Coordination in Power Systems for Efficient Grid Utilization

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Chapter 1

Introduction

Climate change, resource scarcity as well as public and political opinion necessitate changes to the current energy system. Ambitious political goals to reduce carbon emissions are omnipresent. The Kyoto Protocol to the United Nations Framework Convention on Climate Change (UNFCCC) is the largest international treaty on the reduction of greenhouse gas (GHG) emissions (United Nations, 1998). The second commitment period of the Kyoto Protocol aims at reducing GHG emissions against 1990 levels by at least 18% until 2020 (United Nations, 2012).[1] Besides the reduction of carbon emissions, many countries reinforce the restructuring of the energy system to limit dependency on fossil fuel imports (e.g., oil, natural gas) or avoid possibly hazardous technologies (e.g., nuclear). Some examples in addition to Kyoto targets are Japans's aim to cut 10% of electricity consumption by 2030, China's target to reduce energy intensity by 16% until 2015 and the new fuel economy standards in the United States (IEA, 2012b).

The power sector globally accounts for a large share of the total primary energy consumption and carbon emissions. In the United States, the electric power sector accounts for approximately 40% of total primary energy consumption (US Energy Information Administration, 2012)[2] and 33% of total greenhouse gas emissions (US Environmental Protection Agency, 2013). In the European Union, the energy used by power producers accounts for approximately one third of gross inland consumption.[3] Figure 1.1 depicts the primary sources of energy and distribution to different sectors in the EU-27. The electric power system is a crucial starting point in achieving the targets and ensuring reliable electricity supply at the same time.

[1] Many countries with binding targets in the Kyoto Protocol are members of the European Union which is reflected in the EU Roadmap 2050 targets of reducing carbon emissions below 1990 levels by 20% until 2020 and 80–95% until 2050 (European Commission, 2011).

[2] This figure actually represents developed countries. According to IEA (2012a), electricity accounts for approximately 18% of total energy consumption.

[3] For more details on assumptions, see http://epp.eurostat.ec.europa.eu/statistics_explained/index.php/Consumption_of_energy#Further_Eurostat_information.

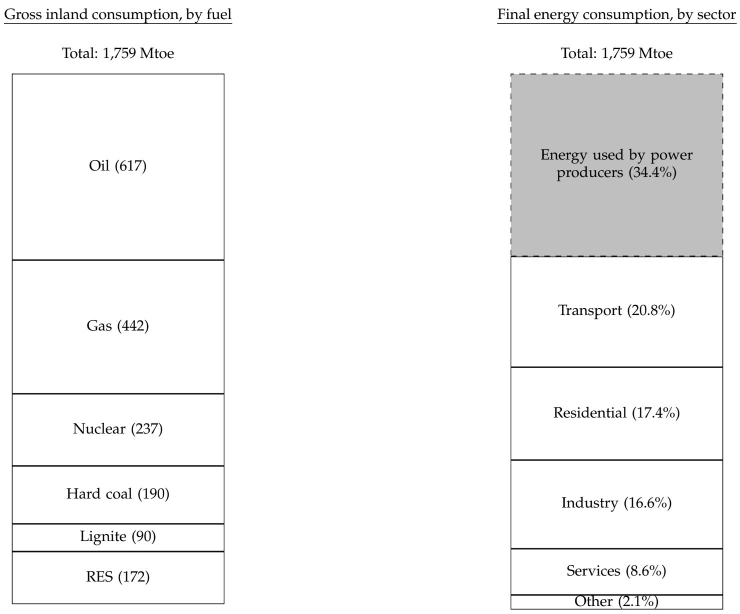

Figure 1.1: EU-27 gross inland consumption by fuel and final energy consumption by sector 2010 in Mtoe (Data source: Eurostat, 2012)[4]

A prominent example of the power system paradigm change is the *Energiewende (energy transition)* in Germany. The German government has set a goal to reduce greenhouse gas emissions by 80–95% in comparison to 1990 levels by 2050 (BMWi and BMU, 2010), with a set nuclear phase-out by 2022 (German Federal Government, 2011). Being a densely populated, industrialized country with limited potentials for generating electricity from continuously available renewable energy sources (e.g., hydro) in comparison to countries like Norway[5], this is an ambitious goal for Germany. Consequently, Germany serves as an international role model and is closely observed and discussed internationally (The Economist, 2012).

1.1 Power Grid Investment and Operation

Globally, the transition and development of power systems lead to considerable investments with power grids accounting for a large share of these expenditures. The International Energy Agency (IEA) estimates total global infrastructure investments of $17 trillion needed in the power sector from 2011-2035 (IEA, 2011b). A share of 58% is due to new power plants, 31% to distribution and 11% to transmission infrastructure. Recent calculations of infrastructure investments are in

[4]One Million tons of oil equivalent (Mtoe) is equal to 11.63 TWh. Missing values to 100% are served by other fuels.

[5]In Norway hydro accounts for 94.7% of total domestic electricity generation (IEA, 2012a).

the same range and show that the power sector accounts for a large share of total infrastructure investments globally (Figure 1.2). In Germany, major investments in grid capacity and new technologies are identified as crucial building blocks for the integration of renewable energy sources, with cost drivers in the distribution as well as in the transmission grid (BNetzA, 2012).

In the context of these investments, the overall goal should be to meet future requirements with an efficient set of measures. Therefore, many parties in the power system are involved and need to be coordinated to achieve efficient capacity management. A grid operator faces the fundamental choice between capacity utilization and capacity provision under uncertainty:

- Infrastructure investments — build additional power grid capacity efficiently
- System operations — use existing infrastructure capacity efficiently

In the long-run, regulatory conditions need to establish incentives for different actors to incorporate the grid infrastructure cost into their decisions. In the short-term, Transmission System Operators (TSOs) and Distribution System Operators (DSOs) can apply coordination measures to fulfill their responsibility of maintaining a balanced power grid and making the most out of infrastructure capacity. These targets get even more important in the light of increasing penetration of intermittent renewable energy sources (RES), which have less or even equal to zero marginal production cost and hence increase the relative weight of capacity investment costs.

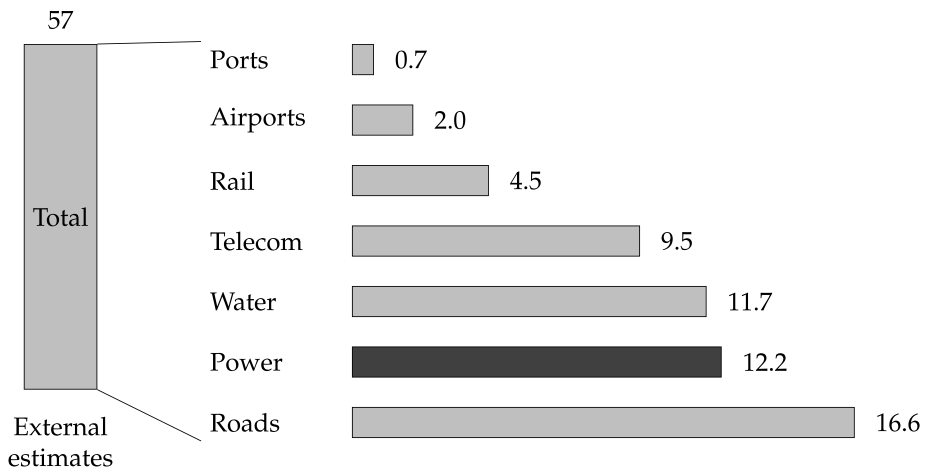

Figure 1.2: Estimated global infrastructure investments by sector required between 2013–2030 in $ trillion (Data source: McKinsey Global Institute, 2013)

1.2 Challenges in Power System Transformation

Today, power systems are developing from central, large and constant generation bases with unidirectional distribution function into more decentralized, intermittent, and bidirectional systems. Until recently, an integrated monopolist internalized all relevant factors and rolled out the centrally planned infrastructure, in typical power systems. This central planning approach is based on historical experience and a controllable supply side that served the predictable and inflexible demand side.

However, major changes are currently in progress in power systems. Most notable is the steadily increasing amount of installed capacity of RES. In contrast to the past, where supply followed demand, electricity demand will increasingly have to match intermittent supply from RES. A large share of this capacity is installed remotely from past fossil-fuel based generators and load centers resulting in new power flow patterns. In addition, power sectors are to a greater extent liberalized and unbundled, which has led to an increased number of actors and stakeholders. The privatization and restructuring began in the UK and Chile in the late 1980s and during the 1990s in many other countries (Sioshansi and Pfaffenberger, 2006). The split into different entities in generation, transmission, distribution, and consumption provides a variety of options which influence the development of the power sector by adapting regulations or introducing new business models (Cossent et al., 2009). Established markets which serve as automated balancing mechanisms observe the effects of RES:

> *"A rising share of wind and solar-generated power during the peakload period could be observed in 2012. As a consequence, the peakload power price frequently fell below the baseload price - the opposite of what usually happens." European Commission (2012)*

From a grid perspective, the large investments, long planning and project realization phases stand in sharp contrast to the new demanded flexibility. Various simple, infrastructure-based solutions are able to meet the flexibility requirements. For example, massive distributed storage could be rolled out to balance all supply and demand mismatches at all locations. Alternatively, the grid could be reinforced such that there is sufficient grid capacity, independent of the spatiotemporal distribution of supply and demand. Another option is siting demand near generation centers or supply near load centers. In special settings, these solutions are discussed: The straightforward solution of using storage is currently used in smart micro grids in remote areas (e.g., the sustainable island La Graciosa[6]). Huge investments into grid capacity are in focus of large interregional transmission projects, e.g., HVDC[7] lines in Europe for large distance

[6] `http://www.endesasmartgrids.com/index.php/en/la-graciosa-en`

[7] High-voltage direct current

balancing of RES. These investments need economic justification to ensure a selection of most beneficial investments. In addition, all investments need a fair balancing against other measures aiming to use infrastructure more efficiently.

1.3 Opportunities for Efficient Use and Development of Power Grids

The utilization of power grid infrastructure results from the spatial distribution of dynamic supply and demand. Consequently, for an efficient use of the grid, all actors that can influence supply, demand, or grid capacity need to be aligned. The incentives that influence the behavior depend on the regulatory design of the power system.

1.3.1 Efficient Use of Capacity

A complementary approach to new investments in grid capacity is flexibility in supply and demand with the purpose of using given resources more efficiently. Within a smart power grid, real-time information from sensors and distributed intelligence can recognize the current conditions and determine appropriate responses (Ramchurn et al., 2012). This information as well as intelligent control and incentive mechanisms to shape supply and demand can be used to achieve better grid utilization and thus limiting investment requirements. There are various alternative approaches to coordinate grid capacity, storage, demand, generation, and other influencing factors. An example is demand response (DR) with the objective of using flexible loads to match intermittent renewable supply (Albadi and El-Saadany, 2008). To mobilize the potential of approaches that foster efficient operation, further changes in the regulatory environment have to be considered. In addition, analysis of real-time data and new technologies (e.g., intelligent substations, smart meters) help to ensure an efficient smart power grid. The question whether benefits of these technologies outweigh their costs is subject of current discussions and analyses (Electric Power Research Institute, 2011). However, the sum of benefits should be considered (Faruqui et al., 2010), and with aging assets the scheduled replacement cycle might be used to speed up the roll-out of smart-grid infrastructure (Joskow, 2012).

1.3.2 Efficient Investment Planning

The central investment incentive for grid operators (TSOs or DSOs) is the remuneration scheme. Depending on the prevailing electricity market design and competition details, grid operators may or may not have incentives for pursuing efficient investment choices (Ehrenmann and Neuhoff, 2009).

However, even with the right incentives for grid operators, investments can still be inefficient due to other actors in the power system. An important influencing factor is the future development of demand and generation. Depending on the location and the fluctuations over time, these may be beneficial for the utilization of infrastructure or may lead to additional investment needs. In the long-run, the incentives to efficiently locate demand and supply may play a major role. In addition, grid planning needs to consider opportunities provided by new technologies, actors, energy services and business models. Enabling the efficient use of capacity provides ample opportunities to reduce the need for grid investments.

1.4 Structure of the Thesis

The goal of this thesis is to develop and evaluate different coordination approaches and incentive systems for efficient operation and investment in grid capacity. Using various research methodologies, these approaches are analyzed both on transmission and distribution grid levels.

The first challenge of efficient operation with given grid resources is addressed by short-term coordination mechanisms for flexible loads that mitigate grid congestion and local infrastructure overloads while at the same time fostering the use of low-cost or renewable generation. The evaluation is mainly based on calculations and simulations on different grid levels, predominantly using real data.

The second challenge concerns the incentives of different actors to pursue investments that are beneficial for power grids. For this purpose, different regulatory regimes and their influence on incentives to consider grid capacity costs in investment decisions are examined. The analysis is based on microeconomic models of power systems including generators, system operators, and consumers. Within this model, the influence of regulatory regimes for grid cost allocation on competition and investment behavior is analyzed. Both research streams mainly focus on data sources and regulatory regimes in the German or Swiss electricity market. Where appropriate, these examples are complemented by different designs and regulations from other international experiences. The following paragraphs provide a quick overview of the topics covered in each chapter of this thesis. A graphical overview of its sections is depicted in Figure 1.3.

Chapter 2 summarizes the basic concepts of the power sector, ranging from the involved actors and the current state of liberalization to the physical laws

Chapter 1: **Introduction**

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Chapter 3: **Pricing and Coordination in Power Systems**

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4.5 Conclusion of Local Load Coordination	5.5 Conclusion of Transmission Pricing and Cost Allocation

Chapter 6: **Conclusion**

Figure 1.3: Structure of the thesis

and challenges of the grid. Serving as the foundation for the subsequent chapters, it highlights the special features that differentiate the power sector from other network industries.

Chapter 3 recapitulates on the state-of-the-art of pricing and incentives. It discusses opportunities to resolve challenges in the power system as well as acceptance issues and presents the current progress of implementation.

The main focus of Chapter 4 is local load coordination approaches. EV charging loads are used as an exemplary flexible load to analyze the potential of different incentive schemes to mitigate overloads. Chapter 4 mainly addresses the following research questions:

- What is the influence of different load coordination mechanisms (e.g., load-based, supply-based) and flexible loads (e.g., EV charging) on load profiles?
- What is the potential of different load coordination alternatives to support efficient grid utilization?

Investment incentives for generators and grid cost allocation under different regulatory regimes are covered in Chapter 5. Motivated by diverse regulatory solutions in different countries, micro-economic models are used to explore the effects on different stakeholders and the power system development. Chapter 5 specifically addresses the following research questions:

- What is the influence of different cost allocation options (e.g., generation or load) on welfare?
- Which allocation of transmission and generation assets results under different regulatory regimes?

Chapter 6 presents a short synthesis of the research outcomes. In addition, it discusses the implications and provides an outlook on open research questions and possible extensions.

1.5 Research Path

The content of this thesis is based on research outcomes of several years. Some parts of this thesis were previously covered and published in journals, conference proceedings, or working papers. This section lays out which articles contain parts of this thesis and how the ideas, research questions, methods, and data relate to each other.

Publications that predominantly concern the potential of flexible demand as well as the interrelation to grid utilization and distribution network expansion:

- *Schuller, A., J. P. Ilg, and C. van Dinther (2012). Benchmarking Electric Vehicle Charging Control Strategies. In Proceedings of the IEEE PES Innovative Smart Grid Technologies (ISGT), pp. 1–8*
  This paper evaluates the potential of flexible EV charging loads to increase wind energy consumption based on a simulation using German data. It demonstrates the potential of flexible loads for the integration of renewable energy sources without considering grid constraints.

- *Flath, C. M., S. Gottwalt, and J. P. Ilg (2012). A Revenue Management Approach for Efficient Electric Vehicle Charging Coordination. In Proceedings of the 45th Annual Hawaii International Conference on System Sciences (HICSS), pp. 1888 – 1896*
  A revenue management approach for EV charging demonstrates how a simple coordination mechanism can efficiently allocate limited charging capacity to consumers with different willingness to pay. The paper is based

on a formal model of demand and supply and in a simple numerical example applies the approach to a fictitious neighborhood with limited grid capacity.

- *Basse, H., F. Salah, and J. Ilg (2012). Nutzung von Demand-Side-Management für Leistungsausgleich und Netzausbauvermeidung: ein komplexer Spagat (Teil 1). EW-das Magazin für die Energie Wirtschaft 22, 48–51*
  This article explores the trade-offs between demand-side management incentives for fostering the consumption of RES and reducing grid utilization from an industry perspective. In addition, it explains the main thoughts and ideas of the EV charging simulation in the Swiss grid planning case study from Section 4.4.

- *Ilg, J. P., H. Lange, and C. M. Flath (2013). Reduction of Congestion in Power Grids. Working paper*
  This working paper focuses on congestions in power grids. It explains and discusses alternative actions for each actor to resolve a congested situation in power grids.

Publications that deal with different coordination mechanisms for EV charging, especially the influence of EV charging on local grid infrastructure and local infrastructure pricing to avoid overloads:

- *Flath, C. M., J. P. Ilg, and C. Weinhardt (2012). Decision Support for Electric Vehicle Charging. In Proceedings of the 18th Americas Conference on Information Systems (AMCIS)*
  The paper develops a more detailed model of flexible EV charging demand in the form of different charging strategies based on real mobility data. With these strategies it is possible to model different levels of information availability (e.g., price forecasts) or risk propensity (e.g., minimum range). This is valuable for more realistic models and provides a basis for the resulting charging load simulations.

- *Salah, F., J. P. Ilg, C. M. Flath, H. Basse, and C. van Dinther (2013). Impact of Electric Vehicles in High-Voltage Grids: A Swiss Case Study. Working Paper*
  The potential impact of EV charging on the power grid and grid planning are presented in this working paper based on Swiss load, grid, and mobility data. In cooperation with BKW FMB Energy Ltd. (BKW) the paper investigates the impact of flexible EV loads on high-voltage substation transformers in 2040, given different scenarios.

- *Flath, C. M., J. P. Ilg, S. Gottwalt, H. Schmeck, and C. Weinhardt (2013). Improving Electric Vehicle Charging Coordination Through Area Pricing. Transportation Science (available online), 1–16*

The main results on local area pricing for EV charging are published in this article. It employs the EV charging strategies to evaluate a local infrastructure coordination mechanism in a single transformer setting. The mechanism combines generation price-based and local utilization-based incentives to foster the use of RES and at the same time adhere to infrastructural constraints.

- *Ilg, J. P., C. M. Flath, F. Salah, and H. Basse (2013). Electric Vehicle Charging Coordination and Local Power Grid Utilization. Working paper* and
  Salah, F., H. Basse, and J. Ilg (2012). Auswirkungen der Elektromobilität auf die Auslastung von Stromnetzen an einem Schweizer Fallbeispiel. In VDE-Kongress 2012, Stuttgart, Germany. VDE VERLAG GmbH
  Based on the potential grid impact of EV charging (Salah et al., 2013), different coordination mechanisms are evaluated in these articles — including the area pricing mechanism presented in Flath et al. (2013).

Publications dealing with transmission pricing, cost allocation of infrastructure, and efficient investment incentives:

- *Ilg, J. P., C. M. Flath, and J. Krämer (2012). A Note on the Economics of Metered Grid Pricing. In Proceedings of the 9th International Conference on the European Energy Market (EEM), pp. 1–6*
  Different cost allocation methods influence competition outcomes and welfare distribution between generation and demand. This paper analyzes the welfare distribution in the case of preexisting investments based on a two-node model.

- *Ilg, J.; Flath, C.; Krämer, J. (2013) Investment and Grid Cost Allocation. Working Paper.*
  Investors factor the regulatory design into their decisions on new investments in generation and transmission capacity. Based on different regulatory regimes on grid cost allocation, the implications on investment behavior are analyzed and discussed in this paper.

Some paragraphs and sections in this thesis are previous versions, extensions, or direct reproductions of own publications or working papers. In addition to this provided list, their use is mentioned explicitly at the end of the introductory paragraphs of each chapter.

Chapter 2

Electric Power System Fundamentals

Similar to other industries, the power sector has a life cycle or value chain for its core product electric power: generation, transmission, distribution, and consumption. Generators that produce electricity, grid operators on different levels that transport and distribute electricity, and consumers who employ electric energy in various applications. Interaction between these core functions depends on the level of vertical integration of different functions and therefore the regulatory design. Nowadays, the interaction also involves wholesale markets as well as sales and distribution functions which are not examined in detail in this thesis. The major difference of the power sector in comparison to many other industries is that electric energy is not easily storable[1] and the delivery time is nearly instantaneous (Stoft, 2002). Therefore, power supply has to equal system load at any time. If not, the system frequency will either decrease in case of excess demand or increase in case of excess supply. In essence, this leads to a much closer coupling of all actors in the power sector than in other industries. Besides non-storability, electricity has additional special characteristics that influence the structure, operation, and development of the power sector (e.g., Erdmann and Zweifel, 2008):

- Usable for many services
- Not easily substitutable
- Technically homogenous, economically heterogeneous
- Variety of generation technologies with different costs
- Variety of transformation options into other energy forms (e.g., chemical, thermal, mechanical)
- Grid-bound transportation

[1] Electric energy can be transformed and stored in other forms with losses.

This chapter provides an overview on the current state and the development of the power sector. It introduces the main actors, the high-level regulatory development and how the actors interact to achieve a stable and secure electricity system as it exists in developed countries. The intention is not to cover all details of the electric power system but rather provide the basis for the research covered in this thesis. It is to support the understanding of the history of the power sector, its rough functionality as well as recent developments influencing the actors. The German power sector serves as a practical example for an industrialized country which is particularly challenged due to the *Energiewende*.

At some points own existing publications are used in this chapter. In detail, some paragraphs in Section 2.5 are based on Flath et al. (2013).

2.1 Regulation

Power system regulation by itself is a huge topic for research and discussion due to the large variety in regulatory approaches globally. The seminal work of Kahn (1988), *The Economics of Regulation*, provides a deeper understanding of the core principles in regulation. This section provides a high-level description of some regulatory notions relevant for this thesis. Therefore, the main focus is on the German electricity market regulation. If a more detailed inspection is necessary, the paragraphs are mentioned and discussed in the respective chapter.

2.1.1 Electricity Market Restructuring

The term *deregulation* is often used in connection with these restructuring developments. In fact, as noted by Vogel (1996), the introduction of competition in the electricity sector does not lead to less regulation — according to Hogan (2002), restructuring is the better term. A synonym for restructuring is the liberalization of the markets used by the European Union (Sioshansi, 2006).

In the past, a state-owned regulated and integrated monopolist typically performed all functions including generation, transmission, and distribution as well as retailing of electricity. Due to assumed inefficiencies, electricity markets started to be deregulated or liberalized globally since the 1980s. Sioshansi (2006) provides a list of countries, including a short description of the main liberalization highlights. The main target across different countries was to create competition in order to achieve more efficient investment and operation for lower end-consumer prices and better service levels. Depending on the approach, restructuring comprises several of the main actions:[2]

[2] This list is not exhaustive, but merely a compilation of typical actions. Jamasb et al. (2005) and Joskow (2008) provide similar lists.

- Privatization of state-owned utilities
- Vertical separation of electricity supply functions (Unbundling)[3]
- Introduction of competition, e.g., in generation and/or retailing[4]
- Establishment of an independent regulator
- Launch of a wholesale market

Joskow (2008) provides a more detailed description of actions and their implementation in different electricity markets. An overview of early regulatory development and structural changes in the US power sector is given in Joskow et al. (1989).

The German electricity market restructuring is mainly driven by EU regulation. Beginning with the first electricity market directive 96/92/EC, the European Union started to liberalize national electricity markets in the 1990s. In addition, the European Commission aimed to improve cross-border transmission capacity and rules to facilitate electricity trades in order to create a single European market (Jamasb et al., 2005). The second energy package focused on the remaining "main obstacles in arriving at a fully operational and competitive internal market [and] relate[d] amongst other things to issues of access to the network, tarification issues and different degrees of market opening between Member States" (Directive 2003/54/EC).[5] The third energy package tackles the challenge that "nondiscriminatory network access and an equally effective level of regulatory supervision in each Member State do not yet exist" (Directive 2009/72/EC).[6] In particular, it focuses on the facilitation of cross-border trading through the expansion of interconnections and common rules. Major parts of the EU goals for electricity market reform have been implemented by the member states. However, the internal European energy market is currently not on track for the planned implementation deadline.[7] In Germany, nearly all these EU energy directives have been fully implemented.[8] In 1998, the first EU electricity market directive was transposed into national legislation with the amended *En-*

[3] Vayrying degrees of unbundling are discussed in Friedrichsen (2012) as well as Erdmann and Zweifel (2008).

[4] Transmission and distribution grids are still monopolies, since it is economically inefficient to duplicate grid infrastructure (Stoft, 2002).

[5] `http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2003:176:0037:0037:EN:PDF`

[6] `http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2009:211:0055:0093:EN:PDF`

[7] `http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=CELEX:52012DC0663:EN:NOT`

[8] `http://ec.europa.eu/energy/gas_electricity/doc/de_energy_market_2011_en.pdf`

ergiewirtschaftsgesetz (EnWG — Energy Industry Act).[9] This included accounting unbundling as well as non-discriminating network access for retail electricity suppliers which led to retail competition. In 2005, the *Bundesnetzagentur* (BNetzA — Federal Network Agency) took on responsibility as a regulator in the energy sector with the commencement of the Energiewirtschaftsgesetz (EnWG — Energy Industry Act). This was accompanied by the switch from negotiated third-party access to regulated third-party access. With the changes since then, further unbundling of the grid activities on transmission and distribution level were put into force in national law. In summary, Germany has basically implemented all main actions of electricity market restructuring.

2.1.2 Other Major Regulatory Influences

The liberalization, which directly changes the structure of the electricity sector, is only one sort of regulatory influence. Other regulatory decisions influencing the environment, behavior and development in this industry are briefly outlined in the following paragraphs.

The support for renewables through quotas or subsidies are one example of regulatory influences (Haas et al., 2008). In 2012, at least 109 countries supported RES by legislation and 118 countries had renewable energy targets in place (Renewable Energy Policy Network, 2012). Feed-in tariffs are implemented in more than 60 different countries with various detailed designs (Couture and Gagnon, 2010). The most prominent example is the support for RES through subsidies and feed-in tariffs in the German Renewable Energy Act (Erneuerbare-Energien-Gesetz — EEG), which led to a share of 31.7% of global photovoltaic capacity installed in a country with limited potential from solar power (Massoon et al., 2013). The feed-in tariffs succeeded in substantially increasing the RES capacity in Germany. As a response, feed-in tariffs for solar PV have been recently reduced[10] and new regulation enforces retrofitting of solar PV installations with control equipment in order to ensure system stability (Systemstabilitätsverordnung — SysStabV). The support led to increases in capacity of other renewable energy sources as well, however, not in the same order of magnitude (see next section).

A parallel regulatory activity is the European Union Emission Trading System

[9] http://www.bundesnetzagentur.de/cln_1932/EN/Areas/Energy/Companies/GeneralInformationOnEnergyRegulation/HistoryOfLiberalisation/historyofliberalisation_node.html

[10] See press release of the Federal Network Agency from April 30, 2013: http://www.bundesnetzagentur.de/SharedDocs/Downloads/DE/Allgemeines/Presse/Pressemitteilungen/2013/130430_EinspVerguetg_PV_Anl_pdf.pdf;jsessionid=40E1FE78C89CBB121C7C53D5BF8E7AA3?__blob=publicationFile&v=2

(EU ETS), which favors energy sources with low greenhouse gas emissions. The European Commission (2009) describes details on the mechanisms and realization. Another development in regulation is the nuclear phase-out decisions (e.g., Germany and Switzerland). Whereas the current strategies of other countries are directly opposed to this decision (e.g., France and Great Britain).
Other regulations and subsidies for green technologies are being implemented or currently discussed, with the magnitude of influence is still to be seen. This includes, amongst others, technology regulation (e.g., consumption efficiency for home appliances), tariff regulation (e.g., grid charge reduction for curtailable loads), exemptions from fees and levies (e.g., large consumers), or tax reductions (e.g., Hybrid or Battery EVs), .

