between these cases. In the following, we analyze the welfare outcomes in more detail.

#### 2.5.3.1 Producer rents

Total producer surplus decreases after introducing storage in all cases. Table 2.5 shows that this is not necessarily the case for individual producer surpluses. A storage operator's surplus may increase after introducing storage due to additional arbitrage profits. A profit-maximizing merchant storage operator, which owns no conventional generation capacity, always makes positive profits from utilizing storage. Arbitrage profits are even larger if storage is operated strategically (compare PC1, PC5 and IC1, IC5). Yet the surpluses of all other generators, which do not participate in storage activities, decrease because they suffer from the price-smoothing effect of storage. As the losses of other players outweigh the storage operator's arbitrage gains, overall producer rent decreases compared to the baseline – a general results that holds for all model runs.

Looking at other storage cases, however, we find that a storage operator that also owns conventional generation capacity may be worse off after introducing storage compared to the baseline (PC2-4, PC6-8, IC3-4, IC7-8). At first glance, this is a surprising result, as profit-maximizing players could decide to not utilize any storage capacity. Another intriguing finding is that strategic storage operation sometimes leads to even bigger losses

**Table 2.5:** Producer rent differences to respective baselines over 13 days in million €. Bold numbers indicate storage operators.

| Cases with perfectly competitive generators | PC1 | PC2 | PC3 | PC4 | PC5 | PC6 | PC7 | PC8 |
|---|---|---|---|---|---|---|---|---|
| EnBW | -2.13 | -2.13 | -2.13 | **-1.67** | -1.72 | -2.14 | -2.17 | **-1.77** |
| E.ON | -5.84 | -5.84 | **-3.08** | **-5.39** | -4.68 | -5.73 | **-2.81** | **-5.70** |
| RWE | -5.13 | -5.13 | -5.13 | **-4.67** | -4.15 | -5.19 | -5.27 | **-5.04** |
| Vattenfall | -3.37 | -3.37 | -3.37 | **-2.14** | -2.72 | -3.40 | -3.45 | **-2.36** |
| Fringe | -3.61 | **-0.85** | -3.61 | **-3.43** | -2.83 | **-0.26** | -3.21 | **-3.43** |
| NoGen | **+2.76** | 0.00 | 0.00 | 0.00 | **+3.05** | 0.00 | 0.00 | 0.00 |
| Total | -17.32 | -17.32 | -17.32 | -17.31 | -13.05 | -16.73 | -16.91 | -18.30 |
| **Cases with oligopolistic generators** | **IC1** | **IC2** | **IC3** | **IC4** | **IC5** | **IC6** | **IC7** | **IC8** |
| EnBW | -1.27 | -1.27 | -1.02 | **-0.87** | -1.19 | -1.49 | -0.36 | **-0.89** |
| E.ON | -4.11 | -4.11 | **-2.21** | **-3.91** | -3.28 | -3.86 | **-0.23** | **-4.19** |
| RWE | -3.53 | -3.53 | -3.02 | **-3.25** | -2.91 | -3.51 | -0.87 | **-3.07** |
| Vattenfall | -2.38 | -2.38 | -1.88 | **-1.67** | -2.00 | -2.47 | -0.57 | **-0.96** |
| Fringe | -1.70 | **+0.37** | -1.39 | **-1.45** | -1.67 | **+0.58** | -0.53 | **-1.95** |
| NoGen | **+2.06** | 0.00 | 0.00 | 0.00 | **+2.62** | 0.00 | 0.00 | 0.00 |
| Total | -10.92 | -10.92 | -9.52 | -11.15 | -8.42 | -10.76 | -2.56 | -11.07 |

for storage operators than the respective non-strategic storage case (PC8 vs. PC4, IC8 vs. IC4). Three effects explain these seemingly counter-intuitive results. They are related to the first-order conditions of the optimization problem listed in the Appendix. First, players imperfectly foresee their decision's impact on market prices in several cases, which results in a lack of coordination between the maximization of arbitrage profits and generation-related profits. For example, the Fringe player in PC2 neither adjusts its generation decisions to the price-smoothing effect of storage, nor does it take into account its conventional generation when deciding on storage inputs and outputs ($\theta_{st,Fringe,t} = \theta_f^{gen} = 0$ in equations 2.5a-2.5c). Whereas the Fringe player makes positive arbitrage profits in PC2, its profits in conventional generation decrease even more due to the price-smoothing effect of storage. The same argument holds for PC2-4. In the cases PC6-8, storage operators are able to anticipate the price effects of storage operation when deciding on storage inputs and outputs as well as on conventional generation ($\theta_f^{st} = 1$). However, players in these cases are assumed not to take into account the price-effects of their conventional generation decisions ($\theta_f^{gen} = 0$). Accordingly, the $\vartheta_{f,i,t}^{gen}\theta_f^{gen}$ terms in the first order conditions are zero while $\vartheta_{f,t}^{out}\theta_f^{st}$ and $\vartheta_{f,t}^{in}\theta_f^{st}$ are positive. In general, $\vartheta_{f,t}^{in}$ is larger than $\vartheta_{f,t}^{out}$, as storage is loaded in off-peak periods, but discharged in peak periods. Players may thus be better of than in the non-strategic storage cases PC2-4, but still worse off than in PCBase.

Second, other strategic generators adjust their production to storage-related price effects. Note that the four strategic generators are able to take into account market price reactions to their conventional generation decisions in the cases IC1-8, as well as to storage decisions in IC5-8 (compare Table 2.4). For example, the storage operator E.ON is able to foresee the price reactions to its conventional generation decisions in IC3, and also of its storage decisions in IC7. Yet storage operators' surpluses still decrease compared

to the baseline in IC3-4 and IC7-8. In these cases, the three other oligopolistic players adjust generation to the new market situation. For example, in IC7, EnBW, RWE and Vattenfall increase their generation levels during E.ON's storage loading periods and slightly decrease them during storage discharging periods, compared to ICBase. As a result, the players that are not involved in storage operations manage to diminish storage-related producer rent losses. Accordingly, their surpluses in IC1-3 and IC5-7 are higher compared to the respective PC cases, in which they are not able to adjust their generation strategically. E.ON in turn plays an optimal strategy given its rivals' generation decisions. The other oligopolistic generators' strategies, however, harm E.ON in such a way that even strategic storage operation leads to a small loss of surplus compared to the baseline (IC7). Accordingly, E.ON is not able to benefit from storage in our model – neither in a perfectly competitive, nor in an oligopolistic market. [34] An additional model run shows that E.ON would be able to benefit from storage if it was the only strategic generator in the market, i.e. if the other three generators were not able to adjust their generation. In this model run (EON7), we assume that the largest generating firm, E.ON, is the only player to have market power regarding conventional generation. That is, $\theta_f^{gen} = 1 \; for \; f = E.ON$, whereas $\theta_f^{gen} = 0 \; for \; f = EnBW, RWE, Vattenfall, Fringe$. Furthermore, we assign all storage capacity to E.ON and assume that it is operated in a strategic way. The results of this additional run are listed in Table 2.6.

**Table 2.6:** Producer rent differences to EONBase in million €. The bold number indicates the storage operator.

| | EON7 |
|---|---|
| EnBW | -0.45 |
| E.ON | **+0.04** |
| RWE | -1.07 |
| Vattenfall | -0.70 |
| Fringe | -0.97 |
| NoGen | 0.00 |
| Total | -3.15 |

There is a third effect which explains the low producer rents of storage operators in the cases PC8 and IC8, in which the total storage capacity is distributed among all generators as in the real world. Overall, producers suffer heavily from storage in these cases because they face a prisoners' dilemma. Producers would be better off if all agreed not to utilize any storage capacity, however, such behavior does not represent a stable Nash-Cournot solution. Each player has an incentive to deviate from this point by using its storage capacity to make some arbitrage profits. The resulting price-smoothing effect harms all other generators, which, in turn, also have an incentive to make arbitrage profits. In the end, cases 4 and 8 (both PC and IC) result in high overall storage utilization with

[34] Note that E.ON's producer surplus is still higher in the strategic IC7 compared to the non-strategic IC3. Besides, E.ON is better off in IC7 compared to not using its storage capacity at all. This can be shown with an additional model run in which E.ON's storage utilization is exogenously fixed to zero. Finally, a sensitivity analysis shows that the finding depends on demand elasticity: Under the assumption of $\sigma = -0.6$, E.ON is able to make a positive profit in the IC7 case.

according price-smoothing, such that all generators are worse off than in the respective baselines.

Finally, our results suggest that pumped hydro storage investments are not attractive for incumbent German generating firms. In the cases with realistic distribution of storage among generators, we find that producer rents are always lower than in the baseline case without storage, irrespective of our assumptions on market imperfections (PC4, PC8, IC4, IC8). Generators are harmed by the price-smoothing effect of storage, which diminishes their surpluses from conventional generation. In contrast, merchant storage operators, which are not involved in conventional generation, make positive arbitrage profits in the counterfactual cases. The same is true for non-strategic generating firms in an oligopolistic market environment (IC2), although to a much lower extent. Pumped storage investments may thus only be attractive for merchant operators and generating firms without market power.[35]

#### 2.5.3.2 Consumer rents

Figure 2.4 indicates that storage has a positive effect on consumer surplus in all modeled cases. Consumer rent is particularly high in those cases in which producer surplus is low, and vice versa. Consumers are better off in most cases with non-strategic storage utilization compared to the respective strategic cases. This is particularly true for IC3 vs. IC7: if a strategic generator in an oligopolistic market environment also has a monopoly over storage, strategic storage utilization harms consumers most. The consumer benefits of storage nearly vanish in IC7. Consequently, storage should not be concentrated in the hand of a large oligopolistic generator from a consumer's point of view. In contrast, in a market with perfectly competitive generators (PC cases), strategic storage impacts consumer rents less. Yet in the cases with realistic distribution of storage between different players, strategic storage does not harm consumers. In contrast, consumers benefit most in PC8 and IC8 due to the aforementioned price-smoothing prisoners' dilemma that storage operators face.

#### 2.5.3.3 Overall welfare

As consumer rent gains are higher than producer losses, storage increases overall welfare in all model runs. Among the cases with perfectly competitive generators, overall welfare does not differ much. Non-strategic storage (PC1-4) generally leads to higher overall welfare than strategic storage utilization (PC5-8). In an oligopolistic market (IC1-8), overall welfare gains of storage are always lower than in PC1-8, whereas differences between the cases are larger. The non-strategic storage cases (IC1-4) still deliver high overall welfare outcomes, but the strategic case IC8 leads to even higher welfare. This is due to

[35] It is clear that drawing definite conclusions on the viability of pumped hydro storage investments in Germany is beyond the scope of this research. Note that we only refer to the arbitrage value of storage. Yet pumped storage facilities can generate additional revenue streams by offering other and higher-value ancillary services to the power market in the real world. For example, the provision of reserve capacity or reactive power may lead to higher revenue streams than arbitrage.

high consumer rents in the IC8 case, which result from the storage operators' prisoner's dilemma discussed above. IC8 and IC 4 have the same distribution of storage capacity among players. As the strategic storage case IC8 leads to higher overall welfare than the non-strategic IC4, we conclude that strategic storage operation may have a market power mitigating effect in an otherwise oligopolistic market environment if capacity is distributed among different strategic players.[36] In contrast, monopolistic storage leads to lower overall welfare levels. Strategic merchant storage (IC5) and strategic storage of a generator that has no market power in generation (IC6) leads to welfare results slightly lower than the non-strategic storage cases. Yet welfare gains of storage nearly disappear when the total storage capacity is controlled by the large strategic generator E.ON due to low consumer rents (IC7). We thus conclude that strategic storage operation in an oligopolistic market should be avoided for welfare reasons, if storage is not distributed among several players that also hold other generation capacity.[37]

Finally, we compare the magnitude of welfare losses from strategic storage utilization with those related to strategic conventional generation. Among all model runs, we find the largest potential welfare losses from strategic storage utilization between IC3 and IC7. Strategic storage leads to welfare losses of nearly €2 million for the modeled 13 days, or around €47 million extrapolated to one year. In the more realistic IC8 case, there are hardly any welfare losses of strategic storage compared to IC4 due to the prisoners' dilemma described above. In contrast, the welfare difference between a perfectly competitive and an oligopolistic generation market (PCBase vs. ICBase) is substantially higher at around €47 million for 13 days, or €1.3 billion for a whole year. Accordingly, we conclude that the strategic use of pumped hydro storage is not a relevant source of market power in Germany, compared to strategic utilization of conventional generation capacity.

### 2.5.4 Sensitivity analyses for different demand elasticities

The model runs discussed above have been calculated for a price elasticity of demand of -0.45, as this value leads to the most realistic results regarding generation levels and prices. We test the robustness of this assumption for alternative values of $\sigma = -0.3$ and $\sigma = -0.6$.[38] Figure 2.5 shows the results regarding storage capacity utilization. Note that the same overall storage capacity is available in all cases. We find that more elastic demand ($\sigma = -0.6$) generally increases storage utilization, as price differences between single hours increase and arbitrage becomes more profitable. In contrast, less elastic

[36] The decreasing effect of storage on spot prices can be compared to the effect of forward markets. These may also mitigate market power and improve efficiency under certain conditions. Adilov (2010) makes a recent contribution to this strand of the literature.

[37] Note that our results partly support the findings by Sioshansi (2010). They argue that growing numbers of storage operators, i.e. increasingly non-strategic storage utilization, increase welfare, whereas merchant storage operation is closest to the welfare maximum. Yet we show that the issue is more complex in a market with imperfectly competitive generators, in particular if storage is distributed between them.

[38] A solver problem occured for IC3 with $\sigma = -0.3$. We thus omit this case.

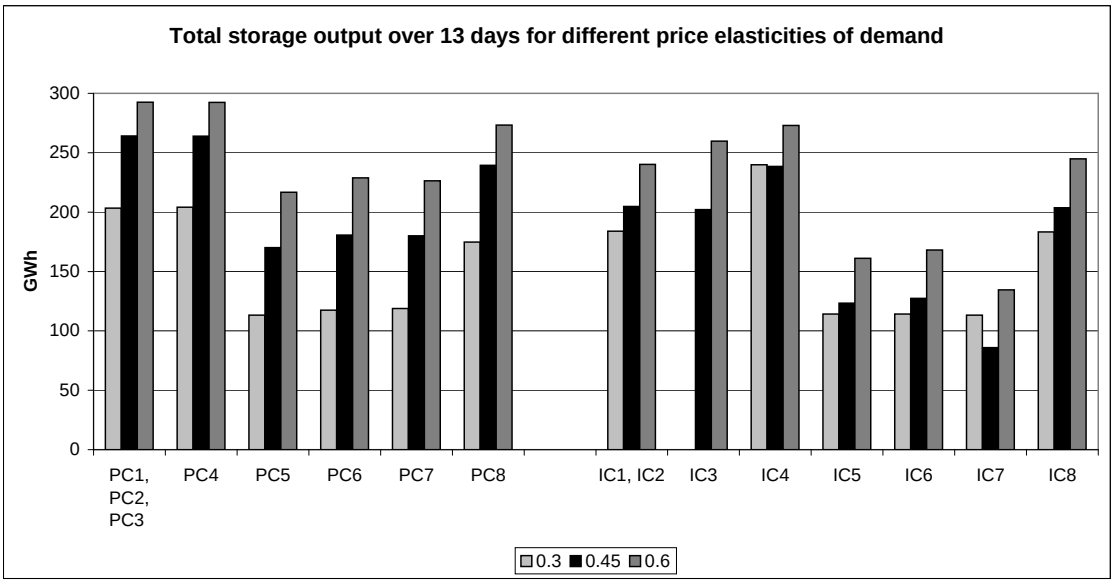


**Figure 2.5:** Total storage output over 13 days for different price elasticities of demand

demand ($\sigma = -0.3$) generally leads to lower storage utilization. Yet the main findings, as discussed in section 2.5.2, hardly change. Strategic storage operators generally under-utilize their capacity. Monopolistic storage operation in a market with strategic generation (IC5-7) leads to the lowest utilization levels. We thus conclude that our storage utilization results are robust against varying assumptions on demand elasticity.

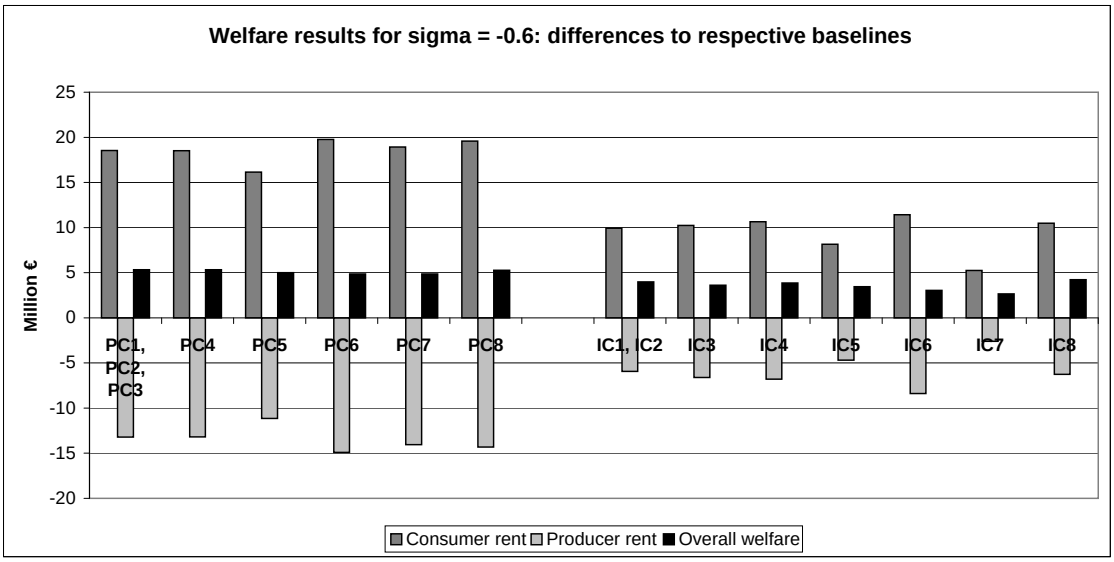


**Figure 2.6:** Welfare results for $\sigma = -0.6$: differences to respective baselines over 13 days

Figures 2.6 and 2.7 show sensitivity results regarding welfare. For $\sigma = -0.6$, results are robust: Non-strategic storage generally leads to higher welfare than strategic storage. IC8 once again provides an exception because of the prisoner's dilemma discussed above. For $\sigma = -0.3$, results slightly change. The overall welfare gain of storage is now lower in the perfect competition cases (PC1-8) than in the imperfect ones (IC1-8). This is because

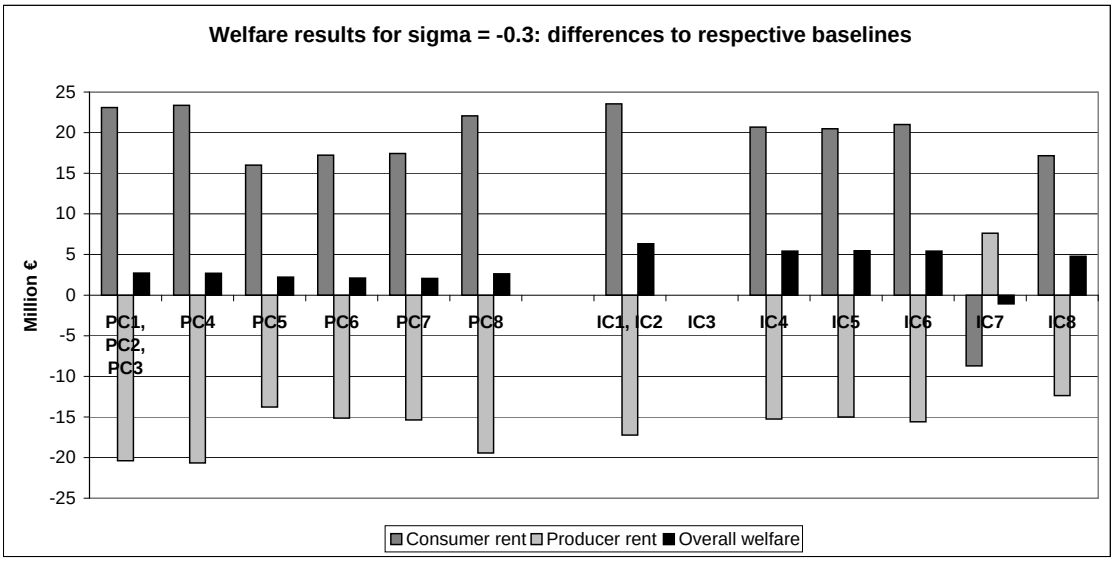


**Figure 2.7:** Welfare results for $\sigma = -0.3$: differences to respective baselines over 13 days

the market power potential of conventional generators increases with lower demand elasticity. Accordingly, the price-smoothing effect of storage is more valuable in an imperfect competition environment. Yet the most notable difference is that monopolistic storage operation by a strategic generator in an imperfect market (IC7) now leads to welfare and consumer rent losses compared to the baseline without storage. This finding, however, only reinforces our previous conclusion that monopolistic storage ownership should be avoided for welfare reasons.

## 2.6 Summary and conclusions

We develop a game-theoretic electricity market model that allows the analysis of strategic electricity storage. We apply the model to the German market and the case of pumped hydro storage. Drawing on different counterfactual and realistic cases, we study the complex interaction between players' decisions on conventional generation and storage under various market power assumptions, and the resulting effects on storage utilization and welfare. Most results are robust for varying assumptions on price elasticity of demand. Although we focus our analysis on the example of pumped hydro storage, the results are applicable to other large-scale storage technologies as well, for example compressed air storage or grid-connected batteries.

We find that storage generally smoothes conventional generation patterns and electricity prices. Our main finding, however, is that not only does the existence of a storage capacity in a market matter, but also storage ownership. Strategic players generally under-utilize their storage capacity. In particular, an oligopolistic generator that exclusively controls the total storage capacity of the market, massively under-utilizes its capacity. In contrast, strategic storage hardly results in under-utilization if the total storage capacity is distributed between several strategic players.

Whereas storage leads to arbitrage profits for the respective players, its price-smoothing effect decreases generation-related producer surplus for all generating firms. Storage operators that also engage in conventional generation may suffer a net loss of their surplus compared to the baseline without storage. There are different reasons for this results, among them a lack of coordination between the maximization of arbitrage profits and generation-related profits as well as adjustments of other strategic generators to the new situation. Moreover, storage operators face a prisoners' dilemma if the total capacity is distributed among several generators. As a consequence of these effects, overall producer rent declines compared to the baseline. In contrast, storage causes an even larger increase in consumer surplus, such that overall welfare increases in all storage cases when compared to the baseline. Nonetheless, welfare results differ substantially between the cases. The positive effect of storage on overall welfare is generally higher in the cases of non-strategic storage operation when compared to the strategic ones. Welfare losses of strategic storage are particularly high if a large oligopolistic generator exclusively controls storage operations. Yet in an oligopolistic market environment, strategic storage operation may lead to high overall welfare, if the total storage capacity is distributed among different players.

Our results might be interpreted such that strategic storage is unlikely to be a relevant source of market power in Germany. As storage is distributed across several strategic generators, which face a prisoner's dilemma, strategic storage neither jeopardizes consumer rent nor overall welfare. Moreover, we find that potential welfare losses of strategic storage, even in a counterfactual worst case scenario, are much lower than the welfare losses from strategic conventional generation. Accordingly, economic regulation to ensure the competitive utilization of existing German pumped hydro capacity is not a priority. However, the situation may change if additional future storage capacity is controlled by single strategic generators. For example, the involvement of oligopolistic generating firms into loading and discharging of future electric vehicle fleets should be scrutinized.

Aside from welfare considerations, high utilization of storage capacity may be a policy objective. For example, the large-scale system integration of fluctuating renewable generators may require storage capacity to be utilized to the greatest possible extent. Although this issue is not explicitly modeled here, strategic under-utilization of storage capacity may provide an obstacle to renewable integration. In this case, regulators should ensure that storage is operated in a non-strategic way or that capacity is suitably distributed between players.

Finally, our results suggest that investing in new storage capacity is not attractive for players that also hold other generation capacity. It should thus not be expected that incumbent German generators will invest in additional storage capacity, although the social welfare outcomes may be positive – even in perfectly competitive markets – due to storage's price-smoothing effect. Whereas policy makers should not be concerned about the utilization of currently installed pumped hydro storage, they may think about ways of incentivizing new storage investments. Providing economic incentives could be

justified by storage-related welfare gains.

# 2.A Appendix

## 2.A.1 Sets, indices, parameters, and variables

**Table 2.7:** Sets, indices, parameters, and variables

| Item | Description | Unit |
|---|---|---|
| **Sets and indices** | | |
| $F$ | Firms with $f \in F$ | |
| $I$ | Generation technologies with $i \in I$ | |
| $T$ | Time with $t \in T$, $\tau \in T$ | hours |
| **Parameters** | | |
| $\sigma$ | Price elasticity of electricity demand | |
| $d0_t$ | Hourly reference demand | MWh |
| $p0_t$ | Hourly reference prices | €/MWh |
| $\overline{x}_{f,i}$ | Available conventional generation capacity | MW |
| $\overline{st}_f^{out}$ | Available pumped storage discharging capacity | MW |
| $\overline{st}_f^{in}$ | Available pumped storage loading capacity | MW |
| $\overline{st}_f^{cap}$ | Available pumped storage capacity | MWh |
| $\xi_i^{up}$ | Ramping up parameter | |
| $\xi_i^{down}$ | Ramping down parameter | |
| $vgc_i$ | Variable generation costs | €/MWh |
| $vstc$ | Variable pumped storage costs | €/MWh |
| $\eta_{st}$ | Storage efficiency | |
| $\theta_f^{gen}$ | Market power parameter for generation | 0 or 1 |
| $\theta_f^{st}$ | Market power parameter for pumped storage | 0 or 1 |
| **Variables** | | |
| $\Pi_f$ | Profit of firm $f$ | € |
| $p_t$ | Price of period $t$ | €/MWh |
| $x_{f,i,t}$ | Generation of firm $f$ with technology $i$ in period $t$ | MWh |
| $X_t$ | Total supply in period $t$ | MWh |
| $stout_{f,t}$ | Generation of firm $f$ in period $t$ from pumped storage | MWh |
| $stin_{f,t}$ | Pumped storage loading of firm $f$ in period $t$ | MWh |
| $\lambda_{f,i,t}^{gen}$ | Shadow price of generation capacity constraint | €/MWh |
| $\lambda_{f,i,t}^{rup}$ | Shadow price of ramping up constraint | €/MWh |
| $\lambda_{f,i,t}^{rdo}$ | Shadow price of ramping down constraint | €/MWh |
| $\lambda_{f,t}^{stout}$ | Shadow price of storage discharging capacity constraint | €/MWh |
| $\lambda_{f,t}^{stin}$ | Shadow price of storage loading capacity constraint | €/MWh |
| $\lambda_{f,t}^{stup}$ | Shadow price of upper storage capacity constraint | €/MWh |
| $\lambda_{f,t}^{stlo}$ | Shadow price of lower storage capacity constraint | €/MWh |
| $\vartheta_{f,i,t}^{gen}$ | Market share of firm $f$ – generation | |
| $\vartheta_{f,t}^{out}$ | Market share of firm $f$ – storage discharging | |
| $\vartheta_{f,t}^{in}$ | Market share of firm $f$ – storage loading | |
| $crent_t$ | Consumer rent of period $t$ | € |
| $prent_{f,t}$ | Producer rent of firm $f$ in period $t$ | € |

### 2.A.2 The mixed complementarity problem

$$0 \leq vgc_i + \lambda^{gen}_{f,i,t} + \lambda^{rup}_{f,i,t} - \lambda^{rup}_{f,i,t+1} - \lambda^{rdo}_{f,i,t} + \lambda^{rdo}_{f,i,t+1} - p_t \left(1 - \frac{\sum_{i \in I} \vartheta^{gen}_{f,i,t}\theta^{gen}_f + \vartheta^{out}_{f,t}\theta^{st}_f - \vartheta^{in}_{f,t}\theta^{st}_f}{\sigma}\right) \perp \quad x_{f,i,t} \geq 0, \ \forall f, i, t \tag{2.5a}$$

$$0 \leq vstc_{st} + \lambda^{stout}_{f,t} + \sum_{\tau=t}^{T} \lambda^{stlo}_{f,\tau} - \sum_{\tau=t}^{T-1} \lambda^{stup}_{f,\tau+1} - p_t \left(1 - \frac{\sum_{i \in I} \vartheta^{gen}_{f,i,t}\theta^{gen}_f + \vartheta^{out}_{f,t}\theta^{st}_f - \vartheta^{in}_{f,t}\theta^{st}_f}{\sigma}\right) \perp \quad stout_{f,i,t} \geq 0, \ \forall f, t \tag{2.5b}$$

$$0 \leq \lambda^{stin}_{f,t} - \sum_{\tau=t}^{T-1} \lambda^{stlo}_{f,\tau+1}\eta_{st} + \sum_{\tau=t}^{T} \lambda^{stup}_{f,\tau}\eta_{st} + p_t \left(1 - \frac{\sum_{i \in I} \vartheta^{gen}_{f,i,t}\theta^{gen}_f + \vartheta^{out}_{f,t}\theta^{st}_f - \vartheta^{in}_{f,t}\theta^{st}_f}{\sigma}\right) \perp \quad stin_{f,i,t} \geq 0, \ \forall f, t \tag{2.5c}$$

$$0 \leq -x_{f,i,t} + \overline{x}_{f,i} \qquad \perp \lambda^{gen}_{f,i,t} \geq 0, \ \forall f, i, t \tag{2.5d}$$

$$0 \leq -x_{f,i,t} + x_{f,i,t-1} + \xi^{up}_i \overline{x}_{f,i} \qquad \perp \lambda^{rup}_{f,i,t} \geq 0, \ \forall f, i, t \tag{2.5e}$$

$$0 \leq -x_{f,i,t-1} + x_{f,i,t} + \xi^{down}_i \overline{x}_{f,i} \qquad \perp \lambda^{rdo}_{f,i,t} \geq 0, \ \forall f, i, t \tag{2.5f}$$

$$0 \leq -stout_{f,t} + \overline{st}^{out}_f \qquad \perp \lambda^{stout}_{f,t} \geq 0, \ \forall f, t \tag{2.5g}$$

$$0 \leq -stin_{f,t} + \overline{st}^{in}_f \qquad \perp \lambda^{stin}_{f,t} \geq 0, \ \forall f, t \tag{2.5h}$$

$$0 \leq -\sum_{\tau=1}^{t} stout_{f,\tau} + \sum_{\tau=1}^{t-1} stin_{f,\tau}\eta_{st} \qquad \perp \lambda^{stlo}_{f,t} \geq 0, \ \forall f, t \tag{2.5i}$$

$$0 \leq -\sum_{\tau=1}^{t} stin_{f,\tau}\eta_{st} + \sum_{\tau=1}^{t-1} stout_{f,\tau} + \overline{st}^{cap}_f \qquad \perp \lambda^{stup}_{f,t} \geq 0, \ \forall f, t \tag{2.5j}$$

$$0 = X_t - d0_t \left(\frac{p_t}{p0_t}\right)^{-\sigma} \qquad , \ p_t \ free, \ \forall \ t \tag{2.5k}$$

Equations (2.5a-2.5k) include market shares $\vartheta^{gen}_{f,i,t}$, $\vartheta^{out}_{f,t}$ and $\vartheta^{in}_{f,t}$ as defined in (2.6a-2.6c). They indicate a player's ability to raise prices beyond marginal costs. (2.5a-2.5k) also include market power parameters $\theta^{gen}_f$ and $\theta^{st}_f$. By exogenously assigning the values 0 or 1, we can "switch" off and on market power for specific firms both regarding generation

and storage operation.

$$\vartheta^{gen}_{f,i,t} = \frac{x_{f,i,t}}{X_t},\ \forall f, i, t \tag{2.6a}$$

$$\vartheta^{out}_{f,t} = \frac{stout_{f,t}}{X_t},\ \forall f, t \tag{2.6b}$$

$$\vartheta^{in}_{f,t} = \frac{stin_{f,t}}{X_t},\ \forall f, t \tag{2.6c}$$

Conditions (2.5a-2.5c) may be interpreted as follows. Equation (2.5a) includes a standard Cournot result: In case of positive market shares $\sum_{i \in I} \vartheta^{gen}_{f,i,t}$ for conventional generation technologies, market prices exceed the sum of marginal costs and shadow prices of player $f$. The larger the market share of a player, the larger its ability to raise prices beyond marginal costs. Whereas this is a common feature of Cournot models, the inclusion of storage-related market shares $\vartheta^{out}_{f,t}$ and $\vartheta^{in}_{f,t}$ is a new contribution to the literature. Positive market shares regarding storage output $\vartheta^{out}_{f,t}$ have the same effect as positive conventional market shares: larger $\vartheta^{out}_{f,t}$ increase a firm's ability to raise prices beyond marginal costs. The market share of storage input $\vartheta^{in}_{f,t}$, however, enters with a negative sign. The reason is that storage operators face costs for each MWh of electricity that is stored at period $t$. Thus, higher prices imply higher storage loading costs. The higher the market share $\vartheta^{in}_{f,t}$ of a player, the larger its interest in low prices during periods of storage loading. Strategic storage operation thus mitigates a strategic generator's incentives to raise prices by withholding conventional capacity during the periods of storage loading. Note that the market shares also enter equations (2.5b) and (2.5c), which may be interpreted accordingly.

# Chapter 3

# Electric vehicles in imperfect electricity markets: the case of Germany

## 3.1 Introduction

Electric vehicles are gaining attention in the light of tighter climate policy and a growing dependency on imported fossil fuels in the transportation sector. Electric vehicles can use a broad range of energy resources, including renewable sources, for mobility purposes. In addition, electric vehicles promise to deliver several benefits compared to internal combustion engines, including greater energy efficiency with lower noise, $CO_2$, and other air pollutants emitted (Samaras and Meisterling, 2008; Bradley and Frank, 2009). The materialization of these benefits largely depends on the means of electricity generation. Yet the interaction of electric vehicle fleets with electricity markets is hardly studied. In particular, there is little research on electric vehicles in the context of market failures like imperfectly competitive electricity markets. The research presented in this chapter intends to fill this literature gap.

Using an extended version of the game-theoretic model ElStorM presented in section 2.3, we examine the market impacts of a hypothetic fleet of one million plug-in electric vehicles (PIEV) on the imperfectly competitive German electricity market. We seperately analyze the market effects of additional load and additional storage capacity on prices, welfare, and electricity generation. We also examine how having different players in charge of electric vehicle operations leads to different patterns of vehicle recharging and storage utilization. In particular, the model allows to investigate the combined decisions of oligopolistic generating firms on generation, vehicle loading, and storage. We also analyze the utilization of excess vehicle battery capacity for arbitrage, i.e. storing electricity in periods of low prices and selling it back to the market in times of higher prices. We examine if arbitrage is a viable strategy in the light of existing pumped hydro storage and battery degradation costs.

The analysis shows that the introduction of PIEV generally increases generator profits and decreases consumer surplus. This is particularly true if vehicles are recharged in an uncontrolled way. In case of controlled loading of the PIEV fleet, welfare distortions as well as vehicle loading costs decrease substantially. If battery capacity that is not needed for daily average driving requirements can be used for grid storage, welfare effects are very different: generator profits decrease, while consumer surplus and overall welfare substantially increase due to a price-smoothing effect of additional storage capacity. Yet battery degradation costs may diminish arbitrage opportunities and related welfare effects. In addition, strategic generating firms tend to under-utilize their battery storage capacity, which may have negative implications for consumers. In contrast, consumers may benefit from a market power mitigating effect of vehicle and storage loading on strategic generators. Finally, electric vehicles increase the utilization of emission-intensive low-cost technologies, in particular if an oligopolistic generator is in charge of PIEV operations.

The remainder of this chapter is structured as follows. First, we briefly discuss the relevant literature. Section 3.3 describes the model and the main assumptions. Section 3.4 includes relevant data and defines different cases of PIEV operation. The results section discusses the impacts of different players controlling the PIEV fleet on market prices, welfare and electricity generation. We also perform a sensitivity analysis regarding battery degradation costs. The last section summarizes and concludes.

## 3.2 Literature

While there are many different designs of electric vehicles, all share the common feature of complementing or completely substituting a conventional internal combustion engine with a battery-electric drive.[39] Future PIEV fleets will have substantial impacts on electricity markets. On the one hand, electric vehicles increase overall electricity demand. This could have negative impacts on network stability, electricity prices, and emissions. Gerbracht et al. (2009) show that uncontrolled vehicle loading will increase German peak load to dangerous levels, even if PIEV fleets are rather small. Vehicle recharging should thus be carried out in off-peak hours in order to minimize negative impacts. On the other hand, future PIEV fleets could also offer valuable services to the electricity system, if bi-directionally connected to the grid and intelligently controlled. Kempton and Tomic (2005a) first develop the idea of integrating electric vehicle fleets into the power system with a "Vehicle-to-Grid" (V2G) concept. Drawing on the empirical fact that around 90% of all vehicles are in a parking position any given time of the day, implementing the V2G concept could realize large synergies between the vehicle fleet and the electricity system (compare also Kempton and Tomic, 2005b). Guille and Gross (2009) provide a framework for integrating PIEV into existing power systems. Within a V2G concept, PIEV fleets

[39] In our model analysis, we do not differ between electric vehicle concepts, as long as the vehicles recharge batteries from the power grid. We are only interested in the cumulative market impact of grid-connected vehicle fleets. For example, we do not distinguish between hybrid electric cars and pure battery electric drives. Schill (2010b) provides an overview of different vehicle concepts.

could smooth the load curve by recharging batteries at nighttime, and deliver peak load by feeding electricity back to the grid in times of high demand. Grid-connected electric vehicles could thus reduce the need for conventional peak power plants, which increases social welfare. However, Peterson et al. (2010) find that arbitrage profits in different U.S. regions do not provide sufficient incentives for grid storage, if battery degradation is taken into account. Aside from arbitrage on the wholesale markte, PIEV could also provide valuable ancillary services like primary, secondary or tertiary control (Tomic and Kempton, 2007). Galus et al. (2010) examine the provision of secondary control services by PIEV fleets. Andersson et al. (2010) find that providing control reserves with PIEV fleets in Germany and Sweden may be an economically viable strategy. Sioshansi and Denholm (2009) demonstrate that the provision of spinning reserves by electric vehicles could increase the efficiency of thermal electricity generation, which in turn decreases emissions. It is suggested that PIEV fleets may also be able to balance fluctuating renewable energy feed-in, for example by taking up excess wind generation (compare Lund and Kempton, 2008; Ekman, 2011). However, Sovacool and Hirsh (2009) argue that there might be large social barriers to implementing the V2G concept.

In this chapter, we focus on the interaction of electric vehicles and imperfectly competitive electricity markets. In contrast to previous studies, we explicitly model the interaction of PIEV operations and the German power market.[40] We endogenously determine the timing of vehicle recharging and storage operations by profit-maximizing players while taking care of market price reactions. Moreover, we allow for imperfect competition. In doing so, we add to the literature that studies imperfectly competitive power markets (see section 2.2). Furthermore, the research complement earlier PIEV analyses that assume perfectly competitive markets, for example Göransson et al. (2010) for Denmark or Sioshansi et al. (2010) for the Ohio power system. Moreover, we explicitly quantify the effect of different players being in charge of electric vehicle operations. We thus quantitatively support the argument brought foreward by Andersen et al. (2009) and Guille and Gross (2009), according to which the "aggregator" – i.e. the actor in charge of vehicle operations – plays a crucial role for integrating electric vehicle fleets into power markets.

More generally speaking, our analysis also enlarges the understanding of how flexible resources are used in imperfect electricity markets. We not only study strategic electricity storage, as in chapter 2, but also the strategic allocation of dispatchable load and its interaction with oligopolistic generation. Although the analysis is motivated by electric vehicles, results may be interpreted in a more general way, as additional storage and dispatchable demand could also be introduced to the market by other technologies.

[40] Note that the analysis focuses on the wholesale market. Ancillary services traded on other markets are excluded, for example the provision of control reserves.

## 3.3 The model

We assume that PIEV operations are either controlled by individual vehicle owners or by service providers. Importantly, all these PIEV operators also act as players on the electricity market: they buy electricity to recharge their vehicles, and they may sell stored electricity back to the market. We further assume that there is a fixed amount of electricity that must be delivered to the electric vehicle fleet each day in order to recharge batteries. Players in charge of PIEV operations have a "commitment to deliver" the daily amount of recharging electricity, whereas the car owners face some kind of "take or pay" situation. We do not further specify the contractual relationship between PIEV service providers and individual car owners, but assume that the operators responsible for vehicle recharging try to acquire the necessary electricity at the lowest possible cost. This procedure allows to obtain fairly general results. Note that we do not analyze the relationship or the exertion of market power between vehicle service providers and individual vehicle owners. Rather, we are interested in the role that PIEV operators might play in an imperfectly competitive electricity market, and in their strategic interaction with other actors in that market.

We use game-theoretic modeling approach, the solution of which represents a Cournot-Nash equilibrium. We build upon the ElStorM model described in 2 and extend it by introducing additional variables, parameters, and constraints related to electric vehicles. Table 3.3 in the Appendix lists all model sets, indices, parameters, and variables. The set of players includes firms that generate electricity only (i.e. traditional utilities), players that are only involved in PIEV operations, and players that combine both activities. Individual vehicle owners may also be players, if they are able to respond to hourly wholesale market prices while recharging their vehicles.[41]

Equations (3.1a-3.1k) describe individual players' constrained maximization problems. Note the similarities to the model outlined in section 2.3. Again, players' indices $f \in F$ are omitted in (3.1a-3.1k) in order to improve readability. The players maximize profits by deciding on a set of hourly ($t \in T$) decision variables, including electricity generation $x_{f,i,t}$ of various technologies $i \in I$, loading $stin_{f,j,t}$ and discharging $stout_{f,j,t}$ of different storage technologies $j \in J$, and – a new feature – the timing of vehicle loading $vload_{f,t}$. The profit function (3.1a) includes revenues from selling electricity that is either generated by a specific technology ($p_t x_{i,t}$) or previously stored ($p_t stout_{j,t}$). It also includes technology-specific variable generation costs ($vgc_i$), variable costs of storage operation ($vstc_j$), costs of storage loading ($p_t stin_{j,t}$), and costs of vehicle recharging ($p_t vload_t$). The latter terms reflect the fact that electricity stored at period $t$ had to be bought or could have been sold on the market at the price of the respective period. The decision variables are subject to a range of constraints, which are shown in (3.1b-3.1k). Due to the complexity of the model, we abstract again from including network constraints

[41] In addition, players may draw on other electricity storage technologies than vehicle batteries. In the model application, we include pumped hydro storage, as this technology is the only large-scale storage technology that is economically feasible.

or different voltage levels.

$$\max_{\substack{x_{i,t}\\ vload_t\\ stin_{j,t}\\ stout_{j,t}}} \sum_{t\in T}\left[p_t\left(\sum_{i\in I} x_{i,t} - vload_t + \sum_{j\in J}(stout_{j,t} - stin_{j,t})\right) - \sum_{i\in I} vgc_i x_{i,t} - \sum_{j\in J} vstc_j stout_{j,t}\right] \tag{3.1a}$$

$$s.t. \quad x_{i,t} - \overline{x}_i \leq 0,\ \forall i,t\ (\lambda^{gen}_{i,t}) \tag{3.1b}$$

$$x_{i,t} - x_{i,t-1} - \xi^{up}_i \overline{x}_i \leq 0,\ \forall i,t\ (\lambda^{rup}_{i,t}) \tag{3.1c}$$

$$x_{i,t-1} - x_{i,t} - \xi^{down}_i \overline{x}_i \leq 0,\ \forall i,t\ (\lambda^{rdo}_{i,t}) \tag{3.1d}$$

$$\sum_{t\in d} vload_t - vldaily_d = 0,\ \forall d\ (\lambda^{vldaily}_d) \tag{3.1e}$$

$$stin_{PIEV,t} + vload_t - \overline{st}^{in}_{PIEV} \leq 0,\ \forall t\ (\lambda^{stin}_{PIEV,t}) \tag{3.1f}$$

$$stin_{j,t} - \overline{st}^{in}_j \leq 0,\ \forall j \neq PIEV, t\ (\lambda^{stin}_{j,t}) \tag{3.1g}$$

$$stout_{j,t} - \overline{st}^{out}_j \leq 0,\ \forall j,t\ (\lambda^{stout}_{j,t}) \tag{3.1h}$$

$$\sum_{\tau=1}^{t} stout_{j,\tau} - \sum_{\tau=1}^{t-1} stin_{j,\tau}\eta_{st,j} \leq 0,\ \forall j,t\ (\lambda^{stlo}_{j,t}) \tag{3.1i}$$

$$\sum_{\tau=1}^{t} stin_{j,\tau}\eta_{st,j} - \sum_{\tau=1}^{t-1} stout_{j,\tau} - \overline{st}^{cap}_j \leq 0,\ \forall j,t\ (\lambda^{stup}_{j,t}) \tag{3.1j}$$

$$x_{i,t}, vload_t, stin_{j,t}, stout_{j,t} \geq 0,\ \forall i,j,t \tag{3.1k}$$

As a large part of the model formulation is similar to section 2.3, we focus on the new parts in the following. As in chapter 2, condition (3.1b) constitutes a generation capacity constraint, whereas (3.1c) and (3.1d) represent ramping up and down restrictions. Condition (3.1e) is a new contribution. It specifies the daily vehicle recharging requirement. We assume that the electric vehicle fleet requires a certain amount of energy for driving purposes that has to be recharged at some point in time for each 24-hour period. $vldaily_{f,d}$ is the daily vehicle recharging requirement (in MWh) for each player. Accordingly, $vldaily_{f,d} = 0$ for players without PIEV operations. Condition (3.1e) does not further restrict the timing of vehicle loading: It can take place during any given hour of the day, or it could be split up over all 24 hours.

Condition (3.1f) ensures that the PIEV battery loading rate does not exceeds the fleet's cumulative connection power $\overline{st}^{in}_{PIEV}$ (in MW). Note that battery loading consists of vehicle recharging for driving purposes and the loading of unused battery capacity for arbitrage. (3.1g) is a similar loading condition for other storage technologies. Likewise, (3.1h) ensures that selling electricity back to the market from storage never exceeds the available storage discharging capacity $\overline{st}^{out}_j$, i.e the fleet connection power in case of PIEV.

The remaining constraints are similar to section 2.3. Condition (3.1i) ensures that

storage output never exceeds the net of previous storage inputs and outputs. (3.1j) represents the upper storage capacity constraint. We consider $\overline{st}^{cap}_{PIEV}$ as a fraction of the overall vehicle battery capacity that is – on average – not utilized for driving purposes and that is thus available for arbitrage. As neither batteries nor pumped hydro storage have perfect roundtrip efficiencies, both (3.1i) and (3.1j) include efficiency losses: only a share $\eta_{st,j}$ of previously stored electricity can be sold back to the market. Finally, (3.1k) ensures non-negativity of the decision variables.

A market clearing condition links the players' constrained maximization problems. Equation (3.2) defines total hourly supply to the wholesale electricity market, consisting of total electricity generation minus vehicle recharging plus storage output minus storage input. (3.3) demands that supply equals demand in all periods, drawing on the same iso-elastic function as in section 2.3. Accordingly, we assume that electricity demand on the wholesale market is elastic, whereas the daily vehicle recharging requirement is fixed.

$$X_t = \sum_{f \in F} \left[ \sum_{i \in I} x_{f,i,t} - vload_{f,t} + \sum_{j \in J} (stout_{f,j,t} - stin_{f,j,t}) \right], \ \forall t \tag{3.2}$$

$$X_t = d0_t \left( \frac{p_t}{p0_t} \right)^{-\sigma}, \ \forall t \tag{3.3}$$

We combine the market clearing condition (3.3) with (3.2), solve for $p_t$ and insert the expression into (3.1a). We then derive the Karush-Kuhn-Tucker optimality conditions (3.6a-3.6n) that are listed in the Appendix. The KKT conditions form a nonlinear mixed complementarity equation system. We implement it as an MCP in GAMS, drawing on the data described in section 3.4. The problem consists of more than 140,000 equations and variables, i.e. is even larger than the one solved in chapter 2.

After solving the model, we calculate consumer rent of period $t$ according to equation (3.4) and producer rent for each player according to equation (3.5). Note that we determine welfare outcomes only for the electricity market, but not for the market for vehicle recharging, as we do not specify the contractual relationship between the service providers responsible for vehicle recharging and individual car owners. Vehicle recharging could also be carried out by individual car owners without the help of a service provider. Accordingly, we do not model costs, revenues or consumer surplus related to the recharging business. Instead, we focus on PIEV-related welfare effects on the electricity market, which are caused by increasing electricity demand and additional storage capacity. The arbitrage profits made by PIEV operators from using excess battery capacity are explicitly included in (3.5), as arbitrage activities take place on the wholesale electricity market. Focusing welfare considerations on the electricity market allows to compare welfare outcomes between different cases with electric vehicles and the Baseline without such vehicles in a meaningful way.

$$crent_t = \int_0^{X_t} p0_t \left(\frac{x}{d0_t}\right)^{-\frac{1}{\sigma}} dx - p_t X_t, \ \forall t \tag{3.4}$$

$$\begin{aligned} prent_{f,t} = & \sum_{i \in I} x_{f,i,t}(p_t - vgc_i) \\ & + \sum_{j \in J} (stout_{f,j,t}(p_t - vstc_j) - stin_{f,j,t} \cdot p_t), \ \forall t \end{aligned} \tag{3.5}$$

## 3.4 Model application

We apply the model to the German wholesale electricity market and run it for two consecutive weeks (336 single hours) in order to reflect different load situations. We use the same hourly EEX reference demand and price data ($d0$ and $p0$) as in chapter 2. Yet we include an additional day in order to cover two complete weeks between 16 and 29 January 2009. The winter period appears particularly suitable, as the effect of additional electricity demand should be greatest in winter, when demand is high. We start the model on a Friday in order to generate meaningful storage patterns over two weekends. As in chapter 2, we assume a price elasticity of $\sigma = -0.45$ for the wholesale power demand. This value allows a good replication of the reference data. For reasons of simplicity and traceability, $\sigma$ is again assumed to be time-invariant.

**Table 3.1:** Generation and pumped hydro storage capacity

| | **EnBW** | **E.ON** | **RWE** | **Vattenfall** | **Fringe** | **RES** | **NoGen** |
|---|---|---|---|---|---|---|---|
| Available generation capacity in MW: | | | | | | | |
| Nuclear | 3,974 | 7,553 | 3,496 | 1,402 | 946 | 0 | 0 |
| Lignite | 398 | 1,302 | 8,494 | 7,201 | 403 | 0 | 0 |
| Hard coal | 1,570 | 5,833 | 2,615 | 979 | 3,604 | 0 | 0 |
| Natural gas | 686 | 2,543 | 1,959 | 1,382 | 4,302 | 0 | 0 |
| Oil | 103 | 348 | 5 | 152 | 127 | 0 | 0 |
| Hydro | 299 | 1,055 | 447 | 0 | 625 | 0 | 0 |
| Wind | 0 | 0 | 0 | 0 | 0 | 25,777 | 0 |
| Available pumped hydro storage capacity: | | | | | | | |
| Loading/discharging rate in MW | 503 | 509 | 512 | 1,447 | 228 | 0 | 0 |
| Capacity in MWh | 1,440 | 1,358 | 1,392 | 3,428 | 440 | 0 | 0 |

We include seven players, among them the four oligopolistic generating firms EnBW, E.ON, RWE, and Vattenfall and a competitive Fringe generator.[42] In contrast to chapter 2, another price-taking player named "RES" is included that holds the total installed wind capacity ($\theta^{gen}_{RES,wind,t} = 0$). In addition, we include a player "NoGen" without any generation capacity that may only engage in vehicle operations. This idea follows Andersen et al. (2009), who argue that new PIEV players will emerge on the market. The NoGen player may either act as a price-taker or in a strategic way, depending on

[42] That is, $\theta^{gen}_f = 1$ for f=EnBW, E.ON, RWE, Vattenfall and $\theta^{gen}_{Fringe,i,t} = 0$ in the KKT conditions (Appendix).

the scenario as defined in section 3.4. We include the same generation technologies as in chapter 2, i.e. nuclear, lignite, hard coal, natural gas, oil, and hydro power. Table 3.1 lists generation capacity available to each players. While the data is largely the same as in section 2.4, the table also includes wind capacity (BMU, 2010b). Note that this capacity is of minor importance, as wind generation is exogenously set according to hourly feed-in levels between 16 and 29 January 2009. In doing so, the German feed-in regulation is reflected, which grants priority feed-in to renewable power sources (compare section 1.3.3). Hourly wind generation data comes from publicly availabe sources provided by German transmission system operators. Table 3.1 also includes available pumped hydro storage capacity. In contrast to chapter 2, we assume that only 50% of the cumulatively installed loading/discharging rate and only 20% of the total pumped hydro storage capacity are available for arbitrage in any given hour. These values are based on an interviews with industry experts and reflect the fact that a substantial share of the German PHS capacity is reserved for frequency control, reactive power supply, and seasonal storage. As for strategic storage utilization, we assume $\theta_f^{st} = 1$ for f=EnBW, E.ON, RWE, Vattenfall, and $\theta_{Fringe}^{st} = 0$. Regarding ramping parameters and variable costs, we rely on the data listed in Table 2.2.

We assume a hypothetic electric vehicle fleet, drawing on the official target of the German government of having one million electric vehicles on the road by 2020 (Bundesregierung, 2009). We derive the characteristics of future PIEV fleets from scenarios developed by Wietschel and Dallinger (2008). Accordingly, one million PIEV have a cumulative connection power of around 5 GW ($\sum_f \overline{st}_{f,PIEV}^{in}$ and $\sum_f \overline{st}_{f,PIEV}^{out}$). The average daily recharging requirement amounts to 4 GWh ($\sum_f vldaily_{f,d}$). From Wietschel and Dallinger (2008), we derive an overall battery capacity of the fleet of 13 GWh, such that around 9 GWh should be available on average for arbitrage ($\sum_f \overline{st}_{f,PIEV}^{cap}$).[43] These numbers certainly represent only rough estimates of future PIEV fleet characteristics. We are, however, more interested in general effects than in absolute numbers in our numerical application.

We estimate that around 80% of all electric vehicles are not on the road, but parked at any given hour (Kempton and Tomic, 2005a, even assume 90%). We furthermore assume that all parked cars are connected to the electricity grid. Accordingly, 80% of the PIEV capacity is available any point in time. Drawing on Sioshansi et al. (2010), we assume a round-trip efficiency of $\eta_{st,PIEV} = 0.9$ for vehicle batteries. That is, for each MWh that is stored in PIEV batteries, only 0.9 MWh can be retrieved again later. As for pumped hydro storage, we assume an average round-trip efficiency of only $\eta_{st,PHS} = 0.75$ (Tiedemann et al., 2008). We initially set variable storage costs $vstc_j = 0$ for both vehicle

[43] Tomic and Kempton (2007), Lund and Kempton (2008), and Ekman (2011) argue that PIEV could provide much-needed flexibility for integrating fluctuating renewable generators into the electricity system. The numbers used in our analysis, however, indicate that the potential of electric vehicles for integrating renewables should not be overestimated: the aggregated battery capacity of one million vehicles that is not required for average daily driving is only 9 GWh. For comparison: the installed German wind capacity of 2009 was around 25 GWh, i.e. vehicle batteries would be fully loaded within less than half an hour during periods with high wind feed-in.

batteries and pumped hydro storage. We relax this assumption in section 3.5.4 to assess the sensitivity of results to non-negligible battery degradation costs.

**Table 3.2:** Overview of scenarios

| | **PIEV resources** | **Player in charge of PIEV fleet** | **Market power assumption** |
|---|---|---|---|
| **BL** | - | - | - |
| **UL** | Loading only | NoGen | Loading exogeous (non-optimal) |
| **LO1** | Loading only | NoGen | Price taker $\theta^{vload}_{NoGen} = 0$ |
| **LO2** | | NoGen | Strategic $\theta^{vload}_{NoGen} = 1$ |
| **LO3** | | RWE | Strategic $\theta^{vload}_{RWE} = 1$ |
| **LS1** | Loading and storage | NoGen | Price taker $\theta^{vload}_{NoGen} = 0$ $\theta^{st}_{NoGen} = 0$ |
| **LS2** | | NoGen | Strategic $\theta^{vload}_{NoGen} = 1$ $\theta^{st}_{NoGen} = 1$ |
| **LS3** | | RWE | Strategic $\theta^{vload}_{RWE} = 1$ $\theta^{st}_{RWE} = 1$ |

We define eight different cases as indicated by Table 3.2. The "Baseline" (BL), which does not include any electric vehicles, serves as a point of reference. In the "Uncontrolled Loading" (UL) scenario, we exogenously assign the daily vehicle recharging requirement of the PIEV fleet to the evening hours between 4pm and 8pm (1 GWh per hour). In doing so, UL constitutes an approximation of the behavior of vehicle owners that plug in their cars for recharging when they get home from work (compare Galus et al., 2010; Göransson et al., 2010). Furthermore, we define different cases with controlled vehicle loading. These differ with respect to the availability of unused battery capacity for grid storage. In the "Loading Only" (LO) cases, the PIEV fleet only represents additional, dispatchable load. In the "Loading and Storage" (LS) cases, it also brings additional storage capacity to the market that can be used for arbitrage. Note that there may be barriers to implementing this option due to technical and institutional constraints. In contrast to PIEV storage, pumped hydro storage is available in all scenarios.

Cases also differ with respect to the player being in charge of PIEV operations, i.e. the NoGen player or an oligopolistic generating firm. The scenarios in which the NoGen player carries out PIEV operations in a non-strategic way (LO1, LS1) represent, on the one hand, a situation in which PIEV operations are carried out by a variety of players that behave as price takers on the electricity market – just like the Fringe player among the generating firms. On the other hand, LO1 and LS1 also represent cases in which individual car owners recharge their vehicles in a decentralized – yet cost-minimizing –

way.[44] In LO2 and LS2, the NoGen player carries out PIEV operations as a centralized, strategic player that anticipates the market's reactions to its decisions. We could think of this player as a monopolistic service provider that has contracted the whole PIEV fleet. In LO3 and LS3, an oligopolistic generating firm has a monopoly on PIEV operations. We chose RWE as an illustrative example due to the company's recent activities in the electric vehicle business.

## 3.5 Results

### 3.5.1 Price effects

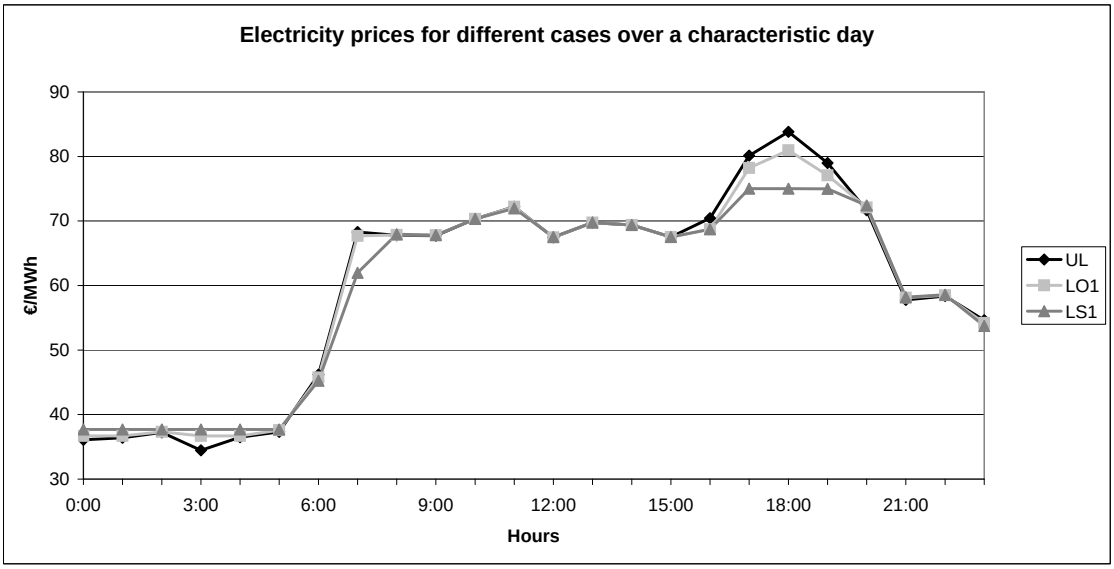


**Figure 3.1:** Electricity prices for different cases over a characteristic day

Figure 3.1 shows the effect of electric vehicles on electricity prices for a characteristic day (Tuesday) and a selection of cases. We find the highest evening peak prices in the uncontrolled loading case (UL) because of additional electricity demand during these hours. In the case of controlled loading (LO1), vehicles are being recharged in periods with the lowest prices. Compared to the Baseline, market prices in LO1 thus increase slightly in off-peak periods.[45] In the LS1 case, in which excess battery capacity can be used for grid storage, batteries are loaded during off-peak periods and discharged during peak hours as this strategy maximizes arbitrage profits. As a result, prices are smoother in LS1 than in LO1.

[44]The LO1 and LS1 cases are conceptually related to scenarios in which the price-taking Fringe generator controls vehicle operations. We obtain the same results for NoGen and for Fringe being in charge of PIEV operations, with the exception of different producer rents.

[45]Additional model runs indicate that PIEV fleets much larger than one million vehicles could be recharged with the existing German power plant fleet without increasing peak prices, if loading is carried out in a controlled – i.e. cost-minimizing – way.

### 3.5.2 Welfare effects

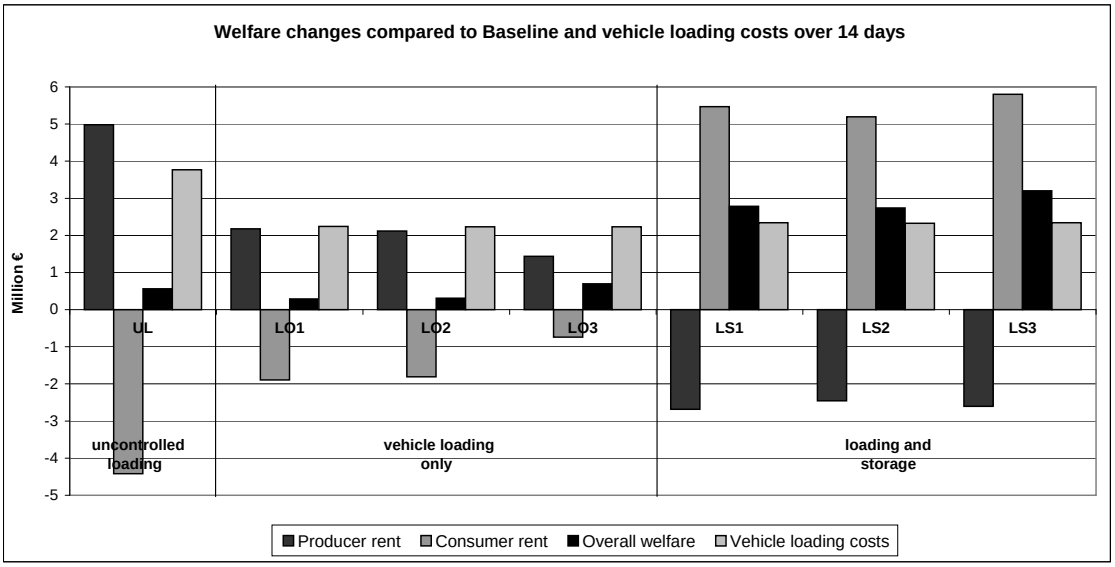


**Figure 3.2:** Welfare changes compared to Baseline and vehicle loading costs over 14 days

Figure 3.2 indicates welfare changes compared to the Baseline in different cases. In the uncontrolled loading case (UL), the introduction of PIEV leads to an increase in producer profits because of higher peak prices. In contrast, consumer rent decreases. We find the same effect for the cases with controlled vehicle loading (LO1-3), although to a much lower extent. Accordingly, the introduction of PIEV harms electricity consumers less if vehicles are loaded in a controlled way. Interestingly, if a strategic generator is in charge of PIEV operations (LO3), consumer rent and overall welfare are slightly higher than in the cases LO1 and LO2. This is because being in control of additional dispatchable load has a market power mitigating effect on the oligopolistic generator. In LO3, RWE strategically decreases market prices in periods of vehicle loading by increasing generation with low-cost technologies.[46]

If excess battery capacity of the PIEV fleet can be used for grid storage, we find very different welfare effects. In LS1-3, producers overall suffer from the introduction of PIEV due to the price-smoothing effect of additional storage capacity in the imperfectly competitive market. In contrast, consumer surplus and overall welfare increase substantially. Consumers now benefit from the PIEV fleet despite the fact that overall demand increases, as the price-driving effect of additional demand is outweighed by the price-smoothing effect of additional storage. In particular, consumers benefit from a storage-related decrease in peak prices, which has a larger effect on consumer rent than price increases in off-peak hours, as demand is higher in peak hours. In addition, storage loading mitigates market power exertion of strategic generators, leading to slightly higher consumer surplus and overall welfare in LS3 compared to LS1 and LS2.[47]

[46] This effect is also visible in the player's first-order condition: note the negative sign for $\vartheta_{f,t}^{vload}$ in equation (3.6a).

[47] Again, this effect is indicated by the negative sign of $\vartheta_{f,t}^{in}$ in equation (3.6a).

During the two weeks modeled here, overall welfare increases between €2.7-3.2 million in LS1-3 compared to UL, whereas consumers are €5.2-5.8 million better off. A rough extrapolation of these values to a whole year leads to overall yearly welfare gains in the range of €70-83 per vehicle, and yearly consumer benefits of around €135-151 per vehicle. These welfare gains may justify public support for integrating electric vehicles into the electricity system. However, PIEV-related welfare effects are small compared to welfare losses related to strategic electricity generation. Comparing the Baseline to a scenario with perfectly competitive generation ($\theta_f^{gen} = 0$ for all players), the assumed oligopolistic market structure leads to welfare losses of around €62 million over the two modeled weeks.

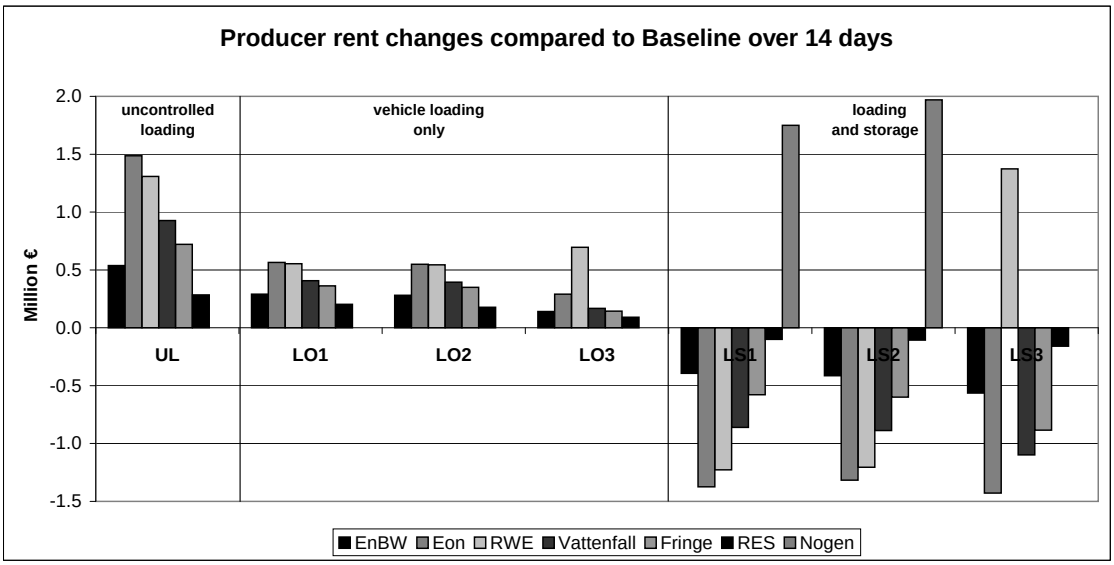


**Figure 3.3:** Producer rent changes compared to Baseline over 14 days

Figure 3.3 shows producer rent changes of single firms compared to the Baseline. All players are better off in the uncontrolled loading case (UL) compared to controlled loading (LO1-3). In LO3, RWE manages to increase its profit compared to LO1-2 by strategically adjusting generation in off-peak periods, whereas all other generating firms suffer. If excess PIEV battery capacity can be used for storage (LS1-3), the respective operator makes a sizeable arbitrage profit, while all other producers suffer from the price-smoothing effect of storage. However, the social welfare gain of PIEV operations in LS1-3 is around two times higher than the respective profit increase of the PIEV operator. Accordingly, players are not able to fully internalize PIEV-related welfare gains.

Cases also differ with respect to the costs of providing the electricity required for daily vehicle recharging. Figure 3.2 shows that vehicle loading costs are much lower in all cases of controlled loading compared to the uncontrolled UL case. This is because PIEV operators in LO1-3 and LS1-3 charge their vehicles with cheap off-peak electricity. Average loading costs in these cases are around €0.04/kWh. With an assumed average electricity consumption of around 20 kWh/100km (compare Sioshansi et al., 2010), energy costs of electric vehicles would be around only €1/100km. Altough this value does neither

include taxes, distribution, and infrastructure costs, nor retailer profits, it indicates that the electricity required for electric vehicles could be supplied at very low costs.

### 3.5.3 Effects on electricity generation

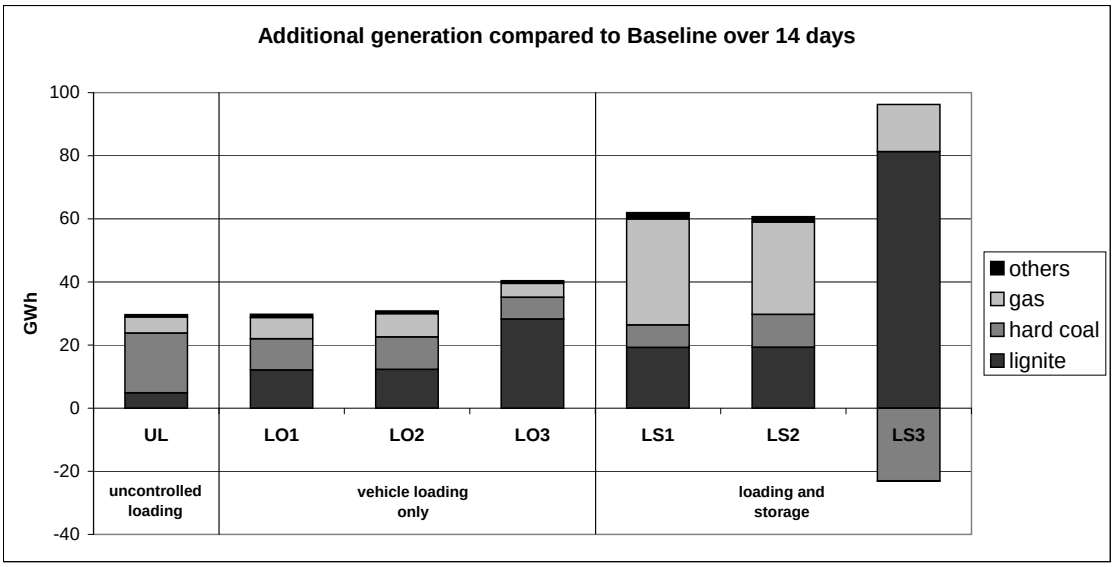


**Figure 3.4:** Additional generation compared to Baseline over 14 days

Figure 3.4 shows that the introduction of electric vehicles increases electricity generation in all cases compared to the Baseline because of additional demand. Generation is generally higher in the cases in which batteries are used for arbitrage (LS1-3), as the decreasing effect of storage on peak prices leads to additional demand in these periods. We find the highest increases in generation for the cases in which an oligopolistic generator controls the PIEV fleet (LO3 and LS3). In these cases, RWE increases generation during periods of vehicle and storage loading in order to strategically decrease market prices.

Figure 3.4 also indicates variations in the mix of additional generation among different cases. In the uncontrolled loading case (UL), most additional generation is provided by hard coal, because it is the least-cost technology that is largely available in the evening hours between 4pm and 8pm. In the cases with controlled loading, vehicle recharging is carried out during nighttime. In these periods, some lignite capacity is available, such that the amount of lignite increases in all cases with controlled loading compared to UL. We find the largest increase in lignite generation in the scenarios in which the strategic player RWE is in charge of vehicle operations. In particular, RWE substantially increases its lignite generation in LS3 in order to strategically decrease market prices during the periods of vehicle recharging and battery loading.

Controlled PIEV loading also smoothes generation patterns of conventional technologies. This effect is expressed by a lower number of binding ramping constraints. In the LO cases, the additional dispatchable load of PIEV decreases the number of binding ramping constraints by around 5% compared to the Baseline over 14 days. In the LS

cases, the number decreases up to 15% because of the smoothing effect of additional storage capacity in the market.[48]

In contrast to Göransson et al. (2010), we do not find that electric vehicles increase the feed-in of wind power. In all model runs, hourly wind generation is equal to the historic feed-in pattern of the modeled two weeks. In the framework used here, a PIEV fleet could only increase wind power feed-in if there was some wind curtailment in the Baseline. For example, wind curtailment is required if overall demand is lower than wind generation, or if there are severe short-term ramping constraints (compare Fink et al., 2009). However, there is no such curtailment in the Baseline during the modeled 336 hours. Accordingly, PIEV do not increase overall wind generation. We acknowledge that our assumptions of perfect foresight over the whole modeled period and unconstrained transmission lead to a systematic under-estimation of wind curtailment requirements. Nonetheless, we consider our findings to be largely representative for the situation in Germany in 2009, as there were only few periods of excess wind supply, that furthermore were largely restricted to specific regions. Consequently, it is unlikely that electric vehicles would have substantially increased wind feed-in in Germany. However, this situation might change in the future. If installed wind generation capacity increases further, cases of excess wind supply will become more frequent.

Summing up, controlled loading of electric vehicles increases the utilization of least-cost generation technologies, that tend to be emission-intensive in Germany (lignite, hard coal). While this effect is already described in the literature, for example by Sioshansi et al. (2010), we find evidence that it may be even stronger in imperfect electricity markets. If an oligopolistic generating firm is controlling PIEV operations, generation with emission-intensive low-cost technologies may increase even stronger compared to cases in which other players are in charge of the PIEV fleet. Accordingly, the emission performance of electric vehicles in imperfect electricity markets may also be worse than proviously thought.

### 3.5.4 Storage utilization and sensitivity to battery degradation costs

So far, we assume zero variable costs of battery storage ($vstc_{PIEV} = 0$). Yet utilizing vehicle batteries for arbitrage may lead to battery degradation costs. As battery degradation heavily depends on battery technology, the depth of discharge, and the kind of loading and discharging cycles, it is difficult to provide a solid number for variable storage costs of future PIEV fleets. For older battery types, Tomic and Kempton (2007) assume values between 80-90 US-$/MWh. For lithium-ion batteries, Andersson et al. (2010) assume depreciation costs of 30-100 €/MWh. These costs may decrease substantially with improved battery technology. We thus perform sensitivity analyses for different battery

[48]Note that ramping-related costs are only indirectly included in our analysis by means of shadow prices $\lambda^{rup}_{f,i,t}$ and $\lambda^{rdo}_{f,i,t}$. An explicit consideration of ramping-related costs, for example due to part load inefficiencies or ramping-related depreciation, would require modeling individual power plants with a mixed integer problem formulation (compare section 1.4). Including such costs is likely to increase the positive effects of PIEV fleets on overall welfare.

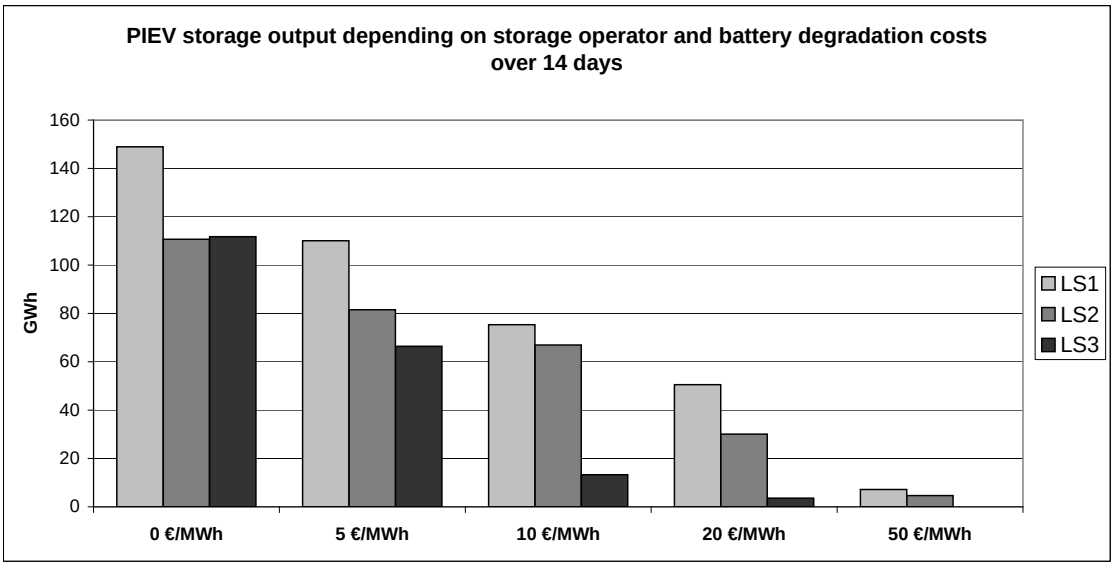


**Figure 3.5:** PIEV storage output depending on storage operator and battery degradation costs over 14 days

degradation costs $vstc_{PIEV}$. Figure 3.5 shows battery storage utilization for values of 0, 5, 10, 20, and 50 €/MWh. It can be seen that the use of PIEV batteries for arbitrage decreases substantially with increasing degradation costs. For 10 €/MWh, only around half the storage capacity is used compared to the case with zero variable storage costs (LS1 and LS2). For 50 €/MWh, hardly any battery storage is used for arbitrage in all cases.

In addition, battery storage utilization depends on the player in charge of PIEV operations. A strategic player (LS2) without generation assets always utilizes less storage capacity than a price-taking one (LS1). This is because of the price-smoothing effect of storage: a strategic player withholds some storage capacity in order not to smooth prices too much, which in turn increases arbitrage profits (compare section 2). This effect is more pronounced if PIEV operations are concentrated with a strategic generating firm. Such a firm is even less interested in smoother prices, as they would decrease peak-load profits of all other generation assets. Accordingly, PIEV storage utilization is lowest in the LS3 cases. In our model, RWE hardly uses any storage if battery degradation costs are larger than 10 €/MWh.

As shown in Figure 3.6, variable storage costs also have welfare implications, as lower storage utilization leads to less smooth prices. Accordingly, the beneficial impact of electric vehicles on consumer rents and overall welfare decreases with higher battery degradation costs. For $vstc_{PIEV} = 50$, welfare results are close to the LO cases, in which arbitrage with vehicle batteries is assumed to be impossible. For $vstc_{PIEV} = 0$ and $vstc_{PIEV} = 5$, the LS3 case – in which the oligopolistic generating firm RWE controls the PIEV fleet – leads to desirable consumer rent outcomes. This is because of the previously described market power mitigating effect of storage loading on the strategic generator. Interestingly, consumers are much worse off in LS3 compared to LS1 and LS2

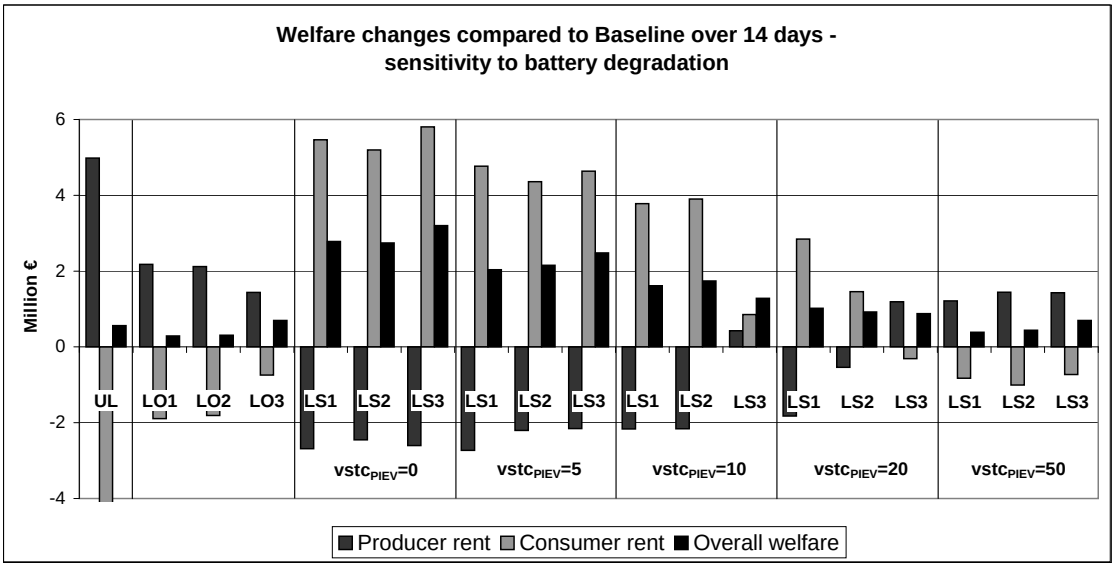


**Figure 3.6:** Welfare changes compared to Baseline over 14 days – sensitivity to battery degradation

for $vstc_{PIEV} = 10$ and $vstc_{PIEV} = 20$. In these cases, RWE hardly uses any battery storage, as arbitrage profits are too small compared to the decreasing effect of storage on peak prices and the related decrease in profits of RWE's other generation assets. As a result, consumers hardly benefit from the additional battery storage capacity in the market. In contrast, the NoGen player still finds it profitable to carry out some arbitrage in the cases of $vstc_{PIEV} = 10$ and $vstc_{PIEV} = 20$, as this player does not own any generation capacity. Accordingly, prices are smoother in LS1 and LS2 compared to LS3, and consumers are better off.

Drawing on these results, we conclude that storage utilization and welfare outcomes of the LS cases strongly depend on battery degradation costs. Higher variable storage costs generally decrease arbitrage opportunities. Current battery degradation costs may thus impose serious obstacles to utilizing PIEV fleets for arbitrage in Germany. This corresponds to the findings of Peterson et al. (2010) for different U.S. markets. Moreover, there are additional fixed costs for setting up bi-directional loading and discharging infrastructure, which we neglect in this analysis. As a consequence, the price-smoothing effect of PIEV grid storage and the related consumer benefits outlined in section 3.5.2 may not materialize. Other markets with higher revenue streams like the provision of control reserve may be more promising for PIEV operators than arbitrage (compare Andersson et al., 2010).

The analysis also shows that the player in charge of PIEV operations has a large impact on consumer surplus in some cases. Yielding control over PIEV batteries to a single strategic generating firm may lead to undesirable results from a consumer perspective, despite the market power mitigating effects of vehicle recharging and storage loading described earlier.

## 3.6 Summary and conclusions

In this chapter, we study the interaction of electric vehicles and imperfectly competitive electricity markets. We use an extension of the game-theoretic Cournot model presented in chapter 2, which we apply numerically to the German case. We find that uncontrolled vehicle recharging, for example by individual vehicle owners, increases already existing evening peak loads and prices. In contrast, players able to respond to hourly wholesale market prices will carry out vehicle recharging in off-peak periods. If unused PIEV battery capacity can be used for arbitrage, this will smooth electricity prices, as batteries will be loaded in off-peak periods and discharged in peak periods.

These price effects have direct welfare implications. In general, the introduction of PIEV increases generator profits and decreases consumer surplus because of additional electricity demand. Welfare distortions, however, are much lower in the case of optimal loading compared to uncontrolled loading. We thus conclude that individuals or service providers that are responsible for recharging electric vehicles should be enabled to respond to hourly market prices. If vehicle batteries can be used for arbitrage, welfare effects are reversed: generator profits decrease, while consumer surplus and overall welfare increase substantially. The analysis indicates that the additional storage capacity of a PIEV fleet has potentially larger welfare implications in an imperfect electricity market than the additional demand. Storage-related welfare gains, although moderate, may provide a rationale for public support of electric vehicles and their grid integration that complements other motivations like lower emissions or a decreased dependency on oil imports. However, a sensitivity analysis indicates that using excess vehicle battery capacity for arbitrage is only viable if variable storage costs are negligible. Current real-world battery degradation costs may seriously diminish arbitrage opportunities and related welfare gains. Providing, for example, control reserve is likely to be a more profitable stragegy for PIEV operators than arbitrage.

If vehicles operations are controlled by a strategic generating firm, we determine two effects with different welfare implications. On the one hand, there is a market power mitigating effect of vehicle loading that benefits consumers. On the other, strategic generators tend to under-utilize PIEV storage capacity, which has negative consumer rent implications. All things considered, it is not possible to make a clear recommendation on which player should be in charge of PIEV operations. However, our analysis shows that the player controlling the vehicle fleet is of minor importance in most cases, as long as electric vehicle recharging is carried out in a controlled way. Furthermore, the potential welfare distortions related to different players in charge of the PIEV fleet are small compared to the welfare effects of market power exertion with conventional generation technologies. Electric vehicle fleets are thus unlikely to be a relevant source of market power in Germany, no matter who controls the fleets. Accordingly, economic regulation of PIEV operations is currently not required with respect to the electricity market. However, there may be potentials for market power exertion on markets for PIEV services. For

example, firms could exploit natural monopolies related to charging infrastructure or billing standards. Future research should examine these market power potentials.

Finally, we find that controlled loading of electric vehicles increases the utilization of low-cost generation technologies that tend to be emission-intensive. $CO_2$ emissions of future electric vehicles should thus be calculated drawing on emission-intensive generation technologies rather than on the average power plant mix. Additional storage capacity further increases low-cost generation. These effects are particularly pronounced if an oligopolistic generator is in charge of PIEV operations. In the light of ambitious climate policy targets, we thus conclude that a shift toward electric mobility has to be accompanied by a complementary expansion of renewable electricity generation.

# 3.A Appendix

## 3.A.1 Sets, indices, parameters, and variables

**Table 3.3:** Sets, indices, parameters, and variables

| Item | Description | Unit |
|---|---|---|
| **Sets and indices** | | |
| $F$ | Players with $f \in F$ | |
| $I$ | Generation technologies with $i \in I$ | |
| $J$ | Storage technologies with $j \in J$ | |
| $T$ | Time with $t \in T$, $\tau \in T$ | hours |
| $D$ | Time with $d \in D$ | days |
| **Parameters** | | |
| $\sigma$ | Price elasticity of electricity demand | |
| $d0_t$ | Hourly reference demand | MWh |
| $p0_t$ | Hourly reference prices | €/MWh |
| $vldaily_{f,d}$ | Daily vehicle loading requirement | MWh |
| $\overline{x}_{f,i}$ | Available generation capacity | MW |
| $\overline{st}^{out}_{f,j}$ | Available storage discharging capacity | MW |
| $\overline{st}^{in}_{f,j}$ | Available storage loading capacity | MW |
| $\overline{st}^{cap}_{f,j}$ | Available storage capacity | MWh |
| $\xi^{up}_i$ | Ramping up parameter | |
| $\xi^{down}_i$ | Ramping down parameter | |
| $vgc_i$ | Variable generation costs | €/MWh |
| $vstc_j$ | Variable storage costs | €/MWh |
| $\eta_{st,j}$ | Storage efficiency | |
| $\theta^{gen}_f$ | Market power parameter for generation | 0 or 1 |
| $\theta^{vload}_f$ | Market power parameter for vehicle loading | 0 or 1 |
| $\theta^{st}_f$ | Market power parameter for storage | 0 or 1 |
| **Variables** | | |
| $\Pi_f$ | Profit of player $f$ | € |
| $p_t$ | Price of period $t$ | €/MWh |
| $x_{f,i,t}$ | Generation of player $f$ by technology $i$ in period $t$ | MWh |
| $X_t$ | Total supply in period $t$ | MWh |
| $vload_{f,t}$ | Vehicle loading of player $f$ in period $t$ | MWh |
| $stout_{f,j,t}$ | Generation of player $f$ in period $t$ from storage | MWh |
| $stin_{f,j,t}$ | Storage loading of player $f$ in period $t$ | MWh |
| $\lambda^{gen}_{f,i,t}$ | Shadow price of generation capacity constraint | €/MWh |
| $\lambda^{rup}_{f,i,t}$ | Shadow price of ramping up constraint | €/MWh |
| $\lambda^{rdo}_{f,i,t}$ | Shadow price of ramping down constraint | €/MWh |
| $\lambda^{vldaily}_{f,d}$ | Shadow price of daily vehicle loading requirement | €/MWh |
| $\lambda^{stout}_{f,j,t}$ | Shadow price of storage discharging capacity constraint | €/MWh |
| $\lambda^{stin}_{f,j,t}$ | Shadow price of storage loading capacity constraint | €/MWh |
| $\lambda^{stup}_{f,j,t}$ | Shadow price of upper storage capacity constraint | €/MWh |
| $\lambda^{stlo}_{f,j,t}$ | Shadow price of lower storage capacity constraint | €/MWh |
| $\vartheta^{gen}_{f,i,t}$ | Market share of player $f$ – generation | |
| $\vartheta^{vload}_{f,t}$ | Market share of player $f$ – vehicle loading | |
| $\vartheta^{out}_{f,j,t}$ | Market share of player $f$ – storage discharging | |
| $\vartheta^{in}_{f,j,t}$ | Market share of player $f$ – storage loading | |
| $crent_t$ | Consumer rent of period $t$ | € |
| $prent_{f,t}$ | Producer rent of player $f$ in period $t$ | € |

### 3.A.2 The mixed complementarity problem

$$0 \leq vgc_i + \lambda^{gen}_{f,i,t} + \lambda^{rup}_{f,i,t} - \lambda^{rup}_{f,i,t+1} - \lambda^{rdo}_{f,i,t} + \lambda^{rdo}_{f,i,t+1} - p_t \left(1 - \frac{\sum_{i \in I} \vartheta^{gen}_{f,i,t}\theta^{gen}_f - \vartheta^{vload}_{f,t}\theta^{vload}_f + \sum_{j \in J}(\vartheta^{out}_{f,j,t}\theta^{st}_f - \vartheta^{in}_{f,j,t}\theta^{st}_f)}{\sigma}\right) \perp \quad x_{f,i,t} \geq 0, \ \forall f, i, t \tag{3.6a}$$

$$0 \leq \lambda^{vldaily}_{f,t} + \lambda^{stin}_{f,PIEV,t} + p_t \left(1 - \frac{\sum_{i \in I} \vartheta^{gen}_{f,i,t}\theta^{gen}_f - \vartheta^{vload}_{f,t}\theta^{vload}_f + \sum_{j \in J}(\vartheta^{out}_{f,j,t}\theta^{st}_f - \vartheta^{in}_{f,j,t}\theta^{st}_f)}{\sigma}\right) \perp \quad vload_{f,t} \geq 0, \ \forall f, t \tag{3.6b}$$

$$0 \leq vstc_j + \lambda^{stout}_{f,j,t} + \sum_{\tau=t}^{T} \lambda^{stlo}_{f,j,\tau} - \sum_{\tau=t}^{T-1} \lambda^{stup}_{f,j,\tau+1} - p_t \left(1 - \frac{\sum_{i \in I} \vartheta^{gen}_{f,i,t}\theta^{gen}_f - \vartheta^{vload}_{f,t}\theta^{vload}_f + \sum_{j \in J}(\vartheta^{out}_{f,j,t}\theta^{st}_f - \vartheta^{in}_{f,j,t}\theta^{st}_f)}{\sigma}\right) \perp \quad stout_{f,j,t} \geq 0, \ \forall f, j, t \tag{3.6c}$$

$$0 \leq \lambda^{stin}_{f,j,t} - \sum_{\tau=t}^{T-1} \lambda^{stlo}_{f,j,\tau+1}\eta_{st,j} + \sum_{\tau=t}^{T} \lambda^{stup}_{f,j,\tau}\eta_{st,j} + p_t \left(1 - \frac{\sum_{i \in I} \vartheta^{gen}_{f,i,t}\theta^{gen}_f - \vartheta^{vload}_{f,t}\theta^{vload}_f + \sum_{j \in J}(\vartheta^{out}_{f,j,t}\theta^{st}_f - \vartheta^{in}_{f,j,t}\theta^{st}_f)}{\sigma}\right) \perp \quad stin_{f,j,t} \geq 0, \ \forall f, j, t \tag{3.6d}$$

$$0 \leq -x_{f,i,t} + \overline{x}_{f,i} \qquad \perp \lambda^{gen}_{f,i,t} \geq 0,\ \forall f,i,t \tag{3.6e}$$

$$0 \leq -x_{f,i,t} + x_{f,i,t-1} + \xi^{up}_i \overline{x}_{f,i} \qquad \perp \lambda^{rup}_{f,i,t} \geq 0,\ \forall f,i,t \tag{3.6f}$$

$$0 \leq -x_{f,i,t-1} + x_{f,i,t} + \xi^{down}_i \overline{x}_{f,i} \qquad \perp \lambda^{rdo}_{f,i,t} \geq 0,\ \forall f,i,t \tag{3.6g}$$

$$0 = -\sum_{t \in d} vload_{f,t} + vldaily_{f,d} \qquad , \quad \lambda^{vldaily}_{f,d}\ free,\ \forall f,d \tag{3.6h}$$

$$0 \leq -stin_{f,PIEV,t} - vload_{f,t} + \overline{st}^{in}_{f,PIEV} \qquad \perp \lambda^{stin}_{f,PIEV,t} \geq 0,\ \forall f,t \tag{3.6i}$$

$$0 \leq -stin_{f,j,t} + \overline{st}^{in}_{f,j} \qquad \perp \lambda^{stin}_{f,j,t} \geq 0,\ \forall f, j \neq PIEV, t \tag{3.6j}$$

$$0 \leq -stout_{f,j,t} + \overline{st}^{out}_{f,j} \qquad \perp \lambda^{stout}_{f,j,t} \geq 0,\ \forall f,j,t \tag{3.6k}$$

$$0 \leq -\sum_{\tau=1}^{t} stout_{f,j,\tau} + \sum_{\tau=1}^{t-1} stin_{f,j,\tau}\eta_{st,j} \qquad \perp \lambda^{stlo}_{f,j,t} \geq 0,\ \forall f,j,t \tag{3.6l}$$

$$0 \leq -\sum_{\tau=1}^{t} stin_{f,j,\tau}\eta_{st,j} + \sum_{\tau=1}^{t-1} stout_{f,j,\tau} + \overline{st}^{cap}_{f,j} \qquad \perp \lambda^{stup}_{f,j,t} \geq 0,\ \forall f,j,t \tag{3.6m}$$

$$0 = X_t - d0_t \left(\frac{p_t}{p0_t}\right)^{-\sigma} \qquad , \quad p_t\ free,\ \forall\ t \tag{3.6n}$$

Equations (3.6a-3.6d) include market shares $\vartheta^{gen}_{f,i,t}$, $\vartheta^{vload}_{f,t}$, $\vartheta^{out}_{f,j,t}$, and $\vartheta^{in}_{f,j,t}$ as defined in (3.7a-3.7d). They indicate a player's ability to raise prices beyond marginal costs. Note the additional PIEV-related market share $\vartheta^{vload}_{f,t}$ compared to chapter 2. Equations (3.6a-3.6n) again include the market power parameters $\theta^{gen}_f$, $\theta^{vload}_f$, and $\theta^{st}_f$. By exogenously assigning the values 0 or 1, we can "switch" off and on market power for specific players regarding generation, PIEV recharging, and storage.

$$\vartheta^{gen}_{f,i,t} = \frac{x_{f,i,t}}{X_t},\ \forall f,i,t \tag{3.7a}$$

$$\vartheta^{vload}_{f,t} = \frac{vload_{f,t}}{X_t},\ \forall f,t \tag{3.7b}$$

$$\vartheta^{out}_{f,j,t} = \frac{stout_{f,j,t}}{X_t},\ \forall f,j,t \tag{3.7c}$$

$$\vartheta^{in}_{f,j,t} = \frac{stin_{f,j,t}}{X_t},\ \forall f,j,t \tag{3.7d}$$

The interpretation of equations (3.6a-3.6d) is largely the same as in chapter 2. There are two notable extensions. First, 3.6b is a new equation that represents the derivative of the objective function with respect to vehicle loading. Second, the PIEV-related market share $\vartheta^{vload}_{f,t}$ enters in (3.6a-3.6d) with a negative sign, just as the storage loading-related market share $\vartheta^{in}_{f,t}$. Accordingly, both electric vehicle recharging and storage loading of different technologies have a price-decreasing effect on strategic generating firms. The higher these market shares of a player, the larger its interest in low prices during the periods of vehicle recharging and/or storage loading. Electric vehicle loading activities

thus mitigate a strategic electricity generator's incentives to exert price-driving market power during the periods of vehicle loading.

# Chapter 4

# Regulated expansion of transmission networks: the effects of fluctuating demand and wind generation

## 4.1 Introduction

Large-scale expansion of renewable energy sources is a major strategy for achieving substantial emission reductions in the power sector. Several studies have shown that an expansion of existing transmission networks is a precondition for integrating large amounts of renewable energy sources into the German and European electricity systems (see, for example, Denny et al., 2010; Weigt et al., 2010). In this context, market failures and related problems of adequate regulation of electricity networks are important. Since electricity transmission networks are natural monopolies, they need to be regulated so as to promote their expansion in a way that social welfare is also taken into account. Network owners have no incentives to remove transmission bottlenecks if this reduces their profits (due to a loss in their congestion rents). This incentive structure is further complicated by asymmetric information between the network owner and the regulator. Thus, incentive compatible network expansion has to be ensured through economic regulation.

The regulation of transmission operation and expansion has been widely discussed by regulatory economists. Finding optimal mechanisms is difficult given the specific physical characteristics of electricity networks like negative local externalities due to loop flows, i.e. electricity flows obeying to Kirchhoff's laws. A range of different regulatory schemes and mechanisms have been proposed and applied so far (Léautier, 2000; Léautier and Thelen, 2009; Hogan et al., 2010; Kristiansen and Rosellón, 2010). However, there is scarce research on optimal transmission regulation in the light of realistic demand patterns and large-scale RES integration. "Classic" regulation aims for expanding networks such that marginal arbitrage gains equal marginal expansion costs. Considering real-world demand fluctuations and RES-specific issues in network regulation analysis may require a different approach. In particular, the timing of electricity dispatch in RES

systems is more frequent and fluctuating than transmission investment decisions.

In this chapter, we discuss how to regulate and expand transmission networks in the light of realistic demand patterns and large-scale wind power in Europe. We combine theoretical research on regulation of transmission expansion, with an application to Europe; we also derive policy implications. In order to analyze these issues, we initially rely on the Hogan-Rosellón-Vogelsang (HRV) mechanism (Hogan et al., 2010) which combines merchant and regulatory structures to promote the expansion of networks. Other extreme approaches to transmission expansion include the traditional central planning within a vertically integrated industry, and the pure market (or merchant) mechanisms. The HRV approach lies in between these two approaches, combining regulation (via price caps) and market incentives via property rights in electricity investment (financial transmission rights, FTRs). We particularly analyze whether the unique variability and unpredictability characteristics of RES have an effect on transmission expansion decisions within the HRV analytical framework.

We are also interested in the relative performance of the HRV mechanism compared to other regulatory regimes for transmission network expansion, including a welfare-maximizing benchmark, a purely merchant approach, and cost regulation. We apply these mechanisms to a stylized model of the central European transmission network. The transmission model represents real power flows, which allows including special characteristics of electricity networks like loop flows. In contrast to earlier applications of the HRV mechanism, we explicitly include both an hourly time resolution and fluctuating wind power, which substantially increases the real-world applicability of the approach. We solve the model numerically and compare welfare outcomes and the optimal levels of network expansion for different cases that vary with respect to demand representation and wind power fluctuations.

We find that network extension in central Europe not only increases social welfare due to diminished congestion, but also leads to a large redistribution of social welfare from consumers to producers in France and Germany. Comparing different regulatory approaches, we find that HRV regulation leads to welfare outcomes that are close to the optimum achieved by a social planner, and far superior to other modelled alternatives. We show that this result is robust over all modelled cases. Our analysis thus quantitatively supports a theoretical claim according to which HRV regulation properly aligns a Transco's incentives with social welfare objectives. We also find that HRV regulation leads to a situation in which a substantial portion of the Transco's income consists of a fixed-tariff part. Likewise, the intertemporal rebalancing of the two-part tariff carried out by the Transco to expand the network is such that the fixed part is much higher than the decrease of the variable part. In fact, the fixed tariff fee turns out to be relatively large compared to extension costs, a distributive issue that can be addressed through the proper choice of weight of profits in the welfare criterion.[49]

[49]Exploring distributive issues in detail is not in the focus of this research, but should be explored in future analyses.

The remainder of the chapter is structured as follows. Section 4.2 reviews the relevant literature. Sections 4.3 and 4.4 introduce the model and its application to a stylized central European example. Results are discussed in section 4.5. The last paragraph summarizes and concludes.