2.2 Generation

Generators represent the supply side in the power system, producing the commodity electricity in power generation plants. This section describes generation characteristics and development with focus on Germany.

2.2.1 Structure

Based on resource availability and historical development, various generation technologies are employed to generate electric energy, leading to fundamentally differing supply mixes. Some countries have enough potential from renewable sources to serve a large share of their load, e.g., Norway with more than 95% from hydro (IEA, 2011a). Other countries follow a nuclear power strategy, e.g., France with approximately 77% generation from nuclear power plants (IEA, 2009). Other industrialized countries rely on a more diverse mix of generation units — an example is the German generation mix (Figure 2.1). On an aggregate level, this roughly corresponds to the average generation portfolio for OECD countries, which generate 61% from fossil fuel, 21% from nuclear, and 18% from renewable sources[11] (IEA, 2012a). The difference in generation mixes led to differing levels of emission and self-sufficiency per country.

Because of existing economies of scale in most generation technologies (Stoft, 2002), a large share of generated electricity stems from large and often fossil fuel-based generation blocks. Figure 2.2 depicts the distribution of power plant unit sizes by generation technology in Germany 2012. The three main generation technologies, lignite, coal and nuclear also have the largest unit sizes in the German power sector. The historically developed mix required

[11] In contrast to Germany mainly hydro.

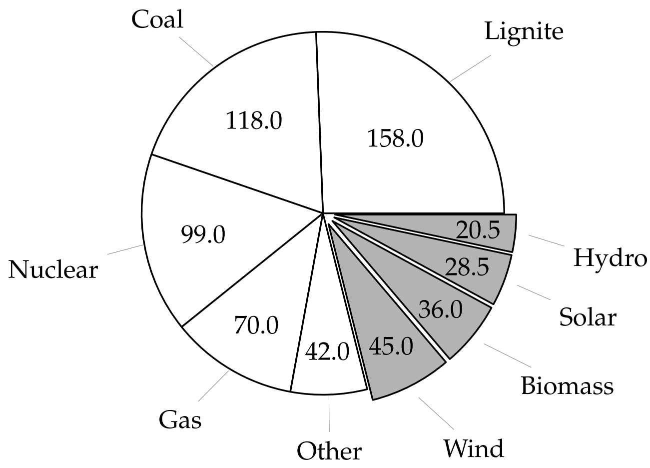


Figure 2.1: Gross power generation by power plant type in Germany 2012 — 617 TWh total with main renewable sources highlighted (Data source: Bundesministerium für Wirtschaft und Technologie, 2013)

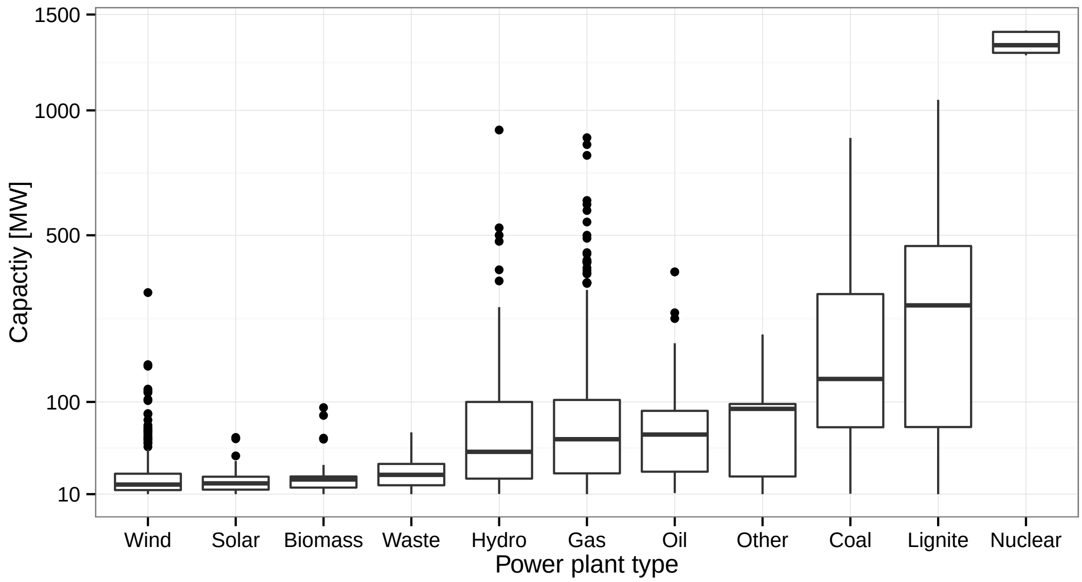


Figure 2.2: Block capacities > 10 MW by power plant type in Germany 2012 (Data source: BNetzA, 2013)[12]

major investments due to the size and long economic lifetime of generation assets. This led to a dominant position of four big generation companies (RWE, E.ON, Vattenfall, EnBW), accounting for >80% of total installed capacity as well as electricity feed-in (Bundeskartellamt, 2011). When focusing on competing generation capacities only, i.e., ignoring RES generators with priority feed-in,

[12]The block capacities are sometimes sums, in cases where one operator combines several power plants. This applies mainly to wind and PV and leads to the unexpectedly high capacity outliers.

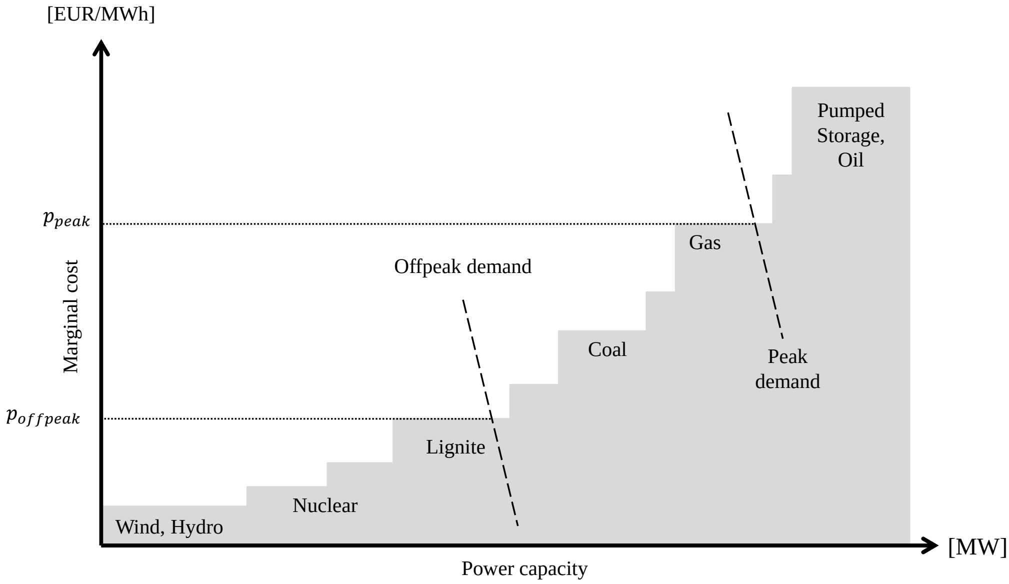


Figure 2.3: Stylized merit order for dispatching (based on Erdmann and Zweifel, 2008)

they still account for 73% of total generation capacity, even after retiring eight nuclear power plants in 2011 (Bundeskartellamt and Bundesnetzagentur, 2012).

In many countries generators are unbundled from distribution and therefore competing on electricity markets to sell their output to retailers. The generation capacity is scheduled in advance in order of increasing marginal cost. Wholesale electricity markets use this as the general principle when matching demand and supply. In day-ahead wholesale markets, retailers submit bids, and generators submit asks. The intersection of the bids and asks is the market clearing price. For each delivery period, generally half hour or hour, an individual market clearing price is determined (Holmberg and Newbery, 2010). Generation units with low short-run marginal costs of production, e.g. hydropower or nuclear power plants, can typically offer lower prices, hence they are in use more frequently. This merit order favors current demand being served by the generator with the lowest cost (Figure 2.3). This also leads to a low utilization of peaking plants which are only used during a few hours of extreme peaks per year (Spees and Lave, 2008). In addition to these simplified general principles, wholesale electricity markets have additional complexities in products and matching (see for example Ockenfels et al., 2008). Market participants have to factor in constraints like ramping cost, optimal efficiency levels, fuel availability, RES priority dispatch, intermittency, and locational differences due to grid congestion. For example, only a small fraction of all power transactions are traded on wholesale markets. In many countries a large share is traded in advance in bilateral over-the-counter (OTC) transactions (Rademaekers et al., 2008; Lijesen, 2007). Most notably, power transactions occur differently depending on the time

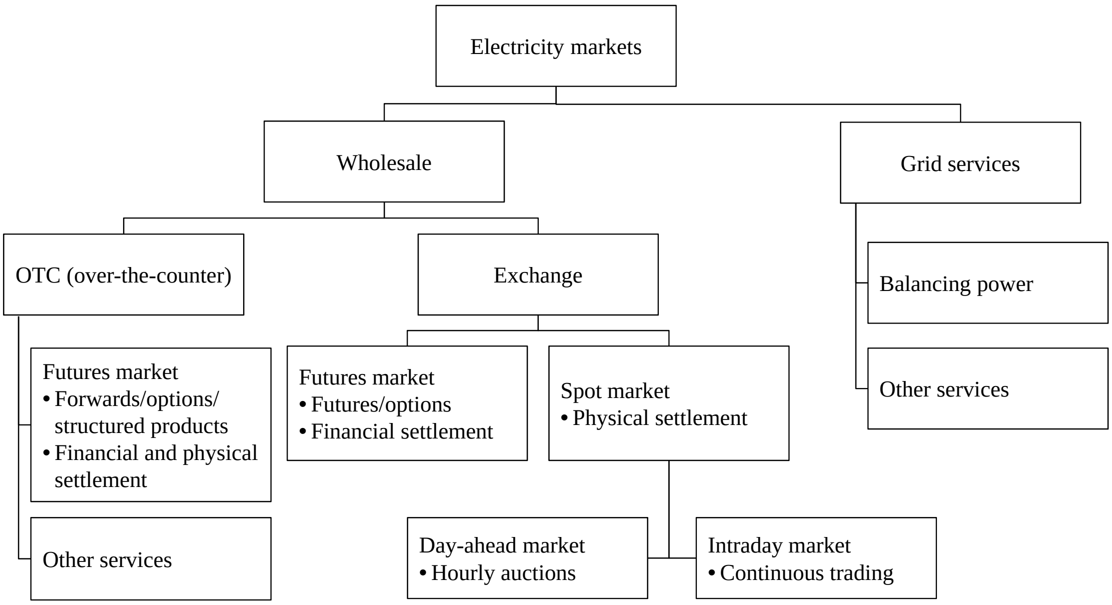


Figure 2.4: Different products on electricity markets, transactions and services for power delivery Judith et al. (2011)

to physical delivery. Figure 2.4 exemplarily depicts different transactions and products traded.

On the long-term end there are bilateral delivery contracts and the scheduling of generation units, but also the planning of generation investment, e.g., type, size, location. On the other extreme, TSOs need to call ancillary services like spinning reserves to balance supply and demand and adhere to physical system limits. A detailed analysis exceeds the dimension of this thesis, since all different types of power transactions have different rules and renumeration schemes. For details on specific electricity markets and rules, please refer to publications about the specific topic, e.g., Stephenson and Paun (2001) on electricity market trading in general, Swider (2006) on trading on markets for grid operators and generators, Ockenfels et al. (2008) on electricity market design.

In addition to the revenue criterion, physical constraints influence the generation schedule for some generation technologies. Many renewable generators are supply-dependent and therefore intermittent. Exemplary patterns of wind and solar generation are depicted in Figures 2.5 and 2.6. The examples illustrate the daily pattern of PV in contrast to the stochastic wind generation. However, both generation types have large short-term variability, which emphasizes the intermittency. In addition to the depicted examples, both generation types experience seasonal differences, e.g., on average lower solar radiation and higher wind speed in winter.

Fossil fuel-based plants need to take into account the cost of their ramping

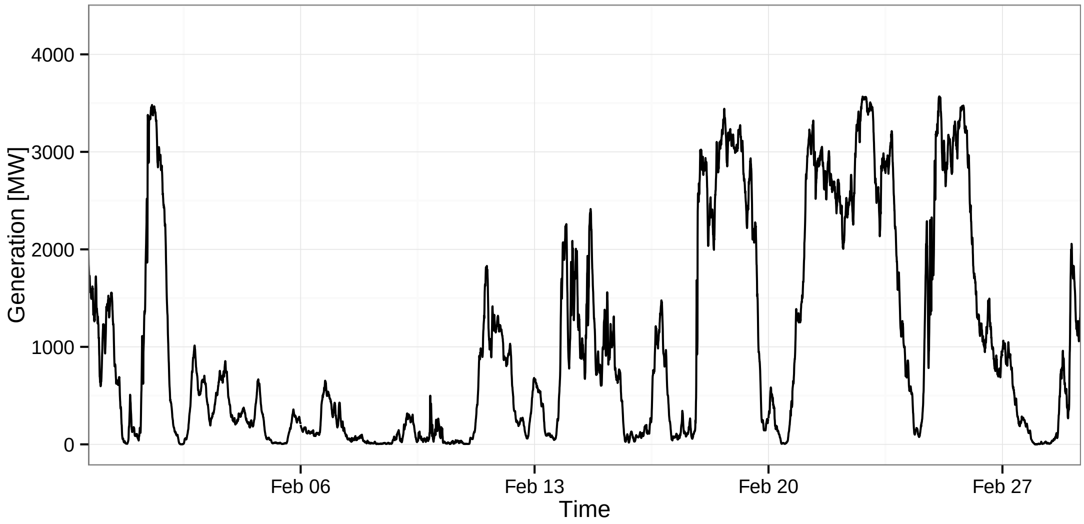


Figure 2.5: Wind power output variability based on total wind generation in Bonneville Power Administration (BPA) control area during an example month in February 2012 [13]

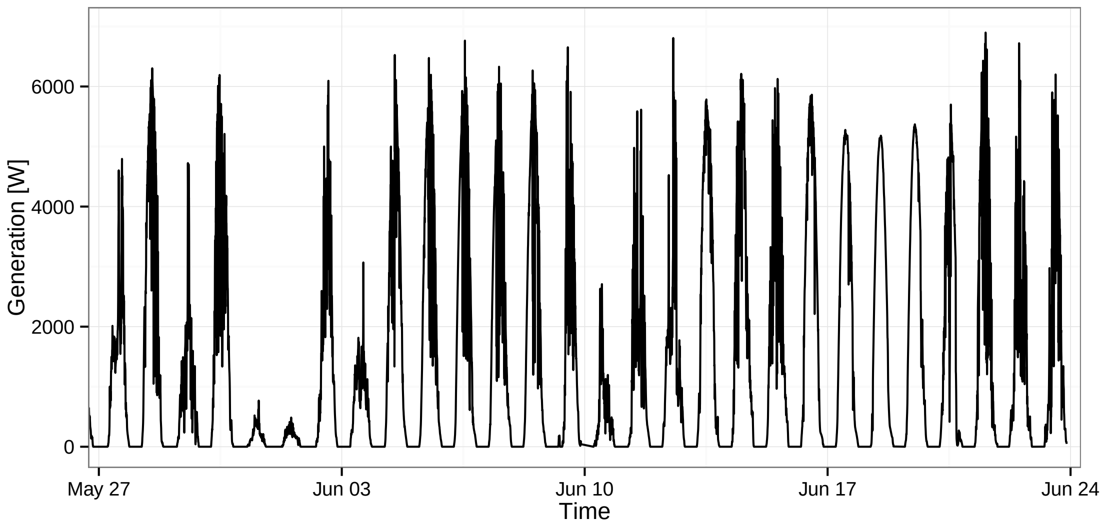


Figure 2.6: Photovoltaic power output variability based on a single rooftop panel installation during example weeks in June 2013 [14]

time, since these generators cannot be switched on and off instantaneously (e.g., nuclear, coal, lignite). These plants provide constant generation curves over time, so called baseload. To serve varying demand, the long-term stable and in-

[13] Wind generation data from 2012 at 5-minute increments from Bonneville Power Administration (mainly Washington, Oregon and Idaho) available at http://transmission.bpa.gov/business/operations/wind/. This data is used because it is a vailable in high 5-minutes resolution.

[14] PV generation data from 2013 at 5-minute increments from a single rooftop installation near Stuttgart, Germany (own source).

	Installed capacity (GW)		Gross power generation (TWh)		Average capacity factor
Coal	30.2	(17.7%)	117.0	(18.6%)	44.3%
Wind	27.2	(16.0%)	37.8	(6.0%)	15.9%
Gas	23.8	(14.0%)	86.8	(13.8%)	41.7%
Lignite	22.7	(13.3%)	145.9	(23.2%)	73.4%
Nuclear	21.5	(12.6%)	140.6	(22.4%)	74.6%
Solar	17.6	(10.3%)	11.7	(1.9%)	7.6%
Hydro	10.4	(6.1%)	27.4	(4.4%)	29.9%
Other	6.2	(3.7%)	25.1	(4.0%)	46.0%
Oil	5.9	(3.4%)	8.4	(1.3%)	16.3%
Biomass	4.8	(2.8%)	28.1	(4.5%)	66.6%
Total	**170.2**		**628.6**		

Table 2.1: Installed capacity and gross power generation by source in Germany 2010 (Data source: Bundesministerium für Wirtschaft und Technologie, 2013)[15]

termittent renewable generation types are supported by short-term controllable generators with low ramping times (e.g., pumped hydro, gas). Therefore, these generators are often used in peak-load hours with high electricity prices.

The capacity factor describes the utilization of a power plant by the ratio of actual energy output over a period of time to the maximum output defined by maximum capacity. For example, the US Energy Information Administration (2011) reports typical capacity factors of 90.3% for nuclear power plants in comparison to 33.9% of renewables (conventional hydropower excluded). Table 2.1 shows the installed generation capacity in Germany in comparison to the gross power generation per type of generator in 2010, sorted by installed capacity. Renewables account for a large share of the installed capacity already. However, the average capacity factors, e.g., wind 15.9%, solar 7.5%, due to intermittent supply explain the low share in total gross power generation of Figure 2.1.

2.2.2 Trends

The goal of reducing carbon dioxide emissions, the development of global fuel markets, and new technologies influence the power generation mix and operation. This section provides a quick overview of current trends which are relevant for the research results in the subsequent chapters. Most notably, the share of renewable energy sources is rising globally. The IEA (2012b) expects RES to account for one-third of total electricity output by 2035. This development is fueled

[15] Data from 2010 is used due the start of the nuclear phase-out which has a major influence on capacity factors. Until now, the share of RES — mainly wind and solar — is still increasing.

by falling technology cost, continued subsidies, and liberalization. In Germany, the subsidies in the context of the *Energiewende* as well as increasing environmental awareness led to major investments into solar and wind power. In July 2012, renewables accounted for approximately 41% of total generation capacity (Bundeskartellamt and Bundesnetzagentur, 2012). Due to supply dependency of most renewable generators, the share of gross generation is lower but steadily increasing. Figure 2.7 depicts the share of gross generation in Germany during the last decade.

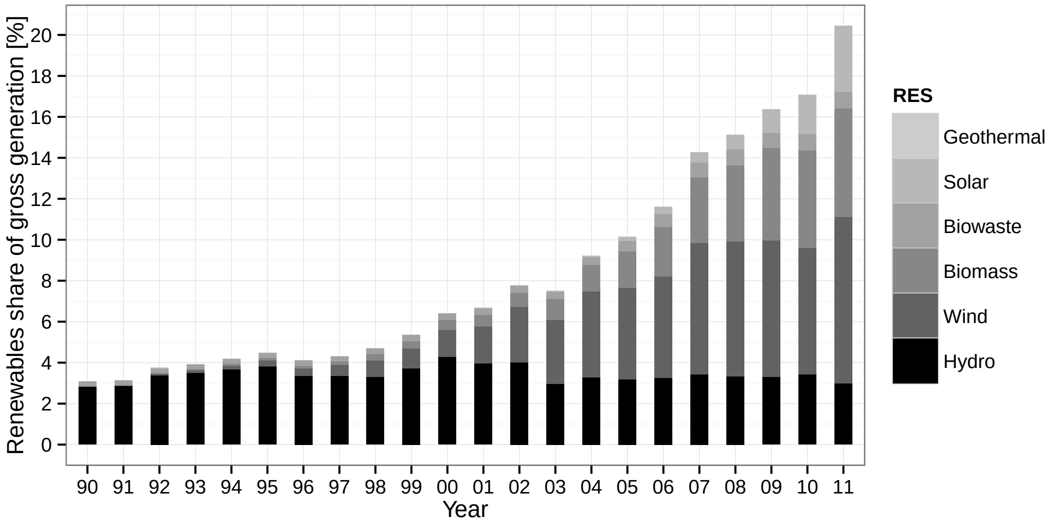


Figure 2.7: Renewables share of gross generation is steadily increasing mainly in wind, biomass and solar (Data source: Bundesministerium für Wirtschaft und Technologie, 2013)

The rise of renewable energy also leads to shifts of generation capacity to locations with good supply of renewable energy sources. In Germany, wind capacity is strongly increasing in the North, whereas solar is installed mainly in the Southern part of the country. In addition, the sizes of these new generators are typically smaller than former fossil fuel-based plants, except for large offshore wind farms. This leads to a more decentralized generation, which is already indicated in Figure 2.2 by sizes per generator type. In addition, small Combined Heat and Power (CHP) plants with increased energy efficiency gain market share with regulatory support (e.g., act on combined heat and power generation in Germany - KWK). So-called *Distributed Generation (DG)* accounted for approximately 20% of total power generation in Germany in 2006 and is still increasing (Bauknecht and Brunekreeft, 2008). In Denmark, DG already represents more than 50% of total generation (Bauknecht and Brunekreeft, 2008). In contrast to the German *Energiewende*, different approaches to reduce carbon dioxide emissions influence the generation mix: the use of carbon capture and storage (CCS) or nuclear are

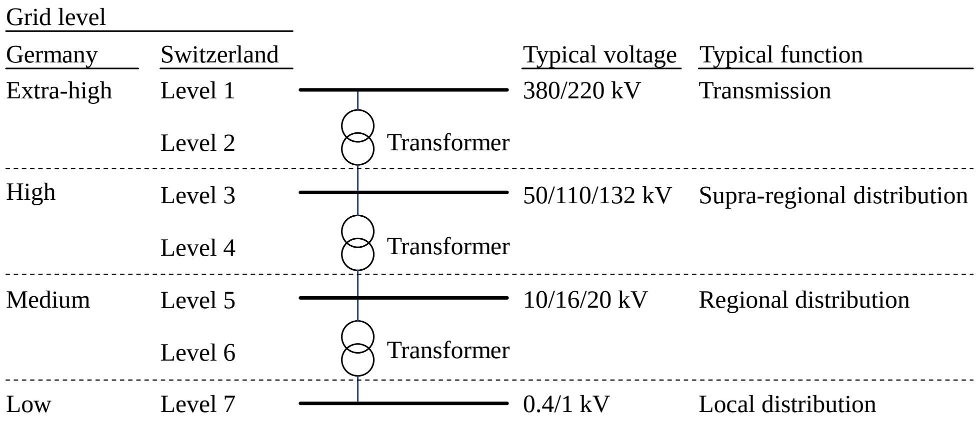


Figure 2.8: Grid and voltage levels and naming according to §2 Nr.6 StromNEV in Germany and Swissgrid in Switzerland[16]

also ways to adhere to the main goal of emission reduction mentioned in the introduction (Islegen and Reichelstein, 2010; van Vuuren et al., 2007).

2.3 Transmission and Distribution

The transmission of electric power occurs nearly instantaneously even over large distances, based on a grid of physical lines. This section describes the main characteristics of the transmission and distribution grid, with the focus on Germany.

2.3.1 Structure

The extra-high voltage grid for long-distance transmission is operated by transmission system operators (TSOs), whereas distribution system operators (DSOs) manage the lower-voltage levels which are originally dedicated to the distribution of electric power to end consumers (Figure 2.8). This thesis focuses on the TSO concept, where ownership and operation of the transmission system are integrated. Another model, which is not applied here, is the split into a transmission owner who is also responsible for physical maintenance and an independent system operator (see Brunekreeft et al. (2005) as well as Balmert and Brunekreeft (2008)). The electric power grid for transmission and distribution is typically divided into four different voltage levels: Extra-high, high, medium and low voltage. Since the exact voltage levels and naming of each grid or voltage level differ by region and specific application, this thesis always refers to the German and Swiss notation as depicted in Figure 2.8.

[16]Source http://www.swissgrid.ch/swissgrid/en/home/grid/transmission_system/grid_levels.html

Extra-high voltage transmission grids are often operated by a few large TSOs (Germany) or even just one monopolistic TSO (Switzerland). In Germany, there are four control zones, each with one responsible TSO (see Figure 2.9).

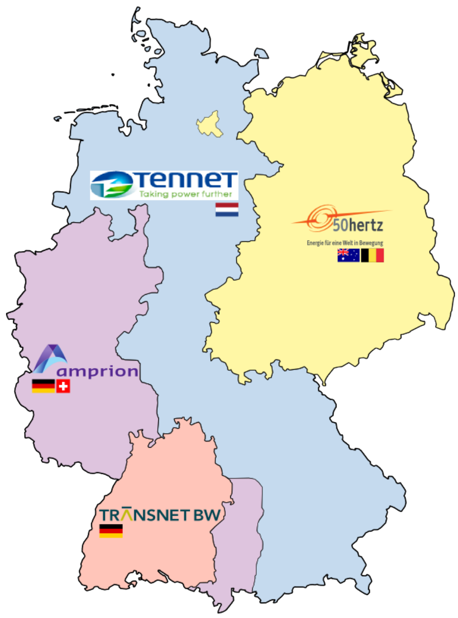


Figure 2.9: The four control zones in Germany[17]

DSOs are responsible for the distribution systems on a regional scale. In 2011, more than 700 DSOs were responsible for approximately 1.9 million kilometers of electric lines and nearly 48 million metering points in Germany (Table 2.2). In comparison, the highest voltage level comprised 630 metering points, which are mainly large industrial customers and pumped storage. Hence, the demand directly connected to the transmission grid already accounts for approximately 10% of total consumption. Table 2.2 shows the structure and size of different voltage levels in Germany. Large generators are typically connected to the higher voltage levels. However, new generation units like photovoltaics or combined heat and power (CHP) plants are increasingly connected to low-voltage grids.

All system operators are responsible for grid stability, security and reliability within their area. TSOs are mainly responsible for providing system security by balancing load fluctuations in the short term through ancillary services in their control area. DSOs cover the operation, maintenance and repair in their region, as well as mid- and long-term planning to accommodate future supply and demand. Since the flow of power is not controllable and the German power grid is interconnected between the control zones and with other European countries, the system stability in one region influences the whole grid. An example of this is the system disturbance in the German transmission grid in November

[17] By Francis McLloyd [CC-BY-SA-3.0 (http://creativecommons.org/licenses/by-sa/3.0)], via Wikimedia Commons

2006 that affected all European countries in the same synchronous area (ERGEG, 2007). To avoid such incidents, the N-1 criterion attempts to ensure that the

Grid data 2011	**Unit**	**TSO**	**DSO**	**Total**
System operators	[#]	4	735	739
Electric circuit length	[km]	34,404	1,869,670	1,904,074
thereof extra-high voltage	[km]	34,314	483	34,797
thereof high voltage	[km]	90	94,932	95,022
thereof medium voltage	[km]	0	532,894	532,894
thereof low voltage	[km]	0	1,241,361	1,241,361
End consumption	[TWh]	44.8	461.3	506.1
thereof commerce and industry	[TWh]	34.7	334.2	368.9
thereof households	[TWh]	0	126	126
thereof pumped storage	[TWh]	10.1	1.1	11.2
End-consumer metering points	[#]	630	47,660,927	47,661,557
thereof commerce and industry	[#]	496	2,894,412	2,894,908
thereof households	[#]	134	44,766,515	44,766,649

Table 2.2: Grid length and metering points per voltage level (Data source: Bundeskartellamt and Bundesnetzagentur, 2012)[18]

most important grid infrastructure components are fail-safe — at least on transmission and supra-regional distribution level. It ensures that at any point in time the failure of one asset (e.g., line, transformer, generator) does not lead to overloads in other infrastructure assets. These high security standards result in high system stability. In Germany, the System Average Interruption Duration Index (SAIDI) for end consumers is as low as 17.44 minutes per year in 2006-2010 (Bundeskartellamt and Bundesnetzagentur, 2012). Since security is crucial in industrialized countries and the grid is a natural monopoly, TSOs and DSOs are the most regulated actors in the power system. However, a detailed analysis of this regulation goes beyond the scope of this thesis. An overview of the regulatory development is provided in Section 2.1. If specific norms are relevant, they are introduced and discussed in the respective section.