## 4.2 Literature

There are two main distinct analytical approaches to transmission investment: one employs the theory based on long-term financial transmission rights (LTFTR, merchant approach), while the other is based on the incentive regulation hypothesis (performance-based-regulation, PBR). The PBR approach to transmission expansion relies on incentive regulatory mechanisms for a transmission company (Transco). One example is Vogelsang (2001) where price-cap regulation solves the duality of incentives for the transmission firm both in the short run (congestion) and in the long run (investment in network expansion). Equilibrium for this duality has been studied by the peak-load pricing literature: in equilibrium, the per-unit marginal cost of new capacity must be equal to the expected congestion cost of not adding an additional unit of capacity (Crew et al., 1995). Alternative regulatory PBR approaches provide the firm with incentives to make efficient investment decisions through penalizing congestion (Wangesteen and Grande, 2000; Léautier, 2000; Joskow and Tirole, 2005). In the international practice, PBR schemes for transmission expansion have been applied in England, Wales and Norway to guide the expansion of the transmission network.[50]

In the Vogelsang (2001) two-part tariff regulatory model, incentives for efficient investment in the expansion of the network are obtained by the rebalancing of fixed and variable charges while convergence to the steady state Ramsey-price equilibrium crucially depends on the type of weights used. Ramsey prices result from the solution of the program where a regulator seeks to maximize social welfare subject to the individual rationality constraint of a firm with increasing returns to scale. The prices are such that they differ from marginal cost inversely proportionally to the elasticity of demand. A Laspeyres index weight (previous period quantity weight) promotes intertemporal convergence of transmission tariffs to Ramsey prices, while average revenue weights (endogenous current period quantity weights) cause divergence from the Ramsey equilibrium (Armstrong et al., 1994).

The merchant approach to transmission expansion is based on auctions of LTFTRs. The long-run concept is important for transmission expansion projects for investors. Such projects usually have an installed lifetime of approximately 30 years, so that auctions allocate FTRs with durations of several years. Incremental LTFTRs implicitly define

[50]During the 1990s, an "uplift management rule" was applied in England and Wales (Léautier, 2000). Such a rule made the Transco responsible for the full cost of an "out-turn" plus any transmission losses. The out-turn defined the cost of congestion as the difference between the price actually paid to generators and the price that would have been paid absent congestion. In Norway, a revenue-cap approach – which precludes having to exactly define the output produced by a Transco – has also been used in practice (Jordanger and Grønli, 2000).

property rights. FTR auctions are carried out within a bid-based security-constrained economic dispatch with nodal pricing of an independent system operator (ISO). The ISO runs a power-flow model that provides nodal prices derived from shadow prices of the model's constraints. FTRs are subsequently derived as hedges from nodal price differences. Externalities in electricity transmission are mainly due to loop flows which arise from interactions in the transmission network. The effects of loop flows imply that transmission opportunity costs and pricing critically depend on the marginal costs of power at every location in the network. Loop flows generate negative externalities on property-right holders. In the merchant approach, the ISO retains some capacity or FTRs in order to deal with such externalities. Equivalently, the agent making an expansion is required to 'pay back' for the possible loss of property rights of other agents (Bushnell and Stoft, 1997; Kristiansen and Rosellón, 2006). In international practice, FTR auctions have been used in the North East of the USA and in California.[51]

A second-best standard that combines the merchant and PBR transmission models is proposed by the HRV model. This is done in an environment of price-taking generators and loads. A crucial aspect is the redefinition of the transmission output in terms of incremental LTFTRs in order to apply the basic price-cap mechanism in Vogelsang (2001) to meshed networks within a power-flow model. The Transco intertemporally maximizes profits subject to a cap on its two-part tariff, but the variable fee is now the price of the FTR output based on nodal prices. Again, the rebalancing between the variable and fixed charges promotes the efficient expansion of the network. The HRV mechanism has already been tested in model-based analyses for simplified grids in Northwestern Europe and the Northeast USA (Rosellón and Weigt, 2011; Rosellón et al., 2011). The testing of the HRV regulatory model results in the Transco expanding the network so that prices develop in the direction of marginal costs. The nodal prices that were subject to a high level of congestion before the expansion converge to a common marginal price level. In any case, these results show that the HRV mechanism has the potential to foster investment in congested networks in an overall desirable direction.[52]

In this chapter we expand the HRV model so as to incorporate the peculiarities of real-world electricity systems and fluctuating renewables into the regulatory logic of the HRV model. In doing so, we also confirm the robustness of some key results obtained by Rosellón and Weigt (2011), which draw on a much simpler representation of demand, and on unrealistic initial price differences between countries. Likewise, we aim to also contribute with a novel application of combined regulatory-PBR mechanisms to the case of fluctuating and geographically dispersed renewables.

[51]Auctions of FTRs or similar congestion revenue rights have recently generated substantial revenues: USD 1.9 billion in PJM, USD 71.1 million in New England, and USD 48.4 million in California (2009 data). In New England, the annual traded volume amounted 60 GW in 2008 (CAISO, 2010a,b; ISO-NE, 2010; NYISO, 2011).

[52]The recently created Agency for the Cooperation of Energy Regulators (ACER) seeks to achieve similar goals for European transmission grids.

## 4.3 The model

The model formulation builds on Rosellón and Weigt (2011). Table 4.8 in the Appendix lists all model sets and indices, parameters, and variables. We assume a market design with nodal pricing based on real power flows and financial transmission rights. A single Transco holds a natural monopoly on the transmission network. The Transco decides on network extension and auctions off transmission capacity in the form of FTRs to market participants. Note that we do not explicitly model this point, but assume that FTR auction revenues are equal to congestion rents of the system. Accordingly, we just assume that the Transco maximizes profit, which consists of congestion rents and a fixed income part. Whereas the Transco is not involved in electricity generation, an independent system operator manages the actual dispatch in a welfare-maximizing way. The ISO collects nodal payments from loads and pays the generators. The difference between these payments is the congestion rent. This congestion rent is transferred to the Transco.[53] We model three different regulatory cases in which we assume the Transco to be unregulated regarding network expansion (NoReg), cost-regulated (CostReg), or HRV-regulated (HRV). We compare these regulatory cases to a baseline case without any network expansion (NoExtension) and to a welfare-maximizing benchmark (WFMax), in which a social planner makes combined decisions on network expansion and dispatch. The problem formulation entails two levels. In the regulatory cases, the Transco's profit maximization constitutes the upper-level optimization problem. In the welfare-maximizing benchmark, the upper-level problem represents the social planner's maximization problem. On the lower level, we formulate the ISO's welfare-maximizing dispatch as a mixed complementarity problem (MCP). The combination of lower and upper level problems constitutes a mathematical program with equilibrium constraints (MPEC).[54]

We assume a standard linear demand function (4.1):

$$p_{n,t,\tau} = a_{n,\tau} + m_{n,\tau} q_{n,t,\tau} \tag{4.1}$$

$p_{n,t,\tau}$ is the electricity price at node $n$ in regulatory period $t$ and hour $\tau$, whereas $q_{n,t,\tau}$ describes the corresponding electricity demand. Given (4.1), the lower level dispatch problem consists of equations (4.2a)-(4.2h). These represent an MCP formulation of the ISO's constrained welfare maximization problem (4.7a-4.7f), which is provided in Appendix 4.A.2. We model real load flows between single nodes according to the DC load flow approach developed by Schweppe et al. (1988) (compare also Stigler and Todem, 2005; Leuthold et al., 2008b, 2010). Note that equations (4.2a)-(4.2h) must be satisfied

[53] More precisely, congestion rents are redistributed to FTR holders. The Transco's FTR auction revenues thus include these payments. As we do not explicitly model FTR auctions, we make the simplifying assumption that congestion rent is transferred to the Transco.

[54] Hobbs et al. (2000) were among the first to apply an MPEC approach to power market modelling. Gabriel and Leuthold (2010) solve power market-related MPEC problems be means of integer programing.

in every single hour $\tau$.

$$a_{n,\tau} + m_{n,\tau} q_{n,t,\tau} - p_{n,t,\tau} \leq 0 \quad \perp \quad q_{n,t,\tau} \geq 0 \tag{4.2a}$$

$$-c_s + p_{n,t,\tau} - \lambda^4_{n,s,t,\tau} \leq 0 \quad \perp \quad g_{n,s,t,\tau} \geq 0 \tag{4.2b}$$

$$-\sum_{l \in L} \frac{I_{l,n}}{X_{l,t}} (\lambda^1_{l,t,\tau} - \lambda^2_{l,t,\tau}) - \sum_{nn} p_{nn,t,\tau} B_{nn,n,t} - \lambda^5_{n,t,\tau} slack_n \leq 0 \quad \perp \quad \Delta_{n,t,\tau} \geq 0 \tag{4.2c}$$

$$\sum_{n} \frac{I_{l,n}}{X_{l,t}} \Delta_{n,t,\tau} - P_{l,t} \leq 0 \quad \perp \quad \lambda^1_{l,t,\tau} \geq 0 \tag{4.2d}$$

$$-\sum_{n} \frac{I_{l,n}}{X_{l,t}} \Delta_{n,t,\tau} - P_{l,t} \leq 0 \quad \perp \quad \lambda^2_{l,t,\tau} \geq 0 \tag{4.2e}$$

$$\sum_{s} g_{n,s,t,\tau} - \sum_{nn} B_{nn,n,t} \Delta_{nn,t,\tau} - q_{n,t,\tau} = 0 \quad , \quad p_{n,t,\tau} \; free \tag{4.2f}$$

$$g_{n,s,t,\tau} - \overline{g}_{n,s} \leq 0 \quad \perp \quad \lambda^4_{n,s,t,\tau} \geq 0 \tag{4.2g}$$

$$slack_n \Delta_{n,t,\tau} = 0 \quad , \quad \lambda^5_{n,t,\tau} \; free \tag{4.2h}$$

Equations (4.2a)-(4.2c) represent the partial derivates with respect to $q_{n,t,\tau}$, $p_{n,t,\tau}$, and the voltage angle $\Delta_{n,t,\tau}$. $I_{l,n}$ is the incidence matrix of the network, which provides information on how the nodes are connected by transmission lines $l$. The parameter $X_{l,t}$ describes the reactance for each transmission line. $B_{nn,n,t}$ is the network susceptance between two nodes. Equations (4.2d) and (4.2e) demand that the power flows on each line do not exceed the respective line's capacity $P_{l,t}$. (4.2f) ensures nodal energy balance: generation minus net outflow has to equal demand at all times. Equation (4.2g) constrains generation of technology $s$ to the maximum available generation capacity at the respective node. Finally, (4.2h) establishes a point of reference for the voltage angles by exogenously setting the parameter $slack_n = 1$ for one node in the network. For all other nodes, $slack_n = 0$.

Whereas the lower-level problem (4.2a)-(4.2h) has to be solved for every single hour $\tau$, the upper-level problem needs to be inter-temporally optimized over all regulatory periods $t$. For the three regulatory regimes, the upper level problem is represented by (4.3):

$$\max_{ext_{l,t}} \Pi = \sum_{t \in T} \left[ \left( \sum_{\tau \in T} \sum_{n \in N} \left( p_{n,t,\tau} q_{n,t,\tau} - \sum_{s \in S} p_{n,t,\tau} g_{n,s,t,\tau} \right) + fixpart_t - \sum_{l \in L} \sum_{tt < t} ec_l ext_{l,tt} \right) \frac{1}{(1+\delta^p)^{t-1}} \right] \tag{4.3}$$

The Transco's only decision variable is capacity extension of transmission lines $ext_{l,t}$, which incurs extension costs $ec_l$ (annuities). In the NoReg case, transmission investments have to be fully recovered by congestion rents, i.e. $fixpart_t$. Accordingly, the Transco will only extend such lines that increase congestion rents. Both future revenues and future costs are discounted with a private discount rate $\delta^p$. In the CostReg case, we assume

that the Transco not only receives congestion rents, but may also charge an additional $fixpart_t^{CostReg}$ which reimburses the line extension cost and grants an additional return on costs ("cost-plus" regulation). Equation (4.4a) shows that the fixed part of a given period includes the costs (annuities) of all network investments made so far plus a return on costs $r$. With positive $r$, the Transco may find it optimal to expand all transmission lines infinitely. We thus include an additional constraint which demands that extension of each line does not exceed the optimal levels as determined by the welfare-maximizing benchmark. That is, no returns are granted on excessive line investments. Note that this requires the regulator to have sufficient knowledge on which lines should be increased. In the HRV case, the Transco may also charge a fixed tariff part, on which equation (4.4b) sets a cap. It includes previous period quantity weights (Laspeyres weights).[55] It also includes a retail price index $RPI$ and an efficiency factor $X$.[56] Summing up, in both the CostReg and the HRV case, the Transco is able to recover network extension costs by the fixed tariff part. In contrast, this is not the case in NoReg.

$$fixpart_{t+1}^{CostReg} = \sum_{l \in L} \sum_{tt > t+1} ec_l ext_{l,tt}(1+r) \tag{4.4a}$$

$$\sum_{n \in N} \sum_{\tau \in T} \frac{(p_{n,t+1,\tau} q_{n,t,\tau} - \sum_{s \in S} p_{n,t+1,\tau} g_{n,s,t,\tau}) + fixpart_{t+1}^{HRV}}{(p_{n,t,\tau} q_{n,t,\tau} - \sum_{s \in S} p_{n,t,\tau} g_{n,s,t,\tau}) + fixpart_t^{HRV}} \leq 1 + RPI - X \tag{4.4b}$$

In the welfare-maximizing benchmark case, the upper level problem does not describe a Transco's profit-maximization, but a social planner's maximization of social welfare. It is described by (4.5). Note that the social planner uses a social discount rate $\delta^s$ which may be smaller than the private discount rate $\delta^p$ used by a Transco.

$$\max_{ext_{l,t}} wf = \sum_{t \in T} \left[ \left( \sum_{\tau \in T} \sum_{n \in N} \left( a_{n,\tau} q_{n,t,\tau} + \frac{1}{2} m_{n,\tau} q_{n,t,\tau}^2 - \sum_{s \in S} c_s g_{n,s,t,\tau} \right) - \sum_{l \in L} \sum_{tt < t} ec_l ext_{l,tt} \right) \frac{1}{(1+\delta^s)^{t-1}} \right] \tag{4.5}$$

In all cases, there are inter-period constraints on line capacity (4.6a), line reactance (4.6b) and network susceptance (4.6c).

$$P_{l,t+1} = P_{l,t} + ext_{l,t} \tag{4.6a}$$

$$X_{l,t+1} = \frac{P_l^0}{P_{l,t+1}} X_l^0 \tag{4.6b}$$

$$B_{nn,n,t+1} = \sum_l \frac{I_{l,n} I_{l,nn}}{X_{l,t+1}} \tag{4.6c}$$

In the numerical application, we initially assume that a line's capacity expansion does

[55] Fur further explanation, see Hogan et al. (2010); Rosellón and Weigt (2011).

[56] We set both $RPI$ and $X$ to zero in the model application, as we assume real prices and neglect efficiency gains.

not change its reactance and susceptance. That is, equation (4.6a) holds, whereas (4.6b) and (4.6c) are neglected. This reduces complexity and improves the numerical solution process. In section 4.5.4.4, we perform a sensitivity analysis in which equations (4.6b) and (4.6c) are included. It shows that the main results also hold under the simplifying assumption of exogenous reactance and susceptance.

## 4.4 Model application

The five MPEC problems are implemented in the General Algebraic Modeling System (GAMS). They are numerically solved on a 64bit Linux System with the solver CONOPT3. We apply the model to a stylized transmission network of central Europe, which includes seven country nodes in Germany, France, Belgium and the Netherlands, eight auxiliary cross-border nodes, and twenty stylized transmission lines (Figure 4.1). In addition, there are eight auxiliary lines in France and Germany, which we assume not to be congested. Network data is derived from Neuhoff et al. (2005), who have used this network for a seminal model comparison analysis. The same network has been used by Rosellón and Weigt (2011).[57]

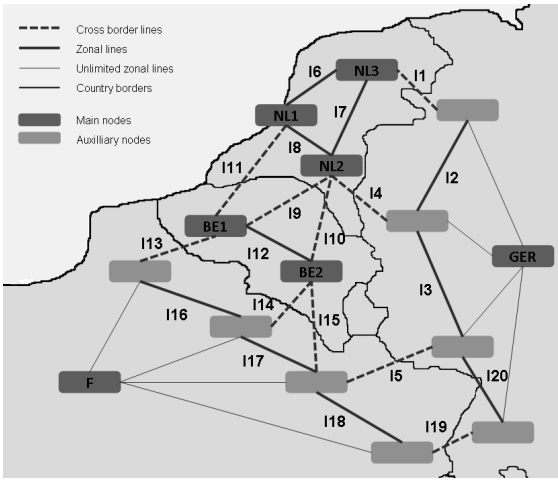


**Figure 4.1:** The stylized central European transmission network

We include eight power generation technologies. Table 4.1 lists variable generation costs and overall available capacity in the stylized network. Data sources include BP (2010), EEX (2011), ENTSO-E (2010b), Eurostat (2010) and IEA (2010a). The values on available capacity also reflect own estimations on a part of the installed capacity not being available any given hour due to outages, seasonal maintenance and other technical restrictions. Table 4.9 in the Appendix shows nodal generation capacity in detail. The distribution of the total capacity among the different nodes in Belgium and the Netherlands is in line with original data used in Neuhoff et al. (2005).

[57] We have encountered data problems in Rosellón and Weigt (2011) regarding the distribution of nodal demand. Obviously, the two Belgian nodes have been confused. We have solved this issue by drawing on original data provided by the Energy research Center of the Netherlands.

**Table 4.1:** Variable generation costs and available capacity

| Technology | Variable generation costs in €/MWh | Overall available capacity in MW |
|---|---|---|
| Nuclear | 9 | 64,858 |
| Lignite | 29 | 15,120 |
| Hard coal | 35 | 35,064 |
| CCGT | 43 | 16,358 |
| Gas turbine | 65 | 16,286 |
| Oil | 72 | 12,584 |
| Hydro | 0 | 9,841 |
| Wind | 0 | 29,790 |

**Table 4.2:** Overview of different cases

| Case | Representation of demand | Wind generation |
|---|---|---|
| Static | Yearly average | Yearly average |
| DRes | 144 hours, representing six characteristic days | Yearly average |
| WindRes | 144 hours, representing six characteristic days | Fluctuating pattern |

We solve the model for three different cases that vary with respect to the time resolution of demand and wind generation. Table 4.2 provides an overview. In the Static case, we assume average yearly demand levels, prices and wind generation. In the DRes case, demand is modeled on an hourly basis for six representative days of the year. We include both a weekday and a weekend day for each of three distinctive demand periods: summer (April to September), winter (November to February) and a shoulder period (March and October). We extrapolate to the whole year by weighting the six days with suitable factors. WindRes extends DRes by adding a fluctuating wind generation pattern derived from historic data. This approach allows separating the effects of demand fluctuations and winding power fluctuations.

Table 4.3 lists nodal reference demand and prices for the Static case. Average yearly nodal demand levels have been calculated from hourly data for 2009 ENTSO-E (2010a). Average yearly reference prices have been calculated from hourly spot market data for 2009 provided by EEX, EPEX and Belpex (day-ahead hourly auctions). In accordance with Rosellón and Weigt (2011), we assume a price elasticity of demand $\epsilon = -0.25$ at the reference point for all nodes and all hours. Given quarter-hourly feed-in data provided by the German TSOs for the year 2009, we calculate an average wind capacity factor of 0.172. This value is used for wind power at all nodes.

In the DRes case, nodal reference demand and prices are modeled on an hourly basis. We group hourly ENTSO-E demand data for the whole year 2009 in six different categories (weekdays and weekend days during summer, winter, and the shoulder period) and calculate average values for each hour of these six representative days. As shown in Figure 4.2, this results in 144 representative hours which adequately represent a whole year. Hourly reference prices for the 144 hours are similarly determined drawing on hourly spot market data for 2009 provided by European power exchanges. Figure 4.3

**Table 4.3:** Nodal reference demand and prices in the Static case

| Node | Description | Reference demand in MW | Reference prices in €/MWh |
|---|---|---|---|
| GER | Germany | 52,941 | 38.91 |
| F | France | 55,748 | 41.61 |
| BE1 | Belgium 1 | 6,893 | 39.39 |
| BE2 | Belgium 2 | 2,822 | 39.39 |
| NL1 | Netherlands 1 | 7,839 | 39.13 |
| NL2 | Netherlands 2 | 1,573 | 39.13 |
| NL3 | Netherlands 3 | 2,759 | 39.13 |

shows the resulting reference price pattern.[58]

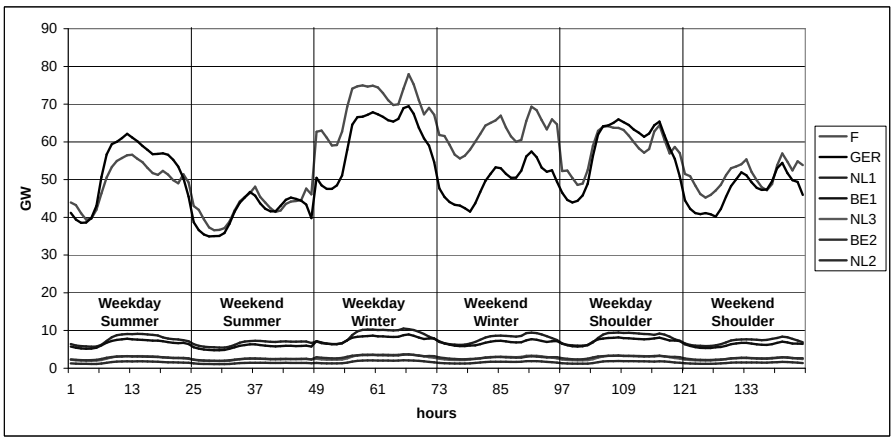


**Figure 4.2:** Hourly nodal reference demand in DRes and WindRes

In the WindRes case, we draw on hourly German wind feed-in of 2009 provided by the German TSOs.[59] We group hourly wind feed-in data of the whole year in six representative days (weekdays and weekend days during summer, winter, and the shoulder period). For each group, we sort the hourly wind values in ascending order and take 24 quantiles. These quantiles are randomly assigned to the 24 hours of each representative day.[60] Figure 4.4 shows the resulting wind pattern in the context of overall reference demand. Taking weighted averages of the resulting 144 representative hourly feed-in values leads exactly to the same overall wind feed-in as in the Static and DRes cases. Note that the wind feed-in pattern is completely unrelated to daily demand fluctuations. In contrast, there is a small seasonal correlation: during winter days, both demand and wind feed-in is higher than during summer days.

It should be noted that this wind pattern shown in Figure 4.4 is not intended to resemble real-world wind feed-in during specific hours. Rather, it is intended to represent the characteristics of fluctuating wind generation during each of the representative six days. Over the 144 hours, many combinations of demand and wind generation occur,

[58]The weighted averages of these 144 hourly values constitute the reference demand and reference price levels in the Static case.

[59]Because of a lack of data, we use the German wind feed-in pattern for the other countries, as well.

[60]Sensitivity tests have shown that other random assignments of hourly wind feed-in values lead to very similar results.

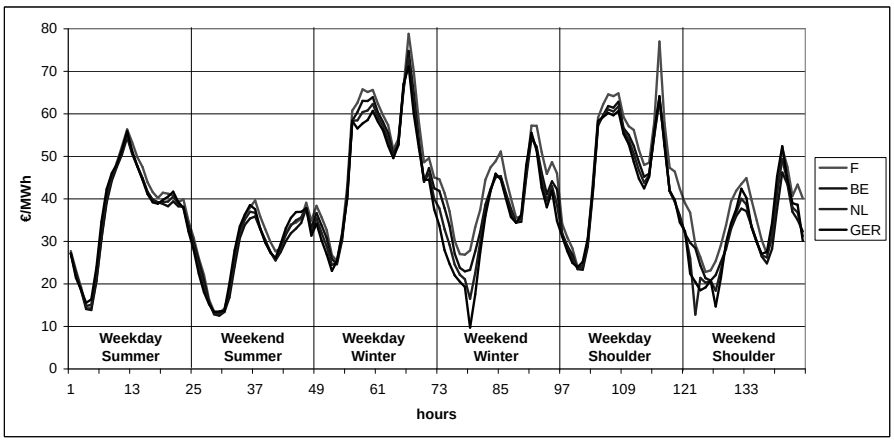


**Figure 4.3:** Hourly nodal reference prices in DRes and WindRes

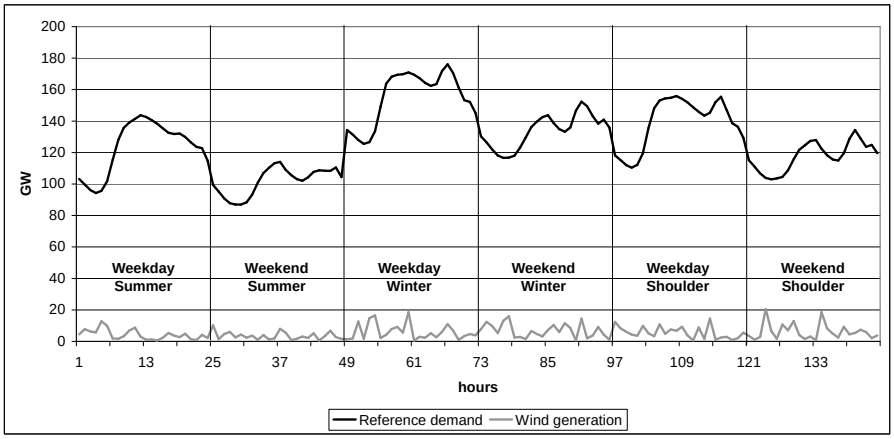


**Figure 4.4:** Wind generation and overall reference demand in WindRes

for example high wind/low demand or low wind/high demand. Overall, this approach captures the essentials of real-world wind power fluctuations quite well. Yet taking quantiles necessarily leads to an under-representation of hours with extremely high wind feed-in.

We solve the model for six regulatory periods ($t_0$-$t_5$), i.e. six years.[61] Network expansion decisions can be made in the first period, but will become effective only in the second one. The social planner in the WFMax case applies a social discount rate $\delta^s$ of 4% for intertemporal optimization over the regulatory periods. In the following, we use the same discount rate for all comparisons of welfare outcomes. In the NoReg, CostReg and HRV cases, the Transco uses a private discount rate $\delta^p$ of 8% for intertemporal profit maximization. We further assume a return on costs $r$ in the CostReg case of 8%. This assumption is motivated by German legislation prior to the introduction of incentive regulation, according to which the regulator granted interest on equity capital of 7.91% for new grid investments (Bundesgesetzblatt, 2005a).

[61] In a sensitivity analysis, we extend the time span to $t_0$-$t_{10}$.

## 4.5 Results

### 4.5.1 The simplified case (Static)

First, we look at the Static case, in which neither demand nor wind fluctuate. Figure 4.5 shows the locations and the levels of overall line extensions in the final period ($t_5$) under all regulatory approaches. In the welfare-maximizing benchmark, the major extensions take place at the border between France and the Netherlands (lines 13, 14, and 15) and between Germany and the Netherlands (line 4). Under HRV regulation, exactly the same lines are expanded – largely at the same level as in WFMax. Cost-based regulation also leads to welfare-optimal expansion of most of these lines. However, the two lines that are most important for decreasing congestion rents are hardly expanded under CostReg: line 4 between Germany and the Netherlands and line 13 between France and Belgium. Substantially expanding these lines would lead to congestion rent losses that would by far outweigh the return on costs paid to the Transco for extending these lines. Under NoReg, hardly any network extension takes place as the Transco does not receive any payments that could outweigh congestion rest losses.

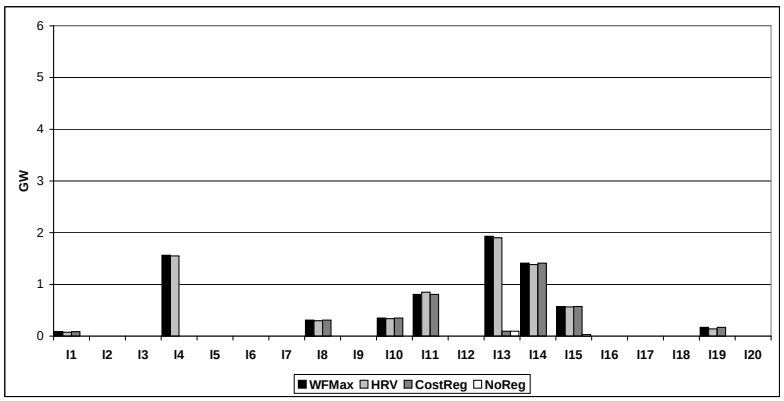


**Figure 4.5:** Line extension in the Static case

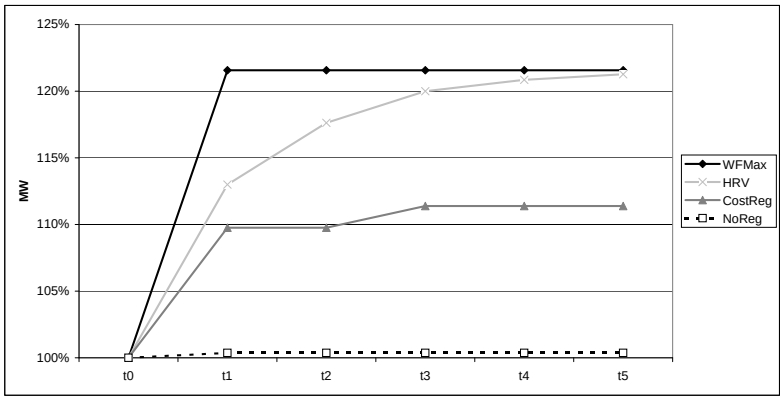


**Figure 4.6:** Time path of overall extension in the Static case

While Figure 4.5 shows the final network expansion level in the final period ($t_5$), it is also interesting to look at the time path of extension in the different cases. Figure 4.6

indicates that all line extensions take place in the first period in the welfare-maximization benchmark. This result should be expected, as delaying investments would only decrease the benefits of extension measures. In the NoReg and CostReg cases, we find a similar result, although there is some activity between t2 and t3 in the cost-based regulatory case. In contrast, HRV regulation leads to incremental upgrades over the different regulatory periods.[62] This result is driven by the yearly rebalancing of the variable and fixed parts of the two-part tariff according to equation 4.4b. Accordingly, the full benefits of HRV regulation materialize in later periods.

Figure 4.7 shows hourly nodal prices before and after network expansion under the different regulatory approaches. In the welfare-maximizing benchmark, price convergence is nearly perfect. Prices increase in France and Germany and decrease in Belgium and the Netherlands. In the HRV case, we find nearly the same results. Yet prices differ strongly in the NoReg and CostReg cases. In these cases, the Transco expands the lines such that price differences between the most cross-border nodes increase. In doing so, the Transco manages to slightly increase congestion rents.

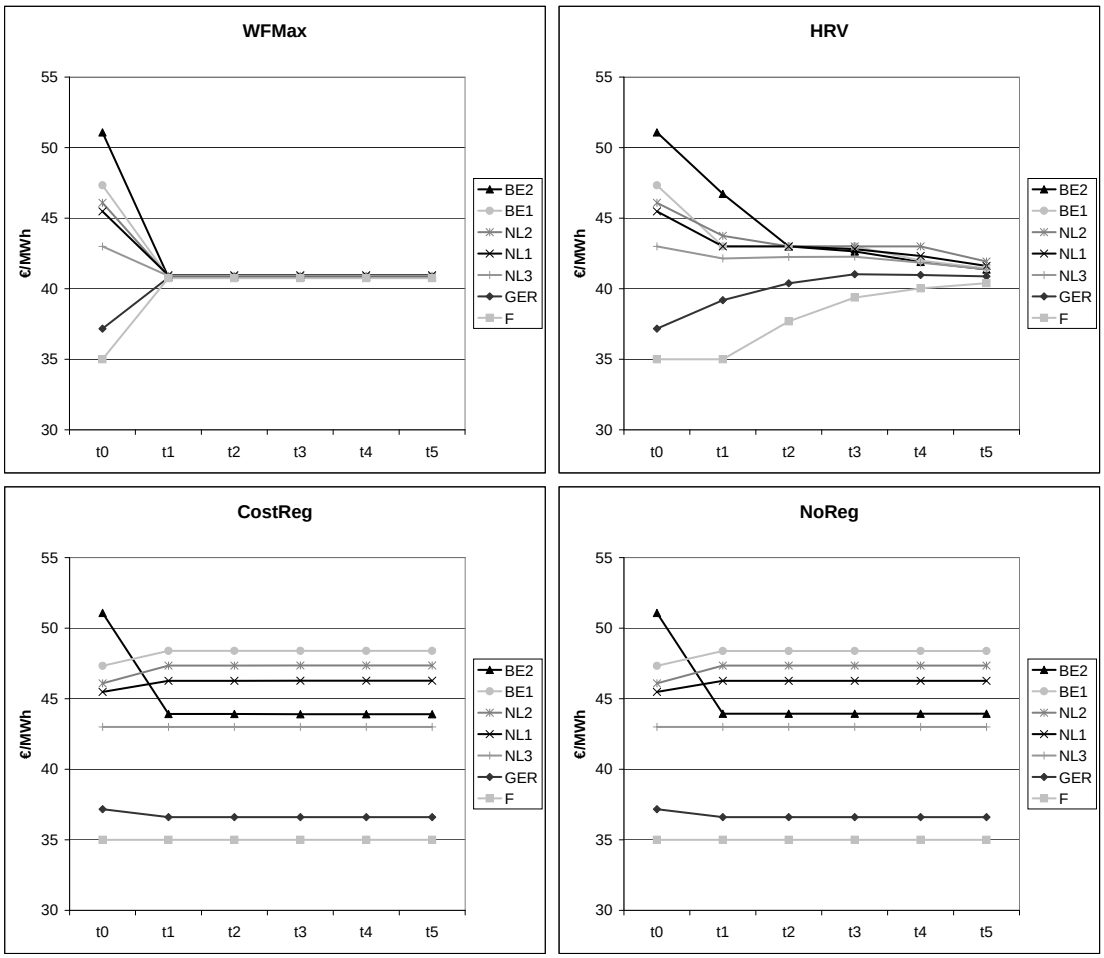


**Figure 4.7:** Convergence of nodal prices in the Static case

[62]Note that we allow for continuous line extension. In the real world, line investments are lumpy. Accounting for indivisibilities may lead to different HRV results. Yet a numerical solution of a discretely constrained MPEC would be extremely challenging.

**Table 4.4:** Welfare results Static: Differences to baseline in bn €

| | Social welfare | Producer rent | Consumer rent | Congestion rent | Extension costs | Transco profit | Fixed part |
|---|---|---|---|---|---|---|---|
| WFMax | +1.94 | +19.04 | -15.57 | -1.5 | +0.03 | - | - |
| NoReg | +0.13 | -1.42 | +1.36 | +0.19 | 0.00 | +0.19 | - |
| CostReg | +0.11 | -1.43 | +1.37 | +0.19 | +0.01 | +0.19 | +0.02 |
| HRV | +1.81 | +13.08 | -11.13 | -0.12 | +0.02 | +1.68 | +1.82 |

After analyzing line extensions and price effects, we look at welfare results. Table 4.4 summarizes welfare outcomes for the Static case.[63] It lists the differences to the baseline without extension (NoExtension) for the different regulatory approaches, i.e. the welfare gains of network extension. A general finding is that network expansion always increases social welfare compared to a situation in which extension is not possible.

Looking at the welfare-maximizing benchmark (WFMax), we find a modest increase of social welfare of less than two billion € over the five regulatory periods due to network expansion. However, there is a much larger distributional effect: producer rents are greatly increased, while consumer rents decrease. This effect can be explained by the fact that increased transmission capacities lead to additional exports from Germany and France and to respective price increases in these countries. Accordingly, consumer rents in Germany and France decrease, whereas consumers in Belgium and the Netherlands benefit from network expansion. As electricity consumption is larger in Germany and France than in Belgium and the Netherlands, overall consumer rent decreases. Congestion rents (and Transco profits) also decrease due to network investments.

Comparing social welfare among the different regulatory cases, we find that HRV regulation results in welfare outcomes close to the welfare-maximizing benchmark. In contrast, both NoReg and CostReg lead to lower welfare gains of extension. Interestingly, the effects on producer and consumer rents are different compared to WFMax and HRV. This is because Transcos do not find it profitable to expand line 4 between Germany and the Netherlands in NoReg and CostReg. Consequently, German exports do not increase in these cases. In contrast, there is even a slight decrease of German exports under NoReg and CostReg due to investments in other lines.[64]

The extension-related decrease in congestion rents is largest in WFMax. HRV only leads to a small decrease in congestion rents, whereas NoReg and CostReg slightly increase network congestion. This is because small line upgrades lead to increasing trade, which outweighs a decreasing price difference between two congested nodes. In other words: profit-maximizing Transcos in NoReg and CostReg expand the network such that congestion is increased. In contrast, the HRV-mechanism gives the Transco an incentive to expand the network such that congestion is relieved. Accordingly, HRV regulation better aligns the Transco's incentives with social welfare objectives compared to NoReg

[63] Note that the table lists cumulative welfare outcomes over all six modelled periods ($t_0$-$t_5$). The same is true for the tables in the next sections.

[64] This finding illustrates the merits of the DC load flow approach: Changes at remote nodes can have an impact on results at other nodes due to loop flows.

and CostReg.

It can be observed that the rebalancing of the two parts of the tariff favors $fixpart_t^{HRV}$, as determined by equation (4.4b), such that Transco profits are highest in the HRV case. The fixed part is very large compared to extension costs and congestion rent losses. According to our results, the fixed part should be paid for by generators. Under both NoReg and CostReg, the Transco is hardly able to increase profits compared to NoExtension.

### 4.5.2 The case with fluctuating demand (DRes)

We now discuss the DRes case, which has a more realistic demand resolution than the Static case. Figure 4.8 shows overall line extensions in the final period ($t_5$) for DRes. In general, optimal line investments are much higher compared to the Static case. In addition, the major extensions take place at different lines. This is because fluctuating demand levels increase network congestion, particularly in peak hours. In the welfare-maximizing benchmark, we now find the major line investments at the border between Germany and France (lines 5 and 19). The lines with the major extensions in the Static case also play a role: lines at the border between France and the Netherlands (lines 13, 14, and 15) and between Germany and the Netherlands (line 4). In addition, extension of the lines between Belgium and the Netherlands (lines 10 and 11) is higher than in the Static case.

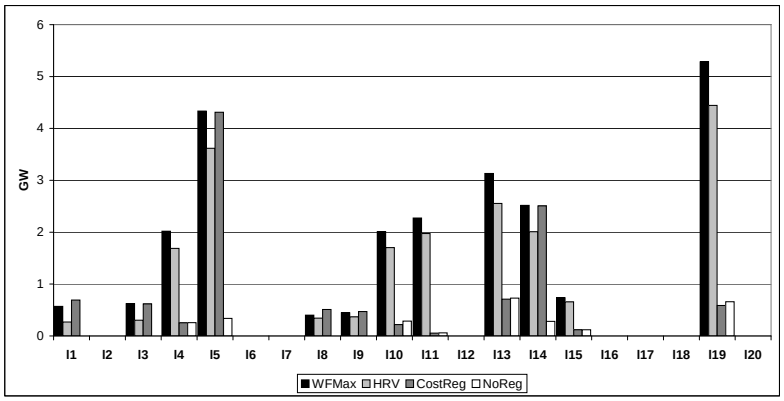


**Figure 4.8:** Line extension in the DRes case

As before, we find that HRV regulation leads to an expansion of all the lines of the welfare-maximizing benchmark. However, HRV-triggered expansion is slightly less close to the welfare-optimum compared to the Static case. In the cost-based regulatory case, the Transco invests in all lines that are expanded in the welfare-maximizing benchmark. Some lines are even expanded beyond the welfare-optimal level because of an additional return on costs (lines 1, 8, and 9). Yet the lines that lead to the highest congestion rents are hardly expanded (lines 4, 13, 15, 19) – a similar finding as in the Static case. Under NoReg, only minor network extension takes place. Under both NoReg and CostReg, the Transco tries to preserve as much fluctuation-related congestion rent as possible.

Figure 4.9 shows the time path of line extensions in the DRes case. While the general results are similar to the Static case, the overall level of network extension is higher. What is more, extensions under HRV regulation increase more slowly compared to the Static case. Obviously, HRV regulation needs more time to approach the welfare-optimal extension level in a more realistic setting.

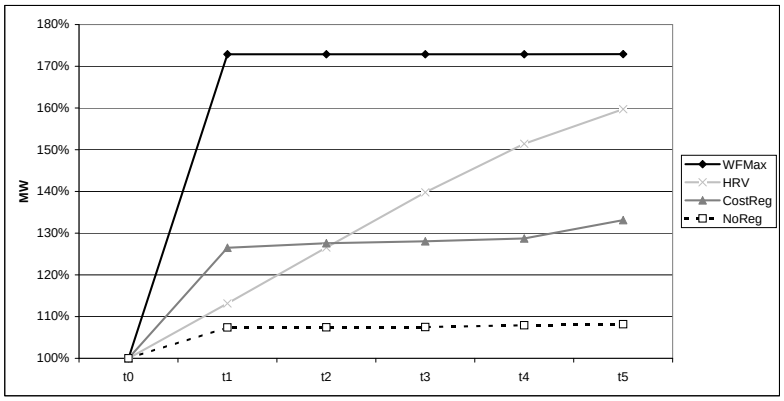


**Figure 4.9:** Time path of overall extension in the DRes case

Figure 4.10 shows hourly prices (six representative days) for Germany and France before and after network expansion. It can be seen that prices in Germany hardly change during most hours. Prices increase in winter peak periods due to additional exports, but decrease in summer off-peak periods due to imports of cheap base load power from France. French prices generally increase during summer because of exports of cheap base load power to the Benelux countries and – to a lower extent – to Germany. During winter peak periods, French prices slightly decrease.

Figure 4.18 in Appendix 4.A.4 shows price convergence over all country nodes for the different cases. It can be seen that the high level of network expansion in WFMax leads to nearly perfect price convergence between the nodes during most hours. The same is true for the HRV case – with the exception of some off-peak prices, during which network congestion is lower. In contrast, both NoReg and CostReg lead to much lower price convergence, as the lines with the highest congestion rents are not sufficiently expanded in these cases. Price convergence in the DRes case is generally highest in winter peak periods and lowest in summer periods with lower demand levels.

Given the price effects discussed above, Table 4.5 lists welfare differences between the different regulatory approaches and the baseline without extension for the DRes case. Looking at WFMax again, we find a larger social welfare gain of network investments compared to the Static case. Simplifying modeling assumptions may thus lead to a substantial underestimation of both expansion requirements and related welfare gains. The distributional effect of transmission investments on producer and consumer rents is qualitatively the same as in the Static case, but much less pronounced. In particular, consumer rents decrease less, as exports from Germany and France no longer increase in all periods. Congestion rents and Transco profits in WFMax decrease more than in the Static case due to higher network investments.

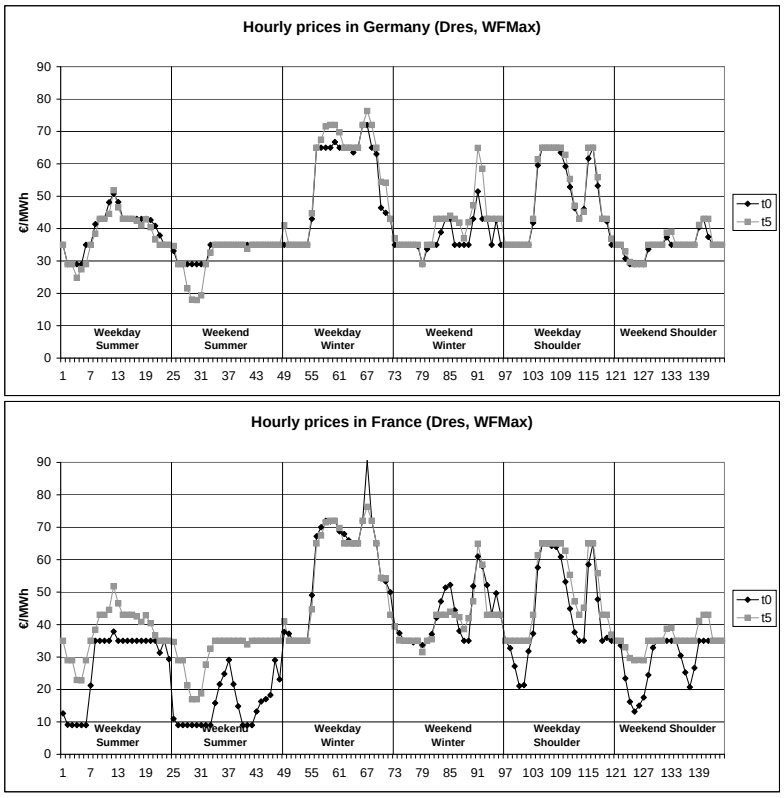


**Figure 4.10:** Hourly prices in France and Germany before and after extension for WFMax and DRes

**Table 4.5:** Welfare results in DRes: Differences to baseline in bn €

| | Social welfare | Producer rent | Consumer rent | Congestion rent | Extension costs | Transco profit | Fixed part |
|---|---|---|---|---|---|---|---|
| WFMax | +2.80 | +11.13 | -5.97 | -2.27 | +0.08 | - | - |
| NoReg | +1.10 | +1.82 | -1.13 | +0.42 | +0.01 | +0.41 | - |
| CostReg | +1.06 | +1.77 | -1.08 | +0.41 | +0.04 | +0.42 | +0.04 |
| HRV | +2.25 | +6.59 | -3.62 | -0.68 | +0.04 | +1.79 | +2.51 |

Comparing social welfare outcomes among different cases, we find again that HRV regulation is still closest to the welfare-maximizing benchmark, although HRV's relative welfare performance compared to WFMax slightly decreases from Static to DRes. The reason for this finding is that the network extension path approaches the social optimum more slowly. Both NoReg and CostReg once more lead to much lower welfare gains of extension, but to better results than in the Static case. We thus conclude that the positive welfare properties of the HRV mechanism are robust to modeling demand fluctuations. Looking at congestion rents, results resemble the Static case, although they are more pronounced. The extension-related decrease in congestion rents is again largest in WFMax. HRV leads to a smaller decrease, whereas NoReg and CostReg once more increase network congestion. Note that network extension costs are roughly the same in CostReg and HRV, but social welfare outcomes of the HRV case are much better. As shown above, this is because the Transco has an incentive to invest in the wrong lines

under CostReg. The fixed part that is necessary to align the Transco's incentives with a socially desirable extension path is even larger than in the Static case. The fixed part outweighs congestion rent losses, such that Transco profits are again highest under HRV regulation. Given the findings discussed in this section, we conclude that using a detailed representation of demand has important implications for modeling transmission network expansion and for assessing the performance of different regulatory approaches.

### 4.5.3 The case with fluctuating wind (WindRes)

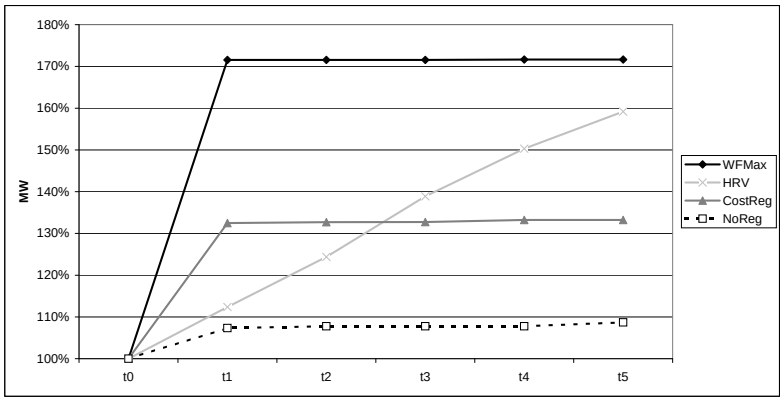


**Figure 4.11:** Time path of overall extension in the WindRes case

Finally, we examine the WindRes case, which includes not only demand fluctuations, but also fluctuating wind power feed-in. Line extensions in WindRes are very similar to the DRes case. As shown in Figure 4.11, we also find a similar extension path as in DRes, which approaches the welfare-optimal level, but does not yet reach it in the final period $t_5$. Accordingly, including fluctuating wind power does not lead to major changes of extension results.

As for electricity prices, results are also similar to DRes, although we find slightly lower convergence in WindRes due to wind power fluctuations. Table 4.6 provides an overview of welfare results in the WindRes case. It can be seen that there are only small changes compared to DRes outcomes. In general, producers are slightly worse off compared to DRes, as wind peaks decrease prices in some periods.

**Table 4.6:** Welfare results WindRes: Differences to baseline in bn €

| | Social welfare | Producer rent | Consumer rent | Congestion rent | Extension costs | Transco profit | Fixed part |
|---|---|---|---|---|---|---|---|
| WFMax | +2.82 | +11.46 | -6.31 | -2.25 | +0.08 | - | - |
| NoReg | +1.09 | +1.81 | -1.15 | +0.44 | +0.01 | +0.43 | - |
| CostReg | +1.09 | +1.99 | -1.30 | +0.44 | +0.05 | +0.44 | +0.05 |
| HRV | +2.30 | +6.80 | -3.69 | -0.76 | +0.04 | +1.79 | +2.59 |

We conclude that including fluctuating wind power in the model leads only to small changes in the outcomes compared to DRes case. This result may be surprising at first glance, but can be explained by the relatively low importance of wind fluctuations in

the light of the overall generation pattern in the central European electricity system of 2009. Accordingly, the beneficial welfare properties of the HRV mechanism also hold in a case with fluctuating wind power. From a modeling perspective, our results show that it is important to represent demand in a realistic way. If this is achieved, fluctuating wind power may be neglected – at least as long as its market share is as low as today. In section 4.5.4.1, we check if this results still holds under the assumption of much-increased wind generation capacity.

### 4.5.4 Sensitivity analyses

#### 4.5.4.1 More regulatory periods

Increasing the number of modeled regulatory periods does not change the general outcomes. The relative performance of HRV regulation slightly improves though, as the benefits of incremental network extension are larger in later periods. Figure 4.12 shows that the network expansion in the HRV case is very close to the social optimum in the last regulatory periods. Modeling a smaller number of regulatory periods thus leads to an underestimation of HRV's welfare benefits. For $t_0$-$t_5$, HRV regulation achieves 80% of the extension-related social welfare gains of the welfare-maximizing benchmark in DRes. In the $t_0$-$t_{10}$ run, this number increases to 87%. Accordingly, HRV's welfare implications are slightly better than suggested by the previously discussed results, if a more realistic time horizon is applied.

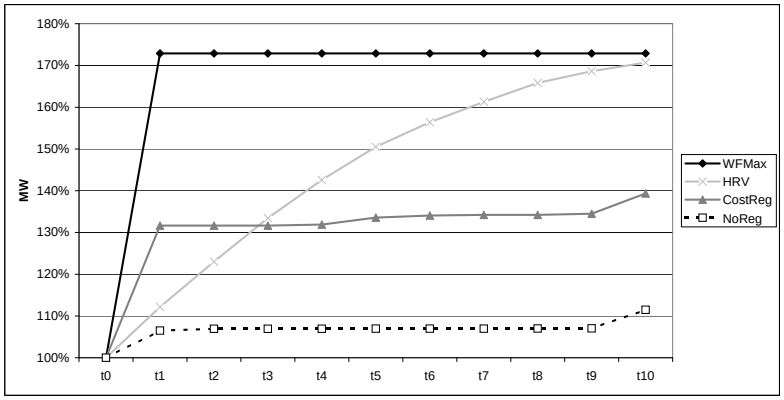


**Figure 4.12:** Time path of overall extension in the DRes case for $t_0$-$t_{10}$

However, increasing the number of regulatory periods from six ($t_0$-$t_5$) to eleven ($t_0$-$t_{10}$) increases execution time for a full model run from around 70 hours to around 270 hours. As the major results do not change, we conclude that modeling $t_0$-$t_5$ is sufficient for adressing our research questions.

#### 4.5.4.2 Higher extension costs

We test the sensitivity of results to our assumption on network extension costs. All previous results have been calculated with costs of 100 €/(MW*km). This value reflects

the costs of incremental upgrades of existing lines and has also been used by Rosellón and Weigt (2011). Yet incremental line upgrades may not always be possible. If it becomes necessary to build new lines from scratch, extension costs may be much higher. We test the effect of different values up to 1000 €/(MW*km) for the DRes case. Figure 4.13 shows that overall extension levels generally decrease with increasing costs. Yet larger cost assumptions decrease the gap between HRV extension results and WFMax: for values of 1000 €/(MW*km), HRV regulation nearly achieves the welfare-optimal extension level.

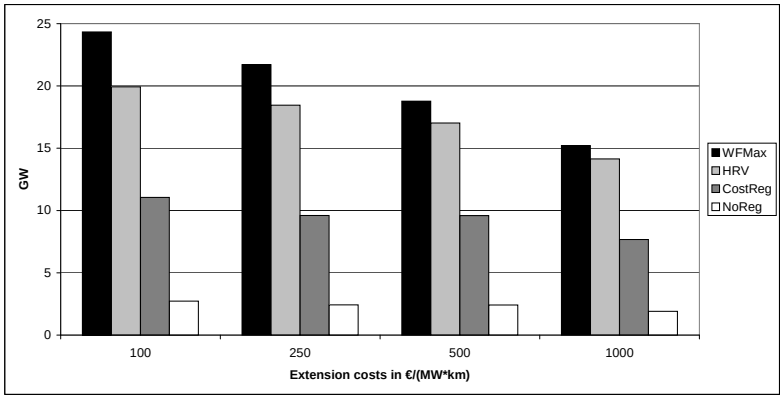


**Figure 4.13:** Overall extension in DRes for different cost assumptions

Figure 4.14 shows social welfare outcomes for the different cases (differences to baseline without extension in bn €). While extension-related social welfare gains slightly decrease with increasing extension costs – due to lower extension –, the welfare findings discussed above are very robust.

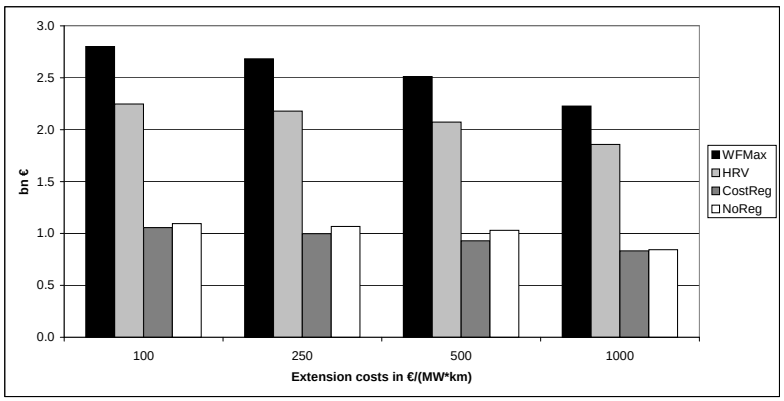


**Figure 4.14:** Welfare results in DRes: Differences to baseline without extension in bn € for different extension costs assumptions

We conclude that increasing extension costs lead to a moderate decrease of network extension and moderate decrease of extension-related welfare gains in all cases. However, the general results do not change. In particular, the relative performance of the HRV mechanism compared to WFMax and to the other regulatory approaches is robust. Interestingly, the fixed tariff part under HRV regulation does not increase with increasing

extension costs, but slightly decreases. Nonetheless, the fixed part is still substantially larger than extension costs even in the case with 1000 €/(MW*km).

#### 4.5.4.3 Higher wind feed-in

In section 4.5.3, we have shown that including fluctuating wind power at 2009 levels hardly changes results. We now check if this conclusion is still valid in a setting with much higher wind capacity. We assume that the available wind capacity in all nodes quadruples (WindRes_x4) and run the model again. Figure 4.15 indicates the differences in line extension between the cases WindRes and WindRes_x4. It shows that increasing wind power increases the optimal amount of overall network investments because of higher (temporary) congestion. In particular, the cross-border lines between Germany and the Netherlands are being expanded (lines 1 and 4). This is because increasing wind capacity leads to a substantial price decrease in Germany, in which the largest wind capacity is assumed to be installed. Accordingly, network congestion between Germany and the Netherlands increases. In addition, lines within the Netherlands (lines 6 and 8) are expanded in order to transmit additional wind power. In contrast, lines between the Netherlands and Belgium (lines 10 and 11) as well as lines between Belgium and France (13 and 14) are slighty less expanded in WindRes_x4 compared to WindRes, as German wind power substitutes exports of nuclear power from France to the Netherlands.

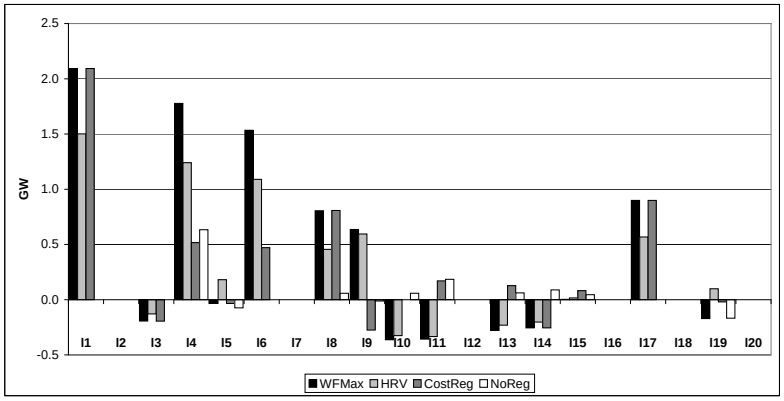


**Figure 4.15:** Line extension differences between WindRes and WindRes_x4

Table 4.7 shows the related welfare results. It can be seen that even under the extreme assumption of quadrupling wind power no general result changes signs compared to WindRes. As for social welfare, a larger capacity of unevenly dispersed wind power increases the welfare gain of network extension, as more congestion is relieved. The extension-related increase in producer rents is lower than in WindRes, whereas consumer rents decrease less. The reason for both effects is that the additional line expansion increases Germany's exports of cheap wind power, which in turn harms producers and benefits consumers in other countries. In both the welfare-maximizing benchmark and the HRV case, extension costs increase by around 30% compared to WindRes. However, the fixed tariff part, which is required to align the Transco's incentives with the socially

**Table 4.7:** Welfare results WindRes_x4: Differences to baseline in bn €

| | Social welfare | Producer rent | Consumer rent | Congestion rent | Extension costs | Transco profit | Fixed part |
|---|---|---|---|---|---|---|---|
| WFMax | +3.65 | +7.01 | -0.6 | -2.67 | +0.11 | - | - |
| NoReg | +1.69 | +1.35 | -0.26 | +0.60 | +0.01 | +0.59 | - |
| CostReg | +1.67 | +1.44 | -0.32 | +0.60 | +0.05 | +0.60 | +0.05 |
| HRV | +3.05 | +4.72 | -0.91 | -0.71 | +0.05 | +2.36 | +3.13 |

preferable extension path, also increases to more than €3 billion over the six modeled regulatory periods.

#### 4.5.4.4 Endogenous line reactance

All results discussed so far have been calculated under the assumption that line reactance does not change with capacity expansion. We perform a sensitivity analysis for all major cases under the more realistic assumption of endogenous line reactance according to equations (4.6b) and (4.6c). Figure 4.19 in Appendix refendoglinereact shows the differences in line extension between endogenous and exogenous line reactance for the cases Static, DRes, and WindRes. For the Static case, the major difference is that lines at the borders between Germany and the Netherlands (line1), Germany and France (lines 5 and 19), within Germany (lines 2 and 3), and within the Netherlands (line 8) are being expanded under NoReg. Note that none of these lines is congested, i.e. expanded in the welfare-maximizing benchmark. By upgrading these lines, the Transco manages to substantially increase network congestion on other lines, more precisely between France and Belgium and between Belgium and the Netherlands. In other words, including endogenous line reactance opens up new market power potentials for the Transco. As a consequence, NoReg leads to less desirable outcomes than in the simplifying runs with constant line reactance. Under CostReg, the Transco can not apply this strategy, as it is only allowed to invest in the lines that are being expanded in the welfare-maximizing benchmark. Figure 4.19 shows that the effects in both the DRes and the WindRes case are less straightforward. Considering endogenous line reactance increases the optimal extension level for some lines, but decreases it for others.

As for welfare outcomes, results do not change much between endogenous and exogenous line reactance. Figure 4.16 shows differences in social welfare for all regulatory cases. The only major differences concern HRV and NoReg in the simplified Static case. Here, modeling endogenous reactance moderately decreases the social welfare gain of extension compared to assuming exogenous reactance. Accordingly, we may have overestimated HRV's performance in the Static case (although HRV still leads to much better welfare results compared to CostReg and NoReg). However, a major point of this research is that the simplified Static case leads to misleading results, anyway, and that it should be substituted by the more realistic DRes and WindRes cases. In these cases, we find hardly any social welfare differences between the runs with endogenous and exogenous line reactance. The same is true for producer, consumer and congestion rents.

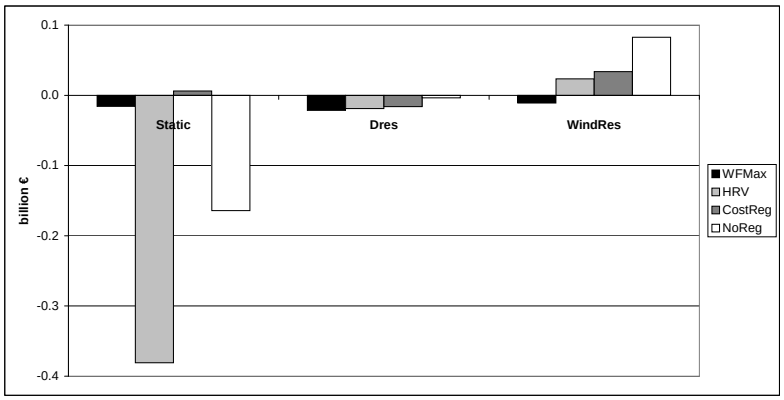


**Figure 4.16:** Social welfare differences between endogenous and exogenous reactance for Static, DRes, and WindRes

Given these results, we conclude that modeling endogenous line reactance has an impact on the locations and the levels of line extension in the different cases. Yet the welfare findings in DRes and WindRes are very similar to the ones determined under the assumption of exogenous line reactance. Making line reactance an endogenous variable substantially increases execution time for a full model run from around 70 hours to more than 230 hours the DRes case. In addition, finding globally optimal solutions gets more challenging. Given the robustness of welfare results, we conclude that our simplifying assumption of exogenous line reactance is justified in order to get meaningful solutions in acceptable execution time.

#### 4.5.4.5 A robust finding: HRV's welfare properties

Figure 4.17 gives an overview of extension-related social welfare gains in all modeled cases relative to the respective welfare-maximizing benchmark (WFMax = 100%). We find that the relative welfare outcomes are very robust over all model runs. HRV regulation is always closest to the welfare optimum. In particular, HRV achieves at least 80% of the socially optimal welfare gains in the DRes and WindRes cases with realistic representations of fluctuating demand and wind power. In contrast, both NoReg and CostReg lead to much lower welfare gains, whereas the NoReg case – which refrains from incentivizing investments – is slightly superior to cost-based regulation in most cases (except the Static case with endogenous line reactance).

## 4.6 Summary and conclusions

We have studied the performance of different regulatory regimes for transmission network expansion in the light of realistic demand patterns and fluctuating wind generation by applying them to a power-flow model of the central European transmission network. In contrast to earlier research, we explicitly include both an hourly time resolution and fluctuating wind power, which substantially increases the real-world applicability of the different approaches. In doing so, we have also adapted the HRV model so as to in-

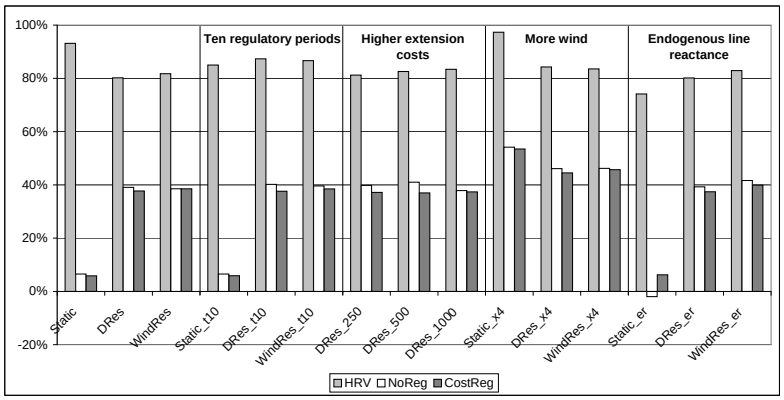


**Figure 4.17:** Social welfare gain of extension compared to WFMax for different model runs

corporate the peculiarities of large-scale RES systems, especially regarding wind power. Mathematically, the problem was formulated as an MPEC model (mathematical problem with equilibrium constraints). Such an application of the HRV mechanism to wind power goes beyond the existing literature which focuses on markets with traditional (mostly fossil fuel) electricity generation only. However, applying the existing HRV regulatory model to markets with large-scale RES requires some strong assumptions (e.g., on the volatility of wind and the short-term dispatching needs) which calls for a future extension of the current model.

Drawing on realistic demand levels, reference prices, and generation capacities, we showed that network extension in central Europe relieves existing congestion and thus increases social welfare. However, this also leads to a large redistribution of social welfare from consumers to producers in France and Germany. Comparing different regulatory approaches, we find that HRV regulation leads to extension and welfare outcomes close to the social optimum. HRV's welfare outcomes are superior to the modelled alternatives of cost-based regulation (CostReg) and a merchant-like approach without additional investment incentives (NoReg). This result is robust over all modelled cases. NoReg leads to inferior welfare results because the Transco finds only very small line extensions profitable. Under cost-based regulation, less congested lines are thoroughly expanded, but there are substantial under-investments for the most congested ones. In contrast, the HRV-mechanism provides the Transco with incentives to expand the network such that congestion is relieved. Accordingly, our numerical results support the theoretical claim by Hogan et al. (2010) that HRV regulation aligns the Transco's incentives with social welfare objectives.

From our analysis, we draw both methodological and policy-related conclusions. On a methodological level, we conclude that details matter in electricity transmission network modeling. In particular, analyzing the real-world implications of different regulatory approaches to transmission expansion requires a detailed representation of fluctuating electricity demand. Only then it is possible to achieve robust results on the location and the level of line upgrades, and the related welfare implications, in particular the relation

of welfare gains, extension costs and fixed income of the Transco. In contrast, a simplified approach systematically underestimates the need for transmission upgrades. We also find that the effect of fluctuating wind power is of minor importance compared to demand fluctuations – at least at the current level of installed wind capacity in central Europe. Drawing on a range of sensitivity analyses, we also show that some simplifications are justified in order to maintain acceptable execution time.

Another more general problem of performance-based regulatory mechanisms is their inconsistency with timing issues of transmission networks. A framework based on the distinction of ultra-short periods, short periods and long periods would then be especially useful in future applications (Vogelsang, 2006). These timing frameworks are especially relevant for the application of regulatory PBR mechanisms – such as the HRV model – to electricity systems characterized by large shares of fluctuating RES technologies, in particular wind and PV. There exists a gap in the literature on such analysis that future research should to fill out.

Finally, we also draw some policy conclusions. Given our numerical results, we can not expect that a Transco in central Europe invests properly in transmission lines without being granted additional incentives. Accordingly, the modeled NoReg approach is not a preferable option for real-world policy makers. Yet cost-based regulation following our CostReg approach is an even less promising option, as it does not provide sufficient incentives for the Transco to invest in the most important lines. In addition, cost-based regulation requires the regulator to have substantial information on network congestion. In contrast, HRV regulation is an option that leaves extension decisions completely to the profit-maximizing Transco, while at the same time leading to desirable welfare outcomes. Moreover, we have shown that its beneficial welfare properties are very robust against fluctuations of demand and wind feed-in. In the light of future large-scale wind integration requirements, HRV regulation may also have favorable characteristics, as it triggers relatively high network extension. In the real world, the large-scale integration of wind power is not only constrained by limited transmission capacity, but also by imperfect foresight and thermal ramping restrictions. Although we did not model these aspects, it is clear that the large network expansion triggered by HRV regulation is generally good for wind integration.

It should be noticed that that the benefits of HRV regulation are related to a relatively large fixed tariff part. The fixed part constitutes a transfer from the Transco's variable income (congestion rents) to its fixed income. Our analysis, however, shows that the fixed part is larger than congestion rent losses, such that overall Transco profit increases substantially. According to our results, the Transco receives the major part of extension-related welfare gains. This constitutes a redistribution of extensions-related gains in producer and consumer rents toward the Transco. This distributive issue could be addressed through a proper choice of weight of profits in the welfare criterion, which is subject to future research. Likewise, the real-world benefits of HRV regulation as modeled in this chapter are put into question by the existence of imperfectly competitive

dispatch in European electricity markets, which may interfere with the optimal HRV expansion paths calculated in this analysis. Last, but not least, HRV regulation would have to be reconciled with the political reality of incentive regulation, which has only recently been introduced in most European countries. For the time being, policy makers in Europe resort to theoretically less efficient, but practically enforceable approaches, at least regarding to such transmission projects that are most urgently required for the integration of renewable energy. Still, the HRV model could provide a benchmark for efficient price signals for investment.

Further research projects in these issues would then be especially timely given the current policy efforts to achieve RES integration within Europe as well as the political progress toward the creation of a fully functional European energy regulator. A leading novel approach on incentive mechanism design for energy transmission networks would be particularly relevant for Europe, where less sophisticated regulatory mechanisms applied so far have not yielded sufficient transmission investment. Formal research on the interdependency of renewable energy and electricity transmission pricing and investment is highly relevant in this context.

# 4.A Appendix

## 4.A.1 Sets, indices, parameters, and variables

**Table 4.8:** Sets, indices, parameters, and variables

| Symbol | Description | Unit |
|---|---|---|
| **Sets and indices** | | |
| $n, nn \in N$ | Nodes | |
| $l \in L$ | Lines | |
| $s \in S$ | Generation technologies | |
| $t \in T$ | Regulatory periods | Years |
| $\tau \in T$ | Dispatch periods | Hours |
| **Parameters** | | |
| $m_{n,\tau}$ | Slope of demand function | |
| $a_{n,\tau}$ | Intercept of demand function | |
| $\overline{g}_{n,s}$ | Maximum hourly generation capacity | MWh |
| $c_s$ | Variable generation costs | €/MWh |
| $ec_l$ | Line extension costs | €/MWh |
| $\epsilon$ | Price elasticity of demand at reference point | |
| $P_l^0$ | Initial line capacity | MW |
| $I_{l,n}$ | Incidence matrix | |
| $X_l^0$ | Initial line reactance | Ω |
| $B_{n,nn,t}$ | Network susceptance matrix of period $t$ | 1/Ω |
| $slack_n$ | Slack node (assumes value 1 for one node, 0 for all others) | |
| $\delta^s$ | Social discount rate | |
| $\delta^p$ | Private discount rate | |
| $r$ | Return on costs (in case of cost-based regulation) | |
| **Variables** | | |
| $wf$ | Social welfare | € |
| $\Pi$ | Transco profit | € |
| $q_{n,t,\tau}$ | Hourly demand | MWh |
| $g_{n,s,t,\tau}$ | Hourly generation | MWh |
| $p_{n,t,\tau}$ | Hourly electricity price | €/MWh |
| $\Delta_{n,t,\tau}$ | Voltage angle | |
| $\lambda^1_{l,t,\tau}$ | Shadow price of positive line capacity constraint | €/MWh |
| $\lambda^2_{l,t,\tau}$ | Shadow price of negative line capacity constraint | €/MWh |
| $p_{n,t,\tau} = \lambda^3_{n,t,\tau}$ | Shadow price of market clearing constraint (electricity price) | €/MWh |
| $\lambda^4_{n,s,t,\tau}$ | Shadow price of generation capacity constraint | €/MWh |
| $\lambda^5_{n,t,\tau}$ | Shadow price of slack constraint | €/MWh |
| $ext_{l,t}$ | Line extension | MW |
| $P_{l,t}$ | Line capacity of period $t$ | MW |
| $X_{l,t}$ | Line reactance of period $t$ | Ω |
| $fixpart_t^{CostReg}$ | Fix tariff part in case of cost-based regulation | € |
| $fixpart_t^{HRV}$ | Fix tariff part in case of HRV regulation | € |

### 4.A.2 ISO's constrained welfare maximization problem

$$\max_{\substack{q,g,\Delta,\\ \lambda^1,\lambda^2,p,\\ \lambda^3,\lambda^4,\lambda^5}} \Pi = \sum_{t\in T}\left[\sum_{\tau\in T}\sum_{n\in N}\left(\int_0^{q^*_{n,t,\tau}} p_{n,t,\tau}(q_{n,t,\tau})dq_{n,t,\tau} - \sum_{s\in S} c_s g_{n,s,t,\tau}\right)\frac{1}{(1+\delta^s)^{t-1}}\right] \tag{4.7a}$$

$$s.t. \quad \sum_n \frac{I_{l,n}}{X_{l,t}}\Delta_{n,t,\tau} - P_{l,t} \leq 0 \qquad (\lambda^1_{l,t,\tau}) \qquad \forall l,t,\tau \tag{4.7b}$$

$$-\sum_n \frac{I_{l,n}}{X_{l,t}}\Delta_{n,t,\tau} - P_{l,t} \leq 0 \qquad (\lambda^2_{l,t,\tau}) \qquad \forall l,t,\tau \tag{4.7c}$$

$$\sum_s g_{n,s,t,\tau} - \sum_{nn} B_{n,nn,t}\Delta_{nn,t,\tau} - q_{n,t,\tau} = 0 \qquad (p_{n,t,\tau}) \qquad \forall n,t,\tau \tag{4.7d}$$

$$g_{n,s,t,\tau} - \overline{g}_{n,s} \leq 0 \qquad (\lambda^4_{n,s,t,\tau}) \qquad \forall n,s,t,\tau \tag{4.7e}$$

$$slack_n \Delta_{n,t,\tau} = 0 \qquad (\lambda^5_{n,t,\tau}) \qquad \forall n,t,\tau \tag{4.7f}$$

### 4.A.3 Generation capacity at different nodes

**Table 4.9:** Generation capacity at different nodes in MW

| | **Nuclear** | **Lignite** | **Hard coal** | **CCGT** | **Gas turbine** | **Oil** | **Hydro** | **Wind** | **Sum** |
|---|---|---|---|---|---|---|---|---|---|
| GER | 14,750 | 15,120 | 19,800 | 8,024 | 7,480 | 5,576 | 1,403 | 23,895 | 96,048 |
| F | 45,547 | 0 | 10,440 | 748 | 4,522 | 2,312 | 8,394 | 3,422 | 75,385 |
| BE1 | 2,976 | 0 | 1,226 | 1,667 | 482 | 1,040 | 32 | 162 | 7,586 |
| BE2 | 1,218 | 0 | 502 | 683 | 198 | 426 | 13 | 162 | 3,201 |
| NL1 | 236 | 0 | 1,994 | 3,372 | 2,321 | 2,080 | 0 | 716 | 10,720 |
| NL2 | 47 | 0 | 400 | 677 | 466 | 418 | 0 | 716 | 2,724 |
| NL3 | 83 | 0 | 702 | 1,187 | 817 | 732 | 0 | 716 | 4,238 |
| Sum | 64,858 | 15,120 | 35,064 | 16,358 | 16,286 | 12,584 | 9,841 | 29,790 | 199,902 |

### 4.A.4 Price convergence in DRes

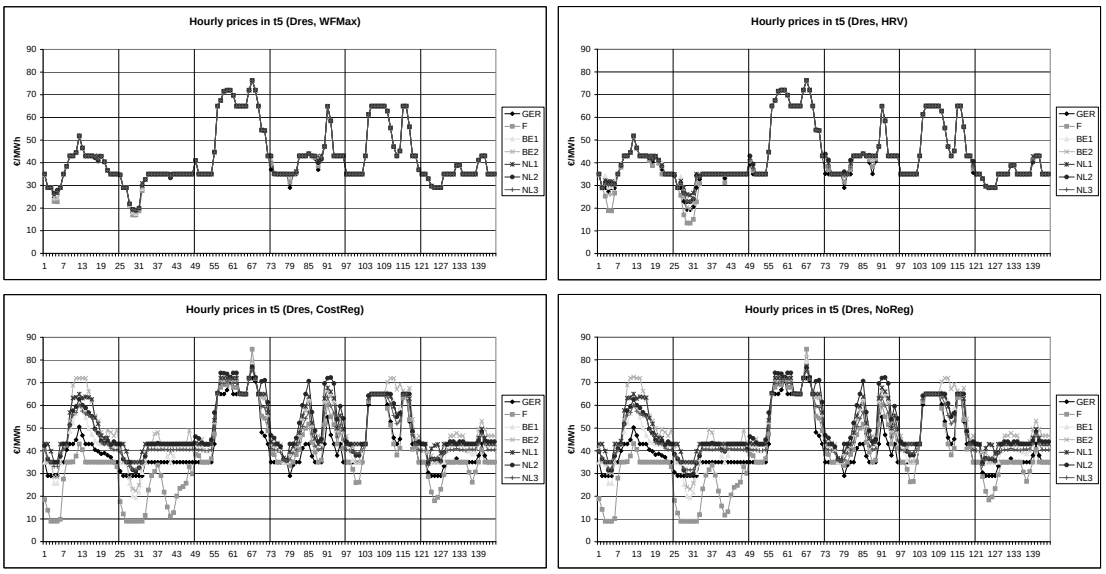


**Figure 4.18:** Convergence of hourly nodal prices under different regulatory approaches in DRes

### 4.A.5 Effect of endogenous line reactance on extension results

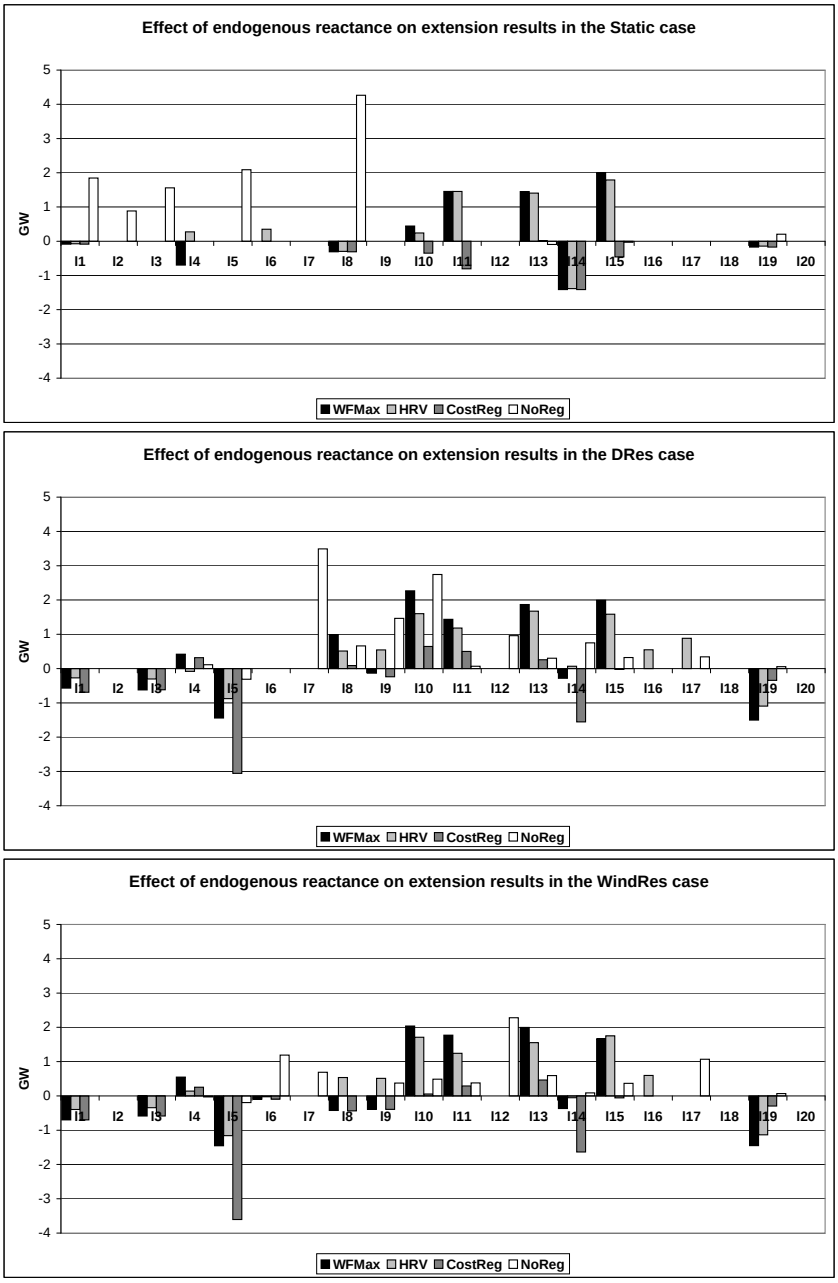


**Figure 4.19:** Line extension differences between endogenous and exogenous reactance for Static, DRes, and WindRes

# Chapter 5

# How emission certificate allocations distort fossil investments: the German example

## 5.1 Introduction and literature

The previous chapters examine the effects of competition-related market failures, i.e. oligopolistic dispatch (chapters 2 and 3) and natural monopolies in transmission (chapter 4). In contrast, the research presented in the following is motivated by environmental externalities, which constitute another important instance of market failure. More precisely, this chapter deals with unintended economic effects of German carbon regulation – which is introduced to internalize $CO_2$ emission externalities – on power plant investments.

During the last years, considerable investments in new coal capacity were brought on the way in the German electricity sector. In total, ten plants are currently under construction, which after completion will add around 11.3 GW to the market (BUND, 2010). Besides, there are plans for more than 12 additional plants. Taking together all projects – the majority of them hard coal – possible expansions amount to approximately 32% of German peak electricity demand in 2008 (Bundesnetzagentur, 2009). Realizing that for several years after liberalization in 1998 natural gas was the predominant option (Brunekreeft and Bauknecht, 2006), this development constitutes a dramatic shift in technology choice.

In a hierarchical analysis, Pahle (2010) explores drivers and decision factors that may have given rise to this "dash for coal". Among them, the German national allocation plans (NAPs) of the EU Greenhouse Gas Emissions Trading System (ETS) have presumably played an important role by providing free certificates for new entrants according to fuel specific benchmarks – see overviews by the German Emissions Trading Authority at the Federal Environment Agency (DEHSt, 2005) for NAP I and Schleich et al. (2009) for NAP II. For conventional fossil fuels this implies that the "dirtier" technology coal re-

ceived a higher absolute allocation than its "cleaner" competitor natural gas. Electricity generators were able to generate windfall profits by passing through opportunity costs – see for example Sijm et al. (2006) and Zachmann and von Hirschhausen (2008). Accordingly, investment incentives were biased toward the dirty technology. This distortion has been widely acknowledged in the literature, for example by Ellermann (2008) and Neuhoff et al. (2006a,b). In this chapter, we use a numerical model to quantify the effects of German allocation rules on thermal investment decisions in Germany around 2005. We find that the windfall profits created by NAP I have further increased an already existing preference for coal investments compared to natural gas. In contrast, counterfactual allocation rules like full auctioning of permits or a single best available technology benchmark would have substantially increased natural gas investment incentives.

Research to assess and quantify the created economic incentives has been surprisingly sparse so far. Kemfert et al. (2006) analyze several environmental and economic effects of European emissions trading. However, they do not explicitly examine power sector investment incentives. In an interview-based study of investment decisions in the German power sector, Hoffmann (2007) draws an ambiguous picture of the EU ETS influences. On the one hand, investments still depend on fundamentals, in particular on fuel prices and respective scenarios. On the other hand, there is evidence that "current projects are only profitable due to the development of the EU ETS" and "did not work out in 2003 due to the (...) non-existence of the EU ETS". Additional support comes from numerical models, albeit applied to other countries (for example, Burtraw and Palmer, 2008). For the UK, Neuhoff et al. (2006b) confirm additional coal power plant investments, but also acknowledge that results may invert if assumptions on gas prices and investor expectations are changed. Laurikka and Koljonen (2006) compare investment opportunities for gas and coal plants in Finland under uncertainty, using stochastic electricity and certificate prices. They conclude that the allowance market can have a significant impact on the expected profitability of gas plants, whereas the value of new coal plant investment remains mainly unaffected. Because they do not take account of passed-through opportunity costs and windfalls profits, their results fall short of assessing the above mentioned investment distortion. One of the few contributions so far explicitly integrating windfall profits is Taschini and Urech (2009), who analyze how expected windfall profits will affect operation and profitability of different technologies. They find that when opportunity costs are internalized, there is a shift toward coal-fired generation somewhat contrary to intuition. However, they use a rather stylized model and a fixed allocation regime not adapted to any particular market. In summary, the distortionary effect of a fuel-specific new entrant reserve and windfall profits on investment and technology has not been quantified for Germany so far (Hentrich et al., 2009). This chapter aims to fill this literature gap, where the above described "dash for coal" suggests that respective distortions in fact played an important role.

Our analysis is based on a discounted cash flow (DCF) model similar to Laurikka and Koljonen (2006) who use a stochastic price distribution. Investment options are evaluated

by their overall performance in the market according to the net present value (NPV) criteria. Related literature applies real options methods (see for example Reedman, 2006; Blyth et al., 2007; Reinelt and Keith, 2007; Szolgayova et al., 2008; Patiño-Echeverri et al., 2009), which considers the value from obtaining information on future uncertainty. These models, however, rely on an exogenous stochastic price process. In contrast, we deterministically compute both the price of electricity and the quantity a plant can sell endogenously, based on a detailed representation of demand and supply (merit order). A comparable method has been used for example by Weigt and von Hirschhausen (2008) for an analysis of short term market power in the German wholesale market. Other applications include the impact of carbon pricing on cycling costs Denny and O'Malley (2009). In this case, combining DCF with a merit order representation poses the distinctive advantage to have a bottom-up representation of fuel costs and allocation schemes. Due to this prices and cash flows can be determined by means of fundamentals, which is an essential requirement in face of our research question.

We retrospectively look at 2005 when the ETS became effective. From this point of reference, we analyze the bias created by free allocation of certificates for either hard coal or natural gas toward the choice of a pending capacity investment. Doing so implicitly assumes that both technologies are the only viable alternatives.[65] Effectively, this breaks down to a comparison of relative rather than absolute profitability, which proves to have important influence on methodology and calibration. An important point in this regard is that we do not intend to capture actual investment decisions, but rather quantify the relative impact on profitability of different technologies.

We also investigate the impact of the length of the period with free allocation on investment decisions. In particular, we are interested in how its length will affect the investment value through the cash flow over the plant's lifetime. A crucial role is played by the discount factor, which determines how important the investor considers future revenues. For example, a high discount factor enforces the effect of an initial free allocation period because the investor puts less weight on future gains, and vice versa. Bergerson and Lave (2007) compare investment values under different schedules for carbon taxation and discount rates (private, social). In accordance to their findings our results also suggest that the interplay of discounting and transitional policy periods may be of high importance for power sector investments. Nonetheless, we find that shorter free allocation periods would not have been sufficient to reverse the economic preference for coal under initial allocation rules (NAP I).

Although our analysis has a retrospective focus, we touch a very topical issue here as several currently unresolved questions could benefit from hindsight. For example, the discussion about initial allocation and efficiency of a trading scheme currently seems to gain new momentum (Hahn and Stavins, 2010). However, sound scientific evidence of this issue is yet far from comprehensive (see, for example, Convery, 2009). Especially inframarginal rents due to free allocation as well as the particular rationality of certificate

[65] For further argumentation that this indeed was the case in Germany see Pahle (2010).

costs pass-through are still only roughly quantified and vaguely understood (Keppler and Cruciani, 2010). Our findings may thus sharpen understanding and provide helpful information for the design of future allocation schemes.

The remainder of this chapter is structured as follows. Section 5.2 introduces the methodology and the model. Section 5.3 includes all relevant data and parameters. Section 5.4 discusses the results. The last section summarizes and concludes.

## 5.2 Methodology and model

### 5.2.1 Investment rationale

We model the investment decision of a generator building a new centralized fossil power plant of typical size (1000 MW). The technologies $k$ under comparison are hard coal and natural gas. The preferred technology is determined by the relative difference of the net present values over the financial lifetime $T_{FL}$ between either option.

The primary cash flow of the plant is determined by two factors: the overall number of hours the plant can sell to the market (full load hours) and the price of electricity $p_t^{el}$ in respective periods.[66] The electricity price is derived endogenously from the merit order based on generators' supply bids and (exogenous) demand in the market. Demand is represented by different periods $j$ subsuming hourly fluctuations over the year. It is characterized by demanded quantity in $d_j$ and duration $hr_j$. We assume marginal cost pricing, thus in each of these periods the electricity price equals the generating costs of the marginal plant. In consequence the new plant sells to the market if demand exceeds its specific position in the merit order, i.e. when it is submarginal as specified in the generation subset of demand $GEN$. Thus the generator acts as a price-taker implying that the new capacity is small compared to the overall market and not part of a larger portfolio which could offer strategic options.[67] Other operating constraints like ramping times are excluded for sake of simplicity.

The cost of generating electricity consists of two parts. First, variable costs depending on the fuel price $p_{k,t}^{fuel}$ and the price of $CO_2$ certificates $p_t^{CO_2}$; and second, capital costs per unit $c_k^{cap}$ for the initial investment and fixed O&M costs $c_k^{OM}$ per year. Yet only the variable costs do affect price formation. To compute fuel and emissions costs, the thermal efficiency $\eta_k$ of the technologies is required. Moreover, the number of $CO_2$ certificates required for compliance is determined by the carbon emission factor $cef_k$, which specifies emissions per unit of fuel used. We allow for asymmetric cost pass-through by differentiating between actual costs of generation – which include full carbon costs – and generators' supply bids $bid_{k,t}$ to the wholesale market. Accordingly, a generator's bid may include only a fraction of the full $CO_2$ costs, which is expressed by the pass-trough rate $ptr_{k,t}$. We provide further explanation and a rationale for asymmetric cost

[66] We assume that the plant just sells electricity to the German wholesale market. We neglect possible additional revenues from the balancing market, as this market is beyond the scope of this research.

[67] This corresponds best to an independent power producer operating a single merchant plant.

pass-through in Section 5.2.2.

Another essential feature of the model is the inclusion of two succeeding periods of emission trading: at first, for a certain time span $T_{FA}$, permits are allocated for free according to a certain scheme which quantifies the allocation $alloc_k$ per MW installed capacity and year (see Section 3).[68] This endowment – multiplied by plant size and $CO_2$ price – constitutes an additional positive cash flow. During the second period, extending over the remaining years $T_{AUC}$, permits are auctioned and must fully be bought from the permit market, which implies a purely negative secondary cash flow and thus no windfall profits.

The NPV is evaluated over the financial lifetime of the potential plant. It comprises the initial capital expenditure as project costs and the sum over the future discounted profits as cash flow. The discount rate $\delta$ used is understood as a specific mark-up inherent to the project that resembles the associated risks and thus the investor's myopia. The overall model reads (see Table 5.1 for a description of sets, indices, parameters, and variables):

$$\begin{aligned} NPV_k = &- cap_k c_k^{cap} \\ &- \sum_{t \in T_{FL}} cap_k c_k^{OM} (1+\delta)^{-t} \\ &+ \sum_{t \in T_{FA}} \left[ \sum_{j \in GEN_{k,t}} (p_{j,t}^{el} - c_{k,t}^{el}) cap_k hr_j + alloc_k cap_k p_t^{CO_2} \right] (1+\delta)^{-t} \\ &+ \sum_{t \in T_{AUC}} \left[ \sum_{j \in GEN_{k,t}} (p_{j,t}^{el} - c_{k,t}^{el}) cap_k hr_j \right] (1+\delta)^{-t} \end{aligned} \tag{5.1}$$

where

$$c_{k,t}^{el} = \frac{p_{k,t}^{fuel} + p_t^{CO_2} cef_k}{\eta_k} \tag{5.2}$$

$$bid_{k,t} = \frac{p_{k,t}^{fuel} + ptr_{k,t} p_t^{CO_2} cef_k}{\eta_k} \tag{5.3}$$

$$GEN_{k,t} = \left\{ j \mid p_{j,t}^{el} \geq bid_{k,t} \right\} \tag{5.4}$$

### 5.2.2 Price formation, generation, and $CO_2$ cost pass-through

An important feature of our analysis is the endogenous determination of electricity prices and full load hours to compute the NPV of a new plant. In order to do so, we make use of a detailed structural representation of the underlying market to create the merit order, i.e. the aggregated supply curve of all power plants. Figure 5.1 shows the stylized

[68] We assume free allocation without ex-post correction. Generators receive a certain amount of certificates which is not adjusted later on according to actual electricity generation.

**Table 5.1:** Sets, indices, parameters, and variables

| Symbol | Description | Unit |
|---|---|---|
| **Sets and Indices** | | |
| $t$ | Year index relative to base year (2005) | |
| $k$ | Technology index: hard coal (HC), natural gas (NG) | |
| $j$ | Demand period index | |
| $T_{FL}$ | Financial life time in years over which the NPV is evaluated | |
| $T_{FA} \subseteq T_{FL}$ | Subset of $T_{FL}$ in which certificates are allocated for free | |
| $T_{AUC} \subseteq T_{FL}$ | Subset of $T_{FL}$ in which certificates are auctioned | |
| **Exogenous Parameters** | | |
| $cap_k$ | Capacity of the model plant | MW |
| $d_j$ | Demand | MW |
| $hr_j$ | Number of hours per year in which demand equals $d_j$ | hour |
| $c_k^{cap}$ | Capital costs | €/MW |
| $c_k^{OM}$ | O&M costs | €/(MW·a) |
| $p_{k,t}^{fuel}$ | Fuel price | €/MWh$_{th}$ |
| $p_t^{CO_2}$ | Price of $CO_2$ certificates | €/t |
| $c_{k,t}^{el}$ | Variable costs of electricity | €/MWh$_{el}$ |
| $alloc_k$ | Annual free allocation of certificates | t/MW |
| $\eta_k$ | Thermal plant efficiency | |
| $cef_k$ | $CO_2$ emission factor | t/MWh$_{th}$ |
| $\delta$ | Discount rate | |
| $ptr_{k,t}$ | Technology-specific pass-through rate of $CO_2$ costs | |
| **Endogenous Variables** | | |
| $p_{j,t}^{el}$ | Electricity price set by bid of marginal plant | €/MWh |
| $bid_{k,t}$ | Supply bid to market | €/MWh |
| $GEN_{k,t} \subseteq j$ | Subset of all demand periods where new capacity can sell to market | |

German merit order and demand distribution in the reference year for given fuel prices (see Section 5.3 for data and assumptions). It comprises all available generation capacity according to their short-run marginal costs, from renewables on the left to peaker plants on the right side.

Over the course of a year, demand varies to a considerable extent; overlaid lines in Figure 5.1 represent annual fluctuations. Due to the marginal cost pricing assumption a plant sells to the market during all periods in which demand exceeds its specific position in the merit order. In turn, given the frequencies of occurrence for different demand levels, this determines the number of full load hours.

Both electricity prices and plant-specific full load hours are highly dependent on the merit order. One of its essential characteristics in this regard is the stepped shape due to the different technologies with distinct cost structures. All capacity of equal technology are represented by a plateau that gradually rises from left to right, corresponding to a decreasing efficiency from new plants (left edge) to older plants (right edge). Less efficient capacity require a higher amount of fuel per unit output, resulting in higher marginal costs.[69] If a market based regulation of $CO_2$ is introduced, compliance costs are added to marginal costs. Figure 5.2 shows the modified German fossil merit order[70] with a carbon

[69]Natural gas plants include both gas turbines and combined cycle natural gas, which explains the jump in marginal costs within the gas block.

[70]In the following we will concentrate on the relevant fossil section of the merit order (lignite, hard coal, natural gas) were all relevant effects take place.

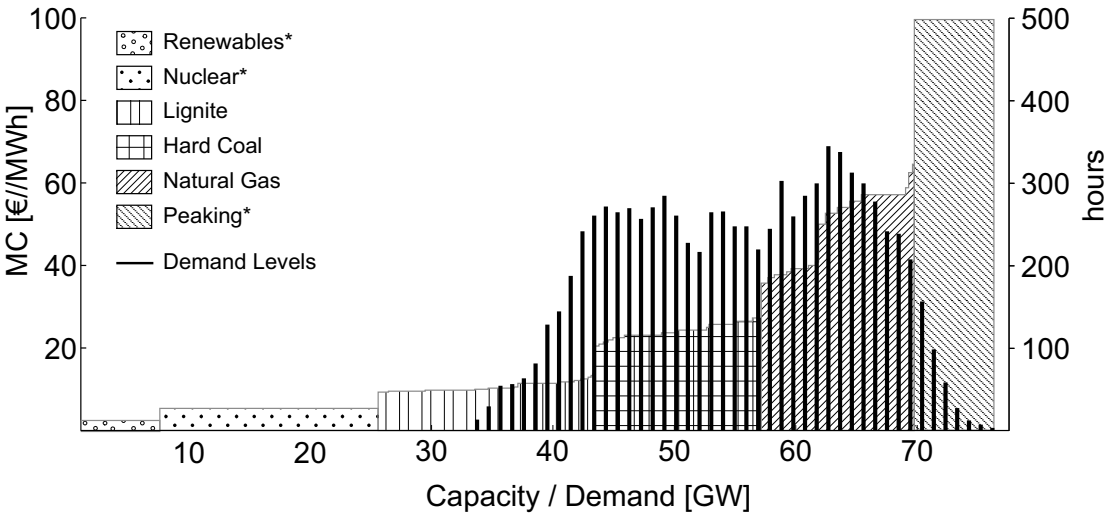


**Figure 5.1:** Stylized German merit order and demand distribution in reference year, without carbon costs (UBA, 2009; ENTSO-E, 2010a, own calculations); *stylized representation

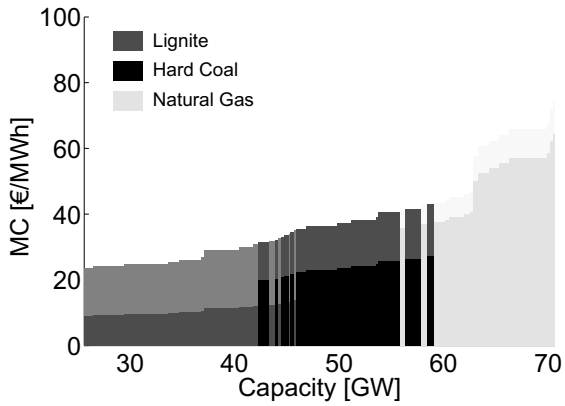


**Figure 5.2:** German fossil merit order (2005) with carbon costs of 15 €/t (lighter shades)

price of 15 €/t, which is fully added to variable costs (lighter shades indicate $CO_2$ costs).

It can be seen that the strict separation into coherent blocks dissolves. This happens because technologies with low fuel costs are disproportionally affected by $CO_2$ costs due to higher emission intensity, in particular lignite and hard coal. As a result, the least efficient plants of one technology block "change positions" with the most efficient plants of the block to the right. That is, old lignite overlaps with new hard coal, and old hard coal with new natural gas. In consequence, the general shape of the merit order also becomes flatter, and the discontinuities between different technologies dissolve.

Under this situation relevant changes accrue to (a) the overall price formation in the market, and (b) the extent to which every single plant can sell to the market. The effect on prices (a) is global and emerges out of the increase of marginal costs in disproportion to fuel costs: the average level rises whereas the overall range is reduced due to the now flatter supply curve. The effect on generation (b) however is plant-specific: the modified marginal costs under $CO_2$ regulation may lead to a change of position of this plant in

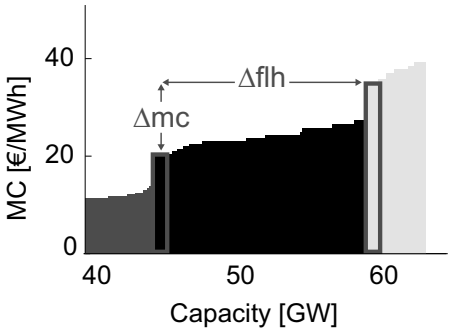


**Figure 5.3:** Merit order: New plants without $CO_2$ costs

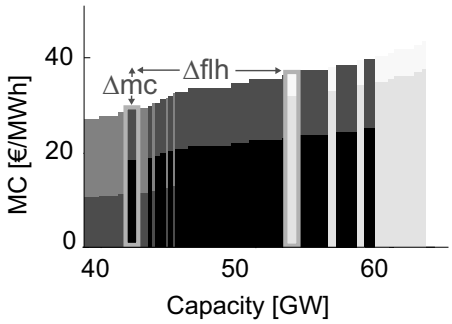


**Figure 5.4:** Merit order: New plants with $CO_2$ costs

the merit order as explained above. In consequence, it can either increase or decrease its generation with a leftward or rightward shift respectively.

Figures 5.3 and 5.4 show the effect of new capacity in more detail. They depict the position of the assumed model plant alternatives in the merit order (grey outlines). Without $CO_2$ pricing (Figure 5.3), both plants are located at the left outer edge of their respective technology blocks and are relatively far apart. With $CO_2$ pricing however (Figure 5.4), blocks dissolve and the distance is reduced. This corresponds to a lower difference in annual full load hours $\Delta flh$, depending on the exact distribution of demand in between. Moreover, the flatter shape of supply under $CO_2$ pricing also reduces the total marginal cost differential $\Delta mc$ between the two options.

This situation would arise if carbon prices were fully added to variable generation costs. If we neglect strategic behaviour or inter-period constraints in electricity generation, it can be expected that rational market players pass through $CO_2$ costs completely to electricity prices. This holds for the case in which certificates are auctioned, but also in a setting where permits are grandfathered or allocated for free without ex-post correction. A profit-maximizing generator has to decide between (a) not generating electricity and selling the permits on the market, and (b) generating electricity and using the permits as a production factor. Generation will thus be an optimal choice only if the profit of generating electricity in case (b) does not fall below the profit of selling the permits in case (a). Accordingly, full pass-through is in principle a fully rational strategy.