2.3.2 Trends

The dominant trend in power grids are the major investments for different reasons, even in countries with existing power grids, and without considering growing demand. First, transmission and distribution assets are aging and may be replaced (Pérez-Arriaga et al., 2013). Second, locational shifts in generation

[18]Potential small deviations from other diagrams in this thesis are due to differing data sources.

caused by new generation (e.g., wind offshore) or decommissioning of old assets (e.g., nuclear phase-out) lead to changes in power flows (ENTSO-E, 2012a). Third, interconnection of markets to allow power flows for market integration (Meeus et al., 2005). Fourth, decentralization of supply and smart distribution grids need new investments to ensure reliable grid operation and enable new coordination and control approaches (see Faruqui et al., 2010). The ENTSO-E (2012a) provides a detailed overview of the reasons in the network development plan for Europe.

The majority of these grid investments is necessary on distribution grid level (IEA, 2011b). However, the focus of most public discussions is on the large transmission and interconnection projects. In Germany, the main example is the *Netzentwicklungsplan* (Power Grid Development Plan),[19] which plans — in addition to the existing network's expansion and optimization — several new high-voltage direct current (HVDC) lines to meet the additional transmission requirements from North to South. These huge investments affect grid operators' financial planning models for the future. Therefore, different regulatory approaches for cost recovery are discussed due to financing issues and to provide a stable framework for efficient investment (Henriot, 2013).

Consumers as ultimate sponsors will face rising grid charges (Bundeskartellamt and Bundesnetzagentur, 2012). In addition to cost, grid investments need tremendous lead time and are often delayed in many countries — especially on the high voltage level (ENTSO-E, 2012a). In Germany, 15 out of 24 extra-high voltage grid investments prioritized by the Energy Line Expansion Act (EnLAG) are currently delayed between one and five years (Bundeskartellamt and Bundesnetzagentur, 2012).

2.4 Consumption

Consumers employ electric energy for various applications such as lighting, cooling and heating, or other electronic appliances. This section describes the main characteristics of the consumer side with the focus on households in Germany.

2.4.1 Structure

When referring to the GHG reduction targets mentioned in the introduction, one has to consider total energy consumption. The leverage of using all sources of increasing energy efficiency (e.g., better insulation of buildings) is high for achieving the targets. However, all approaches discussed in this thesis refer to

[19] http://www.netzentwicklungsplan.de

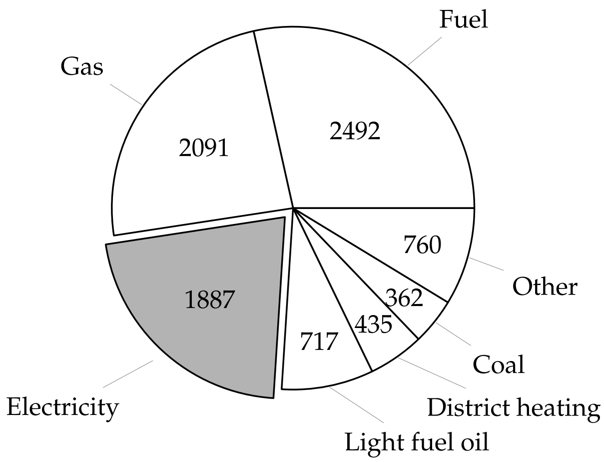


Figure 2.10: Final energy consumption by energy source type in Germany 2011 in Petajoule[20]— 8,744 PJ total (Data source: Bundesministerium für Wirtschaft und Technologie, 2013)

electricity only. In Germany, electricity itself accounts for approximately 22% of total final energy consumption, being third after fuel and gas (see Figure 2.10).

As depicted in Figure 2.11, the main consumers of electricity in Germany are industry and households.

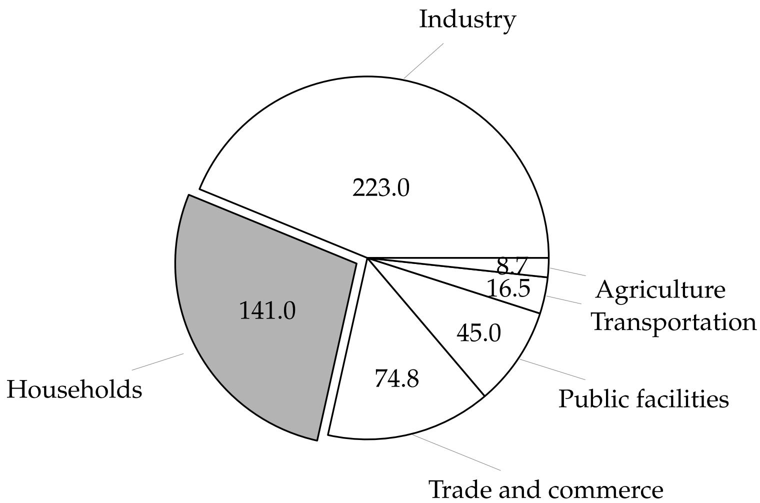


Figure 2.11: Electricity consumption by consumer type in Germany 2010, excluding export, losses, internal consumption and pumped storage — 509 TWh total[21](Data source: Bundesministerium für Wirtschaft und Technologie, 2013)

These loads have the largest impact on total consumption and the system load pattern over time. In particular, the load curves of industrial consumers differ

[20]One petajoule (PJ) is equal to 10^{15} joules and 3.6 PJ = 1TWh. Hence, the final energy consumption of electricity reported here accounts for approximately 524 TWh in 2011.

[21]The 2010 consumption is less than the 524 TWh in 2011 as reported in Figure 2.10.

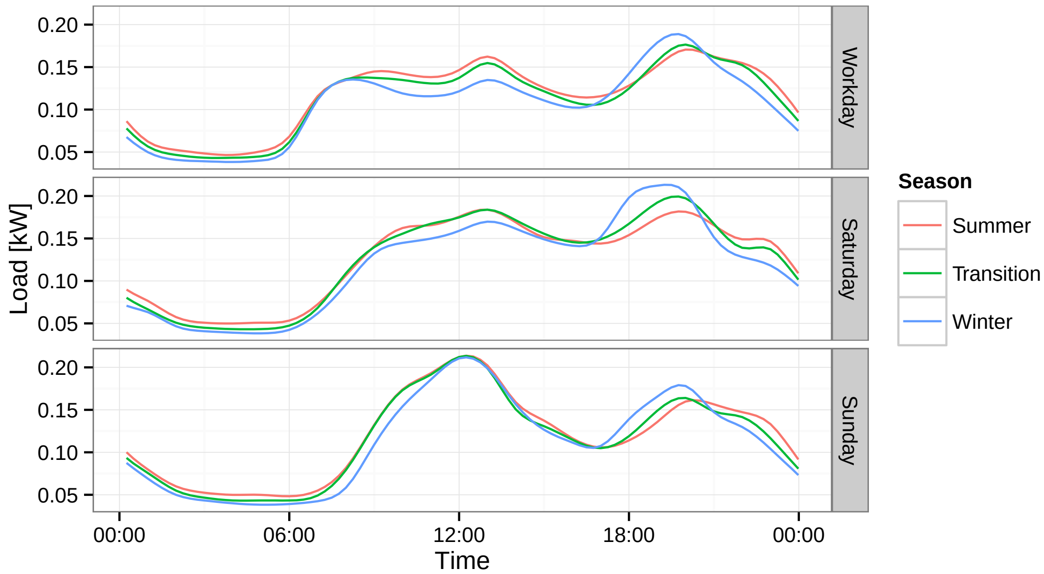


Figure 2.12: Synthetic H0 load profile for different days and seasons in Germany (Data source: `http://www.vsg-netz.de/vsgnetz/Stromnetz/Lastprofilverfahren.php`)

substantially, since they are dependent on the industry and electricity demand in production. Due to these differences and the amount of total consumption, load profiles for industrial customers are measured for billing purposes and special contracts already. The total consumption of a single household is negligible in comparison to total system load. Often — especially for infrastructure sizing — synthetic load profiles are used to account for household consumption (Figure 2.12). These profiles try to represent a typical average household load profile. However, each consumer has his individual and unique load profile, which can deviate considerably from this average pattern. In the face of information availability through smart grids and increasing flexibility through automation and smart appliances, a more individual examination of load profiles seems promising (see Flath et al., 2012). From an overall system perspective, these load profiles add up to the total system load that need to be matched by generation capacity under given grid infrastructure capacities.

Historically, the overarching principle in the power sector was that supply follows demand, i.e. generation capacities are scheduled to match demand. The German load profile has a base load that is constant in the long-term. In addition, there are some typical patterns which repeatedly occur in different time periods (e.g., daily, weekly, monthly, yearly). The remaining fluctuations in demand are stochastic in nature and most difficult to match by generators. As mentioned before, the generators with lowest marginal cost should be scheduled first. Since RES sometimes have priority feed-in by law and their marginal cost are equal to zero, the scheduling of the remaining generation capacities is based on the residual load. With the stochastic nature of demand and the increasing share of intermittent generators, forecasting of residual load is essential. Hahn et al. (2009) provide an overview of existing load forecasting methods and models.

Electricity demand is often assumed to be largely independent from incentives. This is because, only large consumers or special loads like night storage heaters receive adjusted prices which account for different marginal generation cost. However, demand side management (DSM) has been an extensively analyzed concept in the last decade. One goal is to determine the elasticity of demand based on different incentives. An overview of different analyzes of price elasticities is provided by Lijesen (2007). With the rise of the smart grid and automated demand, elasticities are expected to increase. This demand side flexibility is the central element used for price coordination of demand as described in Chapter 4.

2.4.2 Trends

Even in industrialized countries, total electricity demand is still increasing because of numerous new appliances, services and uses based on electric power. In Germany, with some of the highest electricity prices and steady improvements in energy efficiency of different applications, the share of electricity of the total energy consumption increased from 17.3% in 1990 to 21.6% in 2011 (Bundesministerium für Wirtschaft und Technologie, 2013). Some barriers for more efficiency gains on the consumption side are imperfect information, hidden costs, uncertainty, access to capital, and split incentives (Schleich, 2009). Improved information availability can also be used in demand response management with variable prices. The first programs are developing from research test beds to first real offers to end consumers (for details, see Section 3.3). Smart technology roll out is accelerating (e.g., smart meters), leading to more available information and control equipment. Directive 2009/72/EC of the European Parliament and of the Council requires all member states to follow "a timetable with a target of up to 10 years for the implementation of intelligent metering systems" and a minimum of 80% of all consumers to "be equipped with intelligent metering systems by 2020". In addition, new technologies and control algorithms are being developed to increase the flexibility in demand without influencing usage patterns.

2.5 Current and Future Challenges

The current trends in the three major functions and in regulation influence the electric power system operation and development. The following paragraphs briefly summarize key effects and challenges in context of this thesis.[22]

2.5.1 Power Grid Operation and Control

If the crucial balance with generation matching consumption is not achieved, system reliability is at risk and physical destruction of equipment or outages can occur. Currently, balancing is realized by a mixture of storage facilities, sophisticated forecasting tools and different types of generators. Typically, it is impossible or very expensive for large and central power plants to increase or decrease their output on short notice. Therefore, these generators are mainly used to serve base load. Mid load and peak load are served by more flexible generators like natural gas, combined heat and power (CHP) plants, or pumped storage. Overall, the responsible system operator tries to achieve a match of the demand forecast by a schedule for dispatch. Additionally, ancillary service providers absorb deviations from this dispatch schedule by providing short-term balancing for frequency stability (Stoft, 2002). The interaction of these components allows electricity generation to match demand and balance the system.

The increasing share of intermittent, preferred renewable supply and retirement of old generators leads to a shrinking firm capacity, increasing the risk load-generation mismatches. Deviations have to be balanced on short notice, increasing the demand for additional flexible reserve capacity. Demand flexibility is thus mainly used in the form of large curtailable load contracts with industry consumers. Other demand in the current electricity system is almost completely unresponsive. However, with smart grid technology, households can be more responsive as well and may provide decentralized balancing services.

In addition to balancing generation and consumption, further constraints posed by system components have to be adhered to. Often an energy-only wholesale market is in operation without incorporating grid constraints.[23] In contrast, new generators are often built at remote locations, which leads to new power flows. Another aspect is load clustering at specific locations due to similar demand patterns. These effects may lead to high utilization of infrastructure equipment or even overloads. Therefore, the shift to RES and slow grid investments result in rising losses due to grid congestion (Bruninx et al., 2013) (e.g., grid operators have to shed wind farms) and operational risks (Gouveia and Matos, 2009). In Germany, these losses tripled from approximately 127 GWh in

[22] This section contains extended parts of our paper Flath et al. (2013).

[23] The assumption of sufficient grid capacity with no congestion is also called *'copper-plate'* (see Brunekreeft et al., 2005).

2010 to 412 GWh in 2011 (Bundeskartellamt and Bundesnetzagentur, 2012).

2.5.2 Power System Market Design

Unbundling on the one hand leads to more competition and therefore supports the goal of lower end consumer prices. On the other hand, it increases transaction cost, owing to coordination of and communication between separate entities. In addition to this overhead, missing information or wrong incentives for single entities through existing rules may lead to inefficient outcomes (Friedrichsen, 2011). Each entity tries to optimize its own outcome within the given market design. Changes to market design result in modification of single elements (e.g., changing rates) or even business models (e.g., new ancillary service providers). Therefore, design changes need to be evaluated, and configuration needs to avoid adverse incentives.

Specifically the role of the power grid has changed from a top-down distribution grid for a single entity to a grid for transactions and exchanges between different entities. The locations and patterns of load and generation are shifting significantly. This shift in locally different demand and supply dynamics needs to be accounted for by locally efficient incentives. Along with this decentralization comes a change in responsibility from TSOs to DSOs. In the future, more balancing and coordination activity is expected to occur in distribution grids which also raises the need for appropriate regulation and unbundling (Friedrichsen, 2012). As stated before, new grid investments are essential for future power system operation. Some transmission system operators are already experiencing financing issues. Therefore, a market environment is necessary that assures financing as well as efficient investment and operation of power grids at the same time (Neuhoff et al., 2012). Given the high and long-term investment in power grid infrastructure, the expected developments of both the supply and demand side need to be factored in to achieve an efficient overall grid development.

Generators face lower prices on the wholesale market through RES (Sensfuss et al., 2008; European Commission, 2012). Specifically, the feed-in of solar PV power in former high-price periods deteriorates the profitability of flexible generators. Cossent et al. (2009) and Newbery (2010) discuss the necessary changes and challenges in market design to accommodate the increasing share of RES. An obvious example are German generators' announcements to shut down recently built flexible gas power stations — even next to nuclear power plants which are planned to be phased out soon.[24] In this special case, the German regula-

[24]See http://www.bloomberg.com/news/2013-03-12/europe-gas-carnage-shown-by-eon-

tor reacted with compensation payments for fixed costs to keep these generation capacities as reserve.[25] However, in the long term, the market design needs to ensure reasonable profitability for these flexible generators — even if the load factor is low and they serve mainly as a backup. Capacity markets are one measure currently discussed to tackle this challenge (Cramton and Ockenfels, 2012; Stauffer, 2006).

The consumption side itself can contribute significantly to achieve the set targets. In order to tap this potential, the market design needs to incentivize more efficient appliances for reduction or new smart grid technologies for flexibilization of demand. However, even given a market design that incentivizes joint collaboration of different entities, more information is stored and exchanged for coordination. Therefore, system security is not only about reliable supply and demand matching, but also about data security or risk of cyber attacks (Quinn, 2009; Mohsenian-Rad and Leon-Garcia, 2011).

Inadequate market design can cause unwanted market outcomes. One example is the California electricity crisis in California with skyrocketing electricity prices (Borenstein, 2002). In this case, the main reason was the market power of power suppliers under the given market design (Borenstein et al., 2002). This thesis focuses on the analyzes of few incentives based on some coordination approaches and does not attempt to solve all possible failures in market design (see Hogan, 2002; Wilson, 2002; Woo et al., 2003; Newbery, 2010, for more information on market design challenges).

closing-3-year-old-plant-energy.html

[25]See E.ON press release http://www.eon.com/en/media/news/press-releases/2013/5/3/2013-eon-annual-shareholders-meeting--building-the-new-eon.html

Chapter 3

Pricing and Coordination in Power Systems

Following the last chapter on the situation and development of the power sector, this chapter provides an overview of the state of the art in pricing and coordination. First, coordination as referred to in the context of this thesis is defined, and different approaches are introduced. This is followed by a discussion of the short-term and long-term opportunities to avoid grid infrastructure overloads in generation, consumption as well as transmission and distribution. Subsequently, a short overview of cost in electricity provision, current electricity tariffs and prices for end consumers in Germany introduces the focus on monetary incentives. Finally, a simple pricing model with three components is introduced as the foundation for the subsequent analyzes. This is not an exhaustive work on pricing and coordination. It rather gives an understanding of potential and missing prerequisites to tap the potentials analyzed in the following chapters.

This chapter is partly based on own publications. Specifically, Section 3.2 is currently included in our working paper Ilg et al. (2013), and some paragraphs in Section 3.3.3 have previously been published in our paper Flath et al. (2013).

3.1 Coordination and Mechanisms

The seminal work of Malone (1988) defines coordination in the following way:

> "When multiple actors pursue goals together, they have to do things to organize themselves that a single actor pursuing the same goals would not have to do. We call these extra organizing activities coordination."

This thesis focuses on the usage of scarce resources by multiple actors. For the power sector, the main resources are the generation capacity, the available grid capacity as well as external dimensions like technical restrictions or the supply of renewable energies. Black and Larson (2007) identify six different approaches for managing scarce capacity:

- Capacity expansion
- Capacity upgrades
- Substitution
- Rationing (discriminatory or non-discriminatory)
- Loss or degradation of service
- Demand management

The first three items mainly refer to additional investments to secure supply. In contrast, the last three items represent coordination options that employ the demand side by either forcefully rationing and degrading quality or incentivizing to adjust demand.

The focus of this thesis is on mechanisms for grid capacity coordination which either avoid any rationing/degradation and expansion/upgrade or set incentives for efficient operation and investment. Overall, several different coordination mechanisms for limited capacities are analyzed, matching into a standard structure as depicted in Figure 3.1. Each approach tries to coordinate actors

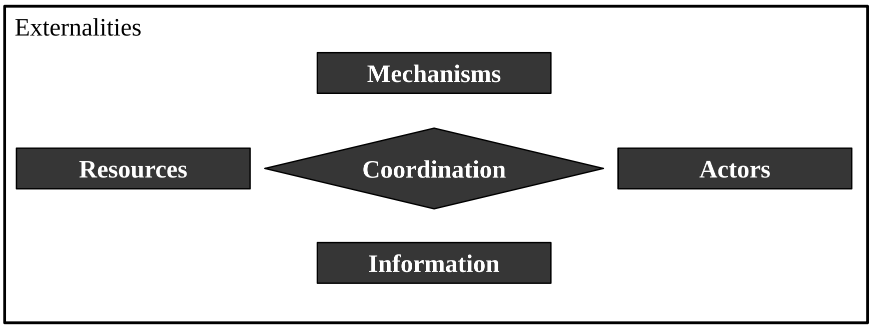


Figure 3.1: Overview of input for planned coordination mechanism framework

within an environment with limited resources (e.g., grid capacity). To this end, it uses a mechanism which could range from central control to a non-binding suggestion. To achieve coordination, data can be collected and transformed into information to be exchanged in various ways — from individual local information to globally available information or forecasts. Ideally, the amount of information exchange necessary should be as minimal as possible. Finally, the coordination outcome may be influenced by externalities that are neither part of the coordination process nor under control of participating actors.

Alderete (2005) names three main goals of congestion management in power systems:

- Be economically efficient
- Send efficient signals to encourage transmission and generation investment
- Facilitate instruments to hedge against congestion

There are helpful suggestions from other industries which may be applied. An example is a pricing scheme for electricity networks based on quality of service similar to DaSilva (2000). Another interesting approach is congestion pricing (MacKie-Mason and Varian, 1995a), e.g., road congestion pricing (Arnott and Small, 1994) based on traffic flow. All these approaches have varying similarities with power grids (e.g., network industries) but also differences (e.g., non-storability). Therefore, they can be applied to design and test new coordination mechanisms, but at the same time they might lead to different outcomes in the context of power grids.

3.2 Options for Coordination in Power Grids

The close coupling and interrelation between the three functions means that each function can influence the whole system state (Chapter 2). In order to achieve robust and efficient coordination outcomes in the power grid, possible bottlenecks as well as influencing options of different actors need to be considered. In addition, an overview of current prices and existing incentives is necessary to understand the current state.[1]

3.2.1 Bottlenecks in Power Grids

A bottleneck in the power system occurs when it is impossible to satisfy all capacity requirements using the lowest cost generation option without overloading infrastructure equipment in the transmission or distribution grid, such as power lines or transformers (Kumar et al., 2005). Congestion in the power grid can occur on different voltage levels and in different infrastructure elements. In order to discuss possible solutions more broadly, this chapter abstracts from a detailed distinction of different bottlenecks.

In general, two different situations can lead to these bottlenecks. Either the grid's infrastructure capacity is not sufficient, or total demand exceeds the maximum generation capacity at a specific point in time. Figure 3.2 conceptionally depicts the two typical causes for bottlenecks in power grids. The first situation occurs if the capacity of one grid infrastructure element x is not sufficient

[1] This Section is currently incorporated in our working paper Ilg et al. (2013).

when transporting the necessary power $d > x$, even if there is enough generation capacity k to satisfy demand $d < k$. The second situation arises if the given generation capacity k is the limiting factor $k < d$ but there is still sufficient grid infrastructure capacity $k < x$.

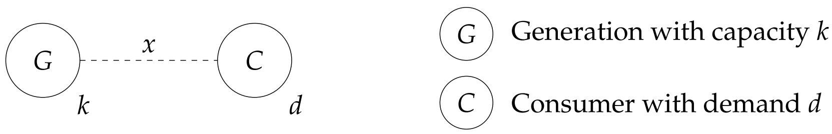


Figure 3.2: Conceptional overview of limited capacities

Typically, these bottlenecks can be distinguished into temporary and structural bottlenecks. Temporary bottlenecks may occur under special circumstances such as maintenance activities and can be mitigated by temporary measures. On the other hand, structural bottlenecks are long-term phenomenons and should be addressed through structural measures of congestion reduction. Specifically, substantial changes in regional demand or supply may cause structural bottlenecks. This can lead to a long-term difference between supply and demand for electricity at a specific location — either due to scarce grid capacity or missing generation capacity.

3.2.2 Reduction of Congestion in Power Grids

This section introduces different temporal and structural measures to reduce congestion through changes in generation capacity, transmission capacity and power consumption. In addition, potential hindrances for the implementation of the respective measures are identified.

Generation

Generators can relieve supply capacity constraints by investments in additional generation capacity. Generators can also reduce transmission in the grid and thus the risk of grid infrastructure congestion in the power system. The temporary instance of this measure is a redispatch of generators in order to adhere to system constraints and still satisfy total demand. Such redispatch normally leads to a deviation from the optimal low-cost solution (Keller, 2004), due to the dispatch of generators with higher marginal cost to avoid short-term constraints. The structural form or long-run form of this measure is the siting decision of new generation capacity. The siting of new generators next to load centers typically results in a reduction of the transmission system load. An extreme example are emergency power generators which currently serve as backup capacity for important and sensitive loads like hospitals or data centers. However, investors have to consider many other factors when selecting a location. For example, renewable energy sources cannot be operated economically efficient at every location. The efficiency of wind turbines and solar power depends heavily on local conditions. The same applies to gas, coal or nuclear power plants which are dependent on fuel and cooling water availability (Rious et al., 2011). In addition, economies of scale apply to many generation technologies (Stoft, 2002), which also influences the siting.

Transmission and Distribution

The expansion of the grid infrastructure is a measure for grid operators to increase the transmission or distribution capacity to avoid congestion. However, grid expansion does not influence total generation capacity and location in the grid. If the generation capacity is remote from main load centers, grid expansion is very expensive. In special cases grid expansion can even lead to additional bottlenecks due to loop flows (Blumsack et al., 2007). Therefore, power system simulations are necessary prior to investments to analyze the effect of more transmission capacity. A temporary instance of this measure is realistic in special cases only (e.g., interim lines in case of damages[2]), since investment costs are extremely high and the projects need a long time for planning as well as construction (Erdmann and Zweifel, 2008). The structural expansion of grid capacity is widely in use, and governments consider it as the solution to avoid bottlenecks, e.g., the Germany Energy Line Expansion Act (EnLAG). Important influencing factors for the decision on transmission investment are resistance in the population against these infrastructure projects (Keller, 2004) as well as long, complicated planning, approval and building processes (Buijs et al., 2011). In addition, the expected shifts of supply due to the nuclear phase-out and most notably due to RES lead to congestions that require expansion (Bruninx et al., 2013). An example is the investment into wind power capacity in the northern part of Germany which requires transmission grid capacity to supply load centers in the South.

Consumption

The reduction of peak demand on the consumer-side can resolve both types of constraints: scarce transmission capacity and missing generation capacity. A drastic variant of this is load shedding — where loads are temporarily disconnected from the electricity grid. Usually, load shedding concerns large consumers, since their load has an effect on grid usage at a specific location and only affects a small number of consumers that typically have special contracts. The system operator compensates affected consumers in case of load shedding,

[2]See, for example, high-voltage line damage due to local tornado: `http://www.50hertz.com/en/file/20121004_PM-Tornado_EN.pdf`

e.g., if large production processes have to be readjusted due to load shedding (Albadi and El-Saadany, 2008). Structural changes are incentives for consumers to change their consumption patterns by pricing schemes, e.g., to encourage long-term reduction of demand peaks. This type of demand response (DR) on prices is one essential element of this thesis, specifically in Chapter 4.

In summary, the three main stakeholders in the power system can reduce congestion by different measures. However, all measures lead to suboptimal results in short-term. The temporary reduction of congestion by generation — the substitution of generation capacity — namely leads to inefficient dispatch, and thus to higher production costs. The temporary reduction of congestion by consumption — load shedding — leads to additional costs due to accrued compensation payments. Because of the high costs associated with the implementation of long-run measures, temporary actions to reduce congestion are in many situations more efficient. The long-term solution by generation and transmission — the location choice for generation capacity and the expansion of grid capacity — both lead to significant investment cost and long-term projects (Rious et al., 2011). Reducing peak demand by changing consumption patterns is basically feasible, but not yet widely implemented.

3.3 Price Incentives for Coordination in Power Systems

The two major approaches to achieve system-beneficial coordination are direct control or establishment of appropriate incentive schemes. Various types of incentives are possible — ranging, for example, from intangible feedback and reputation to more tangible ones like rewards or monetary incentives. This thesis focuses on monetary incentives in the form of prices similar to Eßer et al. (2007) who find in a model that retail electricity prices can reduce peak load significantly. In reality, Reiss and White (2008) find during the California electricity crises that consumers seem to react to considerable price increases.

3.3.1 Electricity Price for End Consumers

When discussing pricing of electricity, the first step is to understand the cost of electricity provision independently from distribution of costs, market mechanisms and regulatory influences. This paragraph briefly describes the cost occurring to serve electricity demand on a high aggregation level without claiming to be exhaustive.