Nonetheless, empirical analyses draw a different picture. For example, Sijm et al. (2006) show that pass-through rates in Germany reached 100% in peak times, but only around 60% in off-peak times.[71] In fact, agreement on the guiding rationalities for pass-through at lower rates than 100% is still pending; for a recent overview of arguments see Keppler and Cruciani (2010). Power plant owners may have a preference for generating electricity rather than selling permits, even if it is the less profitable alternative. Another explanation for incomplete pass-through may be that rates were chosen according to technical constraints, namely operating constraints and related costs. Whereas natural gas plants are very flexible, coal plants generally have considerable ramping and start-

[71] Fell (2010) conducts an empirical estimation for the Nordic electricity market and finds that – in the short run – pass through rates are close to 100% also in off-peak times.

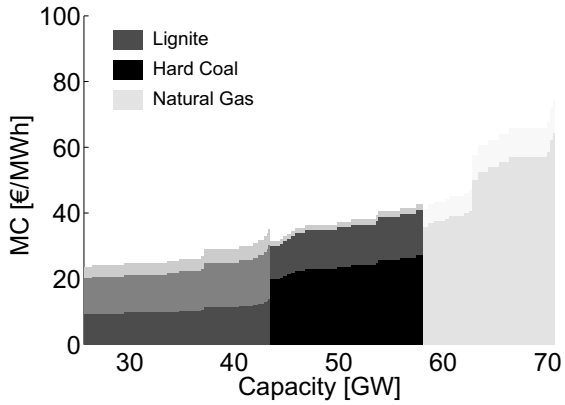


**Figure 5.5:** German fossil merit order (2005) with carbon costs of 15 €/t and flexibility-constrained cost pass-through

up constraints which also affect total plant lifetime (compare Nollen, 2003). A coal generator may find it thus more profitable to sell electricity below marginal costs in a given period than to stop generation during this period and face the ramping-related costs. In order to fully capture this effect, it would be necessary to use a bottom-up electricity generation model which includes inter-period constraints. As this is beyond the scope of this chapter, we focus on technology-specific average pass-through rates that are constant over all hours of a year. We believe these annual average pass-through rates serve well to understand investment incentives over a longer period, as studied in this paper.

Following this line of argument, we assume that coal generators have a preference to retain their "old" position in the merit order. Lignite and hard coal operators set pass-through rates such that technology blocks persist and fuel switch is avoided. This corresponds to a merit order as shown in Figure 5.5, in which shares not passed-through are indicated in light grey. It has been calculated by using the following heuristic: all gas plants are perfectly flexible and thus apply pass-through rates of 100%. The least efficient hard-coal plant chooses its pass-through rate such that it stays left of the most efficient gas plant. All other hard coal plants adjust their pass-through rates such that they stay left of the least efficient hard coal plant. The same procedure applies to the lignite plants. Performing this calculation for 2005 results in pass-through rates of 77% for lignite and 89% for hard coal.[72] Accordingly, generation technologies with lower technical flexibility have lower pass-through rates. Note that our rationale for asymmetric pass-through rates is based on technical considerations, not on market imperfections (compare also Fell, 2010).

The heuristic results in the merit order are shown by Figure 5.5. In addition, we conduct a sensitivity analysis in section 5.4.3 in which the pass-through rate is equal to 100% for all technologies. By doing so, we assess the sensitivity of results to our assumption on technology-specific pass-through rates.

[72]Thus rates found are here are somewhere between the findings of Sijm et al. (2006) and full pass through. A higher $CO_2$ price assumption would result in lower rates closer to Sijm et al.

### 5.2.3 Limitations

The main benefit of our approach lies in making several quantities endogenous, which both is a requirement for our research questions and increases plausibility. Nonetheless, the overall methodology has some shortcomings. There are a number of influencing factors not taken account of that affect generation, price formation and investment rationales in electricity markets. First, as Blyth (2010) and Pahle (2010) point out, in practice the uptake of a certain technology may be influenced by other factors like technological spillovers, additional regulatory biases, or the adherence to an established industrial structure. Second, on short time scales capacity outages, intermittent renewable generation, and ramping constraints lead to contractions and left- or rightward shifts of the fossil block in the overall merit order; also compare Weigt and von Hirschhausen (2008). Third, over the course of the NPV evaluation period the market structure and generation mix are not static, but develop over time as new plants are built or old plants are decommissioned. Taking account of these would require a market investment model, which is both beyond the scope of this chapter and in many ways still considered as a challenge (see, for example, Lise and Kruseman, 2008). Consequently we only operate with a static snapshot of the generation mix in 2005, leaving future investments – even foreseeable ones – aside. And fourth, if the new plant would be built by a generator owning additional plants, then the investment would be optimized given the whole portfolio. Such investment decisions may fundamentally differ from the ones modeled here. We acknowledge this by restricting our model to only capture a single merchant plant as explained above.

In summary, claiming that the resulting NPVs would be the only criterion for deciding on an investment of a certain technology is beyond the potential of our approach. Rather, NPV differences can be understood as one of many contributing factors that we measure by means of the described methodology and its restrictions. Notwithstanding these limits, our intention is not only to quantify the overall outcome, but also to shed light on the micro dynamic effects within the merit order out of which the NPV differences emerge. In fact, because of the investment assessment in relative rather than absolute terms, we level out several of the described distortions as they apply to both hard coal and natural gas capacity. By doing so, we reduce the main element of our analysis to the section of the merit order that separates the potential new hard coal plant from the potential new natural gas plant, namely the segment serving intermediate load.[73] It is essentially this section that determines the difference in NPVs and explains the primary impact of free allocation vs. auctioning.

[73] In Figure 5.1 and Figure 5.5 for example, that section is identical to the full block of hard coal capacity.

## 5.3 Model application

### 5.3.1 EU ETS and German allocation rules

EU ETS allocation rules were implemented by National Allocation Plans (NAP) for Phase I (2005-2007) and II (2008-2012) respectively.[74] In Germany a so called "new entrant" reserve provided certificates to newly built capacity based on technology-specific benchmarks derived from the "best available technology" (BAT).[75] Both NAP I and NAP II define benchmarks of 0.75 $tCO_2$/MWh for hard coal and 0.365 $tCO_2$/MWh for natural gas respectively (Bundesgesetzblatt, 2004a, 2007). However, designs differ considerably with regard to how many years a new plant is entitled to receive free allocation. NAP I grants free certificates for 14 years after commissioning (see Åhman et al., 2007)[76], whereas NAP II restricts provisions to Phase II regardless of when exactly the plant started operation; it thus covers a maximum of five years only. In addition, the NAPs differ in their assumptions on plant utilization, which has an important impact on the actual number of certificates allocated to a plant. NAP I basically guarantees coverage of total annual emissions from power generation by considering the expected yearly production of a plant (Bundesgesetzblatt, 2004a). Accordingly, new coal power plants receive more certificates than new natural gas plants not only explicitly due to higher technology-specific benchmarks, but also implicitly because of higher full load hours. In contrast, NAP II follows a less discriminatory approach by assuming 7500 full load hours per year for either technology. Table 5.2 provides an overview of the allocation for the model power plants (1000 MW).[77]

**Table 5.2:** Annual allocations for model power plants (1000 MW) under NAP I and II

| | **NAP I** | **NAP II** |
|---|---|---|
| Hard coal | 5.25 Mt/a for 14 years (0.75t/MWh·7000h·1000MW) | 5.625 Mt/a for up to 5 years (0.75t/MWh·7500h·1000MW) |
| Natural gas | 2.0075 Mt/a for 14 years 0.365t/MWh·5500h·1000MW | 2.7375 Mt/a for up to 5 years 0.365t/MWh·7500h·1000MW |
| Distortion toward coal | 3.2425 Mt/a | 2.8875 Mt/a |

Considering that the value of emission certificates will be (partly) passed-through to customers, the new entrant provisions break down to a considerable economic advantage

[74] Ziesing et al. (2007) and DEHSt (2009) provide excellent overviews of the development of German allocation rules and the related political debate.

[75] This approach contrasts with the grandfathering mechanism, which has been used for existing power plants, drawing on historic emissions.

[76] Later on, the European Commission decided that free allocation provisions of NAP I had to be restricted to the first ETS period. Nonetheless, we assume that investors in 2005 anticipated 14 years of free allocation. We further assume that there was no ex-post correction of free allocation, although this issue was not settled in Germany around 2005.

[77] We assume that new hard coal plants typically supply base load (about 7000 full load hours per year) and natural gas plants supply intermediate load (5500 full load hours per year), drawing on Konstantin (2007).

for hard coal due to the higher absolute allocations. The distortion was even higher in NAP I than in NAP II because of a longer duration and an allocation based on actual emissions. The relevant question thereby is whether the NAP revision induced a change in technology preference or retained the original one.

The German ETS was initiated with a pledge to generators guaranteeing free permit allocation to new plants for 14 years according to production needs (NAP I). Even though planning and constructing a power plant takes several years, early action and rapid realization could well have led to timely commissioning. Consequently, we use the total length (14 years) in the model application. Yet we do not restrict the analysis to the effects of the factual NAP I allocation, but also investigate investment incentives under the assumption that NAP II would have been applied from the beginning instead of NAP I. We also study the implications of two other counterfactual allocation rules: full auctioning (AUC) of all permits as well as the application of a single best available technology benchmark (SBAT), which explicitly favors carbon-efficient installations (Schleich et al., 2009). Under SBAT allocation rules, the extent of free permit allocation is determined by the requirements of the lowest-emission technology, i.e. natural gas plants. Such an approach was initially planned to be implemented in Germany, but policy makers finally decided to apply a technology-specific benchmark in NAP I, largely because of industry concerns (Ziesing et al., 2007). In addition, we analyse a case without $CO_2$ regulation (NoREG) in order to establish a reference case.

Under any allocation mechanisms, the price for $CO_2$ certificates is both an important model parameter and a crucial element for determining windfall profits. For our ex-post analysis, it is important which expectations investors had at the base year 2005 about the long-term price development. As the market was newly created and subject to many distortions, it all but provided a stable signal and forecasts were rather vague. In this regard, Capoor and Ambrosi (2006) report that during 2003 and 2004 "forward trading mostly responded to political and regulatory expectations rather than to market fundamentals". In fact, early estimates mainly relied on what the EU was envisaging and communicating to stakeholders. In 2003, Point Carbon (2003) reported that the EU Commission indicated a level of 15 €/t. However, during the first emissions trading year 2005 it actually turned out that prices stabilized at 20-25 €/t. Regarding price development, Point Carbon (2006) concluded at the end of 2005 that the market already responded to the fundamentals of power generation, which possibly indicated future price increases in the same order of magnitude as fuel prices. As investors may well have anticipated additional pressure on the price through tighter political targets in the future, even higher expectations on price increases appear justified.

Following this argument and taking account of early signals, we assume an initial price of 20 €/t in 2005 and a yearly real growth rate of 2% in the baseline (compare Table 5.5). In alternative scenarios, we assume a lower price path (15 €/t in 2005, +1% p.a.) and a higher one (25 €/t in 2005, +3% p.a.). These paths should cover many of the scenarios that actually existed on the investors' side. In particular, the implied extreme

cases of around 18 and 45 €/t in 2025 represent the range of possible future emission prices widely discussed. It also should be noted that according to 2005 regulations we exclude the possibility of banking and borrowing certificates. Banking would have allowed investors to save up certificates that could be sold later on when $CO_2$ prices were higher. However, as discounting devalues banked certificates at higher rates (5-10%) than the increasing price of $CO_2$ would increase their value of (1-3%), banking would not have been an economic alternative whatsoever.

### 5.3.2 Fuel costs

In 2005, border trade prices for hard coal and natural gas were around €8 and €16 per $MWh_{th}$ respectively (BMWi, 2010). Transport and trading mark-ups added, final costs for power generation amounted to €9.1 and €20.0 per $MWh_{th}$ (Konstantin, 2007). As regards forecasts around 2005, costs had already increased around 50% for both fuels between 2000 and 2005. According to the IEA World Energy Outlook (WEO), an increasing spread between coal and gas in long run price scenarios was expected around 2005. In the WEO 2004 reference scenario, hard coal prices were thought to increase by 16% until 2030 (annual price increase of +0.6%), while natural gas prices were projected to grow by around +27% during the same time (+0.9% p.a.) (IEA, 2004). Only one year later, IEA's expectations on hard coal prices dropped significantly to -7% until 2030 (-0.3% p.a.), while natural gas prices were projected to grow by even +33% during the same period (+1.1% p.a.) (IEA, 2005). We use these different price projections in alternative scenarios applying average yearly growth rates of +0.15% p.a. for coal and +1.0% p.a. for natural gas in the baseline (copmare Table 5.5).

As for other technologies than hard coal and natural gas, we assume zero fuel costs for renewable energy sources. This ensures that available renewable capacity are always operated (must-run) and represents priority feed-in according to the German Renewable Energy Sources Act (EEG). For peaker plants, which consist of oil and diesel plants as well as pumped hydro storage, we assume fuel costs of 100 €/$MWh_{el}$ (Konstantin, 2007).[78] As a consequence, renewable sources are located at the very left side of the merit order, whereas peaker plants are at the very right side. Fuel cost for nuclear and lignite plants are around 3.5 €/$MWh_{el}$ and 4.0 €/$MWh_{th}$, respectively.[79] We assume fuel costs for other technologies than hard coal and natural gas to be constant in all scenarios.

### 5.3.3 Capital and O&M costs

While economic conditions for fuel costs turned in favor of hard coal around 2005, capital costs developed in the very opposite direction. In 2004, specific investment costs were around 400 €/kW for natural gas and around 800 €/kW for hard coal capacity

[78]The exact price level is not relevant for the modeling results as it levels out by only looking at relative NPVs.

[79]Note that fuel costs for renewables, peaker technologies, and nuclear power plants are related to electricity generation, while fuel costs for all other technologies are related to the thermal energy content.

(Konstantin, 2007). Only two years later, costs had increased to around 500 €/kW for gas and 1100 €/kW for coal plants, mainly due to high global demand for power plants and increased prices for steel and copper (Konstantin, 2009). According to a study by trend:research, new hard coal capacity was even estimated to be as expensive as 1500 €/kW by 2007 (Flauger, 2007). This disproportionate growth in costs may have decreased the relative attractiveness of hard coal, and a number of projects especially by smaller suppliers have indeed been cancelled due to this reason (see Pahle, 2010). The relevance of this development is also analyzed in Section 5.4, where we quantify the effect of increased capital costs (+50% for hard coal, +25% for natural gas).

It should be noted that our above assumptions refer to overnight costs, which do not comprise costs of financing due to either advance expenditures before construction (turnkey costs) or annuity based payoff (fixed charge rates). Both schemes imply additional interest on capital, and thus would require calculating final investment costs based on the discount rate. Even though this is in general more realistic, it is also very specific to both projects and investors and thus hard to implement properly (see Section 5.3.6). That said, and in face of our focus on allocation schemes, we ignore the details on how the investors finance the project and thus how the capital cost is paid off. This approach is in line with standard cost assumptions for electricity modelling.

Aside from investment costs, we consider fixed costs for operation and maintenance (O&M) in the model application. We assume yearly O&M costs of 37.8 €/kW for hard coal and 30.3 €/kW for natural gas in the baseline run (Konstantin, 2007).

### 5.3.4 Generation capacity

For the conventional fossil supply structure of the German market, we draw on public data provided by UBA (2009).[80] We exclude combined heat and power plants for which the merit order dispatch mechanism is not applicable due to heat-controlled operation. In total we consider 150 conventional fossil plants, out of which 52 are lignite, 50 are hard coal, and 48 are natural gas. The overall installed gross capacity are 20.8 GW, 19.0 GW and 12.8 GW respectively. We derive net available generation capacity drawing on average plant availabilities and other technology-specific factors provided by Konstantin (2007). The thermal efficiency is derived on a plant-by-plant basis according to an age-efficiency correlation established by Schröter (2004).

In addition to fossil capacity, the overall supply structure also includes nuclear, renewable and peaker plants. We derive the nuclear capacity of 2005 and its average net availability from the sources mentioned above (Konstantin, 2007; UBA, 2009). As for renewables, their overall installed capacity amounted to 27 GW in 2005 (BMU, 2006). Due to the high share of wind, we only consider average annual availability, which amounts to approximately 7 GW. Peaking capacity consisted mainly of oil and pumped hydro plants (UBA, 2009). Table 5.3 lists the available net generation capacity of all included technologies. These capacity form the merit order based on ranked short-run marginal

[80] We only consider plants that were commissioned before 2005.

**Table 5.3:** Net available capacity of different generation technologies

| Technology | Capacity (GW) | Cumulated capacity (GW) |
|---|---|---|
| RES | 7.1 | 7.1 |
| Nuclear | 18.4 | 25.6 |
| Lignite | 17.8 | 43.3 |
| Hard coal | 13.7 | 57.0 |
| Natural gas | 12.6 | 69.6 |
| Peaker | 8.4 | 78.0 |
| **Total** | **78.0** | |

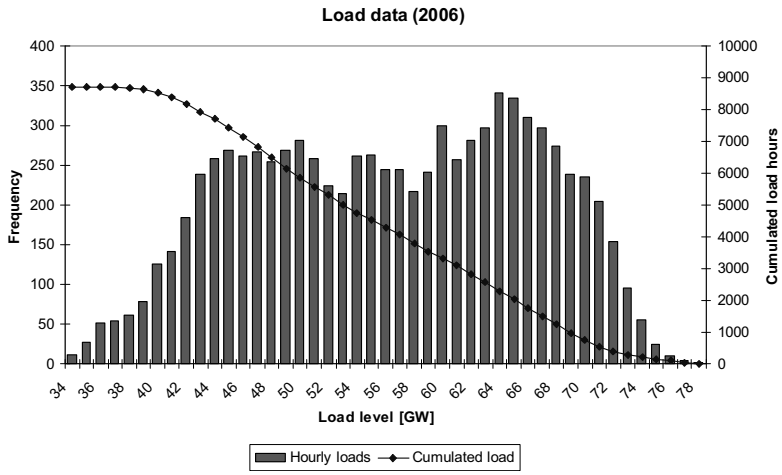


**Figure 5.6:** Load distribution in 2006 (ENTSO-E, 2010a)

costs, which is shown in Figure 5.1.

### 5.3.5 Demand

For demand assumptions we draw on load data provided by ENTSO-E (2010a).[81] Figure 5.6 shows both the distribution of hourly loads in the German network and cumulated load hours for different demand levels. Demand ranged from around 33 GW to a peak value of 78 GW. In order to determine the marginal plant and thus the price of electricity for every hour of the year, we align the load distribution and the merit order derived from the generation capacities listed in Table 3.2. We find that demand fluctuations span from lignite over hard coal and natural gas up to the peaker plants. Thus RES, nuclear and some lignite plants are always in operation, which resembles the real market very well. To compare our model with empirical operational characteristics of fossil power plants, we use cumulated load frequencies to estimate average full load hours for the installed plant capacity of each technology. As shown in Table 5.4, they fit empirical values for 2004 provided by VDEW (as cited in VGB PowerTech, 2005) quite well.[82]

[81] We use data for 2006, since data for 2005 is not available. It is reasonable to assume that German electricity demand pattern did not change significantly between 2005 and 2006. ENTSO-E was formerly known as the Union for the Co-ordination of Transmission of Electricity UCTE.

[82] Here, we use data for 2004 because from 2005 on, empirical full load hours already reflect the impact of certificate pricing.

**Table 5.4:** Estimated model full load hours and empirical values for 2004 for different fossil technologies

| | **Model full load hours (averages)** | **Empirical full load hours 2004 (VGB PowerTech, 2005)** |
|---|---|---|
| Lignite | 7410 | 7230 |
| Hard coal | 4748 | 4460 |
| Natural gas | 2424 | 2730 |

Due to unavailability of data for all hours of the year we excluded cross-border trade with other countries; both exports and imports in 2005 were in the order of 10% of total generation, while the net balance was small. However, this should pose only a minor problem since we focus on the relative profitability of two investments, such that deviations from the real world cancel out. Including trade would be much more relevant in an analysis that aims to reproduce real hourly market outcomes, as for example in Weigt and von Hirschhausen (2008). Furthermore we explicitly aimed to improve the methodology used in similar studies in the grey literature. For example, Garz et al. (2009) only make use of five characteristic demand levels, by which they try to capture daily fluctuations. In doing so they neither describe a method for finding particular levels, nor do they crosscheck resulting full load hours to empirical data. In contrast to this approach we conjecture our representation as considerably more grounded in empirical facts.

With regard to the future development, we assume that demand persists at the 2005 levels for mainly two reasons. First, we can only speculate about growing or falling demand for the next years. There are good reasons for future trends in both upward (economic growth, substitution of other energy carriers by electricity) and downward (energy efficiency, elasticity to higher prices) direction. Second, even if demand changes to some extent, it is unlikely to affect our results, because we only look at NPV differences. These differences are solely determined by the section of the demand distribution that is located between the coal and the gas plant. As indicated by Figure 5.1, coal and gas are located at the center of the demand distribution that is relatively even. Hence a moderate shift in one or the other direction would not change results much.

### 5.3.6 Discount rates and financial lifetime

Net present value calculations require using a discount rate. It reflects the time value of money or the rate of return if the capital is invested in alternative projects, and also comprises a project specific risk mark-up. Thus it depends on specific projects and is generally hard to estimate empirically (Timmins, 1997; Ishii and Yan, 2004). In this context, we draw on a standard discount rate assumption for investments in electricity generation capacities of 7.5%. It represents the mean value of 5% and 10%, which are used by the International Energy Agency (IEA, 2010a). These rates seem commonly agreed; for instance, Fleten et al. (2007) and Patiño-Echeverri et al. (2009) use 5%, whereas Gross et al. (2010) use 10%. The financial lifetime, over which cash flows are

**Table 5.5:** Overview of model parameters. Real numbers, monetary value 2005.

| Parameter | Baseline | Alternative scenarios | Source |
|---|---|---|---|
| $T_{FL}$ in years | 20 | - | Own assumptions drawing on Lindenberger and Hildebrand (2008) |
| $T_{FA} \subseteq T_{FL}$ in years | NAP I: 14<br>NAP II: 5 | 0-20 years of free allocation, full auctioning (AUC), or single best available technology (SBAT) | Bundesgesetzblatt (2004a, 2007) |
| $T_{AUC} \subseteq T_{FL}$ in years | NAP I: 6<br>NAP II: 15 | | |
| $cap_k$ in MW | Hard coal: 1,000<br>Natural gas: 1,000 | -<br>- | Own assumptions |
| $c_k^{cap}$ in €/kW | Hard coal: 800<br>Natural gas: 400 | Hard coal: 1,200 (+50%)<br>Natural gas: 500 (+25%) | Konstantin (2007), own assumptions |
| $c_k^{OM}$ in €/(kW·a) | Hard coal: 37.8 (p.a.)<br>Natural gas: 15.5 (p.a.) | -<br>- | Konstantin (2007) |
| $c_{k,t}^{el}$ in €/MWh$_{el}$ | RES: 0<br>Nuclear: 3.5<br>Peaker: 100.0 | -<br>-<br>- | Konstantin (2007), IEA (2004, 2005), own assumptions |
| $p_{k,t}^{fuel}$ in €/MWh$_{th}$ | Hard coal:<br>9.1 (2005), +0.15% p.a.<br>Natural gas:<br>20.0 (2005), +1.0% p.a.<br>Lignite:<br>4.5 (2005), 0% p.a. | Hard coal:<br>+0.6% / -0.3% p.a.<br>Natural gas:<br>+0.9% / +1.1% p.a.<br>Lignite:<br>- | |
| $p_t^{CO_2}$ in €/t | 20.0 (2005), +2% p.a. | 15.0 (2005), +1% p.a. /<br>25.0 (2005), +3% p.a. | Point Carbon (2006), own assumptions |
| $\eta_k$ | Existing hard coal plants: 32.7-44.3%<br>Model hard coal plant: 46%<br>Existing natural gas plant: 31.2-56.0%<br>Model natural gas plant: 58.0% | | UBA (2009), Schröter (2004) Wietschel et al. (2010) |
| $cef_k$ in t/MWh$_{th}$ | Hard coal: 0.342<br>Natural gas: 0.202<br>Lignite: 0.410 | -<br>-<br>- | Konstantin (2007) |
| $\delta$ | 7.5% | 5.0% / 10.0% | IEA (2010a) |

considered, is assumed to be 20 years (compare Lindenberger and Hildebrand, 2008). For reasons of comparison, we neglect the fact that gas plants generally have lower financial life times than hard coal plants.

Table 5.5 provides a summary of all model parameters. Fixed costs (specific investment and O&M costs) are listed only for hard coal and natural gas plants, as we analyse investments in these technologies only. Fuel costs are provided for lignite, hard coal, and natural gas. For renewable, nuclear and peaker technologies, we use overall variable cost of electricity generation ($c_{k,t}^{el}$) in order to simplify the analysis.

## 5.4 Results

### 5.4.1 Overview

We first compare investment incentives in the reference case without regulation (NoREG) with the factual allocation rules (NAP I) and three possible counterfactuals, all evaluated over 14 years[83]: NAP II, full auctioning (AUC) and a technology neutral single best available technology benchmark (SBAT). Considering later developments and insights by policy makers, it is useful to contrast the results of the factual allocation to the results of counterfactual schemes. Second, we investigate the sensitivity of results to fuel prices and capital costs. Third, we compare the interdependent effects of free allocation period length and size of the discount rate on NPVs. And finally, we examine the sensitivity of results to our assumption of asymmetric cost pass-through.

### 5.4.2 $CO_2$ regulation under different allocation rules

A baseline run without any carbon regulation (NoREG) shows that a hard coal plant is €283 million more profitable than a natural gas plant. Thus hard coal plants would have been the preferred investment choice around 2005. The situation changes considerably after the introduction of the ETS, as shown in Figure 5.7. In the NAP I case, which represents the factual allocation rules by then, hard coal's NPV edge over natural gas increases substantially relative to the reference case. Under baseline assumptions (black dots), a hard coal plant is €717 million more profitable than a comparable natural gas plant. The respective increase in the NPV difference of €434 million originates from disproportionate windfall profits related to technology-specific allocation rules.[84] Applying the counterfactual NAP II allocation rule, the NPV difference increases less pronounced than under NAP I rules to only €452 million. This is essentially due to the non-discriminatory full load hour approach of NAP II (compare Section 5.3.1). The picture changes in the counterfactual case with full auctioning (AUC). Here the natural gas plant has a comparative advantage of around €136 million. We find the same NPV difference for the SBAT case, in which a single best available technology benchmark is applied. In contrast to AUC, SBAT creates windfall profits. However, it does so to the same extent for both technologies. Hence absolute NPVs increase, but the NPV difference remains equal.

Additional model runs show that some allocation rules are highly sensitive to $CO_2$ price assumptions as shown in Figure 5.7. Whereas the NAP I and NAP II cases are relatively robust, the AUC and SBAT regimes are strongly affected by varying assumptions. For example, in a scenario with very low $CO_2$ prices, the relative NPV advantage of hard coal under AUC/SBAT is €102 million. Under the same allocation rules, natural gas investments achieve a NPV edge of €411 million over hard coal in the case of a high

[83] We assume 14 years according to the free allocation period length originally envisaged in 2005 (see Section 5.3.1).

[84] Note that €434 million account for around half the capital costs of the model hard coal plant.

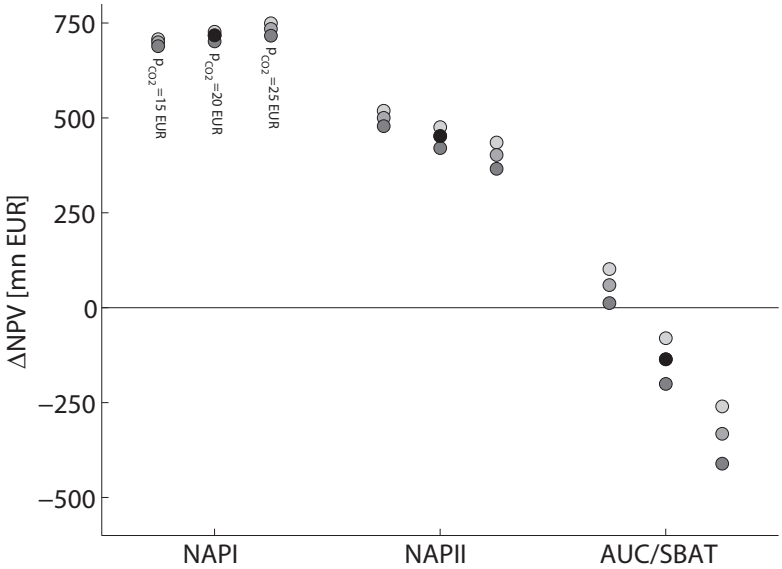


**Figure 5.7:** NPV differences between hard coal and natural gas investments for different allocation rules and $CO_2$ price expectations. Lighter shades indicate lower annual $CO_2$ price increases.

$CO_2$ price path. In general, increasing $CO_2$ prices support natural gas investments under AUC/SBAT – as intended by carbon regulation. Yet under NAP I, higher carbon prices slightly increase hard coal's NPV advantage due to higher windfall profits. Our results thus underline that the introduction of emissions trading may lead to perverse outcomes if allocation rules are not carefully chosen.

### 5.4.3 Sensitivity to fuel prices and capital costs

As expected, results are also sensitive to fuel price paths with the effect that higher fuel prices for a particular technology decrease the NPV difference to this technology's disadvantage (see Table 5.6). Under NAP I and NAP II, different assumptions do not challenge hard coal's NPV edge over gas investments though. Yet in the AUC and SBAT cases, varying fuel price assumptions can result in a change of investment decisions, but only when the lowest $CO_2$ price path applies.

We now look at overall sensitivities of results to fuel and $CO_2$ prices. Under NAP I and NAP II, even the most extreme values for the NPV difference are relatively close to the baseline outcome and are well in the positive range. That is, the investment preference for hard coal under NAP I and II is very robust. In contrast, fuel and $CO_2$ price sensitivities in the AUC and SBAT cases are both more significant and lead to sign changes of the NPV difference. As a matter of fact, emission regulation only unfolds its intended incentives in these schemes. And, given the range of sensitivities under either scheme, $CO_2$ prices pose a higher risk on profitability than fuel prices, which were the previously dominant factors in this respect.

Finally, we examine the effect of increasing capital costs on NPV results. Capital costs of thermal plants have risen considerably during the last years, in particular for coal (see

**Table 5.6:** NPV differences between coal and natural gas plants in million € for different allocation rules and price assumptions (base cases in bold)

| | | | | | *Annual hard coal price inc. [%]* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | -0.3 | | | 0.15 | | | 0.6 | | |
| | | | | | *Annual natural gas price inc. [%]* | | | | | | | | |
| | | | | | 0.9 | 1 | 1.1 | 0.9 | 1 | 1.1 | 0.9 | 1 | 1.1 |
| **NAP I** | *$CO_2$ price 2005 [€]* | 15 | *$CO_2$ price inc. [% p.a.]* | 1 | 738 | 759 | 782 | 686 | 707 | 729 | 631 | 653 | 675 |
| | | | | 2 | 730 | 751 | 773 | 677 | 699 | 721 | 623 | 644 | 667 |
| | | | | 3 | 719 | 741 | 763 | 666 | 689 | 711 | 613 | 634 | 656 |
| | | 20 | | 1 | 759 | 780 | 802 | 706 | 727 | 750 | 652 | 674 | 695 |
| | | | | 2 | 748 | 770 | 791 | 696 | 717 | 739 | 641 | 663 | 684 |
| | | | | 3 | 733 | 754 | 777 | 682 | 701 | 725 | 627 | 649 | 670 |
| | | 25 | | 1 | 778 | 800 | 822 | 726 | 749 | 772 | 672 | 694 | 715 |
| | | | | 2 | 765 | 787 | 809 | 713 | 734 | 756 | 660 | 681 | 702 |
| | | | | 3 | 747 | 769 | 791 | 696 | 717 | 740 | 641 | 663 | 685 |
| **NAP II** | *$CO_2$ price 2005 [€]* | 15 | *$CO_2$ price inc. [% p.a.]* | 1 | 550 | 571 | 593 | 497 | 519 | 540 | 443 | 465 | 486 |
| | | | | 2 | 530 | 552 | 574 | 478 | 500 | 522 | 424 | 445 | 467 |
| | | | | 3 | 508 | 530 | 552 | 456 | 478 | 500 | 402 | 424 | 446 |
| | | 20 | | 1 | 507 | 529 | 550 | 455 | 476 | 498 | 401 | 423 | 444 |
| | | | | 2 | 483 | 504 | 525 | 430 | 452 | 473 | 375 | 398 | 419 |
| | | | | 3 | 453 | 473 | 497 | 401 | 421 | 444 | 346 | 368 | 389 |
| | | 25 | | 1 | 464 | 486 | 508 | 412 | 435 | 458 | 358 | 380 | 401 |
| | | | | 2 | 434 | 456 | 477 | 381 | 402 | 425 | 328 | 349 | 370 |
| | | | | 3 | 396 | 418 | 441 | 345 | 366 | 389 | 290 | 312 | 334 |
| **AUC & SBAT** | *$CO_2$ price 2005 [€]* | 15 | *$CO_2$ price inc. [% p.a.]* | 1 | 133 | 154 | 176 | 80 | 102 | 123 | 26 | 47 | 69 |
| | | | | 2 | 90 | 111 | 133 | 38 | 59 | 81 | -17 | 4 | 27 |
| | | | | 3 | 42 | 64 | 86 | -10 | 12 | 34 | -64 | -42 | -20 |
| | | 20 | | 1 | -49 | -27 | -6 | -101 | -80 | -58 | -156 | -134 | -112 |
| | | | | 2 | -105 | -83 | -62 | -157 | -136 | -114 | -212 | -190 | -169 |
| | | | | 3 | -169 | -148 | -125 | -221 | -201 | -178 | -275 | -253 | -232 |
| | | 25 | | 1 | -232 | -209 | -187 | -283 | -260 | -237 | -337 | -316 | -294 |
| | | | | 2 | -301 | -279 | -258 | -353 | -332 | -310 | -407 | -386 | -364 |
| | | | | 3 | -380 | -359 | -336 | -432 | -411 | -388 | -487 | -464 | -443 |

Section 5.3.3). Higher capital costs partially offset windfall profits gained through free allocation. We quantify this effect by increasing capital costs +50% for hard coal, and +25% for natural gas. As investment costs are fixed and incur only at the initial period, the sensitivity analysis is straight forward. Under the new assumptions, the difference in total capital costs is increased by €300 million, which directly translates into an NPV difference of equal size. As Table 5.6 shows, this reduces the relative advantage of hard coal over gas projects to €417 million under NAP I baseline assumptions. Even in the worst case, the NPV difference is still very large (€313 million). That is, hard coal projects retain a considerable NPV edge over natural gas under NAP I even in the light of higher capital costs. The same is true for NAP II. Yet under alternative allocation regimes like AUC and BAT, higher capital costs would have made natural gas plants the preferred investment choices in all scenarios analyzed here.

### 5.4.4 Free allocation period length and discount rate

In general a higher discount rate puts more weight on early cash flows, thus reducing the benefits of long-term schemes. For example, in this case with a payoff time of 20 years, 5% and 10% discounting lead to a cumulated weighted cash flow of 62% and 72%

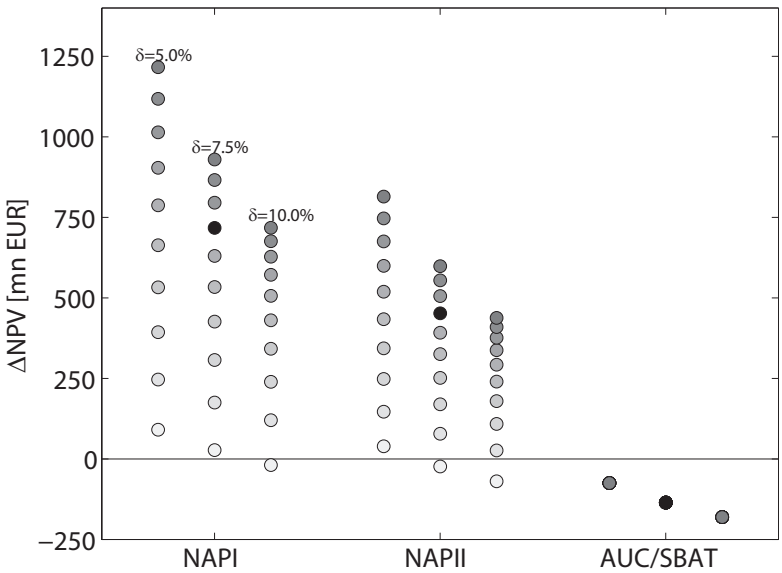


**Figure 5.8:** NPV differences between hard coal and natural gas investments for different allocation rules, allocations lengths, and discount rates (base case assumptions for fuel and $CO_2$ prices)

respectively after ten years already. Accordingly, there is a joint impact of free allocation period length and discount rate on profitability. The length of the free allocation period was a highly discussed policy variable at the time of NAP I discussions. The question arises if there is a turning point in duration from which on the investment distortion may invert. For the case of Germany this implies an answer to the question if a shorter free allocation period, probably in combination with higher discounting, could have created a dedicated incentive for natural gas.

Figure 5.8 shows the results for varying discount factors and allocations lengths (2, 4, 6, ..., 20 years, lighter to darker shades). An apparent observation is the respectable impact of different lengths in the NAP I and NAP II case, which results in much larger NPV variations than the previously analyzed $CO_2$ and fuel price sensitivities. The length of the free allocation period has a substantial impact on the NPV difference between coal and gas investments: in the most extreme cases it rises as high as €1,216 million (NAP I, 20 years, 5%) and as low as €-69 million (NAP II, 2 years, 10%). This is mainly due to the resulting reduction of windfall profits, which are higher for coal than for gas, and thus reduce coal's NPV edge over gas. Higher discounting works in the same direction: it reduces total future cash flows, but leaves upfront capital costs untouched. Due to the higher capital intensity of hard coal compared to natural gas, this reduces hard coal's profitability to a greater extent. Still, the NPV difference remains always positive for NAP I and NAP II except for three extreme cases. Accordingly, hard coal investments remain more profitable than natural gas investments in almost all NAP I/NAP II variations.

The situation is utterly different for the AUC/SBAT cases though. Here it turns out that the length of the free allocation period (SBAT) does not matter. The reason

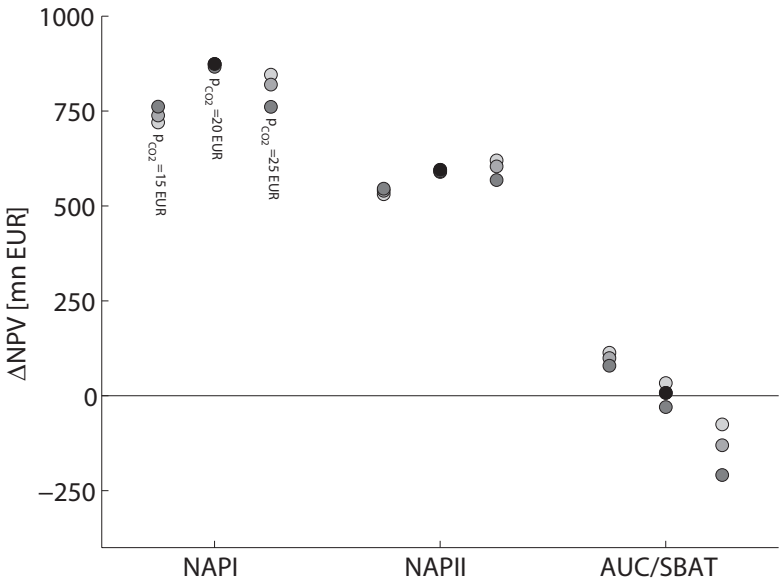


**Figure 5.9:** NPV differences between hard coal and natural gas investments for full cost pass-through

is basically the same as given above for why AUC and SBAT produce identical NPV differences: due to equal allocations, both technologies profit to the same extent given a certain allocation period length. The discount rate plays a role though, but only a minor one. In summary the distinct investment incentive for natural gas provided by AUC/SBAT remains unchanged.

Hence varying policy length has a considerable impact on relative profitability if certificates are allocated in a technology-specific way (NAP I, NAP II). In contrast, there is no influence at all if allocation is technology neutral (SBAT). In the German case, a different allocation period length under NAP I would not have not mattered, as preexisting economic advantages for hard coal were too strong.

### 5.4.5 Sensitivity to asymmetric pass-through rates

The results discussed so far draw on technology-specific pass-through rates, which are heuristically determined as explained in Section 5.2.2. We assess the sensitivity of results to the assumption of asymmetric pass-through rates by re-running the model while assuming full pass-through for all technologies in all periods. Figure 5.9 shows the resulting NPV differences: the main outcomes do not change. However, the relative profitability of hard coal increases in all cases compared to asymmetric cost pass-through (compare Figure 5.7). This result should be expected, as hard coal plants are no longer "forced" to sell electricity at prices slightly lower than their full marginal costs – including full opportunity costs of emission permits – during some periods. As a consequence, natural gas' NPV edge over hard coal vanishes under full auctioning or SBAT.

The results also show that adjusting pass through rates to avoid fuel switch is actually not an optimal strategy for hard coal generators. Under NAP I allocation rules and

baseline assumptions, for example, using asymmetric pass-through rates instead of full pass-through leads to losses of €157 million over the lifetime of the hard coal project. Still, as discussed earlier, there is empirical evidence that asymmetric pass-through occurred. Ramping-related technical constraints which incur additional costs provide a possible rationale (see Section 5.2.2).

## 5.5 Summary and conclusions

Chapter 5 studies the impact of carbon regulation, which is introduced in order to internalize environmental externalities, on fossil power plant investments. More precisely, we examine the distortionary effect of different emission permit allocation rules on investment choices between hard coal and natural gas plants in Germany. We explicitly take into account windfall profits and perform sensitivity analyses regarding fuel prices, capital costs, the length of the free allocation period, and discount rates. To our knowledge, we are the first to quantify the investment distortion toward hard coal created by the German NAP I implementation. We also make a methodological contribution to the literature by combining DCF analysis with a merit order approach, which allows determining electricity prices and plant utilization endogenously. Furthermore, we explicitly consider technology-specific asymmetric pass-through rates.

We find that without carbon regulation, investments into hard coal power plants had a significant NPV edge over natural gas in 2005. This finding may explain why so many hard coal projects were initiated around the time. Introducing regulation has a large impact on NPVs of fossil investments in general, but magnitude and direction of effects heavily depend on allocation rules. Under the factual scheme of 2005 (NAP I), the preference for emission-intensive coal investments, which was prevalent even without carbon regulation, was greatly increased by expected windfall profits. We further find that the length of the free allocation period – heavily discussed at that time – has an important impact on the relative profitability of coal and gas investments. Nonetheless, even the shortest lengths would not have provoked a change in technology choice, notwithstanding three extreme cases. We thus conclude that the particularly long period of free allocations granted in NAP I played a less important role than initially assumed.

Our investigation of counterfactual allocation rules shows that an alternative implementation of NAP II in 2005 would not have changed the overall picture. In contrast, applying full auctioning or a single best available technology benchmark – as initially planned – could have halted or even reversed the "dash for coal", depending on fuel and $CO_2$ price paths. While both options lead to the same relative outcomes, they differ with regard to absolute investment incentives. According to our results, full auctioning would have substantially decreased the profitability of hard coal projects compared to the case without carbon regulation. In contrast, single best available technology allocation would have increased the profitability of both hard coal and gas projects due to windfall profits, while natural gas would have benefited more.

We conclude that the German NAP I did not cause the "dash for coal" in the first place, but greatly spurred and sustained it. While German policy-makers intended not to hamper investments in the power sector by carbon regulation (Matthes and Schafhausen, 2007), they designed an allocation scheme which in the end created perverse incentives and massively promoted investments into emission-intensive hard coal plants. Obviously, policy makers failed to take the effects of free allocation-related windfall profits on coal profitability into account. We have thus shown that the details of implementing carbon regulation can be extremely relevant in a dynamic perspective. Different allocation regimes may not just have distributive effects, but also important consequences for investment choices.

# Chapter 6

# Conclusions

## 6.1 Main findings and policy implications

Since the late 1990s, the German power market has been shaped by economic restructuring, climate policy, and the expansion and integration of renewable energy sources. All of these processes are still evolving. In addition, electric vehicles are projected to have substantial power market impacts by the year 2020. In this thesis, I examine selected market failures and regulatory issues associated with these transformation processes by means of in-depth quantitative analyses. For each research question, a dedicated electricity market model is designed and applied. In doing so, it is possible to shed light on a range of economic questions related to strategic electricity storage utilization, plug-in electric vehicles, regulated transmission network expansion, and power plant investments under different ETS allocation rules.

### 6.1.1 Modeling strategic electricity storage

Chapter 2 examines the utilization of electricity storage by strategic players in an oligopolistic market environment. For this purpose, a game-theoretic market model is developed and applied to the German power market and the case of pumped hydro storage. Simulations of various market structures with different players in charge of storage operations illustrate how strategic players make use of storage capacity, and how market outcomes are affected.

We find that pumped hydro storage smooths hourly conventional electricity generation patterns and – even more so – market prices. Yet it is not only the existence of a given storage capacity that matters, but also which player owns it. In general, strategic storage operators underutilize their capacity compared to competitive players. This effect is particularly strong for a monopolistic storage owner that, at the same time, is also an oligopolistic generating firm. In contrast, if storage is distributed among several such players, they face a prisoner's dilemma situation in which they are not able to withhold capacity. The model illuminates the intricacies of a strategic firm's simultaneous maximization of profits from storage and other generation in an oligopolistic

market environment, in which other strategic generators can react to the firm's decisions by adjusting their own outputs. It is shown that even strategic storage operators may not be able to benefit from storage in some cases. As for overall welfare, the impact of pumped hydro storage is generally positive, as increases in consumer surplus – related to a price-smoothing effect – outweigh losses in generators' surpluses. Non-strategic storage ownership generally leads to desirable welfare outcomes. Nonetheless, strategic storage operation can lead to comparable welfare results if the total storage capacity is distributed among different players in an oligopolistic market. This is due to a market power-mitigating effect of storage loading, and because of a prisoners' dilemma situation. Looking at the real-world ownership structure of storage and generation capacity in 2009, the model shows that pumped hydro storage is not a relevant source of market power in Germany. Importantly, most numerical results are robust for moderate variations of the price elasticity of demand.

A direct policy implication of chapter 2 is that economic regulation of German pumped hydro storage is not required as long as the overall capacity is distributed as in the year 2009. Yet the research also shows that this conclusion would not be valid if storage was monopolistically owned. If the German grid storage capacity is to be substantially increased in the future, policy makers should be careful not to let a single firm gain control over all capacity. If high utilization of future storage capacity as such is a policy objective, for example in the light of renewable energy integration requirements, strategic storage ownership should also be avoided. The research further shows that storage investments are not attractive for incumbent players on the German power market, despite positive effects on social welfare. Accordingly, policy makers may think about ways of incentivizing investments into new storage capacity.

Academically, the research makes a major contribution to the literature of market power in electricity markets. To the best knowledge of the author, it is the first study that explicitly models not only the strategic allocation of storage outputs, but also strategic storage loading decisions. This aspect is neglected in the earlier literature. Another novel aspect relates to the explicit modeling of the complex interactions between strategic generation and storage decisions within a consistent analytical Cournot framework. As storage is gaining attention as one of the major RES integration strategies, this approach will be of particular interest to energy economists. In addition, the results are applicable to storage technologies beyond just pumped hydro storage, including, for example compressed air storage or grid-connected batteries.

### 6.1.2 Electric vehicles in imperfect electricity markets

In chapter 3, the game-theoretic model developed in chapter 2 is extended to analyze the interactions between a hypothetical fleet of one million plug-in electric vehicles and the oligopolistic German power market. Various scenarios are analyzed with different players in charge of grid-connected vehicles. Cases also differ with respect to possible vehicle operations: the fleets may either constitute uncontrolled additional demand, or

they can be utilized as a dispatchable load resource. In addition, excess vehicle battery capacity may also be used as an additional grid storage facility. In the latter case, vehicle batteries can be used for arbitrage, i.e. for storing electricity during periods of low prices and selling it back to the market in times of higher prices.

The analysis shows that players make different use of both the dispatchable load and the storage capacity related to plug-in electric vehicles. First, strategic vehicle loading has a market power-mitigating effect on players that are also oligopolistic generators. This outcome is comparable to the market power-mitigating effect of pumped hydro storage loading determined in chapter 2. Next, strategic players generally underutilize excess battery storage capacity. However, there are only moderate deviations in model outcomes for the cases with different players controlling the vehicle fleet. The reason is that both the electricity demand and the additional storage capacity brought to the market by one million electric vehicles are moderate compared to overall electricity generation and installed pumped hydro storage capacity.

Yet there are substantial differences between the cases of uncontrolled and cost-minimizing vehicle recharging. In the first case, one million PIEV substantially increase generators' profits and decrease consumer surplus, as previously existing peak prices in the evening hours are further increased. In the case of cost-minimizing recharging, welfare distortions are smaller because vehicle loading is carried out in off-peak hours. If excess batteries can also be used for grid storage, welfare results are reversed, such that generators' profits decrease and consumers are better off – notably despite increasing overall power demand. This is due to a strong price-smoothing effect of additional storage capacity in the imperfectly competitive market. Accordingly, it is the storage capacity of a future PIEV fleet that has beneficial and potentially larger welfare implications than the additional electricity demand. Yet analysis shows that the utilization of vehicle batteries for arbitrage purposes is currently not viable due to high battery degradation costs. Instead, markets for ancillary services may be more promising for electric vehicle fleet operators. Comparing potential welfare losses of strategic PIEV operations to the welfare losses related to the strategic use of conventional generation capacity, the research shows that a fleet of one million electric vehicles does not constitute a relevant source for market power on the German wholesale market, no matter who operates it. Regarding the vehicles' impacts on electricity generation, we find an increase in the utilization of low-cost generation technologies that tend to be emission-intensive, in particular if an oligopolistic generator is in charge of PIEV operations.

The model findings lead to several policy conclusions. First, regulators should not be concerned about the question which player should control loading and discharging operations of a fleet of one million PIEV, which is planned to be on the road in Germany by the year 2020. However, the requirement of economic regulation might need to be reassessed if vehicle fleets get much larger than this. It should be noted that this conclusion only refers to the wholesale electricity market. There may indeed be other market power potentials related to charging infrastructure and loading or billing stan-

dards. Policy makers should carefully watch the creation of new natural monopolies in these areas. Probably more important, the analysis shows that both cost-minimizing vehicle recharging strategies and using excess vehicle batteries for grid storage lead to desirable welfare outcomes. Vehicle operators should thus be enabled to respond to real-time prices. Policy makers should consider the promotion of cost-minimizing loading strategies, for example by working toward common technical standards or by supporting the build-up of respective infrastructure. Likewise, power market rules should be adjusted such that vehicle fleet operators are enabled to sell their services.

The research makes an important contribution to the academic literature as the impacts of electric vehicle fleets on power markets is sparsely researched. In particular, previous analyses often draw on exogenous electricity prices, exogenous dispatch of generation, or exogenous vehicle recharging patterns. All these variables are endogenous in the model presented here. Beyond that, the analysis presented in chapter 3 is the first to explicitly and consistently model the strategic interactions between electric vehicle operations, conventional electricity generation, and pumped hydro storage in an oligopolistic electricity market.

### 6.1.3 Regulated expansion of transmission networks

As transmission grid bottlenecks are profitable for the owner of the network, a Transco lacks incentives to remove them. From a social welfare perspective, this leads to inefficiently low network investments. A combined merchant-regulatory approach presented by Hogan, Rosselón, and Vogelsang (HRV, Hogan et al., 2010) promises to solve this "congestion trap". The centerpiece of the mechanism is a two part network tariff that facilitates rebalancing between fixed and variable parts over time. Chapter 4 examines HRV's relative performance regarding social welfare and network extension compared to a non-regulatory, i.e. purely merchant approach, and cost-based regulation. Special consideration is given to realistic fluctuations of demand and wind power. In order to do so, a bi-level numerical model is applied. It entails the Transco's profit-maximizing network expansion decisions on the upper level, and welfare-maximizing dispatch on the lower level. A stylized DC loadflow model of the central European transmission network is used, drawing on a nodal pricing market design.

In a simplified case without demand or wind fluctuations, HRV leads to welfare outcomes far superior to the modeled alternatives. Accordingly, the beneficial welfare properties established by Hogan et al. (2010) are quantitatively confirmed. Results are driven by a large redistribution over time toward the fixed tariff part. In contrast, both the purely merchant and the cost-based regulatory approach do not lead to desirable outcomes. The merchant approach leads to hardly any transmission expansion. In other words, it cannot resolve the congestion trap. Cost-plus regulation stimulates higher network expansion than the merchant approach, but fails to improve social welfare. This is because a cost-regulated Transco invests in the wrong lines, i.e. not in the most congested ones, but in the ones that lead to the lowest decrease in congestion rent. In the

more realistic case with fluctuating demand, these results generally hold. However, the location and the amount of optimal line extensions differ substantially from the simplified case because of the consideration of peak and off-peak periods. In addition, HRV's convergence to the welfare optimum is slower, and the fixed tariff part becomes even larger. Also including wind fluctuations does not lead to major differences in the results, as wind power fluctuations are much smaller than regular variations of demand. A range of sensitivity analyses are also carried out. The beneficial welfare properties of HRV regulation prove to be robust over all modeled cases.

Although the model is rather stylized and not directly applicable to the real-world situation in central Europe, it is possible to draw several important conclusions. First, policy makers should not count on unregulated, profit-maximizing (merchant) transmission carried out by a Transco, as it will not resolve existing congestion traps. Likewise, decision makers should avoid a cost-based regulatory approach, as it will lead to inefficient extensions of the wrong lines. As for HRV regulation, model results are very promising. In the real world, however, the large rebalancing toward the fixed tariff part may pose a severe obstacle to implementing this approach. Large fixed tariff parts are necessary in order to make welfare-maximizing network expansion incentive compatible for the Transco. However, public acceptance of such regulation is rather unlikely, as the increase in network charges – paid for by power consumers – is much higher than network investments. It remains to be clarified by future research if different weights in the cap over HRV's two-part tariff can resolve this issue. For the time being, policy makers may resort to theoretically less efficient, but practically more feasible approaches for network expansion, in particular regarding the lines that are most urgently required for renewable energy integration.

The analysis makes a considerable contribution to the literature on applied regulatory economics. While the HRV mechanism has been numerically applied to different markets before, the research presented in chapter 4 is the first to explicitly consider realistic hourly fluctuations of demand and wind power. The results show that such details are important for examining the robustness of more stylized analyses. Moreover, the analysis is the first to compare HRV's performance with a purely merchant and a cost-based regulatory approach within an integrated modeling framework.

### 6.1.4 How emission certificate allocations distort fossil investments

Chapter 5 examines the effect of different allocation rules for $CO_2$ emission certificates on power plant investments in Germany. The focus is on the first phase of the European emissions trading system, i.e. on the first German National Allocation Plan. Starting in 2005, a discounted cash flow model that mimics the German merit order is used to simulate the effects of the factual permit allocation and different counterfactual allocation schemes on the relative profitability of new hard coal and natural gas power plants. Extensive sensitivity analyses are carried out, in particular regarding fuel and $CO_2$ price developments.

The model results show that hard coal plants were the preferred investment before the onset of the EU ETS. Interestingly, German allocation rules during the first emissions trading phase (NAP I) have further increased the relative profitability of hard coal investments over natural gas projects. The main drivers for this result are allocation-related windfall profits, which have been much larger for hard coal than for natural gas. The German new entry provision of the second ETS phase (NAP II) would not have changed the general picture. In contrast, applying other allocation rules like full auctioning of emission permits or a single best available technology benchmark would not only have decreased the previously existing NPV edge of hard coal over natural gas investments; depending on fuel and $CO_2$ prices, these allocation rules could have made natural gas plants the investment of choice instead of hard coal plants.

The policy implications of chapter 5 are straightforward. The German allocation rules under NAP I have not only sustained, but increased the propensity to invest in emission-intensive hard coal plants. In effect, NAP I has created adverse investment incentives that counteract German climate policy targets. In other words, the details of implementing climate policy instruments are of great importance. Considering that power plant investments are generally long-lived, poorly designed investment incentives can create a heavy burden for the required transition toward a low-carbon power sector. Policy makers should thus take into account that allocation rules do not just have distributive implications, but may also lead to windfall profits, which can have a major influence on investment choices. In this light, decision makers should absolutely stick to their plans of fully auctioning emission certificates to the power sector during the third ETS phase. In case policy makers want to resort to free allocation again in the future – for whatever reasons – the research shows that allocation should be based on a single technology benchmark, ideally on natural gas.

While the existence of disproportionally large windfall profits for hard coal plants during the first trading phase of the EU ETS has been previously known, a major contribution of the research presented in chapter 5 is their solid quantification with a model that represents both Germany's particular allocation rules and its specific power generation structure. Likewise, the quantitative comparison of different counterfactual allocation rules for Germany is a novel aspect in the literature. In addition, the robustness of results is shown taking into account variations in fuel and $CO_2$ price paths, capital costs, lengths of the free allocation period, and discount rates. The research also makes a methodological contribution to the literature by modeling technology-specific asymmetric pass-through rates, and by combining a discounted cash flow analysis with a merit order approach, which allows an endogenous determination of both electricity prices and plant utilization.

## 6.2 Limitations

In the course of writing this thesis, several limitations of power market modeling – and of quantitative economic modeling in general – became apparent. Economic models aim to generate meaningful insights into real-world issues by means of abstraction, simplification, and the application of microeconomic theory. For each research question, an appropriate methodological approach had to be selected, and a decision on the required level of detail had to be made. In doing so, I have encountered an obvious, but nonetheless essential problem of model-based research: a range of simplifying assumptions have to be made in order to reduce complexity, ensure numerical solvability, and make sure that results can be interpreted in a meaningful way. While this is common practice in economic modeling, the effects of particular assumptions on model results are not always clear. In this context, some general issues that are relevant for all chapters of this thesis are discussed in the following.

### 6.2.1 Functional form and price elasticity of demand

To begin with, assumptions on the functional form and the price elasticity of electricity demand can have a substantial influence on the results of power market models. This is particularly true for oligopoly models (chapters 2 and 3). It is difficult to make general statements on the effects of different demand functions on model results, as outcomes can be distorted in all directions. Accordingly, sensitivity analyses are required on a case-by-case basis. In chapter 2.5.4, such an analysis is carried out with respect to the price elasticity of demand. A rather time-consuming evaluation of numerous model runs shows that the general effects are robust for moderate variations of elasticity. However, absolute numbers change substantially. For example, the overall welfare gain related to the introduction of pumped hydro storage as determined in chapter 2.5.4 nearly doubles from around €2.7 million in the case of $\sigma = -0.3$ to around €5.3 million for $\sigma = -0.6$ in the case of perfect competition.[85] It should be noted that more extreme assumptions on demand elasticity, which exceed those of the sensitivity analyses presented in chapter 2, partly lead to heavily distorted results or infeasible solutions. And this only refers to varying assumptions on the elasticity parameter, but not on the functional form of demand. Changing the latter one cannot easily be done in game-theoretic models, as each change necessitates a re-computation of the KKT conditions. Calculating and numerically implementing these for a range of different demand functions would be clearly be beyond the scope of this thesis. In fact, such analyses are usually not carried out in the literature. Nonetheless, quantitatively determining the effects of different demand functions in game-theoretic models would be an interesting avenue for future research.

In this context, another important simplification refers to the differentiation between short- and long-term price elasticity of demand. In chapters 4 and 5, which model a

[85] Likewise, moderate variations of the price elasticity of demand in chapter 4 also lead to substantial differences in absolute outcomes, but to comparable relative effects.

time span of 6-20 years, it is assumed that price elasticity does not change in future years, although empirical analyses suggest that this might not be the case. For example, Narayan et al. (2007) carry out a panel cointegration study of residential electricity demand in G7 countries and find that long-run demand is price elastic, while results for short-term periods are ambiguous.[86] Likewise, assuming the same short-term price elasticity for all periods may be questionable in models with hourly resolution, like the ones used in this thesis. In general, empirical evidence on real-time price elasticity of demand in wholesale power markets is sparse and often contradictory. Using 2003 Dutch data, Lijesen (2007) estimates values that are one or two magnitudes below the short-term elasticities usually cited in the literature.[87] Filippini (1995) finds that demand is less elastic in peak periods than in off-peak periods. Traber and Kemfert (2011a) provide a rationale for this by arguing that market participants have fewer opportunities to obtain electricity from other sources or other countries during these periods. On the contrary, Mountain and Lawson (1992) and Ham et al. (1997) state that demand is less elastic in off-peak hours and more elastic in peak periods. These findings could be explained by the fact that the main off-peak consumers are "must-run" industrial processes. Given these contradictions, assuming uniform elasticity over all modeled hours – as in this thesis – appears to be a reasonable strategy.

The debate on appropriate demand functions and price elasticity in power market models is far from settled. As different studies arrive at very different results, solely relying on empirically estimated parameters is problematic. Empirical estimations can only guide modelers in the process of finding appropriate parameters for power market models with hourly time resolutions. All things considered, it appears justified to use such values that allow a reasonable representation of reference prices and quantities, given cost data and generation capacity. Price elasticities used in this thesis are calibrated according to this heuristic.

### 6.2.2 Strategic interaction between firms

Another problematic decision parameter for power market modelers is the assumption on the strategic interaction between firms in the market. Both a Cournot oligopoly (chapters 2 and 3) and perfect competition (dispatch in chapters 4 and 5) represent extreme assumptions. Their impact is examined by the research presented in chapter 2, which compares model runs for cases with perfect competition and such that assume a Cournot oligopoly. It is shown that market prices increase substantially in the Cournot case compared to perfect competition, whereas generation decreases strongly. Accordingly, an oligopolistic market structure leads to enormous welfare losses compared to a

[86] On the contrary, Lee and Lee (2010) find that long-term electricity of demand is price inelastic. They draw on a panel study of OECD countries for 1978-2004 and different sets of cointegration test methods, among them the Dickey-Fuller test, and conclude that electricity demand depends on income.

[87] Lijesen (2007) estimates values of -0.0014 or -0.0043, depending on the model. The paper also includes a review of studies on short- and long-term price elasticity, most of which derive values between -0.1 and -1.0.

perfectly competitive setting. Yet results may be exaggerated, as the model is calibrated with a focus on the oligopoly case, which is assumed to be the more realistic one. In other words, chapters 2 and 3 are subject to the critique presented by Wolfram (1999) and others, according to which price and quantity distortions in oligopoly models are too high. Applying a conjectural variations approach might provide a remedy, as it allows more flexibility regarding players' perceptions on how their opponents react to their own decisions (compare section 1.4). This approach could lead to less extreme outcomes somewhere between perfect competition and Cournot pricing. As for future research, it would be a worthwhile exercise to reformulate the game-theoretic storage models of chapters 2 and 3, for example along the lines of Day et al. (2002). On the downside, the numerical solution of such a model would most likely be even more challenging than the approach presented here.

### 6.2.3 Representation of technical constraints

Another shortcoming of the models presented in this thesis relates to the simplification of technical restrictions. To be sure, the ElStorM model of chapters 2 and 3 goes beyond many economic models in the literature by including an hourly time resolution and inter-period ramping restrictions – as acknowledged by reviewers of *The Energy Journal* and *Energy Policy*. However, these ramping constraints are rather stylized. What is more, power generation is not modeled on an individual plant base, but at an aggregated level, such that unit commitment constraints are not explicitly represented. In fact, this is a deliberate choice, as modeling individual power plants would result in a mixed integer formulation, which would devaluate the presented approach of implementing KKT conditions in an MCP format. While these simplifications seem justified in order to ensure solvability of the model, it should be noted that neglecting unit commit problems systematically distorts model outcomes. In general, the flexibility of baseload technologies may be overestimated. In contrast, generation costs of these technologies are clearly underestimated, as unit commitment entails losses and inefficiencies related to ramping and part-load operating conditions. Simplifying unit commitment constraints as in chapters 2 and 3, or completely disregarding them as in chapters 4 and 5, thus leads to an underestimation of average market prices. At the same time, prices in off-peak periods may be overestimated, as the costs of ramping power plants down are not properly reflected.

### 6.2.4 Assumption of perfect foresight

Next, a simplifying assumption of perfect foresight is made in all chapters of this thesis. As all models are relatively large, even under perfect foresight, a deterministic approach is chosen in order to ensure computability. Introducing, for example, uncertain electricity demand or random wind power feed-in would require stochastic programming techniques (for an introduction, see Birge and Louveaux, 1997). This would have greatly complicated

the programs and numerical solution processes of the models presented here.[88] The assumption of perfect foresight leads to results that are optimal in an *ex-post* sense. Under imperfect foresight, however, players would generally not have made the same decisions. This generally implies sub-optimal results. Accordingly, assuming perfect foresight systematically leads to an overestimation of both the profits and the social welfare benefits generated from storage (chapters 2 and 3), controlled vehicle loading (chapter 3), and network extension (chapter 4). Likewise, modeled power market prices tend to be less volatile compared to the real world, as extreme price spikes observed in power markets (both positive and negative ones) are related to deviations between planned and actual generation, further exacerbated by ramping restrictions as discussed above. Again, estimating the magnitude of these distortions is not trivial. However, it should be noted that stochastic problems are not at the heart of the research presented in this thesis, which focuses on market failures and regulation. Dedicated modeling of stochastic power market problems provides a promising field for future research, in particular regarding the integration of fluctuating wind power.

### 6.2.5 Rational agents

Yet another important simplification that is common to all models of this thesis refers to the assumption of all agents being well-informed and perfectly rational. It is well-established in economic theory that these assumptions are at most partially valid for real-world agents.[89] The model formulations presented in this thesis ignore this finding. Accordingly, real-world players are likely to make sub-optimal decisions compared to ones modeled in this thesis. For that reason, players' profits may generally be lower than modeled here. Nonetheless, simplifying assumptions on rational and well-informed agents appear justified, as the analytical formulation of chapters 2-5 would otherwise be greatly complicated. Employing an agent-based modeling approach is generally thought to provide a way of dealing with irrational or bounded rational actors (compare Weidlich and Veit, 2008). However, as these models lack theoretical foundation, they can lead to incomprehensible or even arbitrary outcomes. Interpretation of results may thus be very difficult. Accordingly, the use of partial equilibrium models with stylized, perfectly rational actors appears to be a better choice for addressing the research questions examined in this thesis, although real-world players may indeed behave differently than modeled here.

[88] Note that the deterministic models in this thesis are already hard to solve. A run of the bi-level program in chapter 4 requires several days up to weeks, even on a high-performance computer. The models presented in chapters 2-3 are solved within a few minutes up to several hours, depending on elasticities and starting values.

[89] Exploring this issue in more detail is beyond the scope of this thesis. See Mas-Colell et al. (1995) for an introduction. Seminal contributions on prospect theory and bounded rationality are Kahnemann and Tversky (1979) and Simon (1984).

### 6.2.6 Renewable energy integration

While this thesis has examined the utilization and the market effects of different renewable energy integration strategies (storage, electric vehicles, and network expansion), problems of renewable integration as such are not explicitly researched. Instead, the focus is on market imperfections and regulation. Extending the analysis to questions of RES integration was not possible due to the aforementioned omission of unit commitment problems, plant-level ramping restrictions, and imperfect foresight. Yet analyses of renewable energy integration require a proper reflection of the rigidities and inflexibilities of the current German electricity system. Otherwise, it is not possible to examine RES integration issues, for example the question how much storage capacity will be required for full wind integration. Considering unit commitment restrictions and stochastic feed-in is essential for such analyses. As discussed above, it is impractical to include such features in the game-theoretic models of chapters 2 and 3, let alone in the MPEC program in chapter 4. In order to analyze questions of RES integration in a meaningful way, I propose to develop a dedicated bottom-up modeling approach that includes uncertain RES feed-in and unit commitment problems (see concluding section 6.3).

### 6.2.7 What can we learn from power market models?

Summing up, the models presented in this thesis draw on a range of particular assumptions and simplifications. These include the representation of demand, the strategic interaction between players, technical characteristics, perfect foresight, and perfectly rational agents, all of which lead to systematic distortions of model outcomes. As a general consequence, reproducing prices and quantities of real-world power market prices proves to be difficult, in particular regarding extreme price spikes. In fact, this is a common problem of bottom-up power market models, as I learned in the course of writing this thesis. Usually, there is a trade-off between adequately reproducing market prices and quantities generated by different technologies. Accordingly, most scientific articles focus either on prices or on quantities; realistic model outcomes for both are rarely found in the literature. In chapter 2, both prices and quantities are presented, and it can be seen that both are reasonably in line with real-world data. However, this balance could only be achieved after elaborate model calibration, and drawing on the assumption of oligopolistic competition. In general, the issue of model calibration is rarely made explicit in the literature. Models are usually calibrated by choosing an appropriate price elasticity of demand (see above), by scaling available generation capacity of different technologies, or by adjusting cost parameters. In the process of calibrating the models of this thesis, it became clear that results can be heavily influenced by calibration. In chapters 2 and 3, choosing appropriate price elasticity and generation availabilities allow bringing either a perfectly competitive or an oligopolistic setting in line with real-world market prices. Accordingly, I conclude that oligopolistic models should be used with care for real-world market power analyses. Rather, such models should be applied for comparative scenario

analyses, as in this thesis.

In the light of the limitations discussed in this section, one asks the question: what can we learn from quantitative power market models? There is a clear answer to this: Models are for insights, not numbers. While this is a much-cited and well-known saying,[90] I came to appreciate its meaning while working on this thesis. Quantitative model results should always be interpreted with care, as numbers are easily distorted by the implicit and explicit parameter choices of the modeler. Accordingly, a clear communication of decisive parameters and the use of sensitivity analyses are a must if absolute model outcomes are to be interpreted. For this reason, extensive sensitivity analyses are carried out in all chapters of this thesis. Another way to cope with the discussed problems is to avoid interpreting the absolute model outcomes and focus instead on the comparison of different model runs. Taking differences evens out many potential problems. This strategy is applied in all chapters. For example, chapters 2 and 3 do not focus on the absolute value of storage or electric vehicles, but on the differences between cases in which different players make use of them. Chapter 4 compares the relative performance of different regulatory approaches compared to a welfare-maximizing benchmark, instead of highlighting the absolute benefits of network extension. Likewise, chapter 5 focuses on the relative performance of hard coal and natural gas investments, but does not deal with the absolute profitability of either technology.

Many researchers and – even more so – policy makers expect quantitative results from economic models. Yet given the aforementioned limitations, it is much more appropriate to use quantitative models for deriving general effects and qualitative insights. Focusing on qualitative outcomes and relative statements should not be regarded as a weakness of power market modeling; rather, it is a requirement of scientific honesty. Qualitative model insights can still lead to policy-relevant conclusions. For example, chapters 2 and 3 shed light on the intricacies of strategic players' combined decisions on generation, storage, and dispatchable demand, and show that both storage and electric vehicles have a market power-mitigating character. The research of chapter 4 shows that both merchant transmission expansion and cost-based regulation lead to problematic incentives for a Transco. Likewise, chapter 5 reveals the perverse incentives created by the German permit allocation scheme. All these insights are valuable, even without putting emphasis on quantitative outcomes. In this sense, quantitative models can help to inform decision processes without stressing absolute outcomes too much. After all, policy makers should take into account the simplifications and omissions made in all power market models. Accordingly, even very elaborate models can only constitute a contributing factor of real-world policy decisions.

[90] The maxim goes back to Hamming (1962). See also Peace and Weyant (2008).

## 6.3 Perspectives

The transformation of the German power market that is outlined in the introduction of this thesis is far from finished. Debates on more efficient market designs, further European market integration, power sector decarbonization, and ambitious long-term renewable energy targets are ongoing. In particular, the integration of renewable energy sources into power systems and liberalized markets is a major challenge during the first half of the $21^{st}$ century. In order to shed light on currently unresolved economic questions and inform decision makers, advances in power market modeling are indispensible.

As for renewable energy integration, a range of economic questions are largely unanswered. For example, power storage is often referred to as the prime strategy of integrating fluctuating renewables (compare section 1.3.3). However, it is unclear how much storage capacity will be required for RES integration in Germany, which storage technologies are most suitable for dealing with short-term fluctuations and long-term RES intermittency, and how future storage should be optimally dimensioned (regarding power rating and energy storage capacity). Notably, storage is not the only RES integration strategy. It can be complemented and/or substituted by the rollout of demand-side measures, network extension, and more flexible conventional power plants. It has yet to be determined how these strategies interact on the power market, and which combination of measures would enable least-cost RES integration. For example, storage will have an impact on the profitability of DSM investments and vice versa. Likewise, additional storage capacity could decrease the requirements for network expansion. Conversely, foreseeable network expansion projects might render some storage investments obsolete, if, for example, hydro reservoirs in the Alps or Scandinavian countries can increasingly be utilized.

In general, the power market implications of both renewable energy expansion as such and different RES integration strategies are not well researched. What will be the effect on social welfare, market prices, profits, and investment incentives? Are the required investments into storage, DSM measures, and network extension profitable, i.e. will the market provide the required capacity investments? The need for additional supportive policies for the promotion of RES integration, as well as their market implications, should be thoroughly evaluated, depending on power market design and future developments in the German feed-in regulation. And to name yet another important question, what are the effects of different RES integration strategies on the utilization of existing conventional power plants? The research presented in chapters 2-4 suggests that storage, DSM, and network extension may all result in an increasing utilization of emission-intensive baseload plants.

Integrated, model-based analyses are required to investigate these issues in a consistent way and shed light on economic interdependencies between different RES integration strategies. Such analyses require the application of a dedicated bottom-up dispatch model that represents important technical intricacies as well as the most important RES

integration technologies. It must include a range of features that are key to questions of renewable energy integration. For example, such a model should properly reflect the technical rigidities of the German conventional power plant fleet. Accordingly, individual plants' hourly operations must be modeled, following a unit commitment approach with a mixed integer formulation. In addition, the timing of generation decisions is important for renewable energy integration, i.e. unit commitment decision in the light of uncertain wind feed-in. Accordingly, the timing of real-world power markets should be represented, including daily gate closure of the day-ahead market. Likewise, the model has to include the balancing market, which will gain increasing importance for RES integration.In addition, at least a stylized DC loadflow model of the German transmission network is required in order to represent the most important grid bottlenecks. The old "copper plate" assumption of unconstrained transmission networks is clearly no longer valid in a future German power system with high RES penetration.

The most delicate task in the development of such a power market model will be finding the right balance between, on the one hand, including sufficient technical details in order to obtain policy-relevant results, and on the other ensuring manageability and solvability by keeping the formulation as simple as possible. My experiences during the course of writing this thesis will certainly be of great help for this future task. I plan to develop the model and carry out the market analyses sketched out above in the course of a three-year research project "StoRES" (Storage for Renewable Energy Sources), which I have proposed for funding to the German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety.

# Bibliography


Abrell, J., Kunz, F., and Weigt, H. (2008). Start me up: Modeling of power plant start-up conditions and their impact on prices. Electricity Markets Working Paper WP-EM-28. TU Dresden, July 2008. `http://www.tu-dresden.de/wwbwleeg/publications/wp_em_28_Abrell_Kunz_Weigt_Startup.pdf`; last accessed 14 April 2011.

Adilov, N. (2010). Bilateral forward contracts and spot prices. *The Energy Journal*, 31(3):67–82.

Åhman, M., Burtraw, D., Kruger, J., and Zetterberg, L. (2007). A ten-year rule to guide the allocation of EU emission allowances. *Energy Policy*, 35(3):1718–1730.

Akimoto, K., Sano, F., Homma, T., Oda, J., Nagashima, M., and Kii, M. (2010). Estimates of GHG emission reduction potential by country, sector, and cost. *Energy Policy*, 38(7):3384–3393.

Amann, M., Rafaj, P., and Höhne, N. (2009). GHG mitigation potentials in Annex I countries: Comparison of model estimates for 2020. Interim Report IR-09-034. International Institute for Applied Systems Analysis. Laxenburg, Austria.

Andersen, P. H., Mathews, J. A., and Rask, M. (2009). Integrating private transport into renewable energy policy: The strategy of creating intelligent recharging grids for electric vehicles. *Energy Policy*, 37:2481–2486.

Andersson, B. and Bergman, L. (1995). Market structure and the price of electricity: An ex ante analysis of the deregulated Swedish electricity market. *The Energy Journal*, 16(2):97–110.

Andersson, S. L., Elofsson, A. K., Galus, M. D., Göransson, L., Karlsson, S., Johnsson, F., and Andersson, G. (2010). Plug-in hybrid electric vehicles as regulating power providers: Case studies of Sweden and Germany. *Energy Policy*, 38(6):2751–2762.

Armstrong, M., Cowan, S., and Vickers, J. (1994). *Regulatory reform: economic analysis and British experience*. MIT Press, Cambridge.

Baker, J. (2008). New technology and possible advances in energy storage. *Energy Policy*, 36(12):4368–4373.

Baldick, R., Grant, R., and Kahn, E. (2004). Theory and application of linear supply function equilibrium in electricity markets. *Journal of Regulatory Economics*, 25:143–167.

BCG (2011). Revisiting energy storage: There is a business case. Cornelius Pieper and Holger Rubel. Boston Consulting Group. February 2011. `http://www.bcg.com/documents/file72092.pdf`; last accessed 18 April 2011.

Benitez, L. E., Benitez, P. C., and van Kooten, G. C. (2008). The economics of wind power with energy storage. *Energy Economics*, 30(4):1973–1989.

Bergerson, J. A. and Lave, L. B. (2007). Baseload coal investment decisions under uncertain carbon legislation. *Environmental Science & Technology*, 41(10):3431–3436.

Birge, J. R. and Louveaux, F. (1997). *Introduction to Stochastic Programming*. Springer Series in Operations Research and Financial Engineering. Springer, Berlin, Heidelberg.

Blazejczak, J., Braun, F. G., Edler, D., and Schill, W.-P. (2010). Ausbau erneuerbarer Energien erhöht Wirtschaftsleistung in Deutschland. *Wochenbericht des DIW Berlin*, 77:10–16.

Blyth, W. (2010). The economics of transition in the power sector. International Energy Agency. Paris, January 2010.

Blyth, W., Bradley, R., Bunn, D., Clarke, C., Wilson, T., and Yang, M. (2007). Investment risks under uncertain climate change policy. *Energy Policy*, 35(11):5766–5773.

BMU (2006). Erneuerbare Energien in Zahlen – nationale und internationale Entwicklung. Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (BMU). Berlin, May 2006.

BMU (2008). Act on granting priority to renewable energy sources (Renewable Energy Sources Act, EEG). English Translation. Date of issue: 25 October 2008. `http://www.bmu.de/files/english/pdf/application/pdf/eeg_2009_en_bf.pdf`; last accessed 14 March 2011.

BMU (2010a). Erneuerbar beschäftigt! Kurz- und langfristige Arbeitsplatzwirkungen des Ausbaus der erneuerbaren Energien in Deutschland. Study by GWS Osnabrück, DIW Berlin, DLR Stuttgart, Fraunhofer ISI Karlsruhe, ZSW Stuttgart. Berlin, 2010. `http://www.erneuerbare-energien.de/files/pdfs/allgemein/application/pdf/broschuere_erneuerbar_beschaeftigt_bf.pdf`; last accessed 11 April 2011.

BMU (2010b). Erneuerbare Energien in Zahlen: Nationale und internationale Entwicklung. Federal Ministry for the Environment, Nature Conservation

and Nuclear Safety (BMU). Berlin, June 2010. See also Internet-Update, December 2010. http://www.erneuerbare-energien.de/files/pdfs/allgemein/application/pdf/broschuere_ee_zahlen_bf.pdf; last accessed 20 December 2010.

BMU (2010c). "Leitstudie 2010": Langfristszenarien und Strategien für den Ausbau der erneuerbaren Energien in Deutschland bei Berücksichtigung der Entwicklung in Europa und global. Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (BMU). Stuttgart, Kassel, Teltow, December 2010. http://www.bmu.de/files/pdfs/allgemein/application/pdf/leitstudie2010.pdf; last accessed 04 March 2011.

BMU (2011a). Erfahrungsbericht 2011 zum Erneuerbare-Energien-Gesetz (EEG-Erfahrungsbericht). Entwurf, Stand 3.5.2011. Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (BMU). Berlin, May 2011. http://www.erneuerbare-energien.de/files/pdfs/allgemein/application/pdf/eeg_erfahrungsbericht_2011_entwurf.pdf; last accessed 31 May 2011.

BMU (2011b). Erneuerbare Energien 2010: Daten des Bundesministeriums für Umwelt, Naturschutz und Reaktorsicherheit zur Entwicklung der erneuerbaren Energien in Deutschland im Jahr 2010 auf der Grundlage der Angaben der Arbeitsgruppe Erneuerbare Energien-Statistik (AGEE-Stat). Vorläufige Angaben, Stand 23. März 2011. Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (BMU). Berlin, March 2011. http://www.erneuerbare-energien.de/files/pdfs/allgemein/application/pdf/ee_in_zahlen_2010_bf.pdf; last accessed 31 May 2011.

BMWi (2010). Entwicklung von Energiepreisen und Preisindizes. Energiedaten Tabelle 26. 17.03.2010. Federal Ministry of Economics and Technology (BMWi). http://www.bmwi.de/BMWi/Redaktion/Binaer/Energiedaten/energiepreise-und-energiekosten1-entwicklung-energiepreise-preisindizes.xls; last accessed 21 December 2010.

BMWi and BMU (2010). Energy Concept for an Environmentally Sound, Reliable and Affordable Energy Supply. 28. September 2010. Federal Ministry of Economics and Technology (BMWi) and Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (BMU). Berlin, September 2010. http://www.bmu.de/files/english/pdf/application/pdf/energiekonzept_bundesregierung_en.pdf; last accessed 04 March 2010.

Bolle, F. (1992). Supply function equilibria and the danger of tacit collusion : The case of spot markets for electricity. *Energy Economics*, 14(2):94–102.

Borenstein, S. and Bushnell, J. (1999). An empirical analysis of the potential for market power in California's electricity industry. *The Journal of Industrial Economics*, 47(3):285–323.

Borenstein, S., Bushnell, J. B., and Wolak, F. A. (2002). Measuring market inefficiencies in California's restructured wholesale electricity market. *American Economic Review*, 92(5):1376–1405.

BP (2010). BP Statistical Review of World Energy 2010. `http://www.bp.com/statisticalreview`; last accessed 31 January 2011.

Bradley, T. H. and Frank, A. A. (2009). Design, demonstrations and sustainability impact assessments for plug-in hybrid electric vehicles. *Renewable and Sustainable Energy Reviews*, 13(1):115–128.

Brandt, U. S. and Svendsen, G. T. (2006). Climate change negotiations and first-mover advantages: the case of the wind turbine industry. *Energy Policy*, 34(10):1175–1184.

Bresnahan, T. F. (1981). Duopoly models with consistent conjectures. *The American Economic Review*, 71(5):934–945.

Breukers, S., Heiskanen, E., Brohmann, B., Mourik, R., and Feenstra, C. (2011). Connecting research to practice to improve energy demand-side management (DSM). *Energy*, 36(4):2176–2185.

Brunekreeft, G. and Bauknecht, D. (2006). *Electricity Market Reform: An International Perspective*, chapter Energy Policy and Investment in the German Power Market, pages 235–263. In Sioshansi and Pfaffenberger (2006b).

Brunekreeft, G., Neuhoff, K., and Newbery, D. M. (2005). Electricity transmission: An overview of the current debate. *Utilities Policy*, 13(2):73–93.

Büsgen, U. and Dürrschmidt, W. (2009). The expansion of electricity generation from renewable energies in Germany: A review based on the Renewable Energy Sources Act Progress Report 2007 and the new German feed-in legislation. *Energy Policy*, 37(7):2536–2545.

Buijs, P., Bekaert, D., Cole, S., Hertem, D. V., and Belmans, R. (2011). Transmission investment problems in Europe: Going beyond standard solutions. *Energy Policy*, 39(3):1794–1801.

BUND (2010). Geplante und im Bau befindliche Kohlekraftwerke. Bund für Umwelt und Naturschutz Deutschland. Berlin, 4 May 2010. `http://www.bund.net/fileadmin/bundnet/pdfs/klima\und\energie/20100504\klima\liste\kokw\verfahrensstand.pdf`; last accessed 20 May 2010.

Bundesgesetzblatt (1990). Gesetz über die Einspeisung von Strom aus erneuerbaren Energien in das öffentliche Netz. Bundesgesetzblatt, Jahrgang 1990, Teil I, Nr. 67, 2633-2634, 14.12.1990.

Bundesgesetzblatt (1998). Gesetz zur Neuregelung des Energiewirtschaftsrechts. Bundesgesetzblatt, Jahrgang 1998, Teil I, Nr. 23, 730-736, 28.04.1998.

Bundesgesetzblatt (2000). Gesetz für den Vorrang Erneuerbarer Energien (Erneuerbare-Energien-Gesetz – EEG). Bundesgesetzblatt, Jahrgang 2000, Teil I, Nr. 13, 305-309, 31.03.2000.

Bundesgesetzblatt (2004a). Gesetz über den nationalen Zuteilungsplan für Treibhausgas-Emissionsberechtigungen in der Zuteilungsperiode 2005 bis 2007 (Zuteilungsgesetz 2007 – ZuG 2007). Bundesgesetzblatt, Jahrgang 2004, Teil I, Nr. 45, 30.08.2004.

Bundesgesetzblatt (2004b). Gesetz zur Neuregelung des Rechts der Erneuerbaren Energien im Strombereich. Bundesgesetzblatt, Jahrgang 2004, Teil I, Nr. 40, 1918-1930, 31.07.2004.

Bundesgesetzblatt (2005a). Verordnung über die Entgelte für den Zugang zu Elektrizitätsversorgungsnetzen (Stromnetzentgeltverordnung – StromNEV). Bundesgesetzblatt, Jahrgang 2005, Teil I, Nr. 46, 2225-2242, 28.07.2005.

Bundesgesetzblatt (2005b). Zweites Gesetz zur Neuregelung des Energiewirtschaftsrechts. Bundesgesetzblatt, Jahrgang 2005, Teil I, Nr. 42, 1970-2018, 07.07.2005.

Bundesgesetzblatt (2007). Gesetz zur Änderung der Rechtsgrundlagen zum Emissionshandel im Hinblick auf die Zuteilungsperiode 2008 bis 2012. Bundesgesetzblatt, Jahrgang 2007, Teil I, Nr. 38, 10.08.2007.

Bundesgesetzblatt (2008). Gesetz zur Neuregelung des Rechts der Erneuerbaren Energien im Strombereich und zur Änderung damit zusammenhängender Vorschriften. Bundesgesetzblatt, Jahrgang 2008, Teil I, Nr. 49, 2074-2100, 31.10.2008.

Bundeskartellamt (2011). Sektoruntersuchung Stromerzeugung Stromgroßhandel. Main authors: Daniel Judith, Gero Meeßen, Johanna Hartog, Felix Engelsing, Frank Simonis, Lieselotte Locher. Bonn, January 2011. `http://www.bundeskartellamt.de/wDeutsch/download/pdf/Stellungnahmen/110113_Bericht_SU_Strom__2_.pdf`; last accessed 04 March 2011.

Bundesnetzagentur (2009). Monitoringbericht 2009. Bundesnetzagentur für Elektrizität, Gas, Telekommunikation, Post und Eisenbahnen. Bonn. `http://www.bundesnetzagentur.de/SharedDocs/Downloads/DE/BNetzA/Presse/Berichte/2009/Monitoringbericht2009EnergieId17368pdf.pdf?__blob=publicationFile`; last accessed 31 May 2011.

Bundesnetzagentur (2010). Monitoringbericht 2010. Bundesnetzagentur für Elektrizität, Gas, Telekommunikation, Post und Eisenbahnen. Bonn. `http://www.bundesnetzagentur.de/SharedDocs/Downloads/DE/BNetzA/Presse/Berichte/2010/Monitoringbericht2010Energiepdf.pdf?__blob=publicationFile`; last accessed 31 May 2011.

Bundesregierung (2009). German Federal Government's National Electromobility Development Plan. Berlin, August 2009. http://www.bmu.de/files/pdfs/allgemein/application/pdf/nep_09_bmu_en_bf.pdf; last accessed 04 March 2011.

Burtraw, D. and Palmer, K. (2008). Compensation rules for climate policy in the electricity sector. *Journal of Policy Analysis and Management*, 27(4):819–847.

Bushnell, J. (2003). A mixed complementarity model of hydrothermal electricity competition in the Western United States. *Operations Research*, 51:80–93.

Bushnell, J. and Stoft, S. (1997). Improving private incentives for electric grid investment. *Resource and Energy Economics*, 19(1-2):85–108.

Bushnell, J. B. (2008). Vertical arrangements, market structure, and competition: An analysis of restructured US electricity markets. *American Economic Review*, 98(1):237–66.

Butler, L. and Neuhoff, K. (2008). Comparison of feed-in tariff, quota and auction mechanisms to support wind power development. *Renewable Energy*, 33(8):1854–1867.

CAISO (2010a). Market Performance Metric Catalog. Version 1.17. December 23, 2010. California ISO. http://www.caiso.com/2875/2875e49f6f870.pdf; last accessed 28 February 2011.

CAISO (2010b). Market Performance Report On CRRs. January 26, 2010. California ISO. http://www.caiso.com/272b/272b8b042b7a0.pdf; last accessed 28 February 2011.

Capoor, K. and Ambrosi, P. (2006). State and trends of the carbon market 2006. The World Bank. Washington D.C., May 2006.

Carrasco, J. M., Franquelo, L. G., Bialasiewicz, J. T., Galván, E., Guisado, R. C. P., Ángeles Martín Prats, M., León, J. I., and Moreno-Alfonso, N. (2005). Power-electronic systems for the grid integration of renewable energy sources: A survey. *IEEE Transactions on Industrial Electronics*, 53(4):1002–1016.

Connolly, D., Lund, H., Mathiesen, B., and Leahy, M. (2010). A review of computer tools for analysing the integration of renewable energy into various energy systems. *Applied Energy*, 87(4):1059–1082.

Convery, F. J. (2009). Reflections – the emerging literature on emissions trading in europe. *Review of Environmental Economics and Policy*, 3(1):121–137.

Crampes, C. and Moreaux, M. (2010). Pumped storage and cost saving. *Energy Economics*, 32:325–333.

Cramton, P. and Stoft, S. (2006). The convergence of market designs for adequate generating capacity with special attention to the CAISO's resource adequacy problem. A White Paper for the Electricity Oversight Board. 25 April 2006. http://hdl.handle.net/1903/7056; last accessed 15 April 2011.

Crew, M. A., Fernando, C. S., and Kleindorfer, P. R. (1995). The theory of peak-load pricing: A survey. *Journal of Regulatory Economics*, 8(3):215–48.

Dasgupta, P. (2007). Commentary: The Stern review's economics of climate change. *National Institute Economic Review*, 199(4):4–7.

Day, C. J., Hobbs, B. F., and Jong-Shi, P. (2002). Oligopolistic competition in power networks: A conjectured supply function approach. *IEEE Transactions on Power Systems*, 17(3):597–607.

DEHSt (2005). Implementation of Emissions Trading in the EU: National Allocation Plans of all EU states. Brief fact sheets of EU member state allocation plans. Deutsche Emissionshandelsstelle (DEHSt) im Umweltbundesamt. Berlin, November 2005.

DEHSt (2009). Emissionshandel: Auswertung der ersten Handelsperiode 2005-2007. Deutsche Emissionshandelsstelle (DEHSt) im Umweltbundesamt. Berlin, January 2009. http://www.dehst.de/SharedDocs/Downloads/DE/Publikationen/Auswertung_1_Handelsperiode.pdf; last accessed 15 April 2011.

dena (2005). Energiewirtschaftliche Planung für die Netzintegration von Windenergie in Deutschland an Land und Offshore bis zum Jahr 2020 (dena-Netzstudie). dena (German Energy Agency). http://www.dena.de/themen/thema-esd/projekte/projekt/netzstudie-i/; last accessed 13 April 2011.

dena (2010). dena-Netzstudie II. Integration erneuerbarer Energien in die deutsche Stromversorgung im Zeitraum 2015 – 2020 mit Ausblick 2025. dena (German Energy Agency). Berlin, November 2010. http://www.dena.de/themen/thema-esd/projekte/projekt/netzstudie-ii/; last accessed 13 April 2011.

Denholm, P. and Hand, M. (2011). Grid flexibility and storage required to achieve very high penetration of variable renewable electricity. *Energy Policy*, 39(3):1817–1830.

Denholm, P. and Sioshansi, R. (2009). The value of compressed air energy storage with wind in transmission-constrained electric power systems. *Energy Policy*, 37(8):3149–3158.

Denny, E. and O'Malley, M. (2009). The impact of carbon prices on generation-cycling costs. *Energy Policy*, 37(4):1204–1212.

Denny, E., Tuohy, A., Meibom, P., Keane, A., Flynn, D., Mullane, A., and O'Malley, M. (2010). The impact of increased interconnection on electricity systems with large

penetrations of wind generation: A case study of Ireland and Great Britain. *Energy Policy*, 38(11):6946–6954.

Diekmann, J. (2009). Renewable energy in europe: Strong political will required for ambitious goals. *DIW Berlin Weekly Report*, 5:242–250.

DLR (2006). Trans-Mediterranean Interconnection for Concentrating Solar Power. Final Report. German Aerospace Center (DLR). Commissioned by Federal Ministry for the Environment, Nature Conservation and Nuclear Safety Germany (BMU). Stuttgart, June 2006. `http://www.dlr.de/tt/Portaldata/41/Resources/dokumente/institut/system/projects/TRANS-CSP_Full_Report_Final.pdf`; last accessed 14 April 2011.

DPG (2010). Elektrizität: Schlüssel zu einem nachhaltigen und klimaverträglichen Energiesystem. Eine Studie der Deutschen Physikalischen Gesellschaft. `http://www.umweltdaten.de/publikationen/fpdf-l/3958.pdf`; last accessed 13 April 2011.

EEX (2011). EU Emission Allowances. Preise und Handelsvolumen. European Energy Exchange. `http://www.eex.com/de/Marktdaten/Handelsdaten/Emissionsrechte`; last accessed 28 February 2011.

Egerer, J., Bückers, L., and Drondorf, G. (2009). Sustainable energy networks for europe – the integration of large-scale renewable energy sources until 2050. Electricity Markets Working Paper WP-EM-35. TU Dresden, October 2009. `http://www.tu-dresden.de/wwbwleeg/publications/wp_em_35_Egerer_et_al_2050.pdf`; last accessed 14 April 2011.

Ekman, C. K. (2011). On the synergy between large electric vehicle fleet and high wind penetration – an analysis of the Danish case. *Renewable Energy*, 36(2):546–553.

Ellermann, D. A. (2008). New entrant and closure provisions: How do they distort? *The Energy Journal*, Special Issue:63–76.

ENTSO-E (2010a). Hourly load values of a specific country for a specific month. European Network of Transmission System Operators for Electricity. `https://www.entsoe.eu/db-query/consumption/mhlv-a-specific-country-for-a-specific-month`; last accessed 21 December 2010.

ENTSO-E (2010b). Net Generating Capacity on December 31st (in MW). European Network of Transmission System Operators for Electricity. `https://www.entsoe.eu/db-query/miscellaneous/net-generating-capacity`; last accessed 31 January 2011.

Erdmann, G. and Zweifel, P. (2008). *Energieökonomik: Theorie und Anwendungen.* Springer, Berlin, Heidelberg.

EU (1996). Directive 96/92/EC of the European Parliament and of the Council of 19 December 1996 concerning common rules for the internal market in electricity. Official Journal L 027, 30.01.1997. http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=CELEX:31996L0092:EN:HTML; last accessed 15 April 2011.

EU (2003). Directive 2003/87/EC of the European Parliament and of the Council of 13 October 2003 establishing a scheme for greenhouse gas emission allowance trading within the Community and amending Council Directive 96/61/EC. Official Journal L 275/32, 25.10.2003. http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2003:275:0032:0032:EN:PDF; last accessed 15 April 2011.

EU (2008). Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions – 20 20 by 2020 – Europe's climate change opportunity. Commission of the European Communities. COM(2008) 30 final. Brussels, 23.1.2008. http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2008:0030:FIN:EN:PDF; last accessed 29 March 2011.

EU (2009a). Directive 2009/28/EC of the European Parliament and of the Council of 23 April 2009 on the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30/EC. Official Journal L 140/16, 5.6.2009. http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2009:140:0016:0062:EN:PDF; last accessed 12 April 2011.

EU (2009b). EU position for the Copenhagen Climate Conference (7-18 December 2009) – Council conclusions. Council of the European Union. 14790/09, ENV 711. Brussels, 21 October 2009. http://register.consilium.europa.eu/pdf/en/09/st14/st14790.en09.pdf; last accessed 29 March 2011.

Eurostat (2010). Infrastructure – electricity – annual data [nrg_113a], Last update: 23-09-2010. European Commission. http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nrg_113a; last accessed 31 January 2011.

Fell, H. (2010). EU-ETS and Nordic electricity: A CVAR analysis. *The Energy Journal*, 31(2):1–26.

Ferris, M. C. and Munson, T. S. (2000). Complementarity problems in GAMS and the PATH solver. *Journal of Economic Dynamics & Control*, 24:165–188.

Fertig, E. and Apt, J. (2011). Economics of compressed air energy storage to integrate wind power: A case study in ERCOT. *Energy Policy*, 39(5):2330–2342.

Filippini, M. (1995). Electricity demand by time of use: An application of the household AIDS model. *Energy Economics*, 17(3):197–204.

Fink, S., Mudd, C., Porter, K., and Morgenstern, B. (2009). Wind energy curtailment case studies: May 2008 – May 2009. National Renewable Energy Laboratory Report NREL/SR-550-46716. `www.nrel.gov/docs/fy10osti/46716.pdf`; last accessed 13 April 2011.

Flauger, J. (2007). Kraftwerks-Projekten droht das Aus. Handelsblatt, 04.09.2007.

Fleten, S. E., Maribu, K. M., and Wangensteen, I. (2007). Optimal investment strategies in decentralized renewable power generation under uncertainty. *Energy*, 32(5):803–815.

Frondel, M. and Peistrup, M. (2009). Das Automobil der Zukunft – ein Elektroauto? *Energiewirtschaftliche Tagesfragen*, 59(8):64–67.

Frondel, M., Ritter, N., Schmidt, C. M., and Vance, C. (2010). Economic impacts from the promotion of renewable energy technologies: The German experience. *Energy Policy*, 38(8):4048–4056.

Gabriel, S. A. and Leuthold, F. U. (2010). Solving discretely-constrained MPEC problems with applications in electric power markets. *Energy Economics*, 32(1):3–14.

Galus, M. D., Zima, M., and Andersson, G. (2010). On integration of plug-in hybrid electric vehicles into existing power system structures. *Energy Policy*, 38(11):6736–6745.

Garcia, A., Reitzes, J. D., and Stacchetti, E. (2001). Strategic pricing when electricity is storable. *Journal of Regulatory Economics*, 20(3):223–247.

Garz, H., Ötsch, R., Haas, A., Wirtz, P., and Zank, S. (2009). German power utilities – caught in the $CO_2$ trap? Potsdam Institute for Climate Impact Research, West LB. September 2009.

Gerbracht, H., Möst, D., and Fichtner, W. (2009). Elektromobilität – Auswirkungen auf das Energiesystem. *Energiewirtschaftliche Tagesfragen*, 59(11):66–69.

Giebel, G. (2003). The state-of-the-art in short-term prediction of wind power: A literature overview. Project ANEMOS. `http://anemos.cma.fr/download/ANEMOS_D1.1_StateOfTheArt_v1.1.pdf`; last accessed 13 April 2011.

Glachant, J.-M. and Finon, D. (2010). Large-scale wind power in electricity markets. *Energy Policy*, 38(10):6384–6386.

Göransson, L., Karlsson, S., and Johnsson, F. (2010). Integration of plug-in hybrid electric vehicles in a regional wind-thermal power system. *Energy Policy*, 38(10):5482–5492.

Green, R. J. (2007). Nodal pricing of electricity: How much does it cost to get it wrong? *Journal of Regulatory Economics*, 31:125–149.

Green, R. J. and Newbery, D. M. (1992). Competition in the British electricity spot market. *Journal of Political Economy*, 100(5):929.

Greenblatt, J. B., Succar, S., Denkenberger, D. C., Williams, R. H., and Socolow, R. H. (2007). Baseload wind energy: Modeling the competition between gas turbines and compressed air energy storage for supplemental generation. *Energy Policy*, 35(3):1474–1492.

Gross, R., Blyth, W., and Heptonstall, P. (2010). Risks, revenues and investment in electricity generation: Why policy needs to look beyond costs. *Energy Economics*, 32(4):796–804.

Guille, C. and Gross, G. (2009). A conceptual framework for the vehicle-to-grid (V2G) implementation. *Energy Policy*, 37(11):4379–4390.

Haas, R., Panzer, C., Resch, G., Ragwitz, M., Reece, G., and Held, A. (2011). A historical review of promotion strategies for electricity from renewable energy sources in EU countries. *Renewable and Sustainable Energy Reviews*, 15(2):1003–1034.

Hahn, R. W. and Stavins, R. N. (2010). The effect of allowance allocations on cap-and-trade system performance. National Bureau of Economic Research Working Papers. Cambridge, March 2010.

Hall, P. J. and Bain, E. J. (2008). Energy-storage technologies and electricity generation. *Energy Policy*, 36(12):4352–4355.

Ham, J. C., Mountain, D. C., and Chan, M. L. (1997). Time-of-use prices and electricity demand: Allowing for selection bias in experimental data. *The RAND Journal of Economics*, 28(0):S113–S141.

Hamming, R. W. (1962). *Numerical Methods for Scientists and Engineers*. McGraw-Hill, New York.

Hentrich, S., Matschoss, P., and Michaelis, P. (2009). Emissions trading and competitiveness: lessons from Germany. *Climate Policy*, 9(3):316–329.

Herold, J., Rüster, S., and von Hirschhausen, C. (2010). Carbon Capture, Transport and Storage in Europe: A problematic energy bridge to nowhere? CEPS Working Document No. 341. November 2010. `www.ceps.eu/ceps/download/3979`; last accessed 12 April 2011.