The two major functions to serve electricity demand at a specific location are generation as well as transmission and distribution. In both functions, costs are typically split into fixed and variable parts. In generation, the main fixed cost parts are the capital costs for investment into generation capacity that largely depend on the size and type of generator. In addition, there are some fixed operations and maintenance costs independent of utilization. The variable costs of electricity generation typically include fuel cost (e.g., coal, oil, gas), waste and pollution cost as well as variable parts of operation and maintenance expenditures. Therefore, small fossil fuel-based generators require a smaller initial investment than large ones but lead to higher variable cost due to economies of scale (Stoft, 2002). In contrast, RES generators typically require high initial investments but lead to lower variable cost, since these avoid fuel costs. The major elements in transmission and distribution are also fixed investment costs into infrastructure, ranging from high-voltage transmission lines to the components in the low-voltage grid that serves typical household loads. Most maintenance and operation costs in electricity grids are fixed as well and independent from actual load flows. In addition, there are some variable costs mainly due to losses, redispatch or balancing power. Thus, the optimal mix of generation and transmission is dependent on both location and demand patterns.

In addition, other factors — especially taxes and levies — influence the total cost of electricity depending on the market design and regulatory regime. Especially noticeable are the discrepancies between wholesale power prices and end consumer prices. For example, the increasing capacity of wind and solar power led to the situation that the "lowest day-ahead wholesale power prices in the CWE [Central Western Europe] region could be observed in the German market" in 2012 (European Commission, 2012). In situations with high RES generation but low demand even negative prices occur in wholesale electricity markets. However, retail electricity prices for typical German households are among the most expensive in Europe (Figure 3.3).

German Electricity Price for End Consumers

The electricity price for end consumers comprises additional cost factors on top of the pure cost for electricity provision, e.g., service fees for metering and billing. Major additional elements are taxes and levies. This section focuses on the structure of German electricity prices for end consumers, since the German power sector serves as an example in the following chapters. Many of the electricity price elements in Germany also exist in other countries. However, an analysis of different countries would go beyond the scope of this thesis. The average end consumer price of 28.5 ct/kWh (2013) in Germany for a household with 3,500 kWh yearly consumption basically consists of 3 different cost types (BDEW, 2013):

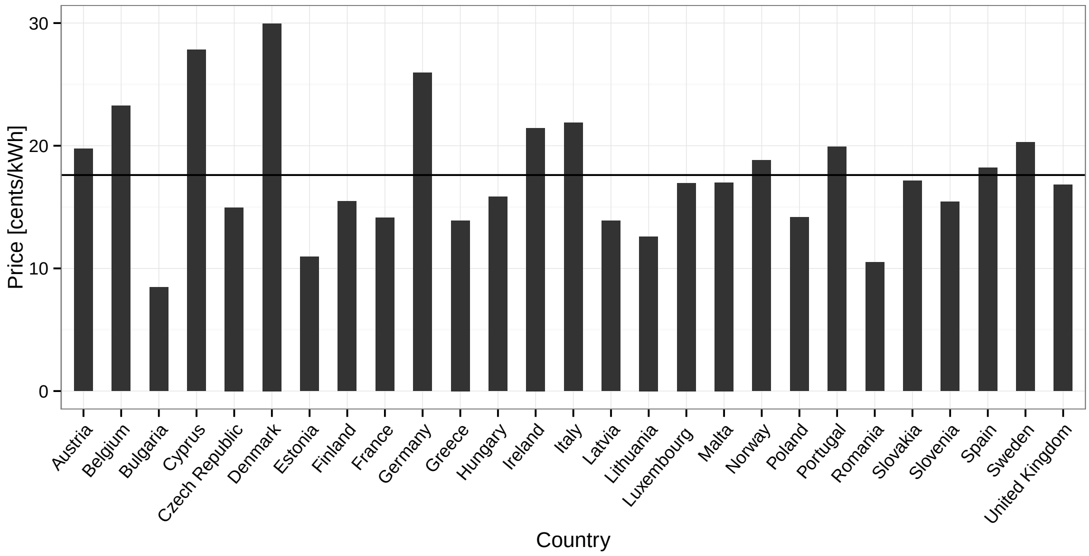


Figure 3.3: Comparison of retail electricity prices in 2012 for households with 2,500 - 5,000 kWh yearly consumption (Data source: Bundesministerium für Wirtschaft und Technologie, 2013)

- Regulated network charges (approximately 20%)
- Electricity procurement and sales (approximately 30%)
- Taxes and levies (approximately 50%)

Regulated Network Charges

The power grid is a natural monopoly, therefore the Incentive Regulation Ordinance (ARegV — Anreizregulierungsverordnung) dictates a revenue-cap for system operators to foster efficiency. The calculation of grid charges in Germany is regulated in the Electricity Network Charges Ordinance (StromNEV — Stromnetzentgeltverordnung). These costs include mainly basic and calculatory cost for grid infrastructure and operation but also ancillary services (§13 StromNEV), losses (§10 StromNEV) and other costs (e.g., metering, billing §17(7) StromNEV). The grid costs are allocated by grid levels in each control area and paid by consumers only (§15 StromNEV). For consumers with load profile measurement, the grid charges are calculated based on §17 StromNEV and consist of a demand charge per year (€/kW) and an energy price per kWh (€/kWh) independent of the distance between supply and demand (§17 StromNEV). However, small consumers like households are not measured and simply pay grid fees based on their energy consumption and a base fee. In addition, according to §19 StromNEV, some large industrial consumers can apply for paying vastly reduced grid charges. Against the background of increasing grid charges due to investments and balancing cost, this exemption has been under discussion recently.[3]

Electricity Procurement and Sales

The procurement of electric power is split into OTC (over-the-counter) and electricity exchange trades. The majority of transactions (volume-based) are processed in form of bilateral OTC deals, but power exchanges in Europe are gaining market share (Rademaekers et al., 2008). In addition to these procurement costs, the electricity supplier needs to cover some administrative and sales costs. Including the profit margin, this price element largely depends on the contract between retailer and customer.

Additional Taxes and Levies

There are multi-facetted taxes and levies for various purposes. This paragraph gives a short description of the main components and explains who has to pay what. The current value of each element is derived from BDEW (2013).

Value-added tax (VAT) is a standard consumption tax paid by end consumers and is set to 19% in Germany.

The *offshore liability charge* was introduced in 2013 to reduce investment risks for offshore wind parks. If the grid connection is delayed, the system operator has to pay compensation to the offshore generators for electricity that cannot be transmitted (§17e EnWG). These costs are allocated to end consumers in the form of offshore liability charge (§17f EnWG). Again, large end consumers pay less per kWh. In 2013, 0.25 cents/kWh is charged for consumption up to 1 GWh, whereas larger consumers pay 0.05 cents/kWh or even 0.025 cents/kWh for all additional consumption above 1 GWh.

The *renewable energy law (EEG) apportionment* is meant to cover the difference between guaranteed RES feed-in tariffs and the actual price realized on the wholesale market. End consumers compensate the difference between feed-in tariff and wholesale price by paying the EEG apportionment. Again, based on §40-42 EEG, large industrial consumers have to pay only a limited share of the EEG apportionment. This is one reason apart from increasing investment into RES that has led to the steadily increasing EEG apportionment in recent years. Another interesting reason are lower wholesale prices in Germany, due to an

[3]For example see the article "The Cost of Green: Germany Tussles Over the Bill for Its Energy Revolution" http://world.time.com/2013/05/28/the-cost-of-green-germany-tussles-over-the-bill-for-its-energy-revolution/

increasing share of RES which at the same time increase the EEG apportionment. At the beginning of 2013 the apportionment was raised from 3.592 cents/kWh to 5.277 cents/kWh.

The so-called *§19 levy* compensates system operators for reduced revenues due to reduced grid charges for large consumers based on §19 StromNEV. This levy is paid by all other consumers per kWh, with reduced burden for consumption over 100 MWh. In 2013, the levy was raised from 0.151 cents/kWh to 0.329 cents/kWh for small consumers.

The *concession fee* compensates municipalities for the usage of roads. System operators have to collect this fee, typically based on the number of inhabitants as indicated in the Concession Fee Ordinance (Konzessionsabgabenverordnung — KAV) and pay it to the municipality. Again, some special contract customers have to pay only limited concession fees, based on §2 KAV.

The *power tax* was introduced as one element of an ecological tax reform. The generated funds are mainly intended to support the German public pension fund. Again, some types of industrial consumers, especially those with large electricity consumption, can get discounted charges. For all other consumers the standard tax rate was 2.05 cents/kWh in 2012.

The *CHP allocation* was introduced to support the German goals for climate protection by increasing the share of CHP electricity generation (§1 KWKG) It is structurally similar to the EEG apportionment but at a lower level. In 2013, it was raised to 0.126 cents/kWh for small consumers, with the charge for consumption above 100 MWh being limited (§9 KWKG).

Comparison of Industry and Household Prices

The German Federal Network Agency and the BDEW publish reports on the development of average electricity prices. To account for the differences in regulation for each element of the end consumer price, end consumer types are differentiated into typical industry and typical household customers [4]. Based on size assumptions and questionnaires, the average price per kWh is determined. The results of the latest BDEW publication on end consumer price elements are depicted in Figure 3.4.

Obviously, there are large differences in cost allocation for some taxes and levies. In the context of this thesis price elements for households are discussed.

[4] The Federal Network Agency even distinguishes a medium-sized business customer

However, the basic understanding of cost allocation as described in this section serves as an important background to understand potential challenges in development and fairness.

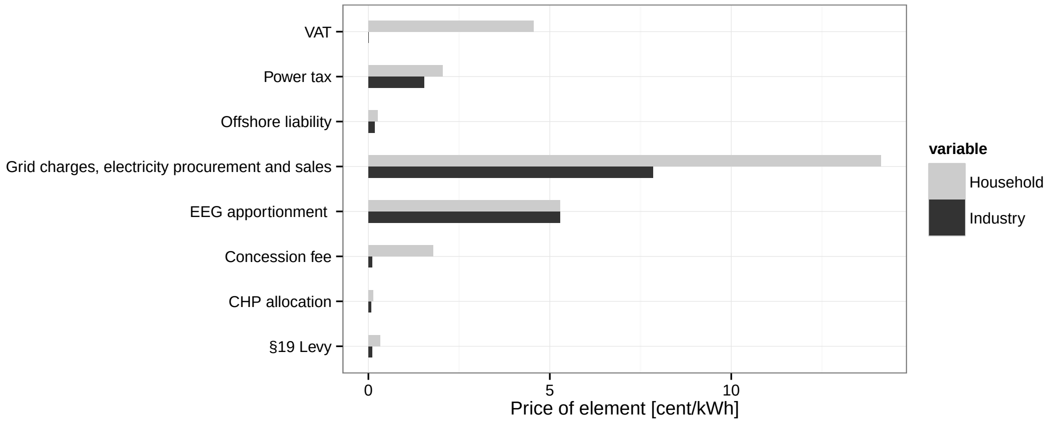


Figure 3.4: Average end consumer electricity price 2013 in Germany by element for households and industry customers (Data source: BDEW, 2013)[5]

3.3.2 Electricity Tariffs State-of-the-Art

Typical electricity tariffs for end consumers like households are based on constant rates per kilowatt hour (kWh) without variable components. This is due to the fact that typical billing of electricity with analog meters required manual meter readings. Early publications on dynamic pricing discussed ideas to communicate dynamic tariffs via telephone circuits or utility radio broadcasting (Schweppe et al., 1988). However, without today's ICT capabilities, they suggested retrieving billing data based on monthly visits of a meter reader (Schweppe et al., 1988). Also, demand charges were assumed to be unsuitable for small consumers due to "the high cost of maximum-demand meters" (Houthakker, 1951). In addition to the technical view, consumers typically prefer less complex rates (Dütschke and Paetz, 2013). For these reasons, only simple tariffs based on time-of-use (TOU) have been used for small consumers in the past. One example are two-zone tariffs with lower cost per kWh during the night implemented by two separate analog meters. With the advent of smart meters and a smart grid communication infrastructure real-time consumption data is available at lower cost. Faruqui et al. (2010) calculate that operational savings can cover a large share of smart meter installation cost in the EU. They claim that in combination with dynamic pricing, the additional infrastructure savings — especially due to peak load reduction — exceed the cost of a smart

[5]As mentioned above, some industry consumers are even exempt from paying some of the charges depicted in this figure (e.g., EEG apportionment).

meter roll-out. Therefore, TOU and load-dependent tariffs are increasingly discussed and often supported by regulation. For example, in Germany, the Energy Industry Act (EnWG) §40(5) constitutes an obligation for electric utilities and retailers to offer such load-dependent or TOU tariffs. Various types of tariffs are tested by different electricity suppliers globally. A recent report to the *Commission for Energy* in Ireland discusses options for dynamic tariffs and provides an non-exhaustive overview of dynamic tariffs that have already been rolled-out to end consumers (Pöyry, 2012). The tariffs presented range from two-zone night-day tariffs with a small price spread of only approximately 10%[6] (Enel, Italy) to hourly real-time pricing which follows wholesale pricing and could range from 1 to 37 cents/kWh (Pepco, United States) (Pöyry, 2012). An analytically-driven approach to design optimal TOU tariffs is provided by Flath (2013a), addressing flexibility in start, length, and the number of time zones as well as update frequency and spreads.

As all these examples demonstrate, most dynamic tariffs for end consumers with low consumption are focusing on total cost per kWh. Tariffs for residential customers do not differentiate between cost elements as mentioned in Section 3.3.1. Some cost or tariff elements are increasingly flexible, however not dynamic, e.g., discounted grid charges for flexible demand. In Germany, §14a EnWG enacts reduced grid fees for controllable loads and mentions electric vehicles in particular. In the context of research projects and small field trials, some more complex and innovative tariffs are investigated and tested. In contrast, large consumers already pay demand charges based on real-time measurements. In Germany, §10(2) MessZV enacts the obligation to measure demand of large consumers on a quarter-hourly basis.[7]

A detailed review would exceed the scope of this thesis. Faruqui and Sergici (2010) provide an overview of different field trial rates. In Germany, several recent electricity tariff trials occurred in different model regions for research purposes. These activities are bundled under the E-Energy funding program.[8]

3.3.3 Dynamic Pricing Theory

Whereas the previous section focused on trials and rolled-out tariffs for end consumers, this section gives a short introduction into the theory of dynamic pricing.[9] The first-best price in real-time electricity pricing is an optimal spot price

[6]The day price is 1.1 times the night price.

[7]According to §12(1) StromNZV, this applies to all end consumers with >100,000 kWh consumption.

[8]See `http://www.e-energy.de/en/index.php` for more details.

[9]The last part of this subsection is a version of some paragraphs of our previously published paper (Flath et al., 2013) with small amendments.

that equals marginal costs at each node in the grid including transmission and generation cost (Green, 2007; Schweppe et al., 1988). This also applies to household end consumers, since "they will consume too much during peak periods and too little during off-peak periods" if their retail tariffs do not incorporate variations in marginal costs (Joskow and Wolfram, 2012). The development in the direction of more dynamic electricity prices as described in the previous section favors some consumers over others. However, so far, the typical flat tariff per kWh is still being offered and the trials and rollouts mentioned above were optional. In Germany, §40(5) EnWG also constitutes the obligation to offer a flat tariff. This may also hinder more dynamic tariffs which are discussed in this thesis. Dynamic tariffs offered by electricity suppliers will only be adversely selected by consumers that are flexible enough and actually save cost (Ackerlof, 1970), whereas other consumers will stay with the flat tariff. Depending on the supply cost of electricity, this may lower the willingness to offer different dynamic tariffs. Another point of view is stated by Faruqui (2010):

> "the presumption of unfairness in dynamic pricing rests on an assumption of fairness in today's tariffs."

This rests on the typical socialization of cost in the electric power sector. More precisely, consumers with flat tariffs pay the exact same price for the same amount of consumption, independent of their individual pattern. A household that consumes mainly in low-demand periods when there might even be excess generation (e.g., from wind power) pays the same as a household that consumes only in high-demand periods where expensive peaking plants need to be dispatched.

Various researchers demonstrate efficiency gains in the electricity system with the application of time-based pricing (Crew and Kleindorfer, 1976; Newsham and Bowker, 2010) and spatial (i.e., nodal or locational) pricing (Green, 2007; Lewis, 2010).

Crew and Kleindorfer (1976) show that time-based pricing is an efficient management option under stochastic demand and generation. Newsham and Bowker (2010) review several North American studies of time-varying pricing. They identify the cost-effective supply of electricity demand by shifting load from peak to off-peak hours as the main objective for its introduction. For example, Green (2007) develops a nodal pricing model, incorporating losses and transmission constraints. For England and Wales, this model shows a welfare increase by 1.3%. Lewis (2010) states that locational prices can be seen as an indicator of electricity system insufficiencies. He uses locational prices as an indicator to determine locations where wind turbines could provide the greatest benefit to the system. Bohn et al. (1984) derive optimal electricity prices over space and time depending on electricity load flow. These prices influence the patterns of production, transmission and use of electricity.

The temporal component of electricity pricing reflects the market price of generation. In wholesale electricity markets generators offer their electricity output to retailers. As described in the previous chapter, various technologies are available for generation, and marginal costs of different power plants depend on fuel prices, operational costs and efficiency levels. Power plants are scheduled in order of increasing short-run marginal costs of production. Last in this order are typically peaking plants (Holmberg and Newbery, 2010). The highest marginal cost generator dispatched determines the market clearing price for all generators in operation (see Figure 2.3). Therefore, availability of generation from renewable sources with zero marginal cost reduces the wholesale price (Sensfuss et al., 2008). Typically, in times with high demand, generation costs are high.

Costs of transmission and utilization of low-voltage grids are the fundamental drivers behind spatial price differences. Consideration of all operational constraints results in nodal prices. Each point where electricity is generated or consumed has a specific price (Bohn et al., 1984). However, this large number of nodal prices may be too complex for the application to end consumers. Zonal pricing reduces this complexity: The price within one area of the grid changes according to the local system state. Zones can be pre-defined or dynamically established depending on grid conditions.[10] Zonal pricing allows a reasonable trade-off between pricing complexity and the coordination ability of the pricing scheme. Hogan (1998a) demonstrates different transmission pricing approaches, and Leuthold et al. (2008) summarize the debate on zonal vs. nodal pricing.

3.3.4 Price Components and Coordination in Focus

Even with the knowledge and research on dynamic pricing of the last decades, still more research needs to be done to understand the influence of rate design on demand as well as the winners and losers (Joskow and Wolfram, 2012). Parmesano (2007) highlights the importance of dynamic rate design to achieve energy efficiency. The general attributes of a sound rate structure have been summarized in the *Principles of Public Utility Rates*, which was originally published in 1961 (Bonbright et al., 1988). This seminal work also identifies three primary criteria to judge a rate structure and therefore help with rate design regulation:

- *Capital Attraction* — enough revenues for utilities to ensure a fair return and desirable levels of quality and safety

[10] A similar example is congestion pricing of roads during peak hours which encourages drivers to either use alternative routes or shift travel times to non-congested hours (see Arnott and Small, 1994).

- *Consumer Rationing* — "discourage the wasteful use of public utility services while promoting all the use [...] justified [...] [between] cost incurred and benefits received"
- *Fairness to Ratepayers* — fair distribution of cost ideally to beneficiaries and without inadequate discrimination

Similar to these criteria, the objective of this thesis is to analyze new coordination approaches that provide alternatives to current investment incentives *(Capital Attraction)*, use of resources *(Consumer Rationing)* and cost allocation *(Fairness to Ratepayers)*. Since physical constraints and system conditions change, the price generally has to vary per location and over time. In a static scenario Schweppe et al. (1985) decompose this price into three components: "generation fuel and maintenance, network losses and variable maintenance, generation and network quality of supply (costs related to unserved energy)".

Given the operational constraints of the electricity system, this thesis analyzes three price components (for different divisions of price and cost components, see, e.g., Houthakker, 1951; Bohn et al., 1984; Stoft, 2002; Parmesano, 2007):

- *Energy Price* – reflects the market price for generation at a specific location
- *Network Price* – reflects the price for transmission of power between locations
- *Local Price* – reflects the price for utilization of low-voltage grid at a location

In the following chapters, the effects and interaction of some instances of these components in different scenarios are analyzed in the face of the primary criteria of rate structure design.

As mentioned above, the supply side coordination in the electric power system exists in the form of wholesale markets, dispatching or ancillary services, given the regulatory interventions such as priority of RES (*Energy Price*). Therefore, Chapter 4 focuses on coordination approaches using the remaining two price components under a given *Energy Price*. Demand side flexibility has been used so far with large industrial consumers only. Hence, the focus is on the operational demand side coordination of small consumers (*Local Price*), possible through ICT-enabled information availability in real time. Structural coordination of demand, supply and the network is in focus of Chapter 5, mainly in the form of cost allocation of long-term investments (*Network Price*) and the inferred impact. The relevant structural coordination approaches are reviewed in detail in Chapter 5.

Chapter 4

Local Load Coordination

This chapter focuses on the potential of load coordination, to ensure adherence to local infrastructure limits in the distribution grid. The focus is on DSOs who are responsible for grid capacity on lower voltage levels for private end consumers. The aim is not to provide ancillary services for system stability on low-voltage level, but to discuss demand response mechanisms for balancing the limits of existing grid infrastructure and the optimal utilization of renewable or low-cost generation. The terms demand response (DR) and demand side management (DSM) are often understood as synonyms. In more detailed definitions DSM is considered as a superset of DR — going beyond load shifting and including long-term energy efficiency measures (Palensky and Dietrich, 2011). In contrast, Albadi and El-Saadany (2008) categorize the reduction of total electricity consumption as DR. An overview of load-shaping objectives of DSM is provided by Gellings (1985), ranging from *peak clipping* (e.g., simple load curtailment), *strategic conservation/load growth* (e.g., energy efficiency) to other objectives of demand shaping, e.g., *valley filling*, *load shifting*, *flexible load shape*. Energy efficiency, which leads to an overall reduction of quantities demanded, is an important factor to reduce GHG emissions and avoid infrastructure overloads. Efficiency measures of small consumers can provide significant savings, since a large part of electricity consumption is wasted in households. For example, in IAE member countries, approximately 10% of total electricity consumption in households stems from stand-by power (IEA, 2001). However, even with an increase in efficiency, the growth (e.g., population, economy) and rebound effects undermine these savings.[1] Hence, continued growth in total electricity demand is projected globally (IEA, 2011b). This chapter intentionally excludes the overall reduction of demand and uses both the terms DR and DSM — where DR mainly refers to measures of load shifting.

In their seminal work, Schweppe et al. (1988) describe the core pricing methodologies to incentivize DR that can nowadays be exploited using smart grid technologies. Oren (2013) categorizes two different DR paradigms: real-

[1] For more details about the rebound effect, see Greening et al. (2000) and Berkhout et al. (2000).

time prices for retail customers and load control contracts differentiated by quality of service. Similarly, Albadi and El-Saadany (2008) classify DR programs into price-based programs and incentive-based programs. Both paradigms are not widespread so far, and Oren (2013) focuses on the paradigm of contracted load control options. This chapter emphasizes the direction of real-time pricing for demand coordination and employs direct load control options such as curtailment as reference scenarios.

A flexible demand side is a necessary prerequisite for any DR application scenario. Retail customers combine various load types with different flexibility. This results in specific control characteristics: Some loads are controllable at all times and might react immediately with continuously flexible higher or lower demand (e.g., heating, ventilation, air-conditioning devices – HVAC), whereas other loads cannot respond instantaneously due to operating characteristics (e.g., washing machines during a washing cycle) or can only consume in discrete power levels (e.g., appliances with on/off-switch only). Some appliance loads are dependent on or constrained by other devices (e.g., a dryer should only run after a washing machine cycle). Other load types even offer the possibility of substituting electric power consumption (e.g., switch heating from electricity to natural gas). The most flexible devices are storage appliances, especially if their charging pattern is not restricted by their type.

However, the mere existence of flexible loads itself is not sufficient to establish DR successfully. Consumers need to allow and enable use of the available flexibility. Specifically, consumer reaction to dynamic prices is subject to discussions, since electricity costs are still too low in comparison to total cost-of-living. The low price elasticity of demand has been confirmed by several studies (Faruqui and Sergici, 2010). Also, the willingness to accept lower quality of service in the form of lower reliability levels for some loads seems limited, given the current high security of supply levels in industrialized nations. However, some studies show high demand for dynamic tariffs[2] and that load control automation helps to increase acceptance rates (Dütschke and Paetz, 2013). Hence, an essential step to ensure consumer acceptance of demand flexibility on a household level is the development of support tools for different load types. These tools need to ensure that consumers' utility is not impaired and that they can easily adjust the service or tool to their personal preferences.

Based on the requirements and characteristics described above, different coordination mechanisms are discussed in this chapter which fit into the coor-

[2]In one program, 93% of all customers preferred the dynamic tariff in comparison to a flat rate (Pöyry, 2012).

dination framework presented in Section 3.1. The main actors are consumers, who can shift flexible parts of their demand to achieve individual targets (e.g., minimize cost, maximize use of RES). At the same time, system operators, retailers and generators are responsible for power provision and want to coordinate the demand in their favor. The central resources in this chapter are local infrastructure limits which need to be adhered to. At the same time, utilization of renewable or low-cost generation is ideally maximized. The coordination mechanisms discussed can be based on different levels of information, e.g., market prices, local prices, local infrastructure utilization, and availability of renewable or other low-cost generation.

First, general alternatives for local load coordination are presented in Section 4.1. Section 4.2 describes electric vehicle charging loads as one practical example. Subsequently, Section 4.3 analyzes in detail the influence of different coordination approaches on EV charging loads in combination with local infrastructure limits. One striking result is that decentralized approaches have the potential to shift loads such that grid limits are adhered to. This decentralized approach can thus avoid central load shedding. Section 4.4 applies the theoretical research results in a Swiss grid planning case study. This practical application demonstrates the potential impact of DR and variable tariffs on high-voltage grid planning. The main assumptions and limitations of the research approach are discussed in Section 4.5.1. Finally, Section 4.5.2 concludes and summarizes the main implications of this chapter.

This chapter contains parts of own publications and working papers. Namely Section 4.2 on electric vehicles as flexible loads contains parts of our papers Flath et al. (2012), Flath et al. (2013) and Salah et al. (2013). In Section 4.3, some subsections — especially the modeling and the sections on uncoordinated, supply-based coordination and dynamic load pricing coordination — are partly reproductions of Salah et al. (2013) and Flath et al. (2013). This section also comprises the results of Flath et al. (2013). The Swiss case study presented in Section 4.4 is an extended version of our results presented in Salah et al. (2013). Finally, the discussion (Section 4.5.1) and conclusion (Section 4.5.2) also repeat some parts of the respective chapters in our papers Flath et al. (2013) and Salah et al. (2013).

4.1 Alternatives for Local Load Coordination

Throughout the rest of this thesis the underlying assumption is the availability of flexible loads and the willingness of consumers to exploit this flexibility. This section describes different contracting and pricing options to incentivize demand in order to match available supply and at the same time ensure adherence to infrastructure limits. To this end, this thesis defines energy consumption e (e.g., measured in kWh or MWh) and load l (e.g., measured in kW or MW). Naturally, the following relation applies:

$$e = \int l(t)\, dt \tag{4.1}$$

This definition critically hinges on the continuous measurement of loads. In practical applications, the average load in discretized periods of time is used l_t^i (Taylor and Schwarz, 1990). An example are quarter-hourly load measurements which are typically used for large industry consumers in Germany. Given short measurement periods Δt, the deviation between an average value and a continuous value becomes small. Assuming such discretized measuring periods of time (Δt), the demand of an individual consumer i in one period consists of two basic parts with the following relation:

- Load l_t^i
- Energy consumption $e_t^i = l_t^i \cdot \Delta t$

4.1.1 Supply-based Incentives

The first goal of demand side coordination is to match a given supply availability through the use of flexibility. As described in the previous chapters, there is a large body of literature on matching intermittent RES to flexible loads. This is achieved by means of smart metering technologies and often introduced in the form of variable tariffs for energy consumption e_t. To account for varying supply situations, an external price signal p_t^{ext} can reflect the supply situation and incentivize or disincetivize consumers with flexible demand (this is one possible realization of the *energy price*). With the assumption of discretized periods of time, the individual electricity costs of consumer i are calculated as the sum of the products of price and quantity:

$$\sum_{t=1}^{T} p_t^{ext} \cdot e_t^i \tag{4.2}$$

During times of high prices (e.g., in situations with low supply from RES) flexible individual consumers lower their consumption e_t^i and may increase their consumption in low-price periods. Total consumption $E_t = \sum_i e_t^i$ is dependent on the current prices and the price elasticity of consumers. Obviously, this demand response can also be realized by direct control based on contracts (Fahrioglu and Alvarado, 2000). An example are load aggregators or retailers that have load control contracts with their customers and try to shift consumption into periods with low power prices (Kirschen, 2003). The aggregation helps to reach a critical mass that can be used to participate in power markets that follow current power market designs.

Researchers have analyzed this type of load coordination from various points of view, using different external price signals or even direct load control. Daryanian et al. (1989) and Ahlert (2010) analyze optimal demand response strategy of storage-type consumers based on spot prices. Gottwalt et al. (2011) compare household demand patterns and electricity bills under flat tariffs and given variable electricity prices. They also analyze resulting load shifts and find that variable electricity prices can lead to significant shifting effects and new total load peaks (*avalanche effects* or *load synchronization*). Kishore and Snyder (2010) show similar results: with flexible residential demand and peak/off-peak pricing they find new peaks in low-price periods based on individual demand optimization. Using simulations, Sioshansi and Short (2009) find that real-time pricing can increase wind generation use and decrease wind curtailment with load demand elasticities. Our paper (Schuller et al., 2012) also demonstrates significant increase in wind-power utilization when incentivizing flexible EV charging loads with a wind-power-based tariff. We observe the same load *avalanche effects* as the previous studies when offering a dynamic price to an EV population.

Therefore, local load limits have to be considered. Even if there is excess renewable energy feed-in in the system, some grid infrastructure components may already operate at their limit. Demand response through direct control or monetary incentives needs to internalize this risk of overloads into the coordination mechanisms. The next sections present the analytical descriptions of examples for the integration of local infrastructure limits into coordination mechanisms. These generic approaches are subsequently applied in simulation models with electric vehicles as flexible demand.

4.1.2 Load Curtailment

Load curtailment is one way to deal with demand peaks given the limits of the local power grid infrastructure (e.g., transformer loads, line limits, voltage drops). In the following, static and dynamic load curtailment are introduced.

Static Load Curtailment (SLC)

A trivial way to stay within tolerable infrastructure limits is to statically limit all individual load levels l^i. A theoretical worst case given full load flexibility is a simultaneity factor of unity, i.e., all consumers demand electricity at the same time.[3] To account for this worst case given a total maximum load of $\overline{L}$ at a specific

[3] This seems unlikely, however with fully flexible loads such situations are theoretically possible.

location, one could limit individual loads homogeneously. Thus, the static load limits $\overline{l^i}$ for all $i \in [1..n]$ loads need to fulfill the condition

$$\overline{l^i} \leq \frac{\overline{L}}{n} \quad . \tag{4.3}$$

$\overline{L}$ needs to be selected such that all infrastructure component limitations are considered.[4] In practical applications, this approach could be implemented by installing fuses that are sized accordingly. Grid expansions are basically planned with a similar approach in mind: The capacity is sized based on the maximum load expected, but considering different types of loads and hence not using the worst case simultaneity factor of unity.[5]

Dynamic Load Curtailment (DLC)

The aggregate load at a specific location can be simplified as $L_t = \sum_{i=1}^{n} l_t^i$. Depending on the load type — interruptable demand contracts (switch on/off only) or continuously controllable loads — the load curtailment is dynamically adjustable based on different aggregate load levels. Baldick et al. (2006) provide a good overview on interruptable load contracts.

This type of control can be exercised by the local DSO, typically with flexible non-critical loads (e.g., refrigerators, HVAC, heat pumps, storage appliances). Generally, two simple types of dynamic load curtailment are possible. The first one follows the "first-come first-serve" philosophy: all loads l_t^i are accepted until the aggregated level $\overline{L}$ is reached. Any additional loads are curtailed completely. The second curtailment option is reducing all loads — either evenly or proportionally based on individual contracts — when the limit $\overline{L}$ is reached. The latter option is only feasible with continuously controllable loads or at least loads with multiple power levels. Hence under *DLC*, individual consumers can consume more than the static limit described in Equation 4.3 as long as the dynamic load is lower than the limit:

$$\sum_{i=1}^{n} l_t^i \leq \overline{L} \quad \forall t \in T \tag{4.4}$$

Multiple extensions can be added to these simple forms of dynamic load curtailment. Based on more complex contracts and communication technology, quality of service differentiation is possible. Each customer may have a quality of service specification for each load type. Hence, the curtailment and demand levels could be specified, e.g., based on load type or level and time (see Oren, 2013).

[4]This is clearly a simplification of possible grid infrastructure situations. In some cases an asymmetrical load limitation might be more useful, e.g., due to voltage drops.

[5]For example, the former DIN VDE 0100-300 lists expected simultaneity factors for different commercial and industrial applications (see `http://www.vde-verlag.de/buecher/leseprobe/lese2867.pdf`).

Optimization approaches can use this information, e.g., for minimizing end-user discomfort while adhering to load limits (Ramanathan and Vittal, 2008). An example of different service levels is analyzed in our paper (Flath et al., 2012), which applies a revenue management approach for electric vehicle charging. We model customer segments with different valuations charging their EVs and use two booking classes to achieve an efficient allocation of the available limited capacity.

4.1.3 Demand-based Incentives

Load curtailment approaches do not take into account different valuations of demand over time, e.g., due to intended application or different price sensitivity of consumers. The integration of limited infrastructure capacity with price signals is the focus of demand-based incentives. A typical format is a demand charge where consumers pay for maximum power consumption (in kW) per billing interval $\Delta t_b \geq \Delta t$. For example, a consumer pays for the highest quarter-hourly (Δt) average load (l_t^i) within 12 hours (Δt_b). This makes sense due to measurement resolution, amount of data and load variability of some appliances (e.g., high starting load of refrigerators). Again, two generic approaches can be imagined: static (individual) and dynamic (aggregate) load-based pricing.

Static Load-Based Pricing (SLP)

Static load-based pricing uses individual demand measurements to apply demand charges. No information about local or total grid load is necessary. In general, consumers pay a charge depending on their load pattern during the billing interval Δt_b.

A typical implementation is that consumers pay a charge per kW for the highest individual load level within one billing interval:[6]

$$p_{t_b}^{SLP} \equiv f\left(\max_{t \in t_b}\left\{l_t^i\right\}\right) \tag{4.5}$$

In a simplified tariff scenario with $\Delta t = \Delta t_b$, the consumers pay a price for their load level per time slot: $p_t^{SLP} \equiv f\left(l_t^i\right)$.

Apart from price elasticity and consumer flexibility, the demand response strongly depends on the load-price function. A simple constant price (per kW) combined with the identical duration of measuring and billing period ($\Delta t = \Delta t_b$) leads to the same incentives as a flat external price signal of supply as introduced in Equation 4.2. This thesis focuses on the goal of avoiding local infrastructure

[6]For sake of brevity a compact notation is used in the following, e.g., $p_{t_b}^{SLP}\left(\max_{t \in t_b}\left\{l_t^i\right\}\right)$.

overloads by means of increasing marginal demand charges. These charges incentivize individual consumers to avoid demand peaks and therefore to 'flatten' their demand profile.

Another possibility to incorporate the individual load level are adjustments to the energy price. The resulting price experienced by the consumer depends on the external price and the individual load level:

$$p_t^{SLP,e} \equiv f\left(l_t^i, p_t^{ext}\right) \tag{4.6}$$

Dynamic Load-Based Pricing (DLP)

Dynamic load-based pricing approaches require more information and data exchange than *SLP* approaches because pricing is based on current aggregate demand $L_t = \sum_i l_t^i$ at a specific location or in an area comprising several consumers. Therefore, each consumer has only limited influence on pricing by adjusting his own demand pattern. The load price in each period Δt_b is dependent on the total load pattern in the billing interval. Charging for the highest load level measured, the price obtains as:

$$p_{t_b}^{DLP} \equiv f\left(\max_{t \in t_b} \{L_t\}\right) \tag{4.7}$$

In comparison to *SLP*, demand is less constrained by high-prices if overall local demand is low and idle system capacity is available. However, given the dependency on other consumers in the location, the individual consumer does not know the exact price in advance because the highest load peak is not determined at the beginning of a period Δt_b. To account for price dependability, prices need to be announced prior to consumption time. One alternative is to use the expected maximum load $E\left[\max_{t \in t_b} \{L_t\}\right]$ and announce this value in advance. With $\Delta t_b = \Delta t$ the price is determined directly in the period of consumption when the aggregate demand of the current period is fixed and therefore converges to a simplified "near real-time" load price. This simplifies 4.7 to:

$$p_t^{DLP} \equiv f\left(L_t\right) \tag{4.8}$$

Similar to *SLP*, *DLP* adjustments through the energy price are also possible. The external price signal p_t^{ext} can be extended by a price signal which includes the respective loads. The resulting energy price depends on:

$$p_t^{DLP,e} \equiv f\left(L_t, p_t^{ext}\right) \tag{4.9}$$

Given the demand charge function setup, consumers are incentivized to reduce demand when local infrastructure is utilized to a greater extent. A similar concept is used for peak-load pricing (e.g., Boiteux, 1960) with the intention to limit demand due to missing generation capacity. The static approach based on booking classes in our paper (Flath et al., 2012) is a modification of peak-load pricing. In this case we model two different prices only, and each consumer can decide to book capacity at a lower price in advance or pay a higher price for adhoc capacity requirements.

4.1.4 Combined Local Load Coordination

Obviously, both load-based pricing methods (*SLP* and *DLP*) cannot guarantee compliance with intended infrastructure limits. Thus, final control of load shedding by the system operator is still necessary. However, given the knowledge about demand elasticity, the respective pricing mechanisms might be adjusted to moderate between grid limits and use of low-cost or renewable supply. For ease of exposition and to ensure price dependability, the billing and measurement periods are synchronized in the following: $\Delta t_b = \Delta t$. The combined coordination approaches as well as the respective objective functions in focus of this thesis are summarized in Table 4.1. In the following, the thesis focuses on the

Coordination	Load constraints	Pricing structure
Supply-based	-	$\sum_{t\in T} p_t^{ext} \cdot e_t^i$
with *SLC*	$\overline{l^i} \leq \frac{\overline{L}}{n}$	$\sum_{t\in T} p_t^{ext} \cdot e_t^i$
with *DLC*	$\sum_{i=1}^{n} l_t^i \leq \overline{L}, \forall t \in T$	$\sum_{t\in T} p_t^{ext} \cdot e_t^i$
with *SLP*	-	$\sum_{t\in T} \left(p_t^{SLP,e}\left(l_t^i, p_t^{ext}\right) \cdot e_t^i + p_t^{SLP}\left(l_t^i\right) \cdot l_t^i \right)$
with *DLP*	-	$\sum_{t\in T} \left(p_t^{DLP,e}\left(L_t, p_t^{ext}\right) \cdot e_t^i + p_t^{DLP}\left(L_t\right) \cdot l_t^i \right)$

Table 4.1: Load coordination mechanisms in focus

economic potential of combining supply-based incentives with load curtailment and demand-based incentives to incorporate infrastructure limits. To this end, the different combinations of local coordination are applied to a population of flexible and price-sensitive consumer types. EV charging demand serves as a generic example for one type of flexible load.

4.2 Electric Vehicle Charging as Flexible Load

Electric vehicle charging load is used as an example in some of our existing publications and working papers. Hence, this section is a combined and extended version of parts of the papers Flath et al. (2012), Flath et al. (2013) and Salah et al.

(2013). For example, the following introduction is based on the paper presented at the Americas Conference on Information Systems (AMCIS) (Flath et al., 2012). The related work part is an extended version of what has been used in the mentioned publications, and the paragraphs on the charging optimization approach as well as the model setup have been used in shorter, amended versions in the respective papers.

Road transportation accounts for over 20% of CO_2 emissions in the USA and the European Union.[7] Therefore, this sector plays a crucial role in meeting global CO2 reduction goals mentioned in Chapter 1. Projections of leading research institutions expect significant growth of EV sales (Cooper et al., 2013; Navigant Research, 2013; OECD/IEA, 2013). Additionally, many countries try to reach challenging targets of electric vehicle (EV) penetration in the next years (German Federal Government, 2009; Department of Energy and Climate Change, 2009; DOE, 2011). While electric vehicles locally always operate (tank-to-wheel) emission-free, the more relevant total emission balance (well-to-wheel) critically hinges on the electricity mix used for charging the vehicle. Figure 4.1 illustrates that EVs can achieve emission reduction only if the electric energy comes from renewable energy sources (e.g., wind or solar).

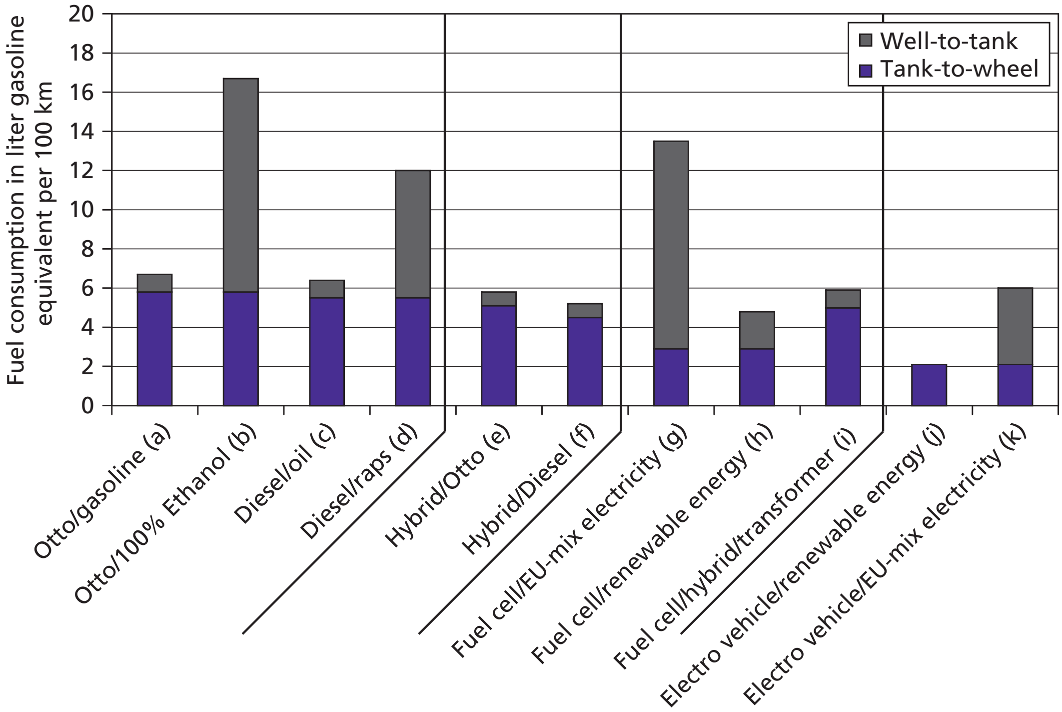


Figure 4.1: Emission statistics of different vehicle technologies (Ballentin et al., 2011)

However, power generation by these sources is highly intermittent and their

[7] See http://ec.europa.eu/clima/policies/transport/vehicles/index_en.htm and http://www.eia.gov/environment/emissions/ghg_report/pdf/0573%282009%29.pdf

increasing share challenges the operational stability of today's power system. Electric vehicles induce additional demand for electric energy. Moreover, these new loads are fairly flexible, since most of the time private cars are not in motion. By using information and communication technology (ICT), the smart grid can provide full visibility to monitor, control and optimize EV charging and enable new services such as variable tariffs by different dimensions, feedback or remote control. The management of EV charging is a promising research field due to three reasons:

- EVs will induce significant new load to the power system
- The smart grid offers new information and control possibilities
- Habits — which are normally difficult to change — have not been developed for EV charging

Large-scale EV charging will interlink the transportation sector with the electric power sector and introduce a significant new load which will put additional stress on the electricity system (Blumsack and Fernandez, 2012). At the same time, these charging loads are temporally flexible and are thus promising candidates for applying DSM approaches. Smart integration of EVs may reduce the threats to power system reliability. Furthermore, they may even offer balancing capacity for intermittent generators and thus help to stabilize the grid (Kempton and Tomić, 2005; Lund and Kempton, 2008). To realize these economic potentials, vehicle operators should adapt their charging behavior based on price signals or cede control of their vehicle (Peças Lopes et al., 2009). The latter is problematic, as customers most probably expect EV usage to be similar to conventional vehicles — non-availability of EVs due to low charging levels will not be accepted by customers. Consequently, EV users will need support systems to achieve truly smart charging behavior on the individual level. This thesis assumes such automation as given to analyze the discussed coordination approaches for flexible loads. In addition to individual flexibility, the grid impact is highly dependent on the number of EVs, the technical details and the objective of charging coordination.

4.2.1 Technical Specifications of Electric Vehicles and Charging Systems

The term *electric vehicle* generally comprises different technical architectures and configurations.[8] Chan (2007) names three general classes: Battery EVs (BEV), Hybrid EVs (HEV) and Fuel Cell EVs (FCEV). In the context of power system

[8]This text comprises parts of our papers (Flath et al., 2013; Salah et al., 2013; Flath et al., 2012) and combines the technical specifications for this thesis.

utilization, BEVs and Plug-in Hybrid EVs (PHEV) are relevant within this thesis because these are directly connected to the power system. An introduction with detailed information on EV architectures is provided by Chan (2007) and Chan et al. (2010). The internal combustion engine (ICE) in HEVs are not in scope of this thesis but would provide further interesting applications as an outside option. The remaining part of this thesis focuses on BEVs only.

Recently, an increasing number of electric vehicles from major OEMs have become available. The most relevant EV characteristics are distance-specific energy consumption, battery capacity and vehicle maximum range. Most notably, battery capacity in BEVs is limited due to cost as well as size and weight, since the volumic energy of batteries is low in comparison to fossil fuel. This results in general in a lower maximum range than today's typical ICE vehicles. Table 4.2 lists this data for a selection of current electric vehicles.

Make and Model	Curb Weight (kg)	Battery Capacity (kWh)	Range (km)	Energy Consumption (kWh/km)
Citroën C-Zero	1,110	16	150	0.107
Ford Transit Electric	2,340	28	130	0.215
Karabag Fiat 500 E	1,120	20	140	0.148
Mitsubishi i-MiEV	1,110	16	150	0.107
Mercedes A-Class E-Cell	1,591	36	255	0.141
Nissan Leaf	1,520	24	160	0.150
Peugeot iOn	1,110	16	150	0.107
Renault Fluence Z.E.	1,610	22	185	0.119
Renault Kangoo Z.E.	1,410	22	170	0.129
Renault Twizzy 75	450	7	100	0.070
Renault Zoe	1,392	22	210	0.105
Smart Fortwo Electric Drive	975	17.6	140	0.126
Tesla Roadster	1,220	53	393	0.135
Think Global Th!nk City	1,038	23	160	0.144
Average	*1,285*	*23*	*178*	*0.129*

Table 4.2: Technical data of current electric vehicles (Salah et al., 2013)

In addition to the technical specification of the EVs, the charging system and battery specifications influence the impact on and interaction with the power grid.[9] The IEC standard 62196-1 specifies four charging modes, ranging from the slow AC mode (up to 3.5 kW) to the fast DC mode (up to 240 kW). Furthermore, the charging speed of EV batteries is limited due to physical constraints of the batteries. Most recent electric vehicles are typically capable to charge in

[9]The term "plug-in" gives the impression that inductive charging is excluded. This thesis abstracts from different technical alternatives and treats conductive and inductive charging connections equally.

slow AC mode (3.5 kW) or fast AC mode (11/22 kW). Thus, refueling is much slower for EVs and can hardly be done en route. The German National Electric Mobility Platform suggests that the future charging infrastructure will consist of a mix of home charging stations, public charging stations and fast charging stations (Nationale Plattform Elektromobilität, 2011). Fast charging stations will represent a very small part of the infrastructure as they are expensive and will be required for long-distance traffic only.

Typical charging speed at home is around 3 kW, which translates into approximately 8 hours charging time for a full charge of a 24 kWh battery. Faster charging speeds at 11 kW are possible with special plugs and quick charging stations with over 50 kW, which are in development and testing. With the fast charging mode, vehicles' batteries can be fully charged in about 30 minutes. Faster charging offers both quick mobility range for driving needs and more flexibility for intelligent charging to support power grids. In the long-term, EVs should not only support the power system by scheduling their charging load appropriately but also by feeding electricity back into the grid. Several research contributions covering that direction envision EVs to provide vehicle-to-grid (V2G) services (Kempton and Tomić, 2005). Since vehicles are parked more than 90% of the time, the wide scale adoption of EVs could provide a flexible storage opportunity for the power system.

4.2.2 Charging Demand and Mobility Needs

Electric mobility faces two major challenges: support the driving needs of the consumer and avoid negative influences or even support the efficiency of the power grid.[10] In comparison to other household loads, EVs have some special characteristics due to technical restrictions and usage patterns. EV charging can increase household demand for electric energy significantly. The US Department of Energy rated the fuel economy of two EVs in 2012 — the Nissan Leaf with 34 kWh/100 miles and the Mitsubishi i-Miev with 30 kWh/100 miles.[11] From a top-down perspective, an average driver with approximately 13,500 miles/year therefore increases the consumption of electric energy by approximately 4,000 kWh.[12] With approximately two vehicles per household, the electrification of individual mobility creates significant additional load on top of existing household consumption. Overall, one EV consumes approximately one third of an

[10] This section is an extended version of sections in our papers Flath et al. (2012) and Salah et al. (2013).

[11] Deviations to table 4.2 are due to different measurements of the Department of Energy and specific manufacturers.

[12] For details, see the US Energy Information Administration http://205.254.135.24/tools/faqs/faq.cfm?id=97&t=3 and the US Department of Energy: http://www1.eere.energy.gov/vehiclesandfuels/facts/2010_fotw618.html.

average US household. A more detailed bottom-up representation of mobility behavior is used in the models of this chapter. This is necessary to analyze feasibility of individual mobility with range-limited EVs and the charging-related grid impact.

Currently, market penetration of EVs is low, mainly due to the small choice of models and high purchase cost. Specifically, battery costs have to drop significantly in order for EVs to be competitive without subsidies (Hidrue et al., 2011). Apart from high cost, one important reason which could impede market penetration is the range limitation of EVs and the resulting range anxiety of mobility users (Eberle and von Helmolt, 2010). However, different datasets indicate that a large share of individual car mobility could be realized by EVs. Using multi-day GPS data from Seattle, Khan and Kockelman (2012) note that EVs with 100 miles range could meet the driving needs of 50% of one-vehicle households and 80% of multiple-vehicle households. Based on another set of real-world drive cycles, Gonder et al. (2007) find that only 5% of the vehicles drive more than 100 miles per day. Despite the limitations, about one third of all drivers could successfully use an EV now available on the market with a few adaptions in their driving pattern (Pearre et al., 2011; Greene, 1985). According to recent studies, electric vehicle penetration is expected to increase in many industrialized countries during the next years. In the most optimistic scenarios, different studies estimate penetration rates of 24% (Becker et al., 2009) or 19% (NRC, 2010) of the US light vehicle fleet in 2030. In Europe, Nemry and Brons (2010) estimate a share between 7% and 27% of electric cars in the fleet by 2030.

4.2.3 Related Work on Charging Coordination of EVs

Research on EV charging coordination gains importance due to the expected rise of EVs. This section provides an overview on different EV charging coordination approaches and research questions in context of this thesis. Shorter versions of this part are included in Flath et al. (2013) and Salah et al. (2013).

For additional views on this topic, the interested reader may refer to other literature overviews (e.g., Bessa and Matos, 2012; Richardson, 2013).

Overview

The discussion on management methods to shift EV charging loads into off-peak periods started already in the early 1980s (Heydt, 1983). Since then, various aspects have been examined by different communities, for example electrical engineering, economics and computer science. The focus has been on impact analysis of individual electric mobility on the electricity grid, and it has been shown that EV charging increases load significantly (Roe et al., 2009; Clement-Nyns et al., 2011; van Vliet et al., 2010). Depending on distribution grid characteristics, this can lead to bottlenecks and power quality issues (e.g., transformer overloads, voltage drops). Different simulations have shown that the electrification level of the current car fleet can reach between 10 – 40% before inducing problems in low-voltage distribution grids (Staats et al., 1998; Rahman and Shrestha, 1993; Richardson et al., 2010). Many of the aforementioned publications focus on grid capacity analysis without taking into account the possibilities of economically motivated charging coordination (Roe et al., 2009; Richardson et al., 2010; Rahman and Shrestha, 1993).

Objective Function

The heterogeneity of actors in today's liberalized power systems leads to different objectives for EV charging coordination. From a generation perspective it is beneficial to optimize the utilization of low-cost generation capacity or use EV charging to smooth the load curve in order to minimize ramping cost (e.g., Guille and Gross, 2009). Sioshansi and Denholm (2010) minimize the total system cost consisting of generation and EV operating costs. Environmental organizations as well as governments often propagate the use of EV charging flexibility to reduce carbon dioxide emissions by integrating renewable energy sources, e.g., use excess wind-power in-feed for EV charging (Lund and Kempton, 2008; Caramanis and Foster, 2009). At the same time, electrical engineers often focus on coordination to provide regulating power (Tomic and Kempton, 2007; Andersson et al., 2010), minimize power losses (Clement et al., 2009; Sortomme et al., 2011), maximize EV integration (Peças Lopes et al., 2009), or reduce emissions as well (Göransson et al., 2010). In contrast, economists minimize cost for power suppliers or EV owners (Sioshansi et al., 2010; Dietz et al., 2011). From a mobility user's point of view the objective is to reduce mobility costs by optimizing the charging schedule based on variable electricity rates (Rotering and Ilic, 2011; Flath et al., 2013).

Coordination Approach

Approaches for EV charging coordination range from central optimal planning (Clement et al., 2009; Lund and Kempton, 2008) to decentralized approaches like time-of-use pricing (Peças Lopes et al., 2009; Clement-Nyns et al., 2011; Qian et al., 2011) or coordination based on local grid parameters (Peças Lopes et al., 2010; Flath et al., 2013). In general, the approaches abstract from direct communication of individual preferences similar to the load coordination approaches described in Section 4.1.

Centrally controlled coordination is often based on assumptions such as a given share of all EV owners using off-peak periods or the option of shedding (curtailing) some EVs on demand by contract (van Vliet et al., 2010; Kempton and

Tomić, 2005; Andersson et al., 2010; Göransson et al., 2010; Sioshansi et al., 2010). Evaluations of EV charging based on intermittent RES infeed often apply central approaches as well (Lund and Kempton, 2008; Li et al., 2013; Markel et al., 2009). Besides that, another model already uses centrally forecasted DR in addition to wind power integration (Wang et al., 2011). However, EV charging with decentralized decisions based on RES price signals or online mechanisms has been used recently (Schuller et al., 2012; Gerding et al., 2011; Dietz et al., 2011). This chapter complements existing research with the integration and evaluation of grid constraints in combination with decentralized coordination approaches of individual EVs.

Grid Impact

In recent years, some research projects and field studies focused on the power system impact of EV charging, similar to this thesis. Farmer et al. (2010) compare different studies and find that available generation capacity is sufficient — even with significant EV penetration — as long as the charging activity is coordinated. An overarching study by Kintner-Meyer et al. (2007) finds that the US power system capacity is sufficient to provide fuel for 84% of the total car, pickup truck and SUV fleet with a daily average drive of 33 miles. The study does not focus on grid issues. However, the authors state that EV charging adds significant new loads and may impact overall grid reliability due to infrastructure utilization. Taylor et al. (2009) recommend analyses on distribution feeder level to investigate which charging behaviors and penetration levels need to be considered or require actions by utilities, respectively. Real data case studies on the grid impact show slightly varying focus, approaches and results. Peças Lopes et al. (2011) propose a framework for the EV grid integration and show in simulations that with a central aggregator EV penetration rates up to 52% are possible in an example medium voltage grid. Based on a reference distribution grid, Qian et al. (2011) simulate different controlled and uncontrolled charging scenarios which result in approximately 36% peak load increase with 20% penetration rate in uncontrolled charging. In a planning model based on two real distribution areas, Pieltain Fernandez et al. (2011) demonstrate the increase of system investment cost and significant energy losses in a 60% EV penetration scenario. In addition, other possible grid impacts like power quality problems or voltage imbalances may occur (Putrus et al., 2009). Roe et al. (2009) investigate the effect of EV charging in a distribution circuit and, in a specific simulation scenario, find a significant reduction of the expected life of the distribution transformer. This thesis adds a Swiss case study which analyzes the influence of EV loads on future grid expansions under different load coordination and EV penetration scenarios.

Several research publications partly use similar model features, input data and evaluation methods as applied in this thesis. Table 4.3 provides an overview of selected publications on EV charging coordination.

Reference	Objective function						Coordination approach			Model features					Input data				Key notions
	Generation cost	System cost (Losses)	EV integration	Aggregator/ User cost	Emissions	Other	Central control	Price signals	Other mechanisms	Battery modeling	Grid constraints	Vehicle-to-grid	Emissions	Simulation	Driving prof.	Load profile	Grid topology	Historic prices	
Acha et al. (2010)		✓					✓				✓	✓		✓		(✓)	(✓)		Time-coordinated optimal power flow helps DSOs to value the storage available in their networks.
Acha et al. (2011)	✓				✓		✓				✓	✓	✓	✓		(✓)	(✓)	✓	Mild effects of EV on 11kW network. EVs in foreseeable future not environmentally advantageous.
Caramanis and Foster (2009)				✓			✓				✓	✓		✓		✓		✓	Proof of concept that EV charging coordination can be beneficial for local infrastructure and reduce cost.
Clement-Nyns et al. (2010)		✓					✓				✓	✓		✓		✓	✓		Analysis of the effect of PHEVs in an IEEE 34 Bus shows that voltage deviation limits as well as transformer limits are reached.
Clement-Nyns et al. (2011)				✓			✓				✓	✓		✓			✓		Uncoordinated charging can lead to local grid problems. Centrally coordinated charging based on two price levels leads to voltage deviations that can be mitigated by voltage constraints.
Fan (2012)				✓				✓			✓			✓					Use of congestion pricing inspired from communication networks with willingness-to-pay function per individual EV.
Galus et al. (2010)				✓			✓					✓		✓	(✓)	✓			Modelling dynamic state changes of EVs controlled by an aggregator including individual utility.
Gerding et al. (2011)				✓					✓		✓			✓	(✓)				Development and evaluation of an online auction allocation mechanism for EV charging capacity, which leads to a higher allocative efficiency than a fixed price system.
Heydt (1983)	✓			(✓)			✓							✓		✓			Investigation of generation and load management cost given different penetration rates. EV load management which shifts load into off-peak hours can reduce peak loads and improve load factors.
Kempton and Tomić (2005)				✓			✓					✓						✓	EVs can provide high-value time-critical system services. Regulation and spinning reserve services can be provided by 3% of California's car fleet.
Lund and Kempton (2008)	✓											✓		✓		✓			Impact model on a national electricity system assuming all EV storage as one big battery. Intelligent charging of EVs improves system efficiency, lowers CO2 emissions and improves the ability to integrate RES.
Papadopoulos et al. (2012)							✓				✓			✓		✓	✓		Evaluation of EV charging effects in LV distribution networks with smart charging and micro-generation. Both can reduce voltage violations and overloads significantly at higher EV penetration rates.

Reference	Objective function						Coordination approach			Model features					Input data				Key notions
	Generation cost	System cost (Losses)	EV integration	Aggregator/ User cost	Emissions	Other	Central control	Price signals	Other mechanisms	Battery modeling	Grid constraints	Vehicle-to-grid	Emissions	Simulation	Driving prof.	Load profile	Grid topology	Historic prices	
Peças Lopes et al. (2009, 2011)			✓	(✓)			✓	(✓)			✓			✓		✓	✓		Comparison of dumb charging to a dual-tariff coordination and a central smart charging coordination to maximize EV integration. Charging coordination can increase the maximum EV integration level.
Qian et al. (2011)				✓			✓	(✓)	✓	(✓)	✓			✓		✓	✓		Evaluation of uncontrolled EV charging on total load at example residential, commercial and industrial feeders. Optimal smart charging with real-time tariff only shows that most charging occurs in low-cost hours.
Rahman and Shrestha (1993)						✓	✓				(✓)			✓		✓			Impact of three simple charging models on total load: all EVs start simultaneously, EVs start sequentially in groups, EVs charge uniformly over time. Main results indicate that distribution grid limits are reached in residential areas at 20% EV penetration.
Sioshansi and Miller (2011)				✓	(✓)		✓						✓	✓	✓			✓	Analysis of cost of EV charging given cases with and without emission constraints. Constraining the emissions induced by EV charging does not largely increase total cost.
Sioshansi (2012)	(✓)			✓			(✓)	✓					✓	✓	✓				Evaluation of EV charging with individual agents under different tariffs on total generation cost and emissions. RTP performs worst in total cost due to resources with nonconvexities (e.g., ramping constraints)
Sortomme et al. (2011)		✓	(✓)				✓				✓			✓			✓		Analysis of the relationship between feeder losses, load factor, and load variance in the context of coordinated PHEV charging. Evaluation of three central algorithms that minimize distribution system impact.
Valentine et al. (2011)	✓						✓							✓	✓	✓		✓	Intelligent charging optimizes costs of generation, including ramping cost in comparison to uncontrolled charging.
Vandael et al. (2011)		(✓)				✓			✓		✓			✓				✓	Multi-agent systems (MAS) solution with negotiation on different grid voltage levels. Hierarchical scheduling approaches of decentralized charge intentions decrease system imbalances.
Wang et al. (2011)	✓						✓							✓	(✓)	✓			Simulation of optimally dispatched PHEV charging load demonstrates cost reduction potential which increases with DR enabled.

Table 4.3: Summary of selected contributions on EV charging coordination

4.2.4 Individual EV Charging Optimization

Economic EV charging optimization can be formulated as a linear program by adapting the classic Daryanian et al. (1989) model formulation for decentralized electricity storage.[13] This section describes the optimal EV charging model used in this thesis to represent individual fully flexible EV agents. The core part of this section is taken from our working paper on the grid impact of EVs in Switzerland (Salah et al., 2013). The model and strategies are extended to facilitate the integration of all mentioned coordination approaches on a generic level. The used scenario and data description partly stems from our paper Flath et al. (2013).

Bottom-up individual driving profiles from the German Mobility Panel (Zumkeller et al., 2010) serve as input for the analysis. This thesis uses the driving profiles of employees due to four reasons: First, employees represent a large fraction of total population. Second, in comparison to other demographic groups, employees drive more. Third, the commuter trips are a good opportunity to be conducted by electric vehicles. Fourth, commuter mobility behavior is fairly consistent over several weeks. Each driving profile provides the origin, departure time, arrival time and destination as well as the distance traveled in a 15 minute time resolution over one week. While the original driving profiles where recorded using conventional vehicles, the optimization assumes them as driven by EVs.

For each modeled electric vehicle $i \in [1..n]$ driving profiles provide the respective information:

- a consumption vector $\gamma^i = \langle \gamma^i_1, ..., \gamma^i_T \rangle$ specifying the required electrical energy for driving in each time slot as well as
- a location vector $\mathbf{a}^i = \langle a^i_1, ..., a^i_T \rangle$ where a^i_t indicates a vehicle's current location area over the collection of time slots $t \in [1..T]$.

Following the time resolution of the EV profiles, all consumption (driving) and charging actions are discretized in 15-minute intervals. In our model the time horizon (T) is set to one week consisting of 672 time slots. The time horizon also spans a (potentially varying) price vector $\mathbf{p} = \langle p_1, ..., p_T \rangle$ indicating the price of electricity at each point in time. Given this discrete time structure, the EVs' charging decisions can be represented as charging vectors $\boldsymbol{\phi}^i = \langle \phi^i_1, ...\phi^i_T \rangle$.[14] The total load at location x at time t then is $\Phi_{t,x} = \sum_{i=1}^{n} \left[\left(\phi^i_t \right) \mathbf{1}_{(x=a^i_t)} \right]$ where $\mathbf{1}_{(x=a^i_t)}$ is the indicator function on the location level. While the mobility dataset

[13] See Sioshansi et al. (2010) or Flath et al. (2013) for similar EV charging models.

[14] When referring to individual vehicle decisions we will sometimes drop the i index from γ^i and $\boldsymbol{\phi}^i$ for ease of exposition.

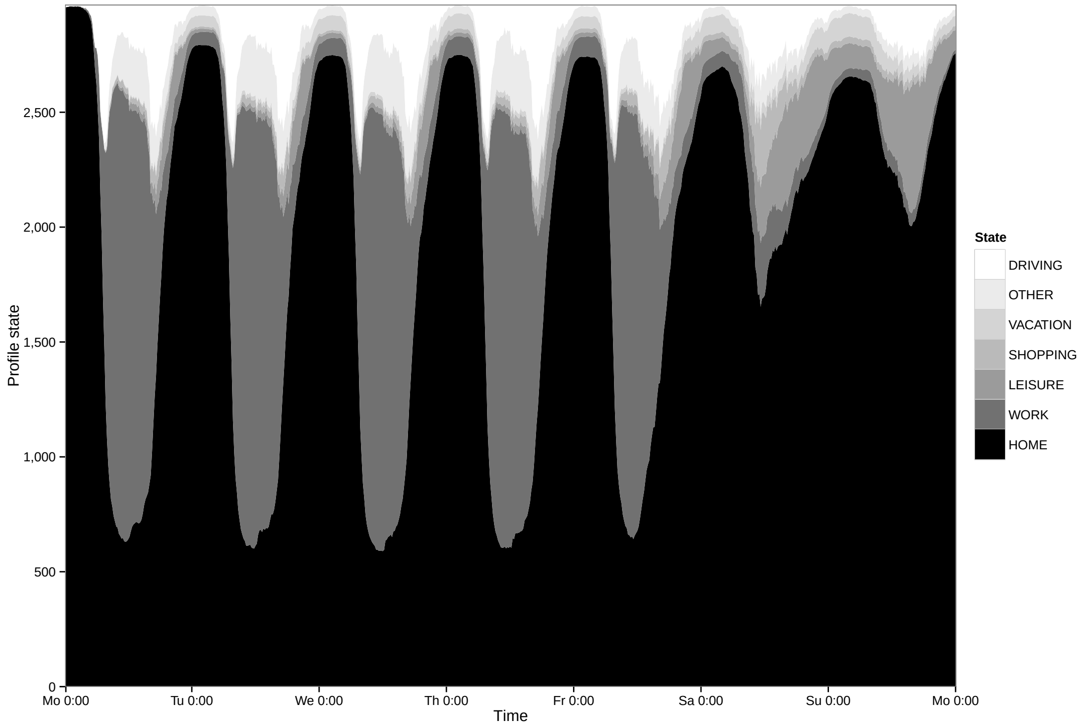


Figure 4.2: Distribution of vehicle locations and states over one week based on 2,966 employee driving profiles (Data source: Zumkeller et al., 2010)

of Zumkeller et al. (2010) provides a multitude of vehicle locations, the charging locations are restricted to home and workplace in line with typical EV scenarios. The driving profiles of employees in Figure 4.2 demonstrate that these two locations account for the highest relative probability of EV locations. Given the assumption that mobility behavior does not change significantly with EVs, it seems most reasonable that charging stations are available at these locations.

Individual charging decisions are given by charging strategies. A charging strategy determines individual charging amounts, given the driving profile and a price vector, that is the mapping $(\gamma^i, \mathbf{a}^i, \mathbf{p}) \mapsto \phi^i$.[15] In the following, this thesis focuses on the individually optimal charging based on a price signal assuming fully price-responsive EV agents.

Decision Variables

A charging program defines the charge amount ϕ_t for each time slot. Together with the static consumption values γ_t it also defines the battery state of charge SOC_t for each time slot. As V2G is not in scope, the charging amount is positive and limited by the maximum charging amount κ. Given the different options for charging speeds (Section 4.2.1), the 11 kW charging mode is used in

[15]See our paper Flath et al. (2012) for a discussion of different charging strategies.

the initial model. Assuming a linear charging process and discretized time slots of 15 minutes — similar to the driving profile resolution — this translates into $\kappa = 2.75$ kWh per time slot. Similarly, the battery level must always be positive and cannot exceed battery capacity $\overline{SOC}$. The model deviates from original car specifications (Table 4.2) and rather uses a fictitious vehicle with $\overline{SOC} = 30$ kWh battery capacity and a consumption of 0.15 kWh/km determining a maximum range of 200 km. The rationale here was to better capture the capabilities of a future standard EV. Without consideration of losses, the 11 kW mode results in a minimum charging time of about 165 minutes for a complete charge for the 30 kWh-battery.

Objective Function

Since the focus is on economic coordination, individual charging cost minimization is the appropriate objective.[16] The charge amounts with the corresponding billing structure allow to determine the total individual charging costs C:

$$\min_{\boldsymbol{\phi}} C(\boldsymbol{\phi}) \tag{4.10}$$

The functional form of $C(\boldsymbol{\phi})$ obviously depends on the payment structure as described before.

Constraints

A valid charge program needs to ensure the relationship between charging amounts (ϕ_t), driving consumption (γ_t) and the vehicle battery level (SOC_t). Specifically, the battery level at time t is determined by the battery level as well as the consumption/charging amounts in $t-1$:

$$SOC_t = SOC_{t-1} + \phi_t - \gamma_t \quad \forall t \in [1..T] \tag{4.11}$$

Furthermore, a terminal battery level SOC_T is specified to prevent the optimization from completely discharging the battery towards the end of the time horizon. The initial charge level allows us to compare the different charging coordination approaches:[17]

$$SOC_T = SOC_0 \tag{4.12}$$

[16] Alternative optimization goals include vehicle availability, emissions or battery health.

[17] This constraint can lead to some driving profiles being infeasible if there is not enough time to restore the full battery towards the end of the optimization horizon. An alternative to account for different terminal battery levels SOC_T is the valuation of the remaining energy in the batteries (Scott et al., 2013).

The total charging amounts under optimal charging are then exogenously given by total consumption and the difference between the initial and terminal SOC.

Moreover, since EVs can only be charged when connected to the grid, the vehicle location a_t extracted from the driving profiles governs the current charging capacity κ_t.[18]

$$\kappa\left(a_t\right) = \begin{cases} \kappa & \text{if } a_t \in \{Home, Work\}, \\ 0 & \text{otherwise.} \end{cases}$$

This current charging capacity then constrains the range from which ϕ_t can be chosen:

$$\phi_t \in [0, \kappa(a_t)] \quad \forall t \in [1..T] \tag{4.13}$$

4.2.5 Solution Procedure and Model Setup

Using the data described in the previous section, EV charging behavior is modeled to calculate the total locational load based on a JAVA program. This section is a combined and extended version of parts of our papers Flath et al. (2012), Flath et al. (2013) and Salah et al. (2013).

Solution Procedure

For each modeled EV a corresponding EV agent encapsulates an appropriate driving profile, a battery state-of-charge (SOC) and a charging decision logic. The iteration over the set of EV agents leads to the individual charging decisions over the model horizon. The aggregation of individual decisions yields the additional load induced by EV charging. In the following, this total EV charging load is used for the evaluation of dynamic load coordination mechanisms (DLC and DLP). Since each decision influences the aggregate load, the coordination approach parameters are updated after each individual EV agent has determined its optimal charging pattern. The optimization horizon for each EV is one week. To this end, the subsequent EV always faces the coordination mechanism parameters after the previous EV's decision. Obviously, in the case of dynamic load coordination this leads to disadvantages for EV agents scheduled later. The introduction of more granular decisions as described in our paper Flath et al. (2013) results in a marginalization of this disadvantage. However, for the analysis of average cost and the influence on local grid utilization, the ordered optimization approach is sufficient. In addition, the EVs are shuffled during the initialization of each week's optimization problem to avoid effects of sorted sequences in the following analyses. Figure 4.3 depicts a program overview (for

[18]Note that while this looks like an if-else condition this is only for compactness of expression. Each $\kappa(a_t)$ is a static expression (i.e. no decision variable) extracted from the driving profiles which are applied to build the set of constraints (4.13).

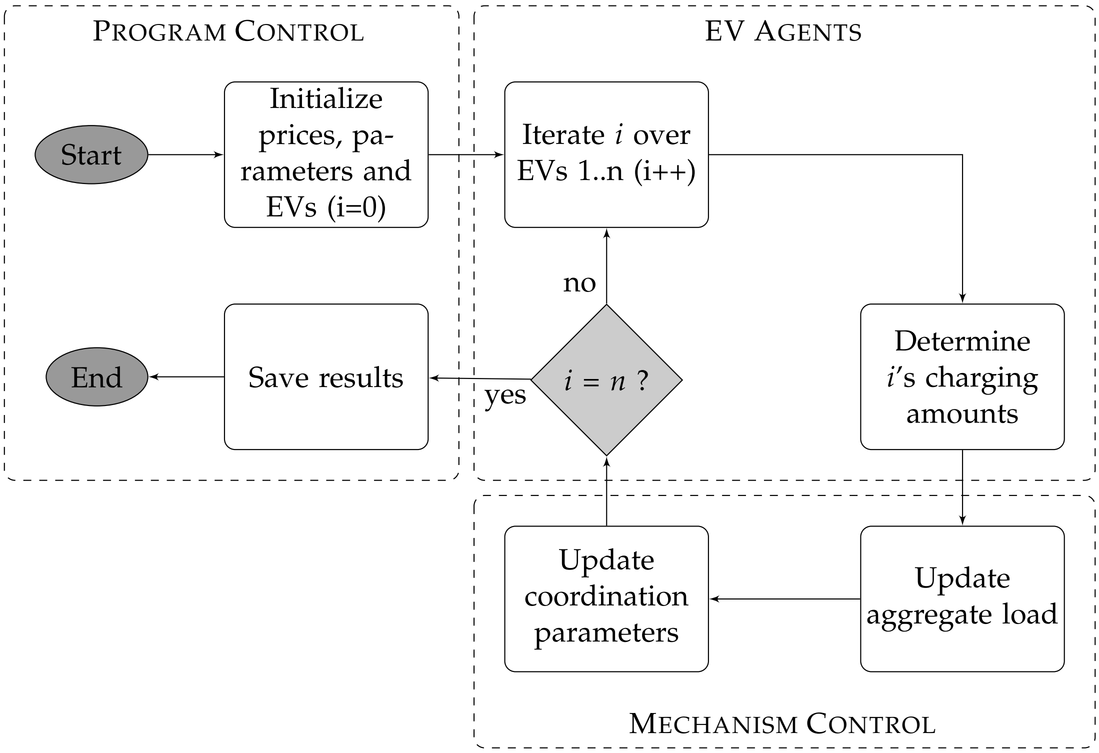


Figure 4.3: Model workflow

one week optimization horizon).

As the decision variables ϕ_t and SOC_t are real-valued and the objective function as well as all constraints are linear, the result is a standard linear optimization program. The industry-standard IBM ILOG CPLEX 12.3 solver facilitates efficient solving of the optimization problems for each modeled vehicle. Given the large problem size when charging schedules for many thousand vehicles are optimized, it is very important to ensure the linearity of the individual optimization programs. This is one reason for some simplifying model assumptions (linear charging model, fixed driving schedules) which otherwise would yield quadratic or mixed-integer problem formulations.

Model Setup for Charging Coordination

A simple scenario setup serves as basis for the analyses of local grid constraints in the context of EV charging.[19] More specifically, the local grid constraint in focus is the capacity limit of the transformer substation in the distribution grid in a specific area (e.g., load limit of the distribution transformer). If this limit is exceeded, the transformer degenerates more rapidly. Recent research on electric mobility shows that such transformer overloads are the central challenge of EV

[19] This section is an amended version of our data description used in the paper published in Transportation Science (Flath et al., 2013).

integration in distribution grids (Stoeckl et al., 2011; Gong et al., 2012). Other physical constraints such as transmission line limits or voltage drops would go beyond the scope of this thesis. As described above, the charging loads are analyzed at two possible charging locations or areas, *Home* and *Work*. The load limit for EV charging in both areas is set to $\Phi_x^{lim} = 2,000$ kW, i.e., approximately 20% of the EV population can charge simultaneously at each location at 11 kW charging power (e.g., assuming one residential and one industrial zone). These are instances of the total maximum load $\overline{L}$ introduced in Section 4.1. Using the locational information of the driving profiles to determine charging locations, this approach is similar to the analysis of residential area load as described by Rahman and Shrestha (1993).

The simulation of individual driving habits and EVs results in high computational requirements (Richardson, 2013). To keep computability on an acceptable level, 1,000 random employee driving profiles out of the 2,966 from the German Mobility Panel (Zumkeller et al., 2010) depicted in Figure 4.2 serve as a model base for EV charging load. Each vehicle is modeled individually as described in the previous section to ensure decentralized coordination based on rational and independent individual decision-making. However, because of excessive trip distances or insufficient charging time between subsequent trips, a driving profile may not be feasible with an EV. In addition, the end SOC_T condition 4.12 of the optimal charging regime results in some profiles becoming infeasible. The reason is that this thesis assumes $SOC_T = SOC_O = \overline{SOC}$ to be able to compare results of uncoordinated and coordinated charging. For these reasons, 100 infeasible driving profiles have to be removed in the base scenario (charging at home and work with charging power 11 kW).[20]

The population charging behavior is evaluated under a time-based variable external price signal which is an instance of p_t^{ext} described in Section 4.1. This thesis uses EPEX SPOT (European Power Exchange) hourly electricity prices from 2012.[21]. These prices are not directly applicable to end-consumers. However, the availability of low-cost generation capacity in the market is somehow reflected by the price variability. This way, the electricity price data also serves as a proxy for renewable generation availability. These prices neither include taxes nor license or transmission fees. Therefore, the average hourly prices of 2012 are normalized to the average retail electricity price in Germany in the same year (approximately 0.26 €/kWh).[22] In addition, the prices are interpolated linearly

[20] 73 profiles are removed due to excessive trip distances. Additional 25 profiles are removed due to $a_T \notin \{\text{Home, Work}\}$, and 2 profiles because the time after the last trip is insufficient to reach $\overline{SOC}$.

[21] `www.epexspot.com/en/market-data/`

[22] The average electricity price in 2012 for households is reported by Bundeskartellamt and

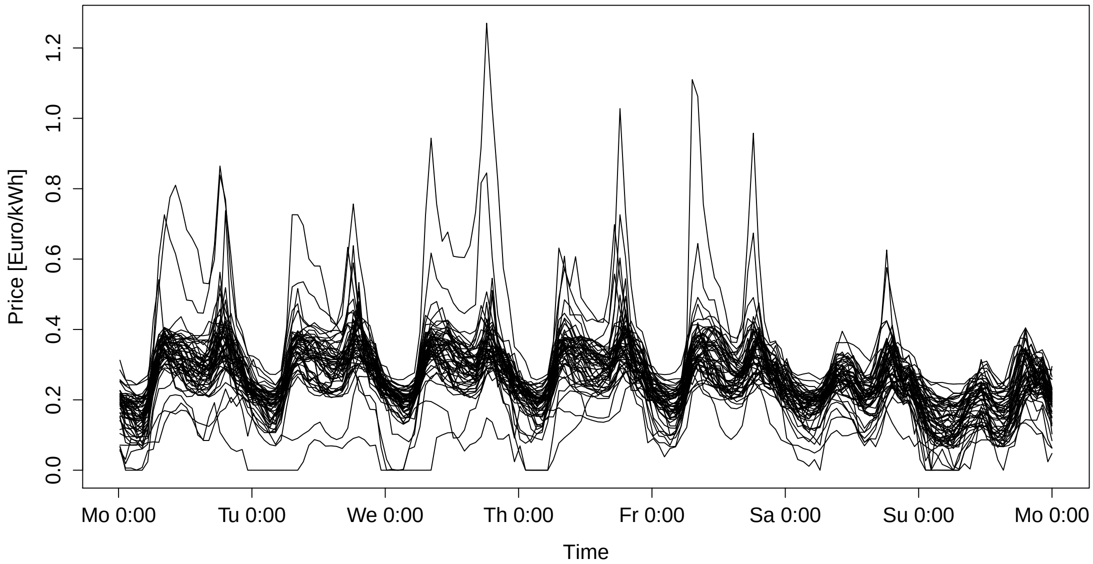


Figure 4.4: Upscaled and interpolated electricity prices of 52 weeks in 2012

to better map hourly prices to the 15-minute resolution of the driving profiles. Finally, all negative prices are set to zero to avoid gains through consumption of electricity for mobility. This is in line with the EU goals of energy efficient tariffs that do not support the waste of energy, e.g., directive 2006/32/EC. Figure 4.4 depicts the upscaled and interpolated electricity prices for one week. This approach follows prior research on smart grid and EV applications (Hartmann and Özdemir, 2011; Gottwalt et al., 2011).

4.3 Evaluation of Local Load Coordination

In the following, instances of the generic coordination approaches from Section 4.1 are analyzed in combination with EV charging. First, quantitative results of the EV charging instances are presented individually. Then, a quantitative and qualitative comparison as well as a sensitivity analysis of the load-pricing approaches are conducted to understand the influence of the different approaches and setups. The sections on uncoordinated, supply-based coordination and dynamic load pricing coordination are partly reproductions of Salah et al. (2013) and Flath et al. (2013). This section also comprises the results of Flath et al. (2013).

Bundesnetzagentur (2012) with 0.2606 €/kWh and by (BDEW, 2013) with 0.2589 €/kWh, respectively.

4.3.1 Local EV Charging Coordination

The effects of local load coordination approaches are analyzed in combination with temporal price-based coordination. First, uncoordinated and supply-based coordination with optimal charging strategies are analyzed as reference cases that ignore the locational dimension. Then, the different decentralized local load coordination approaches as well as an optimal central scenario are evaluated, using EV charging load. The respective IBM ILOG CPLEX optimization programs are provided in Appendix A – D.

Uncoordinated Charging

Uncoordinated charging (UC) without any price incentives serves as a reference scenario to evaluate the results of all other approaches.[23] The practical interpretation is a business-as-usual scenario for EV charging, since most end consumers pay a flat tariff per kWh only. In this case, the EV agents are assumed to pursue a range-maximizing charging strategy. This simplest EV agent behavior is to charge the battery whenever possible, i.e., independent of any other decision factors like SOC or charging costs. Using the battery capacity of $\overline{SOC} = 30$ kWh and the maximum charging amount in one time slot $\kappa = 2.75$ kWh the simple charging strategy is given by

$$\phi_t = \min\left[\kappa(a_t), \overline{SOC} - SOC_t\right] \tag{4.14}$$

where

$$\kappa(a_t) = \begin{cases} \kappa & \text{if } a_t \in \{\text{Home, Work}\}, \\ 0 & \text{otherwise.} \end{cases}$$

This simple charging maximizes EV range at any given time. Moreover, it requires no information on future trips of the EV customer. It can be used to analyze the feasibility of any given driving profile under EV battery restrictions and provides a maximum range benchmark. Therefore, all remaining driving profiles used are feasible under UC.[24] Uncoordinated charging mainly depends on the driving profiles and is expected to result in load spikes due to commuter mobility, i.e., in the morning at *Work* and in the evening at *Home*. Figure 4.5 depicts the resulting loads at the different locations. On the left, it shows the load over time at both charging locations *Home* and *Work* in one example week (672 time slots). On the right, all load levels throughout the simulated 52 weeks with each 672 time slots serve as the base for each location (34,944 time slots per location). The violin plots on the right of Figure 4.5 depict the distribution of occurred load

[23] A version of this section is also used in our working paper Salah et al. (2013).

[24] This charging approach was used to identify the 100 infeasible profiles at 11 kW charging speed.

levels over all 52 weeks. This type of diagram is repeated in this chapter to allow for visual comparison of the different load coordination mechanisms.

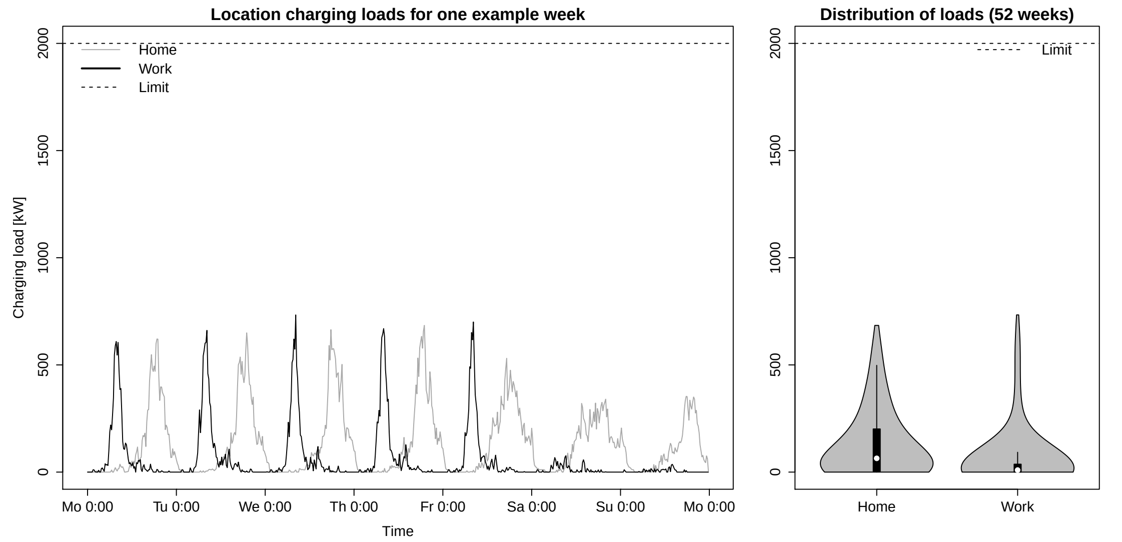


Figure 4.5: Aggregate load curve at *Home* and *Work* locations with uncoordinated charging (UC) in one example week (672 time slots) and distribution of loads over 52 weeks (34,944 time slots)

There are no observations of overloads of the given infrastructure limit at both locations. The distributed arrival times in combination with the charging speed of 11 kW leads to a low simultaneity factor. Since the driving profiles are repeated each week and charging is not price-sensitive, the looping over several weeks does not change this outcome.

However, simple charging is completely static and cannot be influenced by external signals (e.g., no response to price, congestion or renewable generation signals). In the following, the individual EV charging optimization is used — assuming full price-responsiveness on behalf of the EV agents.

Supply-based Charging

The intuitive solution of supply-based (SB) charging coordination uses the exogenous wholesale electricity market price. This serves as a reference scenario of coordination without consideration of resulting loads.[25] To this end, the coordination effect on aggregate load is analyzed under full information both on wholesale prices and trips of each individual EV agent.

Hence, the individual charging optimization model described in Section 4.2.4 is instantiated with a supply-based pricing structure. The individual EV charg-

[25] This section contains is based on parts of our paper Flath et al. (2013) where supply-based charging also serves as reference scenario.

ing objective function is:

$$\min_{\boldsymbol{\phi}} C(\boldsymbol{\phi}) = \sum_{t=1}^{T} \left(p_t^{ext} \cdot \phi_t \right) \tag{4.15}$$

subject to the constraints listed in Section 4.2.4. Given the individual optimization, all EV agents try to shift their charging demand to low-cost periods of the external price signal. Consequently, the aggregate load exhibits extreme spikes greatly exceeding 2,000 kW under wholesale electricity price coordination during low-price periods. Figure 4.6 shows the resulting load pattern for one example week and the load distribution over all 52 weeks. In addition, the exogenous price vector for the example week is depicted below the load pattern. The lower right corner shows the external price signal distribution over all 52 weeks in a violin plot as well. Note that the y-axis for the full year price distribution is different from the example week account for wholesale price spikes that occurred in other weeks of the year 2012.

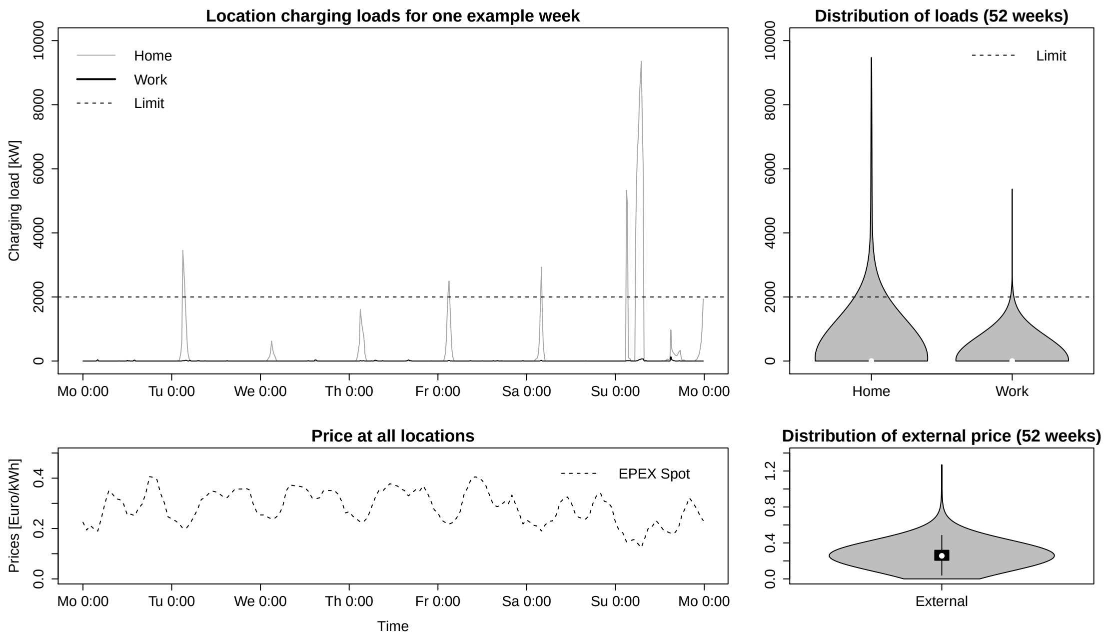


Figure 4.6: Aggregate load curve at *Home* and *Work* locations with supply-based coordination (SB) and external price signal in one example week (672 time slots) and distribution over 52 weeks (34,944 time slots)

The violin plot in the upper right corner shows that extreme load spikes also occur in other weeks of the year. These effects are in line with results from prior research on the effects of price-based coordination in retail markets (Rahman and Shrestha, 1993; Gottwalt et al., 2011). Another interesting outcome is that the charging mainly occurs at the *Home* location, even though charging is possible at both locations. The reason for this is that in the current electricity market low electricity prices typically emerge during low-demand hours at night (see Figure 4.4). Consequently, supply-based EV charging coordination leads to temporal and spatial clustering of charging activity. Therefore, the physical limits of distribution grids may be significantly challenged in residential areas by increasing EV penetration.

Static Load Curtailment

The simple solution to avoid infrastructure overloads through EV charging is to limit the maximum charging speed at the charging station. This is an instance of the SLC approach described above. As indicated in Table 4.1 the pricing structure and therefore the objective function remains the same as with supply-based charging. However, in the EV model setup, the individual charging speed is limited to

$$\frac{\overline{L}}{n} = \frac{2,000kW}{900} \approx 2.2kW. \tag{4.16}$$

This directly translates into $\kappa = 0.55$ kWh per 15 minutes time slot. Given this additional constraint, the individual EV charging optimization leads to lower peak demands, as depicted in Figures 4.7.

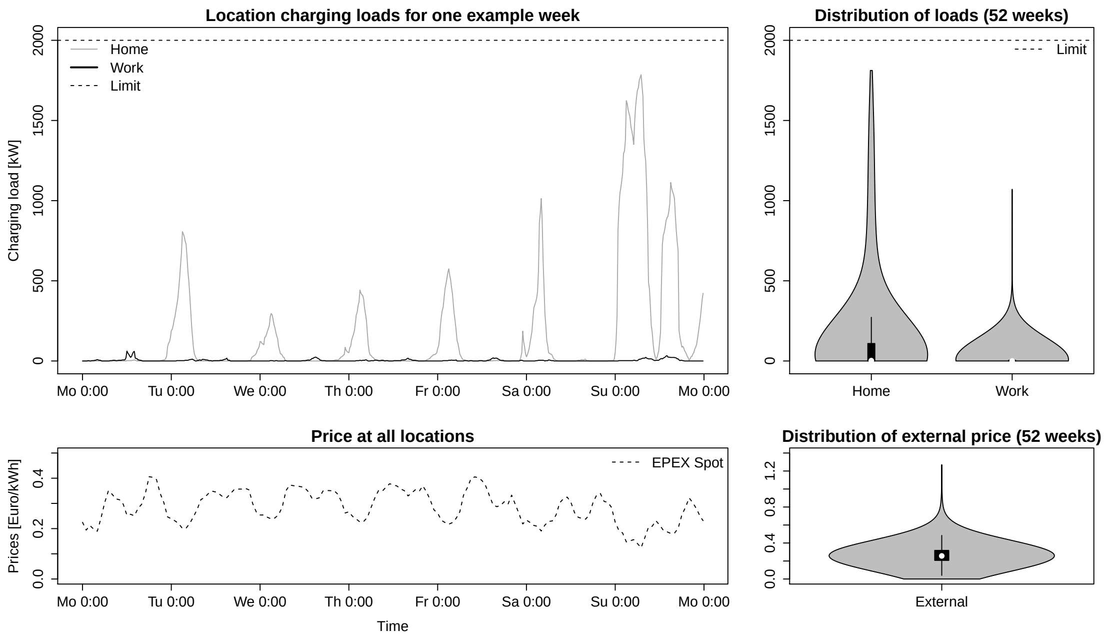


Figure 4.7: Aggregate load curve at *Home* and *Work* locations with static load curtailment (SLC) and external price signal in one example week (672 time slots) and distribution over 52 weeks (34,944 time slots)

However, these reduced loads come at the expense of lower utilization of low-cost generation which will result in higher average wholesale prices paid by consumers. In addition, limited charging speed influences the spontaneous range and renders additional profiles infeasible. These factors will be discussed in the comparison of the different coordination mechanisms at the end of this chapter.

Dynamic Load Curtailment

Obviously, the static load curtailment leads to a reduction of charging speed to avoid overloads. This is desirable if the total system load at a specific location is high. However, given no other loads, a charging speed reduction makes no sense in low-load periods, since it may hinder the consumption of low-cost generation capacity and reduces available driving range. The *DLC* approach, in contrast, starts curtailing charging loads not before total load reaches the defined infrastructure limit at a location. Given the individual charging optimization, this section calculates the "first-come first-serve" alternative only. The second option — reducing all loads equally — results in multiple optimization loops. Under full information, each EV agent needs to update its optimal charging pattern in case of load curtailments. Due to the sequential solution, this increases the required optimization time beyond being acceptable. However, from an overall load and charging cost perspective, the expected results are similar to the "first-come first-serve" alternative. The dynamic load curtailment constraint from Equation 4.4 translates into the following condition at all charging locations:

$$\begin{aligned} \sum_{i=1}^{n} \phi_{t,x}^{i} &\leq \Phi_x^{lim} \quad \forall t \in T \\ \text{where} \quad \Phi_x^{lim} &= 2,000kW \end{aligned} \tag{4.17}$$

Similar to *SLC*, the objective function and other auxiliary conditions remain the same. Given the strict capacity constraint, *DLC* succeeds in keeping the infrastructure limits as depicted in Figure 4.8. At the same time, *DLC* does not restrict consumption needlessly during low-cost time slots. However, it can result in infeasible profiles similar to *SLC*.

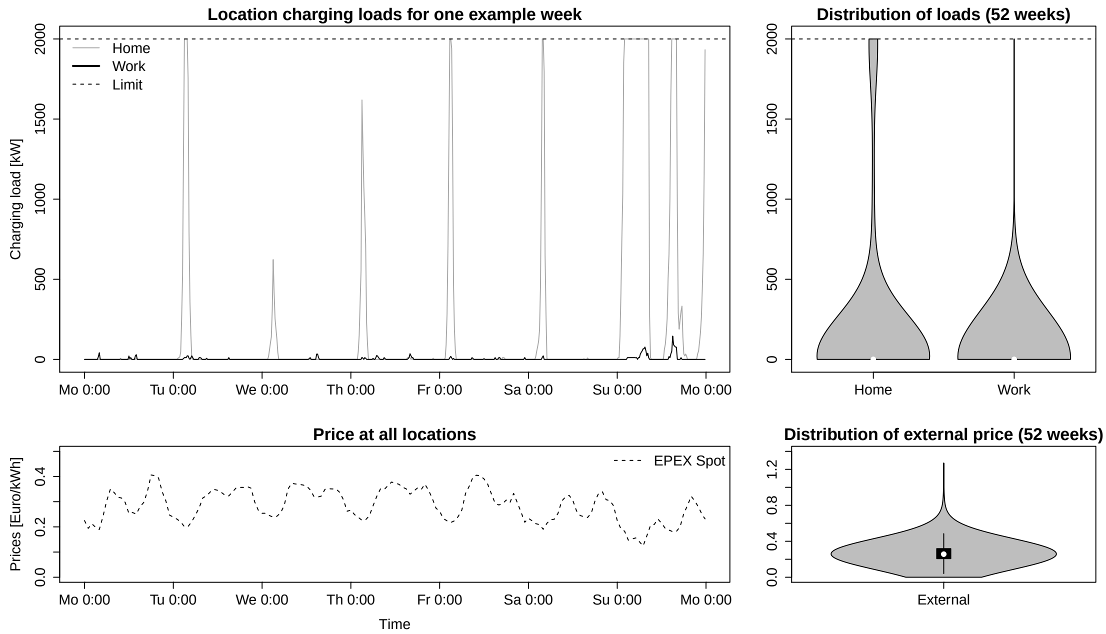


Figure 4.8: Aggregate load curve at *Home* and *Work* locations with dynamic load curtailment (*DLC*) and external price signal in one example week (672 time slots) and distribution over 52 weeks (34,944 time slots)

Static Load-Based Pricing

Load-based pricing coordination aims to overcome central load control and thus can avoid inefficient load curtailments. In the case of EV charging, it focuses on ensuring mobility by avoiding the occurrence of infeasible driving profiles. Price coordination approaches hand over the decision-making to the individual agent and allow for different valuations for the 'charging' or 'mobility service'.

Two different instances of *SLP* are evaluated within this thesis. First, a typical load pricing SLP^{max} based on the maximum load in a billing interval of one week (Δt_b). Second, a continuous load pricing SLP^t where billing and measurement interval have the same duration ($\Delta t_b = \Delta t$). As mentioned in Table 4.1, the price element in the objective function needs to be adjusted for *SLP* approaches. Under SLP^{max}, the objective function adds a payment for the maximum individual load occurred per week. As mentioned above, increasing marginal capacity costs are used to incentivize the use of lower charging speeds:

$$\min_{\boldsymbol{\phi}} C(\boldsymbol{\phi}) = \sum_{t=1}^{T} \left(p_t^{ext} \cdot \phi_t \right) + \mu \cdot \left(\max_{t \in [1..T]} \{\phi_t\} \right)^{\beta} \tag{4.18}$$

This EV charging example utilizes a quadratic function with $\beta = 2$ to represent increasing marginal load cost.[26] In this exemplary instance, factor μ which controls the influence of load price is set to unity. Similarly, the continuous load pricing SLP^t objective function for EV charging is implemented with shorter billing periods:

$$\min_{\boldsymbol{\phi}} C(\boldsymbol{\phi}) = \sum_{t=1}^{T} \left(p_t^{ext} \cdot \phi_t + \tau \cdot \phi_t^2 \right) \tag{4.19}$$

The constant factor τ determines the penalty fee for higher loads per period and is set to $\tau = 0.1$ in the current example. If it is too low, the load level influence on the total price per period is marginal and the resulting charging patterns are close to the purely supply-based coordination. In the case of this factor being too high, the individual optimization tries to minimize load peaks without integrating the external price signal. The selected value ensures in this scenario that most load peaks are reduced to adhering or only slightly exceeding the infrastructure limit. Given the maximum charging speed of $\kappa = 2.75$ kWh in one time slot, the total costs are approximately split even between the *SLP* component and the average external price at this limit. Such scaling is not possible for μ in the SLP^{max} approach because the average influence of the *SLP* component per kWh depends on the total consumption per week, which differs per vehicle. A more detailed sensitivity analysis of both factors is presented in Section 4.3.3. As depicted in the overview, Figures 4.9, and Figures 4.10, both approaches lead to a peak load reduction.

Obviously, the *SLP* approaches cannot guarantee total load to stay within infrastructure limits. Depending on the implementation, the main difference is that SLP^{max} results in an individual optimal selection of a maximum charging speed for a whole week. Whereas, under SLP^t the EV agents balance between energy and load cost in each time slot separately.

[26]The next section of this thesis shortly discusses the reasons for convex cost functions.

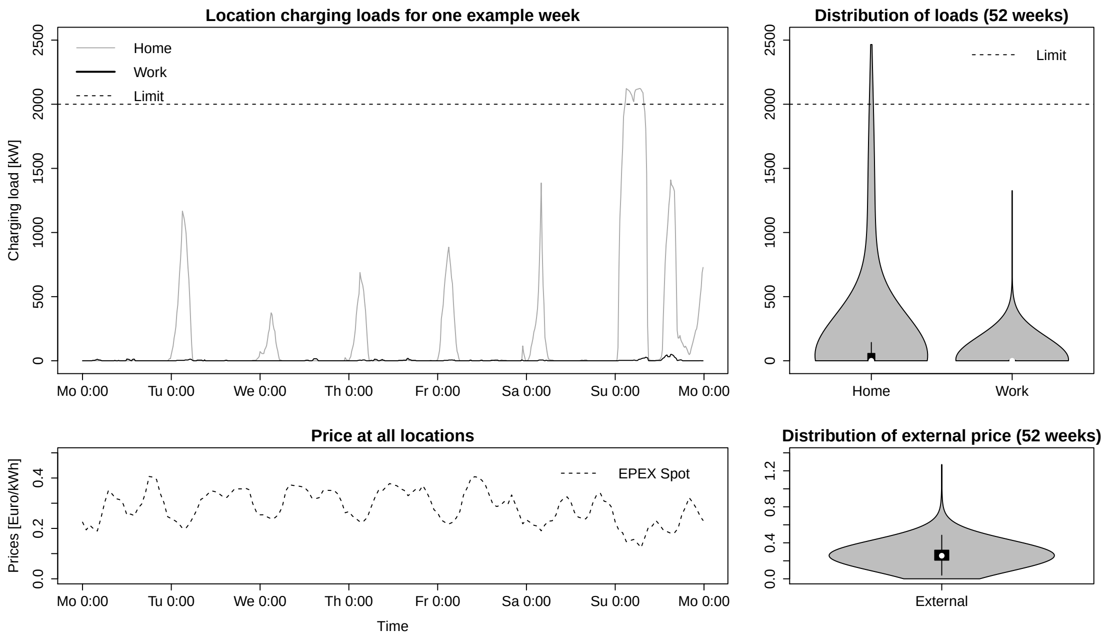


Figure 4.9: Aggregate load curve at *Home* and *Work* locations with SLP^{max} coordination and external price signal in one example week (672 time slots) and distribution over 52 weeks (34,944 time slots)

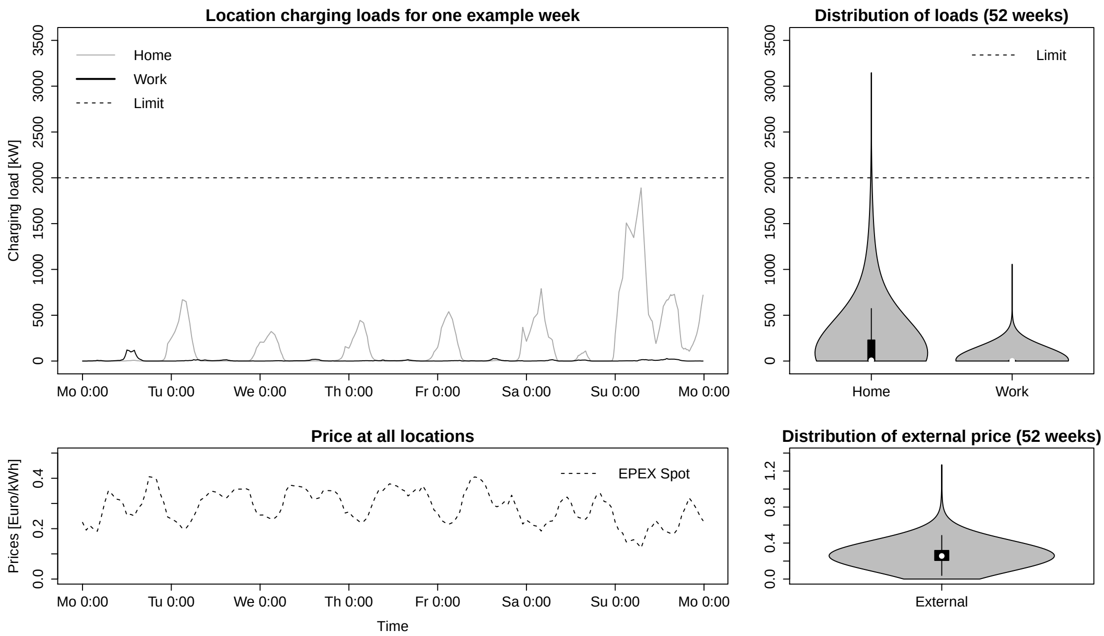


Figure 4.10: Aggregate load curve at *Home* and *Work* locations with SLP^{t} coordination and external price signal in one example week (672 time slots) and distribution over 52 weeks (34,944 time slots)

Dynamic Load-Based Pricing

Static load pricing is not sufficient due to still existing overloads. In addition, in a practical example the available infrastructure capacity might vary over time. Therefore, *DLP* is applied to the EV charging model in the form of dynamic prices at the available charging locations *Home* and *Work*. This section describes in detail the instance of a *DLP* approach in the form of local area pricing, based on our paper (Flath et al., 2013).[27] Following the theory on road pricing (Arnott and Small, 1994), this approach aims to improve coordination by introducing a location surcharge that reflects the difference between the social costs of charging and the private costs of users. In road congestion pricing marginal cost pricing is used, where the price is the sum of marginal costs to the road provider and the opportunity costs of the congestion delay of all drivers. These marginal costs increase with each additional driver according to their influence on average speed. This is not directly comparable with the situation in the power grid. However, there are reasons why a similar capacity pricing scheme seems promising for local power grids:

- Additional utilization increases the risk of grid failures for all users
- Losses increase disproportionately with energy flow
- Infrastructure wear increases with additional load

Due to these reasons, the *DLP* approach needs to fulfill the first condition: The instantaneous dynamic local price component $p^{loc}_{t,x}$ at location x is increasing in the total current load at this location $\Phi_{t,x}$, that is

$$\frac{\partial p^{loc}_{t,x}}{\partial \Phi_{t,x}} > 0. \tag{4.20}$$

As noted by MacKie-Mason and Varian (1995b), there is no need for economic coordination when available capacity greatly exceeds demand. On the other hand, if quantity demanded exceeds quantity supplied, capacity allocation is important to ensure system reliability. Therefore, the increase of the local price component should be increasing in the local utilization level, which leads to a convex cost function:

$$\frac{\partial^2 p^{loc}_{t,x}}{\partial^2 \Phi_{t,x}} > 0 \tag{4.21}$$

This local price needs to be adjusted such that the local load infrastructure limit Φ^{lim}_{x} is not exceeded in any time slot. As substations exhibit temporally varying residual load patterns, it could well be imagined that the infrastructure

[27] This sections is in large parts a reproduction of our paper on area pricing (Flath et al., 2013).

limit itself could be time-varying. Denoting substation utilization by $z = \frac{\Phi_{t,x}}{\Phi_x^{lim}}$ the following pricing function parameterized by ξ is used to determine location-specific prices fulfilling conditions (4.20) and (4.21):

$$p_{t,x}^{loc} = \begin{cases} \frac{e^{\xi z}-1}{e^{\xi}-1} p_{lim}^{loc} & \text{if } z < 1 \\ p_{lim}^{loc} & \text{if } z \geq 1 \end{cases} \tag{4.22}$$

where p_{lim}^{loc} is the locational surcharge at the infrastructure limit $z = 1$. Some exemplary pricing functions using different values for ξ are depicted in Figure 4.11. This *DLP* approach is applied in the model to update the charging prices dynamically given the charging activity at different locations. After a customer's charging decision has been made, the adjusted price for the current location is updated to reflect the load increase and the subsequent customers experience adapted prices.

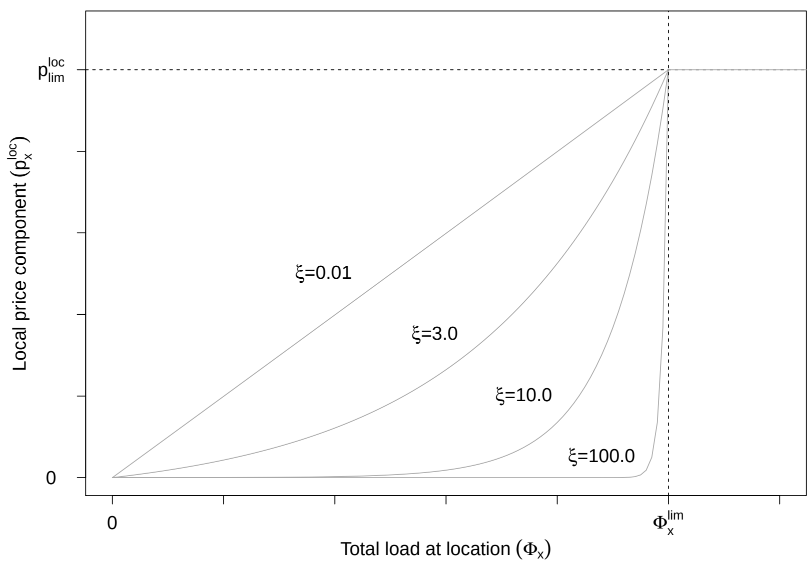


Figure 4.11: Examples of dynamic local pricing function for different values of ξ

In the following, the limit price p_{lim}^{loc} is based on the median price of the external price p^{ext} of the respective week. Given the dynamic adjustment, the share of the local price is especially high in "congested" time slots. As mentioned above, the EV agents optimize their charging pattern based on a price vector including the local price component which is updated after each EV. The shuffling of EVs minimizes the effects of sorted sequences ("unfairness"). To illustrate the effect, the intermediate case ($\xi = 3$) from Figure 4.11 serves as an example. As charging is triggered by low electricity prices, the area price component increases greatly in time slots with low external prices. Figure 4.12 shows the resulting loads and prices at the locations using optimal EV charging in an example week. The depicted prices represent the price level reached after the final EV's charging decision.

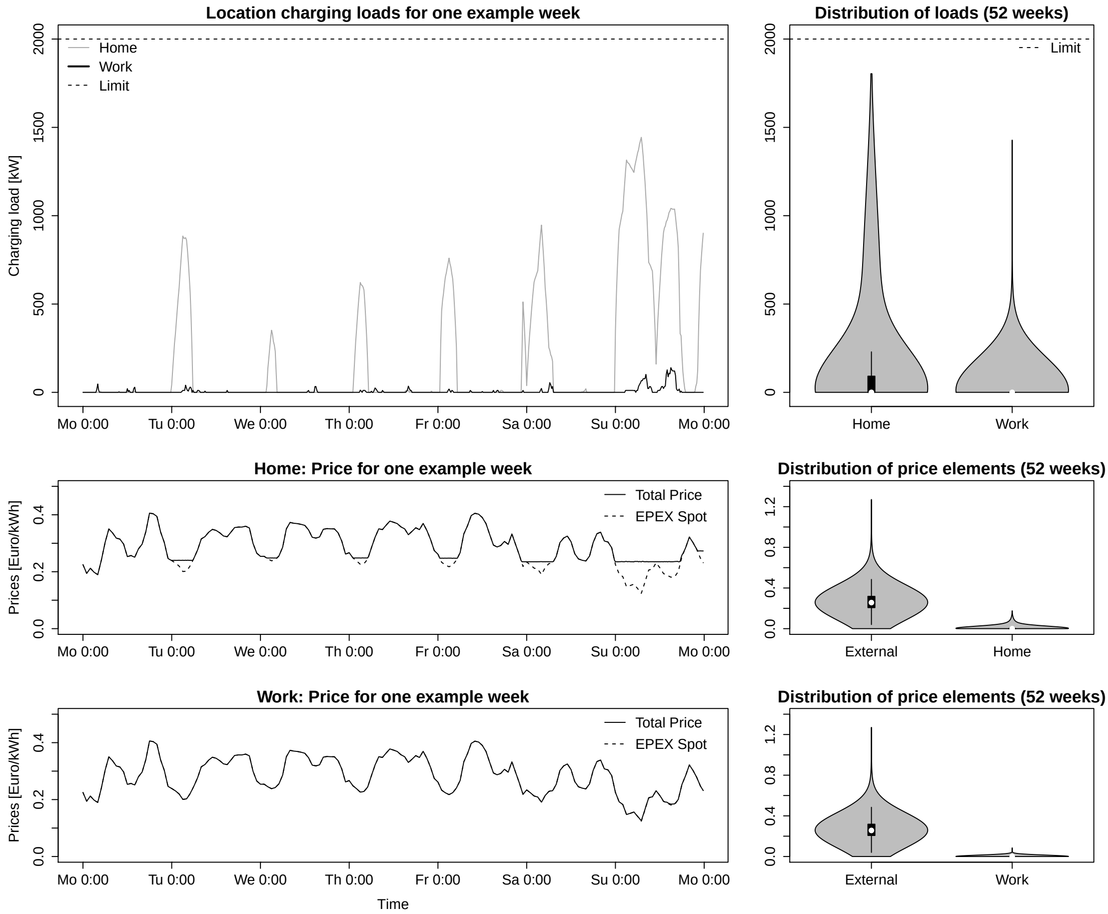


Figure 4.12: Aggregate load curve at *Home* and *Work* locations with *DLP* coordination and external price signal in one example week (672 time slots) and distribution over 52 weeks (34,944 time slots)

Higher loads still occur at the *Home* location because low wholesale electricity prices still occur during nighttime. Notably, the local load in all 52 simulated weeks never reaches the limit Φ^{lim} at any location, which also indicates that the local limit price p_{lim}^{loc} is never reached in both locations. The distribution of the different price elements in the lower right corner shows that the additional local surcharges remain on low levels. Specifically, there is hardly any local surcharge at *Work*, which indicates that load levels are well below the given capacity limit. As mentioned before, the additional revenues generated by location-specific surcharges can be used for other purposes, e.g., capacity expansion. In summary, dynamic local price increases lead to both temporal and spatial shifts in individual charging decisions and reduce load peaks significantly.

Optimal Central Planning of EV Charging

An optimal central planner (*OPT*) serves as a reference case for the quantitative comparison of the different coordination approaches. To this end, the central planner has full information both about wholesale prices and trips of each individual EV agent i. The main difference is that all charging schedules are optimized centrally and not individually for one week:

$$\min_{\boldsymbol{\phi}^i} \sum_i C\left(\boldsymbol{\phi}^i\right) = \sum_i \sum_{t=1}^{T} \left(p_t^{ext} \cdot \phi_t^i\right) \tag{4.23}$$

The optimization is subject to the constraints 4.11, 4.12 and 4.13 for each individual EV. In addition, the maximum load restrictions used in *DLC* at *Home* and *Work* (Equation 4.17) are directly implemented in the optimization model:

$$\sum_{i=1}^{n} \phi_{t,x}^i \leq \Phi_x^{lim} = 2,000 \text{ kW} \quad \forall t \in T.$$

Given this implementation, the CPLEX solver calculates an overall cost minimizing charging pattern for each week which at the same time fulfills the grid limits and ensures mobility needs. The introduced overview graph shows that the load limits are always exactly reached, but never exceeded in time slots with low wholesale prices (Figure 4.13). In the following, this central planner approach serves as a quantitative reference.

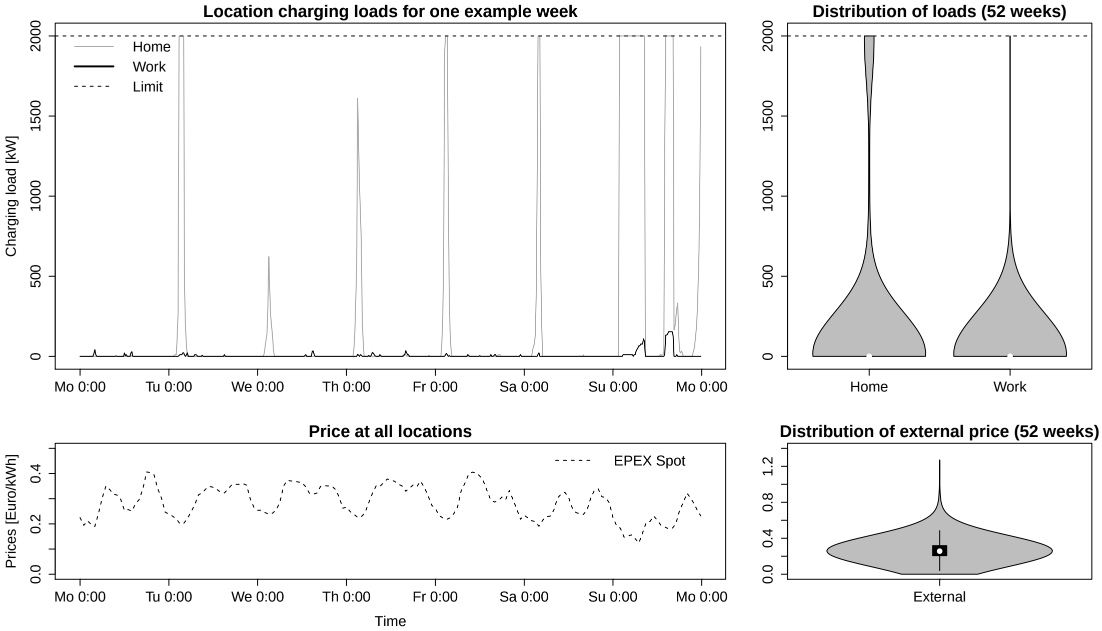


Figure 4.13: Aggregate load curve at *home* and *work* locations given a central planner (OPT) and external price signal in one example week (672 time slots) and distribution over 52 weeks (34,944 time slots)

4.3.2 Quantitative Comparison

Figure 4.14 shows the load variability over 52 weeks for the implemented charging coordination approaches at the *Home* location — where the majority of consumption occurs. For completeness, a similar diagram for the *Work* location is provided in Appendix E. The figure demonstrates that all approaches that combine the external price signal with some form of infrastructure load coordination lead to relatively similar load patterns. The main charging load is clustered in low-cost night hours and at weekends. Overall, the resulting load curves of the DLC approach seem to match the OPT load curves the best. Both approaches fully utilize available capacity in low-cost time slots and do not exceed infrastructure limits by design. The static individual coordination approaches (SLC/SLP) and DLP exhibit very similar patterns. In the following, a more detailed analysis based on important indicators is performed.

Obviously all approaches which incorporate load as an influencing factor of coordination succeed in reducing the loads significantly. However, in detail the approaches vary widely in efficiency and effectiveness. Quantitatively the results of the EV charging coordination approaches are evaluated using the following dimensions:[28]

Average cost (whsl): The average wholesale (whsl) cost per kWh can serve as

[28]We used similar dimensions in our paper Flath et al. (2013).

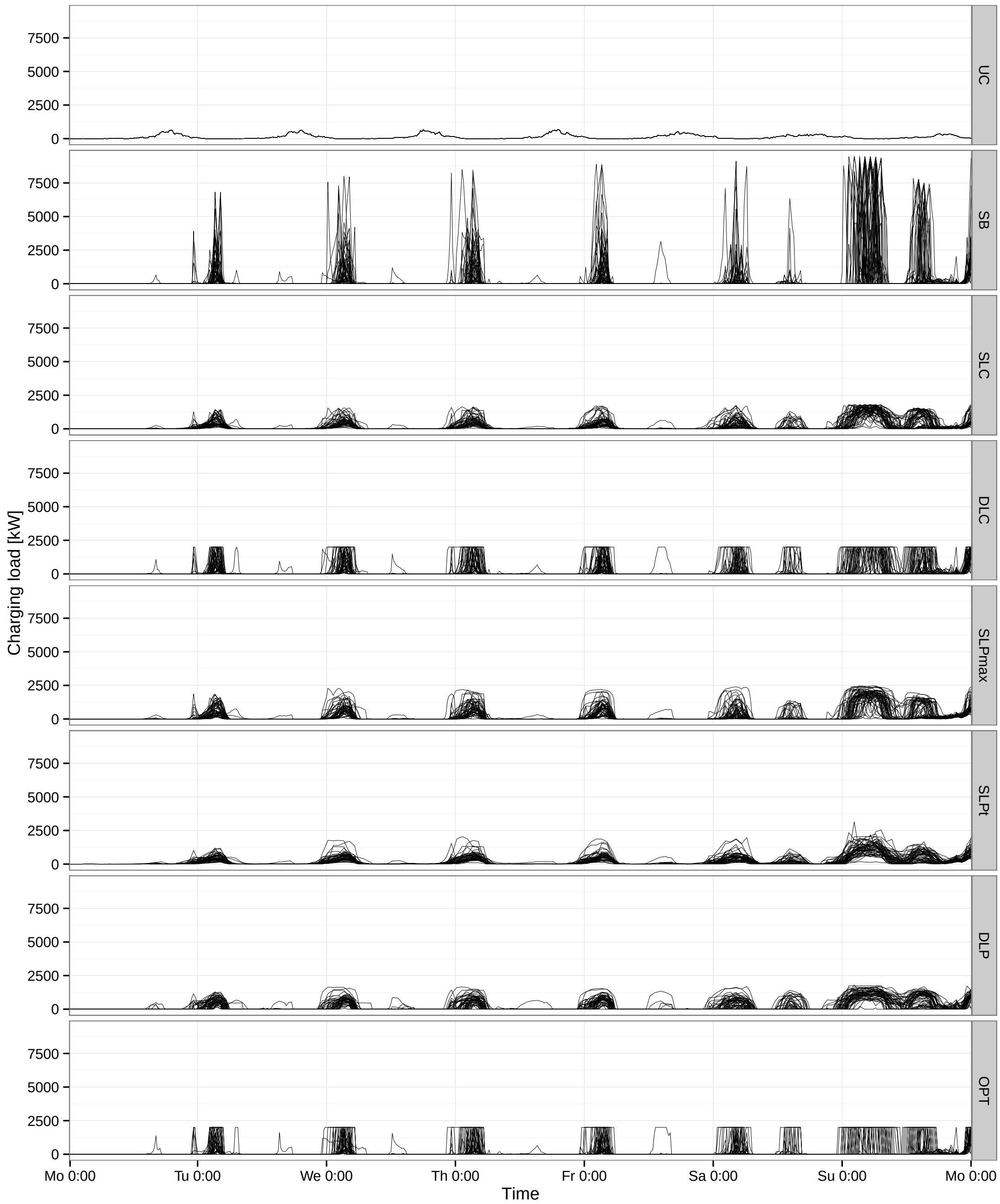


Figure 4.14: Comparison of charging coordination outcomes at *Home* over 52 weeks

an indicator for the ability of the charging coordination to incentivize the consumption of low-cost supply (or RES infeed). With low wholesale cost the important target of integrating the supply availability is achieved. The additional revenues from load-based pricing are intentionally omitted to preserve comparability. As mentioned above, these costs can be redistributed or used for capacity investments. The difference in individual cost is obvious, but not within the scope of this thesis. The cost obtained under *SB* charging coordination provides a lower bound for average wholesale cost.

Average SOC: The average SOC represents the spontaneous range availability of the EV population. In the following, the average SOC is represented in a percentage of the maximum SOC. A higher average SOC indicates a high availability of mobility services. Since range anxiety is one of the main obstacles of EV penetration, this is an important factor for EV adoption (Eberle and von Helmolt, 2010). The UC serves as the maximum possible benchmark in this scenario.

Average infeasible profiles: The average number of infeasible profiles per week indicates the level of guaranteed mobility. Canceling trips which are possible with other charging coordination mechanisms may induce customer dissatisfaction. The risk of infeasible rides may even prevent EVs from gaining share in the individual mobility market. However, there is always the outside option of using a non-electric vehicle to fulfill mobility needs.

Overloads: The number of overloads indicates the effectiveness of congestion mitigation. While overloads should ideally not occur at all, the grid infrastructure elements are able to cope with limited overloads for a short period of time.

Maximum load: The maximum load occurred at each location indicates the magnitude of overloads and therefore helps to understand if given grid infrastructure might tolerate this for a short period. On the other hand, low maximum loads reveal that given capacity is not fully utilized and coordination mechanisms might be adjusted to allow higher loads.

Locational consumption: The share of total charging consumption at the locations *Home* and *Work* stands for the influence of the mechanisms to induce locational load shifts.

The important variables characterizing the outcome of each coordination approach are compared in Table 4.4. In addition to the base case of 2,000 kW, all approaches have been simulated using a local load limit of $\Phi_x^{lim} = 1,000$ kW to investigate potential differences with less spare capacity.

Regarding the wholesale cost, the cost-optimal *SB* benchmark of $0.135\frac{€}{kWh}$ is a hypothetical solution only, since the goal is to avoid overloads and the maximum load of 9,470 kW is not acceptable. The realistic benchmark which incorporates the local infrastructure limits are results of a central planner (*OPT*) with full information: $0.144\frac{€}{kWh}$ ($0.159\frac{€}{kWh}$ at $\Phi_x^{lim} = 1,000$ kW). The other extreme in terms of average wholesale cost is uncoordinated *UC* charging.

			UC		*SB*		*SLC*		*DLC*		SLP^{max}		SLP^{t}		*DLP*		*OPT*	
	Dimension		Home	Work	Home	Work	Home	Work	Home	Work	Home	Work	Home	Work	Home	Work	Home	Work
Limit 2,000 kW	Avg. cost (whsl)	[$\frac{€}{kWh}$]	0.307		0.135		0.155		0.145		0.149		0.163		0.154		0.144	
	Avg. SOC	[pct.]	98.7%		69.9%		68.2%		70.8%		71.7%		73.6%		72.1%		71.1%	
	Avg. Inf. Prof.	[#]	0		0		52.0		1.0		0		0		0		0	
	Overloads	[#]	0	0	975	19	0	0	0	0	425	0	50	0	0	0	0	0
	Max. Load	[kW]	684	733	9,470	5,361	1,812	1,071	2,000	2,000	2,465	1,327	3,146	1,057	1,804	1,428	2,000	2,000
	Home Cons.	[pct.]	68.8%		97.0%		95.9%		96.5%		96.9%		94.9%		93.1%		95.9%	
Limit 1,000 kW	Avg. cost (whsl)	[$\frac{€}{kWh}$]	0.307		0.135		0.175		0.159		0.149		0.163		0.172		0.159	
	Avg. SOC	[pct.]	98.7%		69.9%		66.9%		72.0%		71.7%		73.6%		74.7%		72.7%	
	Avg. Inf. Prof.	[#]	0		0		105.0		5.0		0		0		0		0	
	Overloads	[#]	0	0	1,501	33	0	0	0	0	2,636	21	1,323	4	26	0	0	0
	Max. Load	[kW]	684	733	9,470	5,361	824	484	1,000	1,000	2,465	1,327	3,146	1,057	1,239	797	1,000	1,000
	Home Cons.	[pct.]	68.8%		97.0%		93.4%		95.7%		96.9%		94.9%		91.4%		94.1%	

Table 4.4: EV model results with different charging coordination approaches at 11kW

All load-pricing and load-curtailment approaches succeed in reducing the average wholesale cost in comparison to *UC*. Considering the *OPT* benchmark, *DLC* clearly yields a very good average cost outcome in comparison to the other approaches. However, both load curtailment options result in infeasible profiles due to their nature of external control. This is a major disadvantage of these approaches. The simulation with $\Phi_x^{lim} = 1,000$ kW demonstrates the increasing risk of having infeasible profiles with load curtailment and limited infrastructure capacity.

On the other hand, in terms of overloads, *SLC* and *DLC* can ensure avoidance by design, whereas all load-pricing approaches are prone to experience overloads. As expected, significant overloads occur in supply-based coordination. SLP^{max} and SLP^{t} fail to ensure infrastructure limits in the current setup in both instances. Both do not react to the limit change from 2,000 kW to 1,000 kW, similar to uncoordinated *UC* and cost-optimal *SB* charging. Notably, in the provided instance the *DLP* approach fully avoids overloads at the 2,000 kW level and leads to minor overloads at the 1,000 kW level by incorporating the total load information.

The average SOC is around 70% for all load coordination approaches and yields limited additional insights. This is also caused by the start and end constraints for each week which enforce a full battery (100%). Concerning the exemplary EV used in this simulation, 70% is translated into approximately 140 km of spontaneous range. The dimension of locational consumption affirms the initial finding that with wholesale price-based load coordination, EV charging loads are shifted into night hours when vehicles are at *Home*. Only *UC* yields a stronger dispersion of charging activity over both charging locations.

In summary, *DLC* dominates *SLC* in all dimensions. It is also better than the load-pricing approaches in terms of average wholesale cost. In addition, it ensures adherence to load limits but at the cost of some infeasible profiles. The cost disadvantage of the load-pricing approaches may be caused by the initializations of the factors τ, μ and ξ used. The fact that the maximum loads in the *DLP* scenario do not reach the local limit in the 2,000 kW example supports this assumption. Therefore, the sensitivity of load-pricing approaches will be further investigated in the following.

4.3.3 Sensitivity Analysis of Load-Pricing Approaches to Different Parameter Initializations

Given the dependence of all presented load-pricing approaches on their parameter setup, this section discusses the outcome sensitivity on different initializations. Due to the extensive computation required to optimize all 52 weeks of the year, only a few variations of the relevant parameters are performed to gain an understanding of the resulting impact.

Sensitivity of SLP^{max} Approach

The presented SLP^{max} approach is influenced by varying the constant μ in Equation 4.18 which trades off overloads and costs. The initial implementation with $\mu = 1$ leads to lower wholesale cost in comparison to most other local load coordination approaches (see Table 4.4), but at the same time some overloads occurred at the *Home* location. Increasing the parameter μ results in higher individual load prices even at low charging levels. For this reason, EV agents reduce their charging levels and shift load to time slots with higher wholesale prices. As shown in Table 4.5, the average wholesale price increases and overloads are eliminated. In contrast, lowering μ results in also lower wholesale prices and increasing maximum loads as well as more overloads at the *Home* location.

			μ							
			0.5		1		3		10	
			Home	Work	Home	Work	Home	Work	Home	Work
SLP^{max}	Avg. cost (whsl)	[$\frac{€}{kWh}$]	0.145		0.149		0.158		0.171	
	Avg. SOC	[pct.]	71.2%		71.7%		72.7%		74.6%	
	Avg. Inf. Prof.	[#]	0		0		0		0	
	Overloads	[#]	917	0	425	0	0	0	0	0
	Max. Load	[kW]	3,232	1,824	2,465	1,327	1,885	876	1,291	620
	Home Cons.	[pct.]	97.0%		96.9%		96.5%		95.2%	

Table 4.5: Impact of parameter μ on outcome of SLP^{max} approach

For the scenario discussed in this thesis, the setup which avoids overloads and still uses low-cost wholesale time slots is roughly $1 < \mu < 3$ with average wholesale cost between 0.149 $€/kWh$ and 0.158 $€/kWh$. To determine the optimal setup of parameter μ, the cost of overloads would need to be calculated. Given the large investments and long service life of transformers, this goes beyond the scope of this thesis.

Sensitivity of SLP^t Approach

The SLP^t approach depends on the initialization of τ. The previously discussed instance $\tau = 0.1$, forces EV agents to use high charging speeds in time slots with low wholesale prices only. However, the average wholesale costs are high relative to other approaches in Table 4.4, while overloads can still occur. Instances with higher values for τ reduce the number and magnitude of overloads. The EV agents are faced with higher individual charging cost at low charging levels already. To this end, the charging loads are shifted into other time slots where the sum of external price signal and individual load price is lower. This shift leads to higher average wholesale cost which indicates that SLP^t cannot incentivize the advantageous use of low-cost or renewable generation given greater τ's. However, small τ's result in even more overloads. The optimal setup to avoid overloads is roughly $0.1 < \tau < 0.3$, with average wholesale cost between 0.163 €$/kWh$ and 0.189 €$/kWh$. Similar to μ, the calculation of an optimal τ is dependent on the cost of overloads and goes beyond the scope of this thesis.

Generally, both SLP approaches converge to the SB coordination regime for $\mu \to 0$ or $\tau \to 0$, respectively.

Sensitivity of DLP Approach

DLP area pricing avoids overloads of local infrastructure under a specified parameter set. A similar sensitivity analysis for DLP has previously been conducted in our paper Flath et al. (2013). In the example configuration of the previous sections, infrastructure limits are not exceeded given the 2,000 kW instance. However, the average wholesale prices paid are among the highest, with exception of UC (Table 4.4). The reason might be the setup of the DLP pricing approach with a factor of $\xi = 3$ which is not strongly diverging from a linear price increase (see Figure 4.11). We analyze effects on aggregate load at *Home* for different choices of ξ which controls the sensitivity of the local load coordination. Notably, the load share at *Home* accounts for around 90% of the total charging loads. Table 4.7 depicts the load distribution with varying ξ at both locations. If ξ is set to low values near zero, the local load pricing component tends to increase linearly in the load. This leads to increasing total prices even at low load levels and avoids higher loads. On the one hand, this is favorable for the local infrastructure, as realized loads stay well below the limit level. On the other hand, EV owners are prevented from fully utilizing time slots with low wholesale prices due to a dominating local price component even with available local infrastructure capacity. For higher levels of ξ local prices exhibit very limited increases at low load levels. We observe high loads more often with high ξ initializations, since the locational component increases only with high loads (near transformer capacity limit), while occurrences of medium loads decrease.

			τ							
			0.01		0.1		0.3		0.5	
			Home	Work	Home	Work	Home	Work	Home	Work
SLP^t	Avg. cost (whsl)	[$\frac{€}{kWh}$]	0.139		0.163		0.189		0.203	
	Avg. SOC	[pct.]	70.8%		73.6%		77.0%		78.8%	
	Avg. Inf. Prof.	[#]	0		0		0		0	
	Overloads	[#]	960	14	50	0	0	0	0	0
	Max. Load	[kW]	9,389	3,649	3,146	1,057	1,429	549	1,031	415
	Home Cons.	[pct.]	96.8%		94.9%		91.0%		88.4%	

Table 4.6: Impact of parameter τ on outcome of SLP^t approach

Demand is more concentrated in times of low wholesale prices which reduces charging costs. For high values of ξ the average wholesale charging cost even converges to the results of *OPT* or *DLC*. However, the risk of overloads increases, since the infrastructure is frequently operated at its physical limit and each EV agent individually decides on its own charging pattern. Especially EV agents with long distances and short recharging times — which means low flexibility — increase the risk of ad hoc individual inflexible demand. This uncertainty increases the risk of overloads when infrastructure is more often operated at its limit.[29] In the simulation runs, some sporadic overloads of the transformer could be observed at *Home* for $\xi = 100$.

Overall, ξ has a great effect on the coordination result and the resulting loads. In choosing this parameter, system operators can balance the risk of infrastructure overloads at a specific location against the utilization of available low-cost generation.

[29] The same would apply for uncertainty of other loads that are currently not considered in the model.

		ξ					
		0.01	0.10	1.00	3.00	10.00	100.00
Avg. cost (whsl) [$\frac{€}{kWh}$]		0.165	0.165	0.161	0.154	0.147	0.145
Avg. cost (loc) [$\frac{€}{kWh}$]		0.035	0.034	0.028	0.015	0.003	0.000
Avg. SOC [pct.]		73.8%	73.8%	73.0%	72.1%	71.3%	70.9%
Load distr. at *Home* [% of total]	0-100 kW (%)	64.01	64.37	68.14	75.14	83.99	85.25
	100-500 kW (%)	23.55	22.97	17.13	8.40	3.76	4.56
	500-1,000 kW (%)	10.06	10.20	11.37	10.69	1.62	1.80
	1,000-1,500 kW (%)	2.11	2.19	3.08	5.10	5.46	1.08
	1,500-2,000 kW (%)	0.25	0.26	0.28	0.67	5.17	7.26
	$>$ 2,000 kW (%)	0.00	0.00	0.00	0.00	0.00	0.05
Load share at *Home* (%)		90.59	90.78	92.37	94.48	96.07	96.50
Max. load at *Home* (%)		1,942	1,934	1,855	1,804	1,918	2,013
Load distr. at *Work* [% of total]	0-100 kW (%)	94.64	94.82	96.21	97.76	98.70	98.91
	100-500 kW (%)	5.20	5.01	3.60	1.95	1.08	0.91
	500-1,000 kW (%)	0.12	0.12	0.13	0.21	0.06	0.05
	1,000-1,500 kW (%)	0.03	0.04	0.06	0.08	0.09	0.03
	1,500-2,000 kW (%)	0.00	0.00	0.00	0.00	0.07	0.10
	$>$ 2,000 kW (%)	0.00	0.00	0.00	0.00	0.00	0.00
Load share at *Work* (%)		9.41	9.22	7.63	5.52	3.93	3.50
Max. load at *Work* (%)		1,087	1,097	1,215	1,428	1,773	1,984

Table 4.7: Impact of ξ on average costs and load at *Home* and *Work* with individual EV charging optimization

4.3.4 Qualitative Comparison

From a qualitative perspective the load coordination approaches can be evaluated along seven criteria. An aggregated summary of the comparison is shown in Table 4.8. The central planner is not rated qualitatively, since the central control approach is merely used as a hypothetical quantitative benchmark in this thesis. For each criteria there is a benchmark (*BM*) solution. All other approaches are rated either performing good (+), average (○), or worse (−) than the others, using a qualitative ranking.

Communication complexity Communication complexity depends on the diversity of information, number of senders and receivers, and frequency of communication. Without load coordination, *UC* serves as a benchmark (*BM*), since no information needs to be exchanged, except for billing purposes. *SB*, *SLC* and *SLP* coordination merely require broadcasting of current prices (+). *DLC* needs to add a simple local control signal if maximum capacity is reached (○). In contrast, *DLP* requires an additional local price signal communicated to all end consumers ($-$).

Tariff/contract complexity Nearly the same reasoning as for communication complexity applies to the tariff or contract structure. Again, uncoordinated charging serves as a benchmark (*BM*). *SB* has slightly higher complexity due to variable supply prices ($+$). *SLC* and *SLP* add prices or curtail load based on individual limits which is fairly complex ($\circ$). In contrast, dynamically integrating local load levels, either in the curtailment option (*DLC*) or the pricing function (*DLP*), yields the highest complexity of approaches discussed in this thesis ($-$).

Infrastructure limit protection By design, the load-curtailment approaches *SLC* and *DLC* ensure adherence to infrastructure limits (*BM*). SB is a worst case scenario of load clustering and does not consider infrastructure limits ($-$). Depending on the load type, *UC* keeps the load within the limits ($\circ$). The load pricing approaches are all likely to ensure infrastructure limit protection given a reasonable parametrization ($+$). However, all static approaches benefit from omitting other loads in the presented scenarios.[30]

Consumption guarantee In the EV charging example, profile feasibility can be seen as a proxy for guaranteeing consumption