Hillebrand, B., Buttermann, H. G., Behringer, J. M., and Bleuel, M. (2006). The expansion of renewable energies and employment effects in Germany. *Energy Policy*, 34(18):3484–3494.

Hiroux, C. and Saguan, M. (2010). Large-scale wind power in European electricity markets: Time for revisiting support schemes and market designs? *Energy Policy*, 38(7):3135–3145.

Hobbs, B. F., Metzler, C., and Pang, J. (2000). Strategic gaming analysis for electric power systems: an MPEC approach. *IEEE Transactions on Power Systems*, 15(2):638–645.

Hobbs, B. F., Rothkopf, M., O'Neill, R., and Chao, H., editors (2001). *The Next Generation of Electric Power Unit Commitment Models*. Springer, Berlin, Heidelberg.

Hoffmann, V. H. (2007). EU ETS and investment decisions: The case of the German electricity industry. *European Management Journal*, 25(6):464–474.

Hogan, W. (1992). Contract networks for electric power transmission. *Journal of Regulatory Economics*, 4:211–242.

Hogan, W. (2002). Electricity market restructuring: Reforms of reforms. *Journal of Regulatory Economics*, 21:103–132.

Hogan, W., Rosellón, J., and Vogelsang, I. (2010). Toward a combined merchant-regulatory mechanism for electricity transmission expansion. *Journal of Regulatory Economics*, 38:113–143.

Hortaçsu, A. and Puller, S. L. (2008). Understanding strategic bidding in multi-unit auctions: a case study of the Texas electricity spot market. *The RAND Journal of Economics*, 39(1):86–114.

Ibrahim, H., Ilinca, A., and Perron, J. (2008). Energy storage systems–characteristics and comparisons. *Renewable and Sustainable Energy Reviews*, 12(5):1221–1250.

IEA (2004). *World Energy Outlook 2004 Edition*. International Energy Agency, Paris.

IEA (2005). *World Energy Outlook 2005 Edition*. International Energy Agency, Paris.

IEA (2010a). *Projected Costs of Generating Electricity*. International Energy Agency, Paris.

IEA (2010b). *World Energy Outlook 2010 Edition*. International Energy Agency, Paris.

IPCC (2007). *Climate Change 2007: Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. [Core Writing Team, Pachauri, R.K and Reisinger, A. (eds.)]. IPCC, Geneva, Switzerland, 104 pp.

Ishii, J. and Yan, J. (2004). Investment under regulatory uncertainty: U.S. electricity generation investment since 1996. Center for the Study of Energy Markets Working Paper 127.

ISO-NE (2010). 2009 Annual Markets Report. May 18, 2010. ISO New England. `http://www.iso-ne.com/markets/mktmonmit/rpts/other/amr09_final_051810.pdf`; last accessed 28 February 2011.

Johnsen, T. A. (2001). Hydropower generation and storage, transmission contraints and market power. *Utilities Policy*, 10:63–73.

Jordanger, J. and Grønli, H. (2000). Deregulation of the electricity supply industry – Norwegian experience 1991 – 2000. SINTEF, October 2000.

Joskow, P. L. (2005). Patterns of transmission investment. Massachusetts Institute of Technology, Center for Energy and Environmental Policy Research Working Paper 0504. Cambridge, March 2005.

Joskow, P. L. (2006). *Electricity Market Reform: An International Perspective*, chapter Introduction to Electricity Sector Liberalization: Lessons Learned from Cross-Country Studies, pages 1–32. In Sioshansi and Pfaffenberger (2006b).

Joskow, P. L. and Kohn, E. (2002). A quantitative analysis of pricing behavior in California's wholesale electricity market during summer 2000. *The Energy Journal*, 23(4):1–36.

Joskow, P. L. and Tirole, J. (2000). Transmission rights and market power on electric power networks. *The RAND Journal of Economics*, 31(3):450–487.

Joskow, P. L. and Tirole, J. (2005). Merchant transmission investment. *Journal of Industrial Economics*, 53(2):233–264.

Joskow, P. L. and Tirole, J. (2007). Reliability and competitive electricity markets. *The RAND Journal of Economics*, 38(1):60–84.

Junginger, M., Faaij, A., and Turkenburg, W. C. (2005). Global experience curves for wind farms. *Energy Policy*, 33(2):133–150.

Kahnemann, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2):263–291.

Kemfert, C. and Diekmann, J. (2009). Emissions trading and promotion of renewable energy – we need both. *DIW Berlin Weekly Report*, 5:95–100.

Kemfert, C., Kohlhaas, M., Truong, T., and Protsenko, A. (2006). The environmental and economic effects of European emissions trading. *Climate Policy*, 6:441–455.

Kemfert, C. and Schill, W.-P. (2010). *Smart Solutions to Climate Change: Comparing Costs and Benefits*, chapter Methane Mitigation, pages 172–197. Cambridge University Press, Cambridge, New York.

Kempton, W. and Tomic, J. (2005a). Vehicle-to-grid power fundamentals: Calculating capacity and net revenue. *Journal of Power Sources*, 144(1):268–279.

Kempton, W. and Tomic, J. (2005b). Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy. *Journal of Power Sources*, 144(1):280–294.

Keppler, J. H. and Cruciani, M. (2010). Rents in the European power sector due to carbon trading. *Energy Policy*, 38(8):4280–4290.

Kirschen, D. and Strbac, G. (2004). *Fundementals of Power System Economics*. John Wiley & Sons, Chicester, England.

Klemperer, P. D. and Meyer, M. A. (1989). Supply function equilibria in oligopoly under uncertainty. *Econometrica*, 57(6):1243–1277.

Konstantin, P. (2007). *Praxisbuch Energiewirtschaft*. Springer, 1. Auflage. Berlin, Heidelberg.

Konstantin, P. (2009). *Praxisbuch Energiewirtschaft*. Springer, 2. bearbeitete und aktualisierte Auflage. Berlin, Heidelberg.

Krause, T., Beck, E., Cherkaoui, R., Germond, A., Andersson, G., and Ernst, D. (2006). A comparison of nash equilibria analysis and agent-based modelling for power markets. *International Journal of Electrical Power & Energy Systems*, 28(9):599–607.

Kristiansen, T. and Rosellón, J. (2006). A merchant mechanism for electricity transmission expansion. *Journal of Regulatory Economics*, 29:167–193.

Kristiansen, T. and Rosellón, J. (2010). Merchant electricity transmission expansion: A European case study. *Energy*, 35(10):4107–4115.

Kuntz, L. and Müsgens, F. (2007). Modelling start-up costs of multiple technologies in electricity markets. *Mathematical Methods of Operations Research*, 66:21–32.

Lange, B., Rohrig, K., Ernst, B., Schlogl, F., Cali, U., Jursa, R., and Moradi, J. (2006). Wind power forecasting in Germany – recent advances and future challenges. *Zeitschrift für Energiewirtschaft*, 30(2):115–120.

Langniß, O., Diekmann, J., and Lehr, U. (2009). Advanced mechanisms for the promotion of renewable energy – models for the future evolution of the German renewable energy act. *Energy Policy*, 37(4):1289–1297.

Laurikka, H. and Koljonen, T. (2006). Emissions trading and investment decisions in the power sector – a case study in Finland. *Energy Policy*, 34(9):1063–1074.

Léautier, T.-O. (2000). Regulation of an electric power transmission company. *The Energy Journal*, 21(4):61–92.

Léautier, T.-O. and Thelen, V. (2009). Optimal expansion of the power transmission grid: why not? *Journal of Regulatory Economics*, 36:127–153.

Lee, C.-C. and Lee, J.-D. (2010). A panel data analysis of the demand for total energy and electricity in OECD countries. *The Energy Journal*, 31(1):1–23.

Lemming, J. (2003). Financial risks for green electricity investors and producers in a tradable green certificate market. *Energy Policy*, 31(1):21–32.

Leuthold, F., Weigt, H., and von Hirschhausen, C. (2008a). Efficient pricing for European electricity networks – the theory of nodal pricing applied to feeding-in wind in Germany. *Utilities Policy*, 16(4):284–291.

Leuthold, F., Weigt, H., and von Hirschhausen, C. (2008b). Elmod – a model of the European electricity market. Electricity Markets Working Paper No. WP-EM-00. TU Dresden, July 2008.

Leuthold, F., Weigt, H., and von Hirschhausen, C. (2010). A large-scale spatial optimization model of the European electricity market. *Networks and Spatial Economics*, pages 1–33. Online First.

Lijesen, M. G. (2007). The real-time price elasticity of electricity. *Energy Economics*, 29(2):249–258.

Lindenberger, D. and Hildebrand, B. (2008). *Studie Energiewirtschaftliches Gesamtkonzept*. Energiewirtschaftliches Institut an der Universität zu Köln.

Lise, W., Hobbs, B. F., and Hers, S. (2008). Market power in the European electricity market – the impacts of dry weather and additional transmission capacity. *Energy Policy*, 36:1331–1343.

Lise, W. and Kruseman, G. (2008). Long-term price and environmental effects in a liberalised electricity market. *Energy Economics*, 30(2):230–248.

Lise, W., Linderhof, V., Kuik, O., Kemfert, Claudia snd Östling, R., and Heinzow, T. (2006). A game theoretic model of the Northwestern European electricity market – market power and the environment. *Energy Policy*, 34:2123–2136.

Littlechild, S. (2006). *Electricity Market Reform: An International Perspective*, chapter Foreword: The Market versus Regulation, pages xvii–xxix. In Sioshansi and Pfaffenberger (2006b).

Loisel, R., Mercier, A., Gatzen, C., Elms, N., and Petric, H. (2010). Valuation framework for large scale electricity storage in a case with wind curtailment. *Energy Policy*, 38(11):7323–7337.

Luickx, P. J., Delarue, E. D., and D'haeseleer, W. D. (2008). Considerations on the backup of wind power: Operational backup. *Applied Energy*, 85(9):787–799.

Lund, H. (2006). Large-scale integration of optimal combinations of PV, wind and wave power into the electricity supply. *Renewable Energy*, 31(4):503–515.

Lund, H. and Kempton, W. (2008). Integration of renewable energy into the transport and electricity sectors through V2G. *Energy Policy*, 36(9):3578–3587.

Mansur, E. T. (2008). Measuring welfare in restructured electricity markets. *Review of Economics and Statistics*, 90(2):369–386.

Mas-Colell, A., Whinston, M. D., and Green, J. R. (1995). *Microeconomic Theory*. Oxford University Press, New York, Oxford.

Mathiesen, B. and Lund, H. (2009). Comparative analyses of seven technologies to facilitate the integration of fluctuating renewable energy sources. *Renewable Power Generation*, 3:190–204.

Matthes, F. and Schafhausen, F. (2007). Germany. In Ellerman, D., Buchner, B., and Carraro, C., editors, *Allocation in the European Emission Trading Scheme: Rights, Rents and Fairness*. Cambridge University Press.

McKinsey (2007). Costs and potentials of greenhouse gas abatement in Germany. A report by McKinsey & Company, Inc., on behalf of "BDI initiativ – Business for Climate". Berlin, September 2007. `http://www.mckinsey.com/Client_Service/Sustainability/Latest_thinking/Costcurves.aspx`; last accessed 13 April 2011.

MEF (2009). Declaration of the leaders of the Major Economies Forum on Energy and Climate. L'Aquila, Italy, 09.07.2009. `http://www.g8italia2009.it/static/G8_Allegato/MEF_Declarationl.pdf`; last accessed 29 March 2011.

Menanteau, P., Finon, D., and Lamy, M.-L. (2003). Prices versus quantities: choosing policies for promoting the development of renewable energy. *Energy Policy*, 31(8):799–812.

Meyer, N. I. (2003). European schemes for promoting renewables in liberalised markets. *Energy Policy*, 31(7):665–676.

Milligan, M., Porter, K., DeMeo, E., Denholm, P., Holttinen, H., Kirby, B., Miller, N., Mills, A., O'Malley, M., Schuerger, M., and Soder, L. (2009). Wind power myths debunked. *IEEE Power & Energy Magazine*, 7:89–99.

Morthorst, P. E. (2000). The development of a green certificate market. *Energy Policy*, 28(15):1085–1094.

Mountain, D. C. and Lawson, E. L. (1992). A disaggregated nonhomothetic modeling of responsiveness to residential time-of-use electricity rates. *International Economic Review*, 33(1):181–207.

Moura, P. S. and de Almeida, A. T. (2010). The role of demand-side management in the grid integration of wind power. *Applied Energy*, 87(8):2581–2588.

Narayan, P. K., Smyth, R., and Prasad, A. (2007). Electricity consumption in G7 countries: A panel cointegration analysis of residential demand elasticities. *Energy Policy*, 35(9):4485–4494.

Neij, L. (1999). Cost dynamics of wind power. *Energy*, 24(5):375–389.

Neij, L. (2008). Cost development of future technologies for power generation–a study based on experience curves and complementary bottom-up assessments. *Energy Policy*, 36(6):2200–2211.

Neuhoff, K. (2011). Europe's challenge: A smart power market at the centre of a smart grid. Executive summary. Climate Policy Initiative Smart Power Market Project. January 2011. `http://www.climatepolicyinitiative.org/files/attachments/95.pdf`; last accessed 06 April 2011.

Neuhoff, K., Barquin, J., Boots, M. G., Ehrenmann, A., Hobbs, B. F., Rijkers, F. A., and Vázquez, M. (2005). Network-constrained cournot models of liberalized electricity markets: the devil is in the details. *Energy Economics*, 27(3):495–525.

Neuhoff, K., Åhman, M., Betz, R., Cludius, J., Ferrario, F., Holmgren, Pal, G., Grubb, M., Matthes, F., Rogge, K., Sato, M., Schleich, J., Sijm, J., Tuerk, A., Kettner, C., and Walker, N. (2006a). Implications of announced phase II national allocation plans for the EU ETS. *Climate Policy*, 6(4):411–422.

Neuhoff, K., Keats Martinez, K., and Sato, M. (2006b). Allocation, incentives and distortions : The impact of EU ETS emissions allowance allocations to the electricity sector. *Climate Policy*, 6(1):73–91.

Newbery, D. M. (2010). Market design for a large share of wind power. *Energy Policy*, 38(7):3131–3134.

Newbery, D. M. and Pollitt, M. G. (1997). The restructuring and privatisation of Britain's CEGB – was it worth it? *The Journal of Industrial Economics*, 45(3):269–303.

Nielsen, L. and Jeppesen, T. (2003). Tradable green certificates in selected European countries - overview and assessment. *Energy Policy*, 31(1):3–14.

Nollen, A. (2003). *Lebensdaueranalysen von Kraftwerken der deutschen Elektrizitätswirtschaft*. Forschungszentrum Jülich. April 2003.

NYISO (2011). TCC Data & Information. New York Independent System Operator. `http://www.nyiso.com/public/markets_operations/market_data/tcc/index.jsp`; last accessed 28 February 2011.

Ockenfels, A., Grimm, V., and Zoettl, G. (2008). Strommarktdesign: Preisbildungsmechanismus im Auktionsverfahren für Stromstundenkontrakte an der EEX. Gutachten im Auftrag der European Energy Exchange AG zur Vorlage an die Sächsische Börsenaufsicht. 11. März 2008. `http://www.eex.com/de/document/38614/gutachten_eex_ockenfels.pdf`; last accessed 06 April 2011.

OECD (2008). *Costs of Inaction on Key Environmental Challenges*. Organisation for Economic Co-operation and Development, Paris.

Pahle, M. (2010). Germany's dash for coal: Exploring drivers and factors. *Energy Policy*, 38(7):3431–3442.

Patiño-Echeverri, D., Fischbeck, P., and Kriegler, E. (2009). Economic and environmental costs of regulatory uncertainty for coal-fired power plants. *Environmental Science & Technology*, 43(3):578–584.

Paulus, M. and Borggrefe, F. (2011). The potential of demand-side management in energy-intensive industries for electricity markets in Germany. *Applied Energy*, 88(2):432–441.

Peace, J. and Weyant, J. (2008). Insights not numbers: The appropriate use of economic models. White Paper – Pew Center on Global Climate Change. April 2008. `http://www.pewcenteronthestates.org/uploadedFiles/wwwpewtrustsorg/Reports/Global_warming/insights-not-numbers.pdf`; last accessed 26 April 2011.

Perman, R., Ma, Y., McGilvray, J., and Common, M. (1999). *Natural Resource & Environmental Economics*. Prentice Hall, Harlow. Second Edition.

Perry, M. K. (1982). Oligopoly and consistent conjectural variations. *The Bell Journal of Economics*, 13(1):197–205.

Peterson, S. B., Whitacre, J., and Apt, J. (2010). The economics of using plug-in hybrid electric vehicle battery packs for grid storage. *Energy Policy*, 195:2377–2384.

Point Carbon (2003). Carbon market Europe. June.

Point Carbon (2006). Carbon 2006. Hasselknippe, H. and K. Røine eds. 60 pages.

Puller, S. L. (2007). Pricing and firm conduct in California's deregulated electricity market. *Review of Economics and Statistics*, 89(1):75–87.

Rangel, L. F. (2008). Competition policy and regulation in hydro-dominated electricity markets. *Energy Policy*, 36(4):1292–1302.

Reedman, L. (2006). Using a real-options approach to model technology adoption under carbon price uncertainty: an application to the Australian electricity sector. *Economic Record*, 82(S1):S64–S73.

Reinelt, P. S. and Keith, D. W. (2007). Carbon capture retrofits and the cost of regulatory uncertainty. *Energy Journal*, 28(4):101–127.

Rosellón, J., Myslíková, Z., and Zenón, E. (2011). Incentives for transmission investment in the PJM electricity market: FTRs or regulation (or both?). *Utilities Policy*, 19(1):3–13.

Rosellón, J. and Weigt, H. (2011). A dynamic incentive mechanism for transmission expansion in electricity networks – theory, modeling and application. *The Energy Journal*, 32(1):119–148.

Rutherford, T. F. (1995). Extension of GAMS for complementarity problems arising in applied economic analysis. *Journal of Economic Dynamics and Control*, 19:1299–1324.

Samaras, C. and Meisterling, K. (2008). Life cycle assessment of greenhouse gas emissions from plug-in hybrid vehicles: Implications for policy. *Environmental Science & Technology*, 42(9):3170–3176.

Schill, W.-P. (2010a). Electric vehicles: Charging into the future. *DIW Berlin Weekly Report*, 6:207–214.

Schill, W.-P. (2010b). Elektromobilität in Deutschland – Chancen, Barrieren und Auswirkungen auf das Elektrizitätssystem. *Vierteljahreshefte zur Wirtschaftsforschung*, 79:139–159.

Schill, W.-P., Diekmann, J., and Kemfert, C. (2010). Energy and climate policy: USA continues to trail behind, despite positive change. *DIW Berlin Weekly Report*, 6:27–35.

Schleich, J., Rogge, K., and Betz, R. (2009). Incentives for energy efficiency in the EU emissions trading scheme. *Energy Efficiency*, 2(1):37–67.

Schmidt, S., Kemfert, C., and Höppe, P. (2010). The impact of socio-economics and climate change on tropical cyclone losses in the USA. *Regional Environmental Change*, 10(1):13–26.

Schröter, J. (2004). Auswirkungen des europäischen Emissionshandelssystems auf den Kraftwerkseinsatz in Deutschland. Diplomarbeit. Institut für Energietechnik, Fachgebiet Energiesysteme, TU Berlin. 4 February 2004.

Schweppe, F., Caramanis, M., Tabors, R., and Bohn, R. (1988). *Spot Pricing of Electricity*. Kluwer Academic Publishers, Boston/Dordrecht/London.

Scott, T. J. and Read, E. G. (1996). Modelling hydro reservoir operation in a deregulated electricity market. *International Transactions in Operational Research*, 3(3-4):243–253.

Sensfuß, F., Ragwitz, M., and Genoese, M. (2008). The merit-order effect: A detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany. *Energy Policy*, 36(8):3086–3094.

Sherif, S., Barbir, F., and Veziroglu, T. (2005). Wind energy and the hydrogen economy–review of the technology. *Solar Energy*, 78(5):647–660.

Sijm, J., Neuhoff, K., and Chen, Y. (2006). $CO_2$ cost pass-through and windfall profits in the power sector. *Climate Policy*, 6(1):49–72(24).

Simon, H. A. (1984). *Models of Bounded Rationality, Volume 1: Economic Analysis and Public Policy*. MIT Press, Cambridge.

Sinden, G. (2007). Characteristics of the UK wind resource: Long-term patterns and relationship to electricity demand. *Energy Policy*, 35(1):112–127.

Sioshansi, F. P. (2008). Competitive electricity markets: Questions remain about design, implementation, performance. *The Electricity Journal*, 21(2):74–87.

Sioshansi, F. P. and Pfaffenberger, W. (2006a). *Electricity Market Reform: An International Perspective*, chapter Why Restructure Electricity Markets?, pages 35–48. In Sioshansi and Pfaffenberger (2006b).

Sioshansi, F. P. and Pfaffenberger, W., editors (2006b). *Electricity Market Reform: An International Perspective*. Elsevier, Oxford, UK.

Sioshansi, R. (2010). Welfare impacts of electricity storage and the implications of ownership structure. *The Energy Journal*, 31(2):189–214.

Sioshansi, R. and Denholm, P. (2009). Emissions impacts and benefits of plug-in hybrid electric vehicles and vehicle-to-grid services. *Environmental Science & Technology*, 43(4):1199–1204.

Sioshansi, R., Denholm, P., Jenkin, T., and Weiss, J. (2009). Estimating the value of electricity storage in PJM: Arbitrage and some welfare effects. *Energy Economics*, 31:269–277.

Sioshansi, R., Fagiani, R., and Marano, V. (2010). Cost and emissions impacts of plug-in hybrid vehicles on the Ohio power system. *Energy Policy*, 38(11):6703–6712.

Sioshansi, R. and Oren, S. (2007). How good are supply function equilibrium models: an empirical analysis of the ERCOT balancing market. *Journal of Regulatory Economics*, 31:1–35.

Söderholm, P. (2008). The political economy of international green certificate markets. *Energy Policy*, 36(6):2051–2062.

Söderholm, P. and Sundqvist, T. (2007). Empirical challenges in the use of learning curves for assessing the economic prospects of renewable energy technologies. *Renewable Energy*, 32(15):2559–2578.

Song, Y., Ni, Y., Wen, F., Hou, Z., and Wu, F. F. (2003). Conjectural variation based bidding strategy in spot markets: fundamentals and comparison with classical game theoretical bidding strategies. *Electric Power Systems Research*, 67(1):45–51.

Sovacool, B. K. (2009). The intermittency of wind, solar, and renewable electricity generators: Technical barrier or rhetorical excuse? *Utilities Policy*, 17(3-4):288–296.

Sovacool, B. K. and Hirsh, R. F. (2009). Beyond batteries: An examination of the benefits and barriers to plug-in hybrid electric vehicles (PHEVs) and a vehicle-to-grid (V2G) transition. *Energy Policy*, 37(3):1095–1103.

SRU (2011). Wege zur 100% erneuerbaren Stromversorgung. Sondergutachten. German Advisory Council on the Environment (SRU). Berlin, January 2011. http://www.umweltrat.de/SharedDocs/Downloads/DE/02_Sondergutachten/2011_Sondergutachten_100Prozent_Erneuerbare.pdf; last accessed 13 April 2011.

Stern, N. (2006). Stern review on the economics of climate change. UK Treasury. London, UK.

Sterner, M. (2009). *Bioenergy and renewable power methane in integrated 100% renewable energy systems: Limiting global warming by transforming energy systems.* PhD thesis, Faculty of Electrical Engineering and Computer Science of the University of Kassel. Kassel University Press.

Stigler, H. and Todem, C. (2005). Optimization of the Austrian electricity sector (Control Zone of VERBUND APG) by nodal pricing. *Central European Journal of Operations Research*, 13:105–125.

Stoft, S. (2002). *Power System Economics. Designing Markets for Electricity.* IEEE Press, Piscataway, NJ.

Strbac, G. (2008). Demand side management: Benefits and challenges. *Energy Policy*, 36(12):4419–4426.

Ströbele, W., Pfaffenberger, W., and Heuterkes, M. (2010). *Energiewirtschaft. Einführung in Theorie und Politik.* Oldenbourg, München. 2. Auflage.

Szolgayova, J., Fuss, S., and Obersteiner, M. (2008). Assessing the effects of $CO_2$ price caps on electricity investments – a real options analysis. *Energy Policy*, 36(10):3974–3981.

Taschini, L. and Urech, S. (2009). The real option to fuel switch in the presence of expected windfall profits under the EU ETS. *The Journal of Energy Markets*, 31(1):1–21.

Tiedemann, A., Srikandam, C., Kreutzkamp, P., Roth, H., Gohla-Neudecker, B., and Kuhn, P. (2008). Untersuchung der elektrizitätswirtschaftlichen und energiepolitischen Auswirkungen der Erhebung von Netznutzungsentgelten für den Speicherstrombezug von Pumpspeicherwerken. Abschlussbericht. dena (German Energy Agency). http://www.dena.de/de/themen/thema-esd/publikationen/publikation/pumpspeicherstudie/; last accessed 13 September 2010.

Timmins, C. (1997). *Price as a policy tool for dynamic resource allocation: the case of the municipally owned water utility.* PhD thesis, Standford University.

Tol, R. S. (2002a). Estimates of the damage costs of climate change. Part I: Benchmark estimates. *Environmental and Resource Economics*, 21:47–73.

Tol, R. S. (2002b). Estimates of the damage costs of climate change, Part II: Dynamic estimates. *Environmental and Resource Economics*, 21:135–160.

Tomic, J. and Kempton, W. (2007). Using fleets of electric-drive vehicles for grid support. *Journal of Power Sources*, 168(2):459–468.

Torriti, J., Hassan, M. G., and Leach, M. (2010). Demand response experience in Europe: Policies, programmes and implementation. *Energy*, 35(4):1575–1583.

Traber, T. and Kemfert, C. (2009). Impacts of the German support for renewable energy on electricity prices, emissions, and firms. *The Energy Journal*, 30:155–178.

Traber, T. and Kemfert, C. (2011a). Gone with the wind? – Electricity market prices and incentives to invest in thermal power plants under increasing wind energy supply. *Energy Economics*, 33:249–256.

Traber, T. and Kemfert, C. (2011b). Refunding ETS proceeds to spur the diffusion of renewable energies: An analysis based on the dynamic oligopolistic electricity market model EMELIE. *Utilities Policy*, 19(1):33–41.

Traber, T., Kemfert, C., and Diekmann, J. (2011). German electricity prices: Only modest increase due to renewable energy expected. *DIW Berlin Weekly Report*, 6:37–45.

Tradewind (2009). Integrating wind: Developing Europe's power market for the large-scale integration of wind power. European Wind Energy Association (Co-ordinator). `http://www.trade-wind.eu/fileadmin/documents/publications/Final_Report.pdf`; last accessed 13 April 2011.

UBA (2009). Datenbank "Kraftwerke in Deutschland". Federal Environment Agency (UBA). Dessau-Roßlau, 10.07.2009.

UBA (2010). Submission under the United Nations Framework Convention on Climate Change and the Kyoto Protocol 2010: National Inventory Report for the German Greenhouse Gas Inventory 1990 – 2008. Federal Environment Agency (UBA). Dessau-Roßlau, June 2010. `http://www.umweltdaten.de/publikationen/fpdf-l/3958.pdf`; last accessed 13 April 2011.

Vandezande, L., Meeus, L., Belmans, R., Saguan, M., and Glachant, J.-M. (2010). Well-functioning balancing markets: A prerequisite for wind power integration. *Energy Policy*, 38(7):3146–3154.

VDE (2008). Energiespeicher in Stromversorgungssystemen mit hohem Anteil erneuerbarer Energieträger – Bedeutung, Stand der Technik, Handlungsbedarf. Verband der Elektrotechnik und Elektronik (VDE), Dezember 2008.

Ventosa, M., Baíllo, l., Ramos, A., and Rivier, M. (2005). Electricity market modeling trends. *Energy Policy*, 33:897–913.

Verbruggen, A. and Lauber, V. (2009). Basic concepts for designing renewable electricity support aiming at a full-scale transition by 2050. *Energy Policy*, 37(12):5732–5743.

VGB PowerTech (2005). Zahlen und Fakten zur Stromerzeugung 2005. VGB PowerTech e.V., Essen.

Viscusi, W. K., Harrington, Jr., J. E., and Vernon, J. M. (2005). *Economics of Regulation and Antitrust*. Fourth Edition. MIT Press, Cambridge.

Vogelsang, I. (2001). Price regulation for independent transmission companies. *Journal of Regulatory Economics*, 20:141–165.

Vogelsang, I. (2006). Electricity transmission pricing and performance-based regulation. *The Energy Journal*, 27(4):97–126.

Voogt, M., Boots, M., Schaeffer, G., and Martens, J. (2000). Renewable electricity in a liberalized market-the concept of green certificates. *Energy & Environment*, 11(1):65–79.

Wangesteen, I. and Grande, O. (2000). Alternative models for congestion management and pricing. Impact on network planning and physical operation. CIGRE Seesion Papers 37-203_2000. Paris, August/September 2000.

WBGU (2009). Solving the climate dilemma: The budget approach. Special Report. German Advisory Council on Global Change (WBGU). Berlin, 2009.

Weber, A., Graeber, D., and Semming, A. (2010). Market coupling and the CWE project. *Zeitschrift für Energiewirtschaft*, 34(4):303–309.

Weidlich, A. and Veit, D. (2008). A critical survey of agent-based wholesale electricity market models. *Energy Economics*, 30(4):1728–1759.

Weigt, H. (2009). Germany's wind energy: The potential for fossil capacity replacement and cost saving. *Applied Energy*, 86(10):1857–1863.

Weigt, H., Jeske, T., Leuthold, F., and von Hirschhausen, C. (2010). "Take the long way down": Integration of large-scale North Sea wind using HVDC transmission. *Energy Policy*, 38(7):3164–3173.

Weigt, H. and von Hirschhausen, C. (2008). Price formation and market power in the German wholesale electricity market in 2006. *Energy Policy*, 36(11):4227–4234.

Weitzman, M. L. (2007). A review of the Stern review on the economics of climate change. *Journal of Economic Literature*, 45(3):703–724.

Werenfels, I. and Westphal, K. (2010). Solar power from North Africa: Frameworks and prospects. SWP Research Paper 2010/RP 03. Berlin, May 2010. `http://www.swp-berlin.org/fileadmin/contents/products/research_papers/2010_RP03_wrf_wep_ks.pdf`; last accessed 13 April 2011.

Wietschel, M., Arens, M., Dötsch, C., Herkel, S., Krewitt, W., Markewitz, P., Möst, D., and Scheufen, M. (2010). *Energietechnologien 2050 – Schwerpunkte für Forschung und Entwicklung*. ISI-Schriftenreihe Innovationspotenziale. Fraunhofer ISI, Karlsruhe.

Wietschel, M. and Dallinger, D. (2008). Quo Vadis Elektromobilität? *Energiewirtschaftliche Tagesfragen*, 58(12):8–16.

Willems, B., Rumiantseva, I., and Weigt, H. (2009). Cournot versus supply functions: What does the data tell us? *Energy Economics*, 31(1):38–47.

Wilson, R. (2002). Architecture of power markets. *Econometrica*, 70(4):1299–1340.

Wissel, S., Rath-Nagel, S., Blesl, M., Fahl, U., and Voß, A. (2008). Stromerzeugungskosten im Vergleich. Institut für Energiewirtschaft und Rationelle Energieanwendung, Stuttgart. `http://www.ier.uni-stuttgart.de/publikationen/arbeitsberichte/Arbeitsbericht_04.pdf`; last accessed 13 September 2010.

Wolfram, C. D. (1999). Measuring duopoly power in the British electricity spot market. *American Economic Review*, 89(4):805–826.

Woo, C., Zarnikau, J., Moore, J., and Horowitz, I. (2011). Wind generation and zonal-market price divergence: Evidence from Texas. *Energy Policy*, In Press, Corrected Proof.

WWF (2009). Blueprint Germany. A strategy for a climate-safe 2050. Öko-Institut and Prognos. Commissioned by WWF Deutschland. Berlin, 15 October 2009. `http://www.wwf.de/fileadmin/fm-wwf/pdf_neu/WWF_Blueprint_Germany.pdf`; last accessed 13 April 2011.

Zachmann, G. and von Hirschhausen, C. (2008). First evidence of asymmetric cost pass-through of EU emissions allowances: Examining wholesale electricity prices in Germany. *Economics Letters*, 99(3):465–469.

Ziesing, H.-J., Diekmann, J., Kohlhaas, M., Betz, R., Bradke, H., Köwener, D., Rogge, K., Schleich, J., Walz, R., Cames, M., and Matthes, F. C. (2007). Entwicklung eines nationalen Allokationsplans im Rahmen des EU-Emissionshandels. UBA Texte 17|07. Federal Environmental Agency (UBA), Dessau-Roßlau.

# Appendix: Source codes

## A.1 GAMS code for chapter 2

```
option savepoint=1 ;


sets
f firms / EnBW, Eon, RWE, Vattenfall, Fringe/
i generation technologies / nuclear, lignite, hardcoal, gas, oil, hydro /
t time period (hours) /1*312/

alias (f, ff) ;
alias (i, ii) ;
alias (t, tt) ;


parameters
*------- general parameters: -----------------------
sigma(t)         elasticity of demand
d0(t)            hourly reference demand in MWh
p0(t)            hourly reference price in €perMWh
xwind(t)         hourly wind feed-in
mpowergen(f)     generation market power parameter
mpowerstor(f)    storage market power parameter
*------- conventional generation: ------------------
maxgen(f,i)      maximum generation capacity of firm and technology in MW
genavail(f,i)    availability of generation
vgc(i)           variable generation costs
*------- ramping of conventional generation: -------
rampup(i)        ramping up factor of conventional technologies
rampdown(i)      ramping down factor of conventional technologies
*------- storage: ----------------------------------
stmaxout(f)      maximum storage output of firm in MW
stmaxin(f)       maximum storage input of firm in MW
stcap(f)         storage capacity in MWh
stcapavail(f)    availability of storage capacity
vstc             variable storage costs in €perMWh
steta            efficiency of storage generation
;

*------- Import parameters (...)

*------- conventional generation: ------------------
positive variables
x(f,i,t)         generation of firm and technology in MWh
gencap(f,i,t)    shadow price of generation capacity constraint in €perMWh ;
variables
thetagen(f,i,t)  generation market share of firm
p(t)             price for (conventional -?) electricity in €perMWh
totgen(t)        total generation in MWh
*------- ramping of conventional generation: -------
positive variables
rup(f,i,t)       shadow price of ramping up constraint in €perMWh
rdo(f,i,t)       shadow price of ramping down constraint in €perMWh ;
variable dx(f,i,t) load gradient ;
*------- storage: ----------------------------------
positive variables
stout(f,t)       generation from storage in MWh
stin(f,t)        feed into storage in MWh
stoutcap(f,t)    shadow price of storage generation capacity constraint in €perMWh
stincap(f,t)     shadow price of storage loading rate restriction in €perMWh
stup(f,t)        shadow price of storage upper capacity constraint in €perMWh
stlo(f,t)        shadow price of storage lower capacity constraint in €perMWh ;
variables
thetastin(f,t)   storage in market share of firm
thetastout(f,t)  storage out market share of firm ;
*------- rent: -------------------------------------
variables
cr(t)            consumer rent of period t
pr(f,t)          producer rent of period t ;
```

```
 72 equations
 73 *------- market clearing: -------------------------
 74 mclear(t)        market clearing (demand equals supply)
 75 tconv(t)         total conventional generation
 76 *------- conventional generation: ------------------
 77 focx(f,i,t)      FOC of firm's profits wrt generation
 78 gencapcon(f,i,t) maximum generation capacity constraint
 79 mshgen(f,i,t)    generation market share of firm
 80 *------- ramping of conventional generation: -------
 81 rupcon(f,i,t)    ramping up constraint
 82 rdocon(f,i,t)    ramping down constraint
 83 dxdef(f,i,t)     definition of dx
 84 *------- storage: ----------------------------------
 85 focstout(f,t)    FOC of firm's profits wrt stout
 86 focstin(f,t)     FOC of firm's profits wrt stin
 87 stoutcapcon(f,t) storage maximum generation capacity constraint (power of generator)
 88 stincapcon(f,t)  storage maximum loading rate condition (power of pump)
 89 stupcon(f,t)     storage filling condition (lake never overflowing)
 90 stlocon(f,t)     storage emptying condition (lake never less than empty)
 91 mshstout(f,t)    storage discharging market share of firm
 92 mshstin(f,t)     storage loading market share of firm
 93 *------- rent: -------------------------------------
 94 consrent(t)      consumer rent in period t
 95 prodrent(f,t)    producer rent in period t
 96 ;
 97
 98 *------- market clearing: -------------------------
 99 mclear(t) ..     totgen(t) =e= d0(t)*(p(t)/p0(t))**(-sigma(t)) ;
100 tconv(t) ..      totgen(t) =e= sum((f,i),x(f,i,t))+sum(f,stout(f,t))
101                  -sum(f,stin(f,t))+xwind(t) ;
102 *------- conventional generation: ------------------
103 focx(f,i,t) ..   vgc(i)+gencap(f,i,t)+rup(f,i,t)-rup(f,i,t+1)-rdo(f,i,t)+rdo(f,i,t+1)
104                  =g= p(t)*(1-(sum(ii,thetagen(f,ii,t))*mpowergen(f)
105                  +thetastout(f,t)*mpowerstor(f)-thetastin(f,t)
106                  *mpowerstor(f))/sigma(t)) ;
107 gencapcon(f,i,t) .. maxgen(f,i)*genavail(f,i) =g= x(f,i,t) ;
108 mshgen(f,i,t) .. thetagen(f,i,t) =e= x(f,i,t)/(sum((ff,ii),x(ff,ii,t))
109                  +sum(ff,stout(ff,t))-sum(ff,stin(ff,t))+xwind(t)) ;
110 *------- ramping of conventional generation: -------
111 rupcon(f,i,t) .. (rampup(i)$(ord(t)>1)+1$(ord(t)=1))*maxgen(f,i)*genavail(f,i)
112                  =g= dx(f,i,t) ;
113 rdocon(f,i,t) .. (rampdown(i)$(ord(t)>1)+1$(ord(t)=1))*maxgen(f,i)*genavail(f,i)
114                  =g= -dx(f,i,t) ;
115 dxdef(f,i,t) ..  dx(f,i,t) =e= x(f,i,t)-x(f,i,t-1) ;
116 *------- storage: ----------------------------------
117 focstout(f,t) .. vstc+stoutcap(f,t)+sum(tt$(ord(tt) ge ord(t)),stlo(f,tt))
118                  -sum(tt$(ord(tt) ge (ord(t)-1)),stup(f,tt+1))
119                  =g= p(t)*(1-(sum(i,thetagen(f,i,t))*mpowergen(f)
120                  +thetastout(f,t)*mpowerstor(f)-thetastin(f,t)
121                  *mpowerstor(f))/sigma(t)) ;
122 focstin(f,t) ..  -sum(tt$(ord(tt) ge (ord(t)+1)),stlo(f,tt))*steta
123                  +sum(tt$(ord(tt) ge ord(t)),stup(f,tt))*steta+stincap(f,t)
124                  =g= -p(t)*(1-(sum(i,thetagen(f,i,t))*mpowergen(f)
125                  +thetastout(f,t)*mpowerstor(f)-thetastin(f,t)
126                  *mpowerstor(f))/sigma(t)) ;
127 stoutcapcon(f,t) .. stmaxout(f)*stgridavail(f) =g= stout(f,t) ;
128 stincapcon(f,t) .. stmaxin(f)*stgridavail(f) =g= stin(f,t) ;
129 stupcon(f,t) ..  stcap(f)*stcapavail(f)
130                  =g= sum(tt$(ord(tt) le ord(t)),stin(f,tt))
131                  *steta-sum(tt$(ord(tt) le (ord(t)-1)),stout(f,tt)) ;
132 stlocon(f,t) ..  0 =g= sum(tt$(ord(tt) le ord(t)),stout(f,tt))
133                  -sum(tt$(ord(tt) le (ord(t)-1)),stin(f,tt))*steta ;
134 mshstout(f,t) .. thetastout(f,t) =e= stout(f,t)/(sum((ff,ii),x(ff,ii,t))
135                  +sum(ff,stout(ff,t))-sum(ff,stin(ff,t))+xwind(t)) ;
136 mshstin(f,t) ..  thetastin(f,t) =e= stin(f,t)/(sum((ff,ii),x(ff,ii,t))
137                  +sum(ff,stout(ff,t))-sum(ff,stin(ff,t))+xwind(t)) ;
138 *------- rent: -------------------------------------
139 consrent(t) ..   cr(t) =e= p0(t)*d0(t)**(1/sigma(t))*sigma(t)/(1-sigma(t))
140                  *(1**((-1+sigma(t))/sigma(t)) -totgen(t)**((-1+sigma(t))/sigma(t)))
141                  -p(t)*totgen(t) ;
142 * We integrate from 1 to totgen
```

```
prodrent(f,t) .. pr(f,t) =e= sum(i,(x(f,i,t)*(p(t)-vgc(i))))
                 +(stout(f,t)*(p(t)-vstc))-stin(f,t)*p(t) ;


model ElStorM / mclear.p, tconv.totgen, focx.x, gencapcon.gencap, mshgen.thetagen,
rupcon.rup, rdocon.rdo, dxdef.dx, focstout.stout, focstin.stin,
stoutcapcon.stoutcap, stincapcon.stincap, stupcon.stup, stlocon.stlo,
mshstout.thetastout, mshstin.thetastin, consrent.cr, prodrent.pr / ;


* Load appropriate starting values
execute_loadpoint 'ElStorM_p.gdx' ;


solve ElStorM using mcp ;
```

## A.2 GAMS code for chapter 3

```
option savepoint=1 ;


sets
f firms / EnBW, Eon, RWE, Vattenfall, Fringe, RES, NoGen /
i generation technologies / nuclear, lignite, hardcoal, gas, oil, hydro, wind /
j storage technologies / pumpstorage, piev /
t time period (hours) /1*336/
d days /1*14/

alias (f, ff) ;
alias (i, ii) ;
alias (j, jj) ;
alias (t, tt) ;


parameters
*------- general parameters: -----------------------
sigma(t)         elasticity of demand
d0(t)            hourly reference demand in MWh
p0(t)            hourly reference price in €perMWh
xwind(t)         hourly wind feed-in
mpowergen(f)     generation market power parameter
mpowerstor(f)    storage market power parameter
mpowervload(f)   vehicle loading market power parameter
*------- conventional generation: ------------------
maxgen(f,i)      maximum generation capacity of firm and technology in MW(!)
genavail(f,i)    availability of generation
vgc(i)           variable generation costs
*------- ramping of conventional generation: -------
rampup(i)        ramping up factor of conventional technologies
rampdown(i)      ramping down factor of conventional technologies
*------- storage: ----------------------------------
stvmaxout(f,j)   maximum storage or vehicle output of firm and technology in MW
stvmaxin(f,j)    maximum storage or vehicle input of firm and technology in MW
stcap(f,j)       storage capacity in MWh
stcapavail(f,j)  availability of storage capacity
vstc(j)          variable storage costs in €perMWh
steta(j)         efficiency of storage generation
*------- vehicle loading: --------------------------
dailyvload(f,d)  daily loading requirement of firm in MWh
stvgridavail(f,j) storage and vehicle grid availability
;

*------- Import parameters (...)


*------- conventional generation: ------------------
positive variables
x(f,i,t)         generation of firm and technology in MWh
gencap(f,i,t)    shadow price of generation capacity constraint in €perMWh ;
variables
thetagen(f,i,t)  generation market share of firm
p(t)             price for (conventional -?) electricity in €perMWh
totgen(t)        total generation in MWh
*------- ramping of conventional generation: -------
positive variables
rup(f,i,t)       shadow price of ramping up constraint in €perMWh
rdo(f,i,t)       shadow price of ramping down constraint in €perMWh ;
variable dx(f,i,t) load gradient ;
*------- storage: ----------------------------------
positive variables
stout(f,j,t)     generation from storage in MWh
stin(f,j,t)      feed into storage in MWh
stvoutcap(f,j,t)  shadow price of storage generation capacity constraint in €perMWh
stvincap(f,j,t)   shadow price of storage loading rate restriction in €perMWh
stup(f,j,t)      shadow price of storage upper capacity constraint in €perMWh
stlo(f,j,t)      shadow price of storage lower capacity constraint in €perMWh ;
variables
thetastin(f,j,t) storage in market share of firm
thetastout(f,j,t) storage out market share of firm ;
```

```
*------- vehicle loading: -------------------------
positive variable
vload(f,t)       vehicle loading
variables
lambdadailyvl(f,d) shadow price of weekly vehicle loading requirement
thetavload(f,t)  vehicle loading market share ;
*------- rent: -------------------------------------
variables
cr(t)            consumer rent of period t
pr(f,t)          producer rent of period t ;


equations
*------- market clearing: -------------------------
mclear(t)        market clearing (demand equals supply)
tconv(t)         total conventional generation
*------- conventional generation: ------------------
focx(f,i,t)      FOC of firm's profits wrt generation
gencapcon(f,i,t) maximum generation capacity constraint
mshgen(f,i,t)    generation market share of firm
*------- ramping of conventional generation: -------
rupcon(f,i,t)    ramping up constraint
rdocon(f,i,t)    ramping down constraint
dxdef(f,i,t)     definition of dx
*------- storage: ----------------------------------
focstout(f,j,t)  FOC of firm's profits wrt stout
focstin(f,j,t)   FOC of firm's profits wrt stin
stvoutcapcon(f,j,t) storage maxim. generation capacity constraint (power of generator)
stvincapcon(f,j,t) storage maximum loading rate condition (power of pump)
stupcon(f,j,t)   storage filling condition (lake never overflowing)
stlocon(f,j,t)   storage emptying condition (lake never less than empty)
mshstout(f,j,t)  storage discharging market share of firm
mshstin(f,j,t)   storage loading market share of firm
*------- vehicle loading: -------------------------
focvload(f,t)    FOC of firm's profits wrt vload
eq_dailyvl(f,d)  weekly vehicle loading requirement
mshvload(f,t)    vehicle loading market share of firm
*------- rent: -------------------------------------
consrent(t)      consumer rent in period t
prodrent(f,t)    producer rent in period t
;

*------- market clearing: -------------------------
mclear(t) ..      totgen(t) =e= d0(t)*(p(t)/p0(t))**(-sigma(t)) ;
tconv(t) ..       totgen(t) =e= sum((f,i),x(f,i,t))+sum((f,j),stout(f,j,t))
                  -sum((f,j),stin(f,j,t))-sum(f,vload(f,t)) ;
*------- conventional generation: ------------------
focx(f,i,t) ..    vgc(i)+gencap(f,i,t)+rup(f,i,t)-rup(f,i,t+1)-rdo(f,i,t)+rdo(f,i,t+1)
                  =g= p(t)*(1-(sum(ii,thetagen(f,ii,t))*mpowergen(f)
                  +sum(j,thetastout(f,j,t))*mpowerstor(f)-sum(j,thetastin(f,j,t))
                  *mpowerstor(f)-thetavload(f,t)*mpowervload(f))/sigma(t)) ;
gencapcon(f,i,t) .. maxgen(f,i)*genavail(f,i) =g= x(f,i,t) ;
mshgen(f,i,t) ..  thetagen(f,i,t) =e= x(f,i,t)/(sum((ff,ii),x(ff,ii,t))
                  +sum((ff,jj),stout(ff,jj,t))-sum((ff,jj),stin(ff,jj,t))-vload(f,t));
*------- ramping of conventional generation: -------
rupcon(f,i,t) ..  (rampup(i)$(ord(t)>1)+1$(ord(t)=1))*maxgen(f,i)*genavail(f,i)
                  =g= dx(f,i,t) ;
rdocon(f,i,t) ..  (rampdown(i)$(ord(t)>1)+1$(ord(t)=1))*maxgen(f,i)*genavail(f,i)
                  =g= -dx(f,i,t) ;
dxdef(f,i,t) ..   dx(f,i,t) =e= x(f,i,t)-x(f,i,t-1) ;
*------- storage: ----------------------------------
focstout(f,j,t) .. vstc(j)+stvoutcap(f,j,t)+sum(tt$(ord(tt) ge ord(t)),stlo(f,j,tt))
                  -sum(tt$(ord(tt) ge (ord(t)-1)),stup(f,j,tt+1))
                  =g= p(t)*(1-(sum(i,thetagen(f,i,t))*mpowergen(f)
                  +sum(jj,thetastout(f,jj,t))*mpowerstor(f)-sum(jj,thetastin(f,jj,t))
                  *mpowerstor(f)-thetavload(f,t)*mpowervload(f))/sigma(t)) ;
focstin(f,j,t) .. -sum(tt$(ord(tt) ge (ord(t)+1)),stlo(f,j,tt))*steta(j)
                  +sum(tt$(ord(tt) ge ord(t)),stup(f,j,tt))*steta(j)+stvincap(f,j,t)
                  =g= -p(t)*(1-(sum(i,thetagen(f,i,t))*mpowergen(f)
                  +sum(jj,thetastout(f,jj,t))*mpowerstor(f)-sum(jj,thetastin(f,jj,t))
                  *mpowerstor(f)-thetavload(f,t)*mpowervload(f))/sigma(t)) ;
```

```
stvoutcapcon(f,j,t) .. stvmaxout(f,j)*stvgridavail(f,j) =g= stout(f,j,t) ;
stvincapcon(f,j,t) .. stvmaxin(f,j)*stvgridavail(f,j) =g= stin(f,j,t)$(ord(j)=1)
                    + (stin(f,j,t)+vload(f,t))$(ord(j)=2) ;
stupcon(f,j,t) .. stcap(f,j)*stcapavail(f,j)
                    =g= sum(tt$(ord(tt) le ord(t)),stin(f,j,tt))
                    *steta(j)-sum(tt$(ord(tt) le (ord(t)-1)),stout(f,j,tt)) ;
stlocon(f,j,t) .. 0 =g= sum(tt$(ord(tt) le ord(t)),stout(f,j,tt))
                    -sum(tt$(ord(tt) le (ord(t)-1)),stin(f,j,tt))*steta(j) ;
mshstout(f,j,t) .. thetastout(f,j,t) =e= stout(f,j,t)/(sum((ff,ii),x(ff,ii,t))
                    +sum((ff,jj),stout(ff,jj,t))-sum((ff,jj),stin(ff,jj,t))-vload(f,t));
mshstin(f,j,t) .. thetastin(f,j,t) =e= stin(f,j,t)/(sum((ff,ii),x(ff,ii,t))
                    +sum((ff,jj),stout(ff,jj,t))-sum((ff,jj),stin(ff,jj,t))-vload(f,t));
*------- vehicle loading: -------------------------
focvload(f,t) ..  lambdadailyvl(f,'1')$(ord(t) le 24)
                    +lambdadailyvl(f,'2')$(ord(t) ge 25 and ord(t) le 48)
                    +lambdadailyvl(f,'3')$(ord(t) ge 49 and ord(t) le 72)
                    +lambdadailyvl(f,'4')$(ord(t) ge 73 and ord(t) le 96)
                    +lambdadailyvl(f,'5')$(ord(t) ge 97 and ord(t) le 120)
                    +lambdadailyvl(f,'6')$(ord(t) ge 121 and ord(t) le 144)
                    +lambdadailyvl(f,'7')$(ord(t) ge 145 and ord(t) le 168)
                    +lambdadailyvl(f,'8')$(ord(t) ge 169 and ord(t) le 192)
                    +lambdadailyvl(f,'9')$(ord(t) ge 193 and ord(t) le 216)
                    +lambdadailyvl(f,'10')$(ord(t) ge 217 and ord(t) le 240)
                    +lambdadailyvl(f,'11')$(ord(t) ge 241 and ord(t) le 264)
                    +lambdadailyvl(f,'12')$(ord(t) ge 265 and ord(t) le 288)
                    +lambdadailyvl(f,'13')$(ord(t) ge 289 and ord(t) le 312)
                    +lambdadailyvl(f,'14')$(ord(t) ge 313 and ord(t) le 336)
                    +stvincap(f,'piev',t)
                    =g= -p(t)*(1-(sum(i,thetagen(f,i,t))*mpowergen(f)
                    +sum(j,thetastout(f,j,t))*mpowerstor(f)-sum(j,thetastin(f,j,t))
                    *mpowerstor(f)-thetavload(f,t)*mpowervload(f))/sigma(t)) ;
eq_dailyvl(f,d) .. sum(t$(ord(t) le 24),vload(f,t))$(ord(d)=1)
                    +sum(t$(ord(t) ge 25 and ord(t) le 48),vload(f,t))$(ord(d)=2)
                    +sum(t$(ord(t) ge 49 and ord(t) le 72),vload(f,t))$(ord(d)=3)
                    +sum(t$(ord(t) ge 73 and ord(t) le 96),vload(f,t))$(ord(d)=4)
                    +sum(t$(ord(t) ge 97 and ord(t) le 120),vload(f,t))$(ord(d)=5)
                    +sum(t$(ord(t) ge 121 and ord(t) le 144),vload(f,t))$(ord(d)=6)
                    +sum(t$(ord(t) ge 145 and ord(t) le 168),vload(f,t))$(ord(d)=7)
                    +sum(t$(ord(t) ge 169 and ord(t) le 192),vload(f,t))$(ord(d)=8)
                    +sum(t$(ord(t) ge 193 and ord(t) le 216),vload(f,t))$(ord(d)=9)
                    +sum(t$(ord(t) ge 217 and ord(t) le 240),vload(f,t))$(ord(d)=10)
                    +sum(t$(ord(t) ge 241 and ord(t) le 264),vload(f,t))$(ord(d)=11)
                    +sum(t$(ord(t) ge 265 and ord(t) le 288),vload(f,t))$(ord(d)=12)
                    +sum(t$(ord(t) ge 289 and ord(t) le 312),vload(f,t))$(ord(d)=13)
                    +sum(t$(ord(t) ge 313 and ord(t) le 336),vload(f,t))$(ord(d)=14)
                    =e=
                    dailyvload(f,'1')$(ord(d)=1)
                    +dailyvload(f,'2')$(ord(d)=2)
                    +dailyvload(f,'3')$(ord(d)=3)
                    +dailyvload(f,'4')$(ord(d)=4)
                    +dailyvload(f,'5')$(ord(d)=5)
                    +dailyvload(f,'6')$(ord(d)=6)
                    +dailyvload(f,'7')$(ord(d)=7)
                    +dailyvload(f,'8')$(ord(d)=8)
                    +dailyvload(f,'9')$(ord(d)=9)
                    +dailyvload(f,'10')$(ord(d)=10)
                    +dailyvload(f,'11')$(ord(d)=11)
                    +dailyvload(f,'12')$(ord(d)=12)
                    +dailyvload(f,'13')$(ord(d)=13)
                    +dailyvload(f,'14')$(ord(d)=14)
;
mshvload(f,t) ..  thetavload(f,t) =e= vload(f,t)/(sum((ff,ii),x(ff,ii,t))
                    +sum((ff,jj),stout(ff,jj,t))-sum((ff,jj),stin(ff,jj,t))
                    -vload(f,t)) ;
*------- rent: -------------------------------------
consrent(t) ..    cr(t) =e= p0(t)*d0(t)**(1/sigma(t))*sigma(t)/(1-sigma(t))
                    *(1**((-1+sigma(t))/sigma(t))-totgen(t)**((-1+sigma(t))/sigma(t)))
                    -p(t)*totgen(t) ;
* we integrate from 1 to totgen
prodrent(f,t) ..  pr(f,t) =e= sum(i,(x(f,i,t)*(p(t)-vgc(i))))
                    +sum(j,(stout(f,j,t)*(p(t)-vstc(j))))-sum(j,(stin(f,j,t)*p(t))) ;
```

```


model ElStorM / mclear.p, tconv.totgen, focx.x, gencapcon.gencap, mshgen.thetagen,
rupcon.rup, rdocon.rdo, dxdef.dx, focstout.stout, focstin.stin,
stvoutcapcon.stvoutcap, stvincapcon.stvincap, stupcon.stup, stlocon.stlo,
mshstout.thetastout, mshstin.thetastin, consrent.cr, prodrent.pr,
focvload.vload, eq_dailyvl.lambdadailyvl, mshvload.thetavload / ;


* Load appropriate starting values
execute_loadpoint 'ElStorM_p.gdx' ;

x.fx('RES','wind',t) = xwind(t) ;


solve ElStorM using mcp ;
```

## A.3 GAMS code for chapter 4

```
option
    limrow = 0,
    limcol = 0,
    solprint = off,
    sysout = off;

option savepoint=1 ;


sets
n                Node                                    /n1*n15/
s                Type of plant                           /s1*s9/
l                Line                                    /l1*l28/
t                Time periods for network expansion      /t0*t5/
tau              Time periods for dispatch (hours)       /1*144/
columns          columns in Excel                        /c1/
;

set weekday_summer(tau) /1*24/;
set weekend_summer(tau) /25*48/;
set weekday_winter(tau) /49*72/;
set weekend_winter(tau) /73*96/;
set weekday_shoulder(tau) /97*120/;
set weekend_shoulder(tau) /121*144/;
set wind(s) /s9/;
set realnodes(n) /n1*n7/;
set t_initial(t) /t0/;

Alias    (n,nn);
alias    (t,tt);

Parameters
year_summer     scale to one year
year_winter     scale to one year
year_shoulder     scale to one year
sdr      social discount rate
pdr      private discount rate
ror      rate of return for cost-plus regulation
int      interest rate for extension costs (annuity)
dur      duration of extension investment
anf      annuity factor (capital recovery factor)
;
year_summer = 52.143/12*6 ;
year_winter = 52.143/12*4 ;
year_shoulder = 52.143/12*2 ;
sdr = 0.04 ;
pdr = 0.08 ;
ror = 0.08 ;
int = 0.08 ;
dur = 20 ;
anf = (1+int)**dur * int / ((1+int)**dur - 1) ;

scalars
epsilon          Demand elasticity at reference point            / -0.25 /
;

Parameter revision(s)    Factor for defining the availabilty of plant types
/s1      0.72
s2       0.72
s3       0.72
s4       0.68
s5       0.68
s6       0.68
s7       0.4
s8       0.6
s9       1.0/
;

*------- Line parameters: -------------------------

parameter P_max(l)       max Capacity of line l
```

```
/
l1          2971
l2          1842
l3          1842
l4          896
l5          1326
l6          1842
l7          1842
l8          1842
l9          641
l10         641
l11         936
l12         1842
l13         898
l14         1207
l15         267
l16         2762
l17         1842
l18         3329
l19         1282
l20         3329
l21         20000
l22         20000
l23         20000
l24         20000
l25         20000
l26         20000
l27         20000
l28         20000
/
;

parameter X(l)       Reactance of line l
/l1         12.21372516
l2          69.22912356
l3          42.95031339
l4          28.25678513
l5          25.43110662
l6          33.0604386
l7          50.01450968
l8          29.10448868
l9          61.03465588
l10         41.82004199
l11         34.19071
l12         31.08246364
l13         55.38329885
l14         45.2108562
l15         156.4776426
l16         22.22867097
l17         27.12651372
l18         38.24945533
l19         11.4748366
l20         41.30941176
l21         45.8993464
l22         45.8993464
l23         45.8993464
l24         45.8993464
l25         45.8993464
l26         45.8993464
l27         45.8993464
l28         45.8993464/
;

parameter
length(l)        transmission line length
/l1         100
l2          230
l3          180
l4          60
l5          90
l6          120
```

```
l7         140
l8         100
l9         120
l10        80
l11        85
l12        130
l13        100
l14        80
l15        120
l16        120
l17        100
l18        220
l19        25
l20        260
l21        400
l22        400
l23        400
l24        400
l25        400
l26        400
l27        400
l28        400/
;

table Incidence(l,n)     Connects lines with nodes
    n1 n2 n3 n4 n5 n6 n7 n8 n9 n10 n11 n12 n13 n14 n15
l1  0  0  0  0  0  0  -1 1  0  0   0   0   0   0   0
l2  0  0  0  0  0  0  0  1  -1 0   0   0   0   0   0
l3  0  0  0  0  0  0  0  0  1  -1  0   0   0   0   0
l4  0  0  0  0  -1 0  0  0  1  0   0   0   0   0   0
l5  0  0  0  0  0  0  0  0  0  1   0   0   0   -1  0
l6  0  0  0  -1  0 0  1  0  0  0   0   0   0   0   0
l7  0  0  0  0  -1 0  1  0  0  0   0   0   0   0   0
l8  0  0  0  -1 1  0  0  0  0  0   0   0   0   0   0
l9  0  0  0  0  1  -1 0  0  0  0   0   0   0   0   0
l10 0  0  -1 0  1  0  0  0  0  0   0   0   0   0   0
l11 0  0  0  1  0  -1 0  0  0  0   0   0   0   0   0
l12 0  0  -1 0  0  1  0  0  0  0   0   0   0   0   0
l13 0  0  0  0  0  1  0  0  0  0   0   -1  0   0   0
l14 0  0  1  0  0  0  0  0  0  0   0   0   -1  0   0
l15 0  0  1  0  0  0  0  0  0  0   0   0   0   -1  0
l16 0  0  0  0  0  0  0  0  0  0   0   1   -1  0   0
l17 0  0  0  0  0  0  0  0  0  0   0   0   1   -1  0
l18 0  0  0  0  0  0  0  0  0  0   0   0   0   1   -1
l19 0  0  0  0  0  0  0  0  0  0   -1  0   0   0   1
l20 0  0  0  0  0  0  0  0  0  -1  1   0   0   0   0
l21 0  1  0  0  0  0  0  0  0  0   0   -1  0   0   0
l22 0  1  0  0  0  0  0  0  0  0   0   0   -1  0   0
l23 0  1  0  0  0  0  0  0  0  0   0   0   0   -1  0
l24 0  1  0  0  0  0  0  0  0  0   0   0   0   0   -1
l25 1  0  0  0  0  0  0  -1 0  0   0   0   0   0   0
l26 1  0  0  0  0  0  0  0  -1 0   0   0   0   0   0
l27 1  0  0  0  0  0  0  0  0  -1  0   0   0   0   0
l28 1  0  0  0  0  0  0  0  0  0   -1  0   0   0   0
;

Parameter H(l,n)         Flow sensivity matrix ;
H(l,n) = 1/X(l) * Incidence(l,n);

Parameter B(n,nn)        Network susceptance matrix ;
B(n,nn) = SUM(l, Incidence(l,n) * H(l,nn) );

Parameter Slack(n)       Slack bus
/n1       1/
;

parameter
ec       extension cost factor ;
ec(l) = 100 * length(l) ;

*------- Generation capacity per type and firm: ----
```

```
214
215 Parameters
216 g_max(n,s,tau) generation capacity
217 c(n,s) generation costs
218 p_ref(tau,n) reference demand (linear demand function p = a + m*q)
219 m(n,tau)   Slope of demand function
220 a(n,tau)   Intercept of demand function
221 q_ref(n,tau) hourly reference demand
222 ;
223
224 *------- Import parameters (...)
225
226 m(n,tau)$q_ref(n,tau) = p_ref(tau,n)/(epsilon*q_ref(n,tau));
227 a(n,tau)$q_ref(n,tau) = p_ref(tau,n)-q_ref(n,tau)*m(n,tau);
228
229
230 *------- MCP format without extension: -------------
231 *------- Provides a good starting point ------------
232
233 positive variables
234 lambda1(l,t,tau)         positive line capacity restriction
235 lambda2(l,t,tau)         negative line capacity restriction
236 lambda4(n,s,t,tau)       generation capacity constraint
237 ;
238 variables
239 price(n,t,tau)           or lambda3 - market clearing
240 lambda5(n,t,tau)         slack constraint
241 ;
242
243 equations
244 FOC_q(n,t,tau)
245 FOC_g(n,s,t,tau)
246 FOC_delta(n,t,tau)
247 FOC_lambda1(l,t,tau)
248 FOC_lambda2(l,t,tau)
249 FOC_price(n,t,tau)
250 FOC_lambda4(n,s,t,tau)
251 FOC_lambda5(n,t,tau)
252 IFOC_q(n,t,tau)
253 IFOC_g(n,s,t,tau)
254 IFOC_delta(n,t,tau)
255 IFOC_lambda1(l,t,tau)
256 IFOC_lambda2(l,t,tau)
257 IFOC_price(n,t,tau)
258 IFOC_lambda4(n,s,t,tau)
259 IFOC_lambda5(n,t,tau)
260 ;
261
262 FOC_q(n,t,tau) ..        0 =g= (a(n,tau) + m(n,tau) * q(n,t,tau)) + price(n,t,tau)
263 ;
264 FOC_g(n,s,t,tau) ..      0 =g= -c(n,s) - price(n,t,tau) - lambda4(n,s,t,tau)
265 ;
266 FOC_delta(n,t,tau) ..    0 =g= (-sum(l,lambda1(l,t,tau) * H(l,n))
267                          + sum(l,lambda2(l,t,tau) * H(l,n))
268                          + sum(nn,price(nn,t,tau) * B(nn,n))
269                          - lambda5(n,t,tau) * slack(n))
270 ;
271 FOC_lambda1(l,t,tau) ..  0 =g= (sum(n,H(l,n) * delta(n,t,tau)) - P_max(l))
272 ;
273 FOC_lambda2(l,t,tau) ..  0 =g= (-sum(n,H(l,n) * delta(n,t,tau)) - P_max(l))
274 ;
275 FOC_price(n,t,tau) ..    0 =e= (sum(s,g(n,s,t,tau))
276                          - sum(nn,B(n,nn) * delta(nn,t,tau)) - q(n,t,tau))
277 ;
278 FOC_lambda4(n,s,t,tau) .. 0 =g= (g(n,s,t,tau) - revision(s) * g_max(n,s,tau))
279 ;
280 FOC_lambda5(n,t,tau) ..  0 =e= (slack(n) * delta(n,t,tau))
281 ;
282
283 IFOC_q(n,t,tau) $(t_initial(t)) .. 0 =g= (a(n,tau) + m(n,tau) * q(n,t,tau))
284                          + price(n,t,tau)
```

```
;
IFOC_g(n,s,t,tau) $(t_initial(t)) .. 0 =g= -c(n,s) - price(n,t,tau)
                        - lambda4(n,s,t,tau)
;
IFOC_delta(n,t,tau) $(t_initial(t)) .. 0 =g= (-sum(l,lambda1(l,t,tau) * H(l,n))
                        + sum(l,lambda2(l,t,tau) * H(l,n))
                        + sum(nn,price(nn,t,tau) * B(nn,n))
                        - lambda5(n,t,tau) * slack(n))
;
IFOC_lambda1(l,t,tau) $(t_initial(t)) .. 0 =g= (sum(n,H(l,n) * delta(n,t,tau))
                        - P_max(l))
;
IFOC_lambda2(l,t,tau) $(t_initial(t)) .. 0 =g= (-sum(n,H(l,n) * delta(n,t,tau))
                        - P_max(l))
;
IFOC_price(n,t,tau) $(t_initial(t)) .. 0 =e= (sum(s,g(n,s,t,tau))
                        - sum(nn,B(n,nn) * delta(nn,t,tau)) - q(n,t,tau))
;
IFOC_lambda4(n,s,t,tau) $(t_initial(t)) .. 0 =g= (g(n,s,t,tau)
                        - revision(s) * g_max(n,s,tau))
;
IFOC_lambda5(n,t,tau) $(t_initial(t)) .. 0 =e= (slack(n) * delta(n,t,tau))
;

model MCP_wo_extension_initial /
IFOC_q.q
IFOC_g.g
IFOC_delta.delta
IFOC_lambda1.lambda1
IFOC_lambda2.lambda2
IFOC_price.price
IFOC_lambda4.lambda4
IFOC_lambda5.lambda5
/;

model MCP_wo_extension /
FOC_q.q
FOC_g.g
FOC_delta.delta
FOC_lambda1.lambda1
FOC_lambda2.lambda2
FOC_price.price
FOC_lambda4.lambda4
FOC_lambda5.lambda5
/;


solve MCP_wo_extension_initial using mcp ;

execute_loadpoint 'MCP_wo_extension_initial_p.gdx'
q.l, g.l, delta.l , lambda1.l, lambda2.l, price.l, lambda4.l, lambda5.l ;

q.l(n,t,tau) $(ord(t) ge 1) = q.l(n,'t0',tau) ;
g.l(n,s,t,tau) $(ord(t) ge 1) = g.l(n,s,'t0',tau);
delta.l(n,t,tau) $(ord(t) ge 1) = delta.l(n,'t0',tau);
lambda1.l(l,t,tau) $(ord(t) ge 1) = lambda1.l(l,'t0',tau);
lambda2.l(l,t,tau) $(ord(t) ge 1) = lambda2.l(l,'t0',tau);
price.l(n,t,tau) $(ord(t) ge 1) = price.l(n,'t0',tau);
lambda4.l(n,s,t,tau) $(ord(t) ge 1) = lambda4.l(n,s,'t0',tau);
lambda5.l(n,t,tau) $(ord(t) ge 1) = lambda5.l(n,'t0',tau);

solve MCP_wo_extension using mcp ;


*------- WF-Maximization with extension (MPEC): ----

parameter cap_0(l)
;
cap_0(l) = P_max(l);
;

```

```
356 positive variables
357 extension(l,t)   line extension
358 ;
359 variables
360 cap(l,t)         line capacity
361 wf_MPEC_wfmax    welfare
362 ;
363
364 equations
365 eq_wfmax
366 eq_linecap
367 eq_extension
368
369 MPEC_wfmax_q(n,t,tau)
370 MPEC_wfmax_g(n,s,t,tau)
371 MPEC_wfmax_delta(n,t,tau)
372 MPEC_wfmax_lambda1(l,t,tau)
373 MPEC_wfmax_lambda2(l,t,tau)
374 MPEC_wfmax_price(n,t,tau)
375 MPEC_wfmax_lambda4(n,s,t,tau)
376 MPEC_wfmax_lambda5(n,t,tau)
377 ;
378
379 eq_wfmax ..      wf_MPEC_wfmax =e= (sum((t,tau),
380                  (sum(n, (a(n,tau) * q(n,t,tau) + 0.5 * m(n,tau) * sqr(q(n,t,tau))))
381                  - sum((n,s), g(n,s,t,tau) * c(n,s)))
382                  *((5$weekday_summer(tau)+2$weekend_summer(tau))*year_summer
383                  + (5$weekday_winter(tau)+2$weekend_winter(tau))*year_winter
384                  + (5$weekday_shoulder(tau)+2$weekend_shoulder(tau))*year_shoulder)
385                  *1/((1+sdr)**(ord(t)-1)))
386                  - sum((l,t), 1 / ((1+sdr)**(ord(t)-1)) * ec(l) * cap_0(l) * anf
387                  * sum(tt$(ord(tt) lt ord(t)),extension(l,tt)) ) ) / 1000000000
388 ;
389 eq_linecap(l,t+1) .. cap(l,t+1) =e= cap(l,t) + cap_0(l) * extension(l,t)
390 ;
391
392 MPEC_wfmax_q(n,t,tau) .. 0 =g= (a(n,tau) + m(n,tau) * q(n,t,tau)) + price(n,t,tau)
393 ;
394 MPEC_wfmax_g(n,s,t,tau) .. 0 =g= -c(n,s) - price(n,t,tau) - lambda4(n,s,t,tau)
395 ;
396 MPEC_wfmax_delta(n,t,tau) .. 0 =g= (-sum(l,lambda1(l,t,tau) * H(l,n))
397                  + sum(l,lambda2(l,t,tau) * H(l,n))
398                  + sum(nn,price(nn,t,tau) * B(nn,n)) - lambda5(n,t,tau) * slack(n))
399 ;
400 MPEC_wfmax_lambda1(l,t,tau) .. 0 =g= (sum(n,H(l,n) * delta(n,t,tau)) - cap(l,t))
401 ;
402 MPEC_wfmax_lambda2(l,t,tau) .. 0 =g= (-sum(n,H(l,n) * delta(n,t,tau)) - cap(l,t))
403 ;
404 MPEC_wfmax_price(n,t,tau) .. 0 =e= (sum(s,g(n,s,t,tau))
405                  - sum(nn,B(n,nn) * delta(nn,t,tau)) - q(n,t,tau))
406 ;
407 MPEC_wfmax_lambda4(n,s,t,tau) .. 0 =g= (g(n,s,t,tau) - revision(s)*g_max(n,s,tau))
408 ;
409 MPEC_wfmax_lambda5(n,t,tau) .. 0 =e= (slack(n) * delta(n,t,tau))
410 ;
411
412 model WF_max_MPEC_reduced /
413 eq_wfmax
414 MPEC_wfmax_q.q
415 MPEC_wfmax_g.g
416 MPEC_wfmax_delta.delta
417 MPEC_wfmax_lambda1.lambda1
418 MPEC_wfmax_lambda2.lambda2
419 MPEC_wfmax_price.price
420 MPEC_wfmax_lambda4.lambda4
421 MPEC_wfmax_lambda5.lambda5
422 /;
423
424 model WF_max_MPEC /
425 eq_wfmax
426 eq_linecap
```

```
427 MPEC_wfmax_q.q
428 MPEC_wfmax_g.g
429 MPEC_wfmax_delta.delta
430 MPEC_wfmax_lambda1.lambda1
431 MPEC_wfmax_lambda2.lambda2
432 MPEC_wfmax_price.price
433 MPEC_wfmax_lambda4.lambda4
434 MPEC_wfmax_lambda5.lambda5
435 /;
436
437 cap.fx(l,t) = cap_0(l);
438
439 solve WF_max_MPEC_reduced maximizing wf_MPEC_wfmax using mpec;
440 solve WF_max_MPEC_reduced maximizing wf_MPEC_wfmax using mpec;
441
442 cap.lo(l,t) = -inf;
443 cap.up(l,t) = inf;
444 cap.fx(l,'t0') = cap_0(l);
445
446 solve WF_max_MPEC maximizing wf_MPEC_wfmax using mpec;
447 solve WF_max_MPEC maximizing wf_MPEC_wfmax using mpec;
448 solve WF_max_MPEC maximizing wf_MPEC_wfmax using mpec;
449 solve WF_max_MPEC maximizing wf_MPEC_wfmax using mpec;
450
451
452 *------- MPEC with profit maximization of Transco - no_reg, HRV or cost_reg:
453
454 Variable
455 profit                Profit of TRANSCO
456 fix_part(t)           fix part of transmission tariff
457 ;
458
459 variable
460 fix_costreg(t)        fix part for costreg
461 ;
462
463 equations
464 return_no_reg
465 return_cost_reg
466 return_HRV
467 price_cap_costreg
468 price_cap
469 line_cap
470 line_cap0
471
472 MPEC_q(n,t,tau)
473 MPEC_g(n,s,t,tau)
474 MPEC_delta(n,t,tau)
475 MPEC_lambda1(l,t,tau)
476 MPEC_lambda2(l,t,tau)
477 MPEC_price(n,t,tau)
478 MPEC_lambda4(n,s,t,tau)
479 MPEC_lambda5(n,t,tau)
480 ;
481
482 * Upper-level problems:
483 return_no_reg .. profit =e= (sum(t,  1 / ((1+pdr)**(ord(t)-1))
484                  * (sum((n,tau), -price(n,t,tau) * q(n,t,tau)
485                  *((5$weekday_summer(tau)+2$weekend_summer(tau))*year_summer
486                  + (5$weekday_winter(tau)+2$weekend_winter(tau))*year_winter
487                  + (5$weekday_shoulder(tau)+2$weekend_shoulder(tau))*year_shoulder))
488                  - sum((n,tau), -price(n,t,tau) * sum(s, g(n,s,t,tau))
489                  *((5$weekday_summer(tau)+2$weekend_summer(tau))*year_summer
490                  + (5$weekday_winter(tau)+2$weekend_winter(tau))*year_winter
491                  + (5$weekday_shoulder(tau)+2$weekend_shoulder(tau))*year_shoulder)
492                  ))) - sum((l,t), 1 / ((1+pdr)**(ord(t)-1)) * ec(l) * cap_0(l)
493                  * anf * sum(tt$(ord(tt) lt ord(t)),extension(l,tt)) ) )/1000000000
494 ;
495 return_HRV..     profit =e= (sum(t,  1 / ((1+pdr)**(ord(t)-1))
496                  * (sum((n,tau), -price(n,t,tau) * q(n,t,tau)
497                  *((5$weekday_summer(tau)+2$weekend_summer(tau))*year_summer
```

```
                 + (5$weekday_winter(tau)+2$weekend_winter(tau))*year_winter
                 + (5$weekday_shoulder(tau)+2$weekend_shoulder(tau))*year_shoulder))
                 - sum((n,tau), -price(n,t,tau) * sum(s, g(n,s,t,tau))
                 *((5$weekday_summer(tau)+2$weekend_summer(tau))*year_summer
                 + (5$weekday_winter(tau)+2$weekend_winter(tau))*year_winter
                 + (5$weekday_shoulder(tau)+2$weekend_shoulder(tau))*year_shoulder)
                 ))) + sum(t, 1 / ((1+pdr)**(ord(t)-1)) * fix_part(t))
                 - sum((l,t), 1 / ((1+pdr)**(ord(t)-1)) * ec(l) * cap_0(l) * anf
                 * sum(tt$(ord(tt) lt ord(t)),extension(l,tt)) ) )/1000000000
;
return_cost_reg .. profit =e= (sum(t,  1 / ((1+pdr)**(ord(t)-1))
                 * (sum((n,tau), -price(n,t,tau) * q(n,t,tau)
                 *((5$weekday_summer(tau)+2$weekend_summer(tau))*year_summer
                 + (5$weekday_winter(tau)+2$weekend_winter(tau))*year_winter
                 + (5$weekday_shoulder(tau)+2$weekend_shoulder(tau))*year_shoulder))
                 - sum((n,tau), -price(n,t,tau) * sum(s, g(n,s,t,tau))
                 *((5$weekday_summer(tau)+2$weekend_summer(tau))*year_summer
                 + (5$weekday_winter(tau)+2$weekend_winter(tau))*year_winter
                 + (5$weekday_shoulder(tau)+2$weekend_shoulder(tau))*year_shoulder)
                 ))) + sum(t, 1 / ((1+pdr)**(ord(t)-1)) * fix_costreg(t))
                 - sum((l,t), 1 / ((1+pdr)**(ord(t)-1)) * ec(l) * cap_0(l) * anf
                 * sum(tt$(ord(tt) lt ord(t)),extension(l,tt)) ) )/1000000000
;
price_cap_costreg(t+1) .. fix_costreg(t+1) =e= fix_costreg(t)
                 + sum(l, ec(l) * cap_0(l) * anf * extension(l,t) * (1+ror) )
;
price_cap(t+1) .. sum((n,tau), -price(n,t+1,tau)*q(n,t,tau)
                 *((5$weekday_summer(tau)+2$weekend_summer(tau))*year_summer
                 + (5$weekday_winter(tau)+2$weekend_winter(tau))*year_winter
                 + (5$weekday_shoulder(tau)+2$weekend_shoulder(tau))*year_shoulder)
                 + price(n,t+1,tau) * sum(s, g(n,s,t,tau))
                 *((5$weekday_summer(tau)+2$weekend_summer(tau))*year_summer
                 + (5$weekday_winter(tau)+2$weekend_winter(tau))*year_winter
                 + (5$weekday_shoulder(tau)+2$weekend_shoulder(tau))*year_shoulder))
                 + fix_part(t+1)
                 =l=
                 sum((n,tau), -price(n,t,tau)*q(n,t,tau)
                 *((5$weekday_summer(tau)+2$weekend_summer(tau))*year_summer
                 + (5$weekday_winter(tau)+2$weekend_winter(tau))*year_winter
                 + (5$weekday_shoulder(tau)+2$weekend_shoulder(tau))*year_shoulder)
                 + price(n,t,tau) * sum(s, g(n,s,t,tau))
                 *((5$weekday_summer(tau)+2$weekend_summer(tau))*year_summer
                 + (5$weekday_winter(tau)+2$weekend_winter(tau))*year_winter
                 + (5$weekday_shoulder(tau)+2$weekend_shoulder(tau))*year_shoulder))
                 + fix_part(t)
;
line_cap(l,t+1) .. cap(l,t+1) =e= cap(l,t) + cap_0(l) * extension(l,t)
;
line_cap0(l,t)$(ord(t) eq 1) .. cap(l,t) =e= cap_0(l)
;

* Lower-level problem:
MPEC_q(n,t,tau) .. 0 =g= (a(n,tau) + m(n,tau) * q(n,t,tau) + price(n,t,tau))
;
MPEC_g(n,s,t,tau) .. 0 =g= (-c(n,s) - price(n,t,tau) - lambda4(n,s,t,tau))
;
MPEC_delta(n,t,tau) .. 0 =g= (-sum(l,lambda1(l,t,tau) * H(l,n))
                 + sum(l,lambda2(l,t,tau) * H(l,n))
                 + sum(nn,price(nn,t,tau) * B(nn,n))
                 - lambda5(n,t,tau) * slack(n))
;
MPEC_lambda1(l,t,tau) .. 0 =g= (sum(n,H(l,n) * delta(n,t,tau)) - cap(l,t))
;
MPEC_lambda2(l,t,tau) .. 0 =g= (-sum(n,H(l,n) * delta(n,t,tau)) - cap(l,t))
;
MPEC_price(n,t,tau) .. 0 =e= sum(s,g(n,s,t,tau))
                 - sum(nn,B(n,nn) * delta(nn,t,tau)) - q(n,t,tau)
;
MPEC_lambda4(n,s,t,tau) .. 0 =g= (g(n,s,t,tau) - revision(s) * g_max(n,s,tau))
;
MPEC_lambda5(n,t,tau) .. 0 =e= (slack(n) * delta(n,t,tau))
```

```
;


model MPEC_no_reg /
return_no_reg
line_cap
line_cap0
MPEC_q.q
MPEC_g.g
MPEC_delta.delta
MPEC_lambda1.lambda1
MPEC_lambda2.lambda2
MPEC_price.price
MPEC_lambda4.lambda4
MPEC_lambda5.lambda5
/;

model MPEC_no_reg_reduced /
return_no_reg
MPEC_q.q
MPEC_g.g
MPEC_delta.delta
MPEC_lambda1.lambda1
MPEC_lambda2.lambda2
MPEC_price.price
MPEC_lambda4.lambda4
MPEC_lambda5.lambda5
/;

model MPEC_HRV /
return_HRV
price_cap
line_cap
line_cap0
MPEC_q.q
MPEC_g.g
MPEC_delta.delta
MPEC_lambda1.lambda1
MPEC_lambda2.lambda2
MPEC_price.price
MPEC_lambda4.lambda4
MPEC_lambda5.lambda5
/;

model MPEC_HRV_reduced /
return_HRV
price_cap
MPEC_q.q
MPEC_g.g
MPEC_delta.delta
MPEC_lambda1.lambda1
MPEC_lambda2.lambda2
MPEC_price.price
MPEC_lambda4.lambda4
MPEC_lambda5.lambda5
/;

model MPEC_cost_reg /
return_cost_reg
price_cap_costreg
line_cap
line_cap0
MPEC_q.q
MPEC_g.g
MPEC_delta.delta
MPEC_lambda1.lambda1
MPEC_lambda2.lambda2
MPEC_price.price
MPEC_lambda4.lambda4
MPEC_lambda5.lambda5
/;
```

```
model MPEC_cost_reg_reduced /
return_cost_reg
price_cap_costreg
MPEC_q.q
MPEC_g.g
MPEC_delta.delta
MPEC_lambda1.lambda1
MPEC_lambda2.lambda2
MPEC_price.price
MPEC_lambda4.lambda4
MPEC_lambda5.lambda5
/;

fix_part.fx('t0') = 0 ;
fix_costreg.fx('t0') = 0 ;

*------- Load results of MCP_wo_extension (...)

extension.fx(l,t) = 0 ;
cap.l(l,t) = 0 ;
cap.fx(l,t) = cap_0(l);

solve MPEC_no_reg_reduced maximizing profit using mpec;
solve MPEC_no_reg_reduced maximizing profit using mpec;

cap.lo(l,t) = -inf;
cap.up(l,t) = inf;
cap.fx(l,'t0') = cap_0(l);
extension.lo(l,t) = 0;
extension.up(l,t) = inf;

solve MPEC_no_reg maximzing profit using mpec;
solve MPEC_no_reg maximzing profit using mpec;
solve MPEC_no_reg maximzing profit using mpec;
solve MPEC_no_reg maximzing profit using mpec;


*------- Load results of MCP_wo_extension (...)

extension.fx(l,t) = 0 ;
cap.l(l,t) = 0 ;

cap.fx(l,t) = cap_0(l);

solve MPEC_HRV_reduced maximizing profit using mpec;
solve MPEC_HRV_reduced maximizing profit using mpec;

cap.lo(l,t) = -inf;
cap.up(l,t) = inf;
cap.fx(l,'t0') = cap_0(l);
extension.lo(l,t) = 0;
extension.up(l,t) = inf;

solve MPEC_HRV maximzing profit using mpec;
solve MPEC_HRV maximzing profit using mpec;
solve MPEC_HRV maximzing profit using mpec;
solve MPEC_HRV maximzing profit using mpec;


*------- Load results of WF_max_MPEC_p (...)

parameter cap_wfmax(l,t);
cap_wfmax(l,t) = cap.l(l,t);

*------- Load results of MCP_wo_extension (...)

extension.fx(l,t) = 0 ;
cap.l(l,t) = 0 ;
cap.fx(l,t) = cap_0(l);

```

```
solve MPEC_cost_reg_reduced maximizing profit using mpec;
solve MPEC_cost_reg_reduced maximizing profit using mpec;

cap.lo(l,t) = -inf;
cap.up(l,t) = cap_wfmax(l,t);
cap.fx(l,'t0') = cap_0(l);
extension.lo(l,t) = 0;
extension.up(l,t) = inf;

solve MPEC_cost_reg maximzing profit using mpec;
solve MPEC_cost_reg maximzing profit using mpec;
solve MPEC_cost_reg maximzing profit using mpec;
solve MPEC_cost_reg maximzing profit using mpec;

```

## A.4 Matlab code for chapter 5

```
                                    meritOrder.m
function [dt el_price ptrs] = meritOrder(RUN,t,dls,new_cap)

% Parameters
% RUN: configuration as defined in invest.m
% t: year, required to access data in RUN
% new_cap: technology of new capacity ('HC','NG')

Figure = 0;                         % produce figure: 0=no, 1=yes
Figure_Option_Year = 20;            % year for which to produce figure
Figure_Option_Demand = 1;           % include demand in the figure: 0=no, 1=yes
Figure_Option_Export = 0;           % export only (figure not shown): 0=no,
1=yes
Figure_Option_NewPlant = 1;         % include/indicate position of new plant:
0=no, 1=yes
Figure_Export_Driver = '-deps';     % driver used to export figures -> sets file
format
Figure_Export_Dir = './figures/';   % target directory for export

PriceFuel.LG = RUN.p_fuel_0_lignite;
CarbonEF.LG = RUN.ef_lignite;
PriceFuel.HC = RUN.p_fuel_coal(t);
CarbonEF.HC = RUN.ef_coal;
Efficiency.NewHC = RUN.etha_coal;
PriceFuel.NG = RUN.p_fuel_gas(t);
CarbonEF.NG = RUN.ef_gas;
Efficiency.NewNG = RUN.etha_gas;
PriceCO2 = RUN.p_co2(t);

global existing_caps;
global existing_effs;
global existing_techs;
if size(existing_caps)==0
    [existing_techs existing_caps existing_effs] =
textread('capacities.csv','%s%f%f', 'delimiter', ';');
end

caps = existing_caps/1000;  % convert capacity to GW
effs = existing_effs;
techs = existing_techs;

% apply scaling factor
for i = 1:length(caps)
    switch techs{i}
    case 'LG'
        caps(i) = caps(i) * RUN.scaling_lignite;
    case 'HC'
        caps(i) = caps(i) * RUN.scaling_coal;
    case 'NG'
        caps(i) = caps(i) * RUN.scaling_gas;
    end
end

% insert the new capacity into merit order
switch new_cap
    case 'HC'
        caps(end+1) = RUN.cap/1000;  % convert capacity to GW
        effs(end+1) = RUN.etha_coal *100;
        techs{end+1} = 'HC';
    case 'NG'
        caps(end+1) = RUN.cap/1000;  % convert capacity to GW
        effs(end+1) = RUN.etha_gas * 100;
        techs{end+1} = 'NG';
end

if RUN.flexible_ptr == 1 % & t<=RUN.t_fa_years
    % flexible ptr
    LGInds = find(strcmp(techs,'LG')==1);
    HCInds = find(strcmp(techs,'HC')==1);
    NGInds = find(strcmp(techs,'NG')==1);
```

```
                                    meritOrder.m
    % NG always 100%
    PTR.NG = 100;
    % least efficient HC, most efficient NG
    HCLoEff = min(effs(HCInds));
    NGHiEff = max(effs(NGInds));
    mc_diff = (PriceFuel.NG + PriceCO2*CarbonEF.NG)*100/NGHiEff - PriceFuel.HC *
100/HCLoEff;
    PTR.HC = floor(mc_diff/(PriceCO2*100/HCLoEff*CarbonEF.HC)*100);
    % least efficient LG, most efficient HC
    LGLoEff = min(effs(LGInds));
    HCHiEff = max(effs(HCInds));
    mc_diff = (PriceFuel.HC + PriceCO2*PTR.HC/100*CarbonEF.HC)*100/HCHiEff -
PriceFuel.LG * 100/LGLoEff;
    PTR.LG = floor(mc_diff/(PriceCO2*100/LGLoEff*CarbonEF.LG)*100);
else
    % always full pass through (100%)
    PTR.LG = 100;
    PTR.HC = 100;
    PTR.NG = 100;
end
ptrs = [PTR.LG PTR.HC PTR.NG];

% compute marginal costs [mcs] (or better costs per unit of electricity) as
% sum of fuel costs and co2 costs
for i=1:length(caps)
        fcs(i) = PriceFuel.(char(techs(i))) * 100/effs(i);
        co2cs(i) = PriceCO2 * PTR.(char(techs(i)))/100 * 100/effs(i) *
CarbonEF.(char(techs(i)));
        co2cs_full(i) = PriceCO2 * 100/effs(i) * CarbonEF.(char(techs(i)));
        mcs(i) = fcs(i) + co2cs(i);
end

[Y inds] = sort(mcs);
cap_cum = RUN.nuc_res_caps;
for ind=inds
    cap_cum = cap_cum + caps(ind);
    rank_abs(ind) = cap_cum;
end

% determine prices...
el_price = [];
for i = 1:length(dls)
    if dls(i)<=cap_cum
        % MC of marginal plant
        higher = find(rank_abs>=dls(i));
        el_price(end+1) = min(mcs(higher));
    else
        % Peaking price
        el_price(end+1) = RUN.p_el_peak;
    end
end

% finde demand threshold for new plant
dt = rank_abs(end);
```

combine.m

```
function rv = combine(ranges)

global STORE;
STORE = ranges;
combine_recursive(ranges,1);
rv = STORE(2:end);
clear STORE;


function rv = combine_recursive(ranges,fieldno)

global STORE;
nofields = length(fieldnames(ranges));
fnames = fieldnames(ranges);
field = char(fnames(fieldno));

for i=ranges.(field)
    ranges2 = ranges;
    ranges2.(field) = i;
    if fieldno<nofields
        combine_recursive(ranges2,fieldno+1);
    else
        STORE(end+1) = ranges2;
    end
end
```

```
                                        invest.m
% Version 20100526
% Configuration: all parameters can be modified through the RANGE structure in
'invest.m'
% Figures: figures can be configured in 'meritOrder.m' (see comments)
% Returns: all results are contained in the RUNS structure -> for example type
'RUNS(1)' after execution

clear all;

RANGE.c_cap_coal = [800];           % capacity costs coal [1000EUR/MW]
RANGE.c_cap_gas = [400];            % capacity costs gas [1000EUR/MW]
RANGE.c_om_coal = 37.8;             % fixed annual o&m costs coal [1000EUR/MW]
(def: 37.8)
RANGE.c_om_gas = 15.5;              % fixed annual o&m costs gas [1000EUR/MW]
(def: 30.3)
RANGE.p_fuel_0_lignite = [0.004];   % initial lignite fuel price [1000EUR]
RANGE.p_fuel_0_coal = [0.0091];     % initial coal fuel price [1000EUR]
RANGE.p_fuel_0_gas = [0.020];       % initial gas fuel price [1000EUR]
RANGE.p_fuel_inc_coal = [0.0015];              % anual coal price increase
% RANGE.p_fuel_inc_coal = [-0.003 0.0015 0.006];   % anual coal price increase
RANGE.p_fuel_inc_gas = [0.01];                 % anual gas price increase
% RANGE.p_fuel_inc_gas = [0.009 0.01 0.011];       % anual gas price increase
RANGE.p_co2_0 = [0.020];                        % initial co2 price [1000EUR]
% RANGE.p_co2_0 = [0.015 0.020 0.025];             % initial co2 price [1000EUR]
RANGE.p_co2_inc = [0.02];                      % anual co2 price increase
% RANGE.p_co2_inc = [0.01 0.02 0.03];              % anual co2 price increase
RANGE.t_years = [20];               % total dcf period
% RANGE.t_fa_years = [14];            % length of free allocation period
RANGE.t_fa_years = [0:2:20];        % length of free allocation period
% RANGE.df = [0.075];                 % discount factor
RANGE.df = [0.05 0.075 0.10];       % discount factor
RANGE.alloc_mode = 3;               % mode: 1=NAPI, 2=NAP2, 3=single BAT (gas),
4=auctioning
RANGE.flexible_ptr = 1;             % flexible pass through rate: 0=no, 1=yes
RANGE.alloc_flh_coal = 7500;        % German ETS full load hours coal (NAPII)
RANGE.alloc_flh_gas = 7500;         % German ETS full load hours gas (NAPII)
RANGE.alloc_bat_coal = 0.75;        % German ETS best available technology (BAT)
benchmark coal [t/MWh_el] (def: 0.75)
RANGE.alloc_bat_gas = 0.365;        % German ETS best available technology (BAT)
benchmark gas [t/MWh_el] (def: 0.365)
RANGE.etha_coal = 0.46;             % new plant efficiency coal
RANGE.etha_gas = 0.58;              % new plant efficiency gas
RANGE.ef_lignite = 0.41;            % emission factor lignite [t/MWh_th]
RANGE.ef_coal = 0.342;              % emission factor coal [t/MWh_th]
RANGE.ef_gas = 0.202;               % emission factor gas [t/MWh_th]
RANGE.cap = 1000;                   % size of new capacity [MW]
RANGE.nuc_res_caps = 25.6;          % cumulated capacities of RES & nuclear [GW]
RANGE.p_el_peak = 0.100;            % electricity price (peaking) [1000EUR]
RANGE.scaling_lignite = 0.855;      % capacity scaling lignite
RANGE.scaling_coal = 0.72;          % capacity scaling hard coal
RANGE.scaling_gas = 0.98;           % capacity scaling natural gas

% ranges are combined to produce unique parameters settings -> each is a 'run'
RUNS = combine(RANGE);

% load demand levels (34-78GW)
demand = dlmread('consumption.csv',';');
% resize data in one big column, remove missing values (-99)
demand = reshape(demand, 365*24, 1);
demand(find(demand == -99)) = [];
% compute frequency (hours) and demand levels, WOLF (Körnung)
hours =  hist(demand/1000,[0.5:1:79.5]);
dls = find(hours~=0);

% open log file
flog = fopen('invest.log','w+');

for n = 1:length(RUNS);
```

```
                                    invest.m
    fprintf(flog, sprintf('%s Run %i of %i\n', datestr(clock), n,
length(RUNS)));

    % set index for auctioning (0=no, 1=yes)
    RUNS(n).auct_index(1:RUNS(n).t_fa_years) = 0;
    RUNS(n).auct_index(RUNS(n).t_fa_years+1:RUNS(n).t_years) = 1;

    for t = 1:RUNS(n).t_years

        % compute this year's prices for fuels & co2
        RUNS(n).p_fuel_coal(t) = RUNS(n).p_fuel_0_coal *
(1+RUNS(n).p_fuel_inc_coal)^(t-1);
        RUNS(n).p_fuel_gas(t) = RUNS(n).p_fuel_0_gas *
(1+RUNS(n).p_fuel_inc_gas)^(t-1);
        RUNS(n).p_co2(t) = RUNS(n).p_co2_0 * (1+RUNS(n).p_co2_inc)^(t-1);


        % NATURAL GAS
        % feed fuel costs to merit order to get (i) demand threshold,
        % (ii) prices and (iii) pass through rates
        [dt el_price ptrs] = meritOrder(RUNS(n),t,dls,'NG');
        RUNS(n).dt_gas(t) = dt;
        RUNS(n).p_el_with_gas(t,:) = el_price;
        RUNS(n).flh_gas(t)= 0;
        RUNS(n).ptrs(t,:) = ptrs;
        % iterate over demand levels
        j = 0;
        for dl = dls
                j = j+1;
                if dl>=dt
                    RUNS(n).rev_gas_el(t,j) = ...
                        (RUNS(n).p_el_with_gas(t,j) - ...

(RUNS(n).p_fuel_gas(t)+RUNS(n).p_co2(t)*RUNS(n).ef_gas)/RUNS(n).etha_gas) ...
                        *hours(dl) *RUNS(n).cap *(1+RUNS(n).df)^(-t+1);
                    RUNS(n).flh_gas(t) = RUNS(n).flh_gas(t) + hours(dl);
                else
                    RUNS(n).rev_gas_el(t,j) = 0;
                end
        end
        % O&M costs
        RUNS(n).om_gas(t) = RUNS(n).c_om_gas * RUNS(n).cap *
(1+RUNS(n).df)^(-t+1);

        % HARD COAL
        % feed fuel costs to merit order to get (i) demand threshold,
        % (ii) prices and (iii) pass through rates
        [dt el_price ptrs] = meritOrder(RUNS(n),t,dls,'HC');
        RUNS(n).dt_coal(t) = dt;
        RUNS(n).p_el_with_coal(t,:) = el_price;
        RUNS(n).flh_coal(t)= 0;
        RUNS(n).ptrs(t,:) = ptrs;
        % iterate over demand levels
        j = 0;
        for dl = dls
                j = j+1;
                if dls(j)>=dt
                    RUNS(n).rev_coal_el(t,j) = ...
                        (RUNS(n).p_el_with_coal(t,j) - ...

(RUNS(n).p_fuel_coal(t)+RUNS(n).p_co2(t)*RUNS(n).ef_coal)/RUNS(n).etha_coal) ...
                        *hours(dl) *RUNS(n).cap *(1+RUNS(n).df)^(-t+1);
                    RUNS(n).flh_coal(t) = RUNS(n).flh_coal(t) + hours(dl);
                else
                    RUNS(n).rev_coal_el(t,j) = 0;
                end
        end
        % O&M costs
        RUNS(n).om_coal(t) = RUNS(n).c_om_coal * RUNS(n).cap *
```

invest.m

```
(1+RUNS(n).df)^(-t+1);

        % revenues from free allocations: alloc*cap*pco2
        % default = 0 (AUCT)
        RUNS(n).alloc_revs_coal(t) = 0;
        RUNS(n).alloc_revs_gas(t) = 0;
        % NAP I
         if t<=RUNS(n).t_fa_years & RUNS(n).alloc_mode == 1
             % as many as used
             RUNS(n).alloc_revs_coal(t) = RUNS(n).ef_coal / RUNS(n).etha_coal *
RUNS(n).flh_coal(t) * RUNS(n).cap * RUNS(n).p_co2(t) *(1+RUNS(n).df)^(-t+1);
             RUNS(n).alloc_revs_gas(t) = RUNS(n).ef_gas / RUNS(n).etha_gas *
RUNS(n).flh_gas(t) * RUNS(n).cap * RUNS(n).p_co2(t) *(1+RUNS(n).df)^(-t+1);
         end
         % NAP II
         if t<=RUNS(n).t_fa_years & RUNS(n).alloc_mode == 2
             RUNS(n).alloc_revs_coal(t) = RUNS(n).alloc_bat_coal *
RUNS(n).alloc_flh_coal * RUNS(n).cap * RUNS(n).p_co2(t) *(1+RUNS(n).df)^(-t+1);
             RUNS(n).alloc_revs_gas(t) = RUNS(n).alloc_bat_gas *
RUNS(n).alloc_flh_gas * RUNS(n).cap * RUNS(n).p_co2(t) *(1+RUNS(n).df)^(-t+1);
         end
         % SBAT
         if t<=RUNS(n).t_fa_years & RUNS(n).alloc_mode == 3
             RUNS(n).alloc_revs_coal(t) = RUNS(n).alloc_bat_gas *
RUNS(n).alloc_flh_coal * RUNS(n).cap * RUNS(n).p_co2(t) *(1+RUNS(n).df)^(-t+1);
             RUNS(n).alloc_revs_gas(t) = RUNS(n).alloc_bat_gas *
RUNS(n).alloc_flh_gas * RUNS(n).cap * RUNS(n).p_co2(t) *(1+RUNS(n).df)^(-t+1);
         end

    end
    % compute npv
    RUNS(n).npv_coal = sum(sum(RUNS(n).rev_coal_el)) +
sum(RUNS(n).alloc_revs_coal) - sum(RUNS(n).om_coal) - RUNS(n).cap *
RUNS(n).c_cap_coal;
    RUNS(n).npv_gas = sum(sum(RUNS(n).rev_gas_el)) + sum(RUNS(n).alloc_revs_gas)
- sum(RUNS(n).om_gas) - RUNS(n).cap * RUNS(n).c_cap_gas;
    RUNS(n).npv_diff = RUNS(n).npv_coal - RUNS(n).npv_gas;
end

fprintf(flog, sprintf('%s Done\n', datestr(clock)));
fclose(flog);

% order struct RUNS
RUNS = orderfields(RUNS);

% exit only on cluster
if (isunix)
    exit
end
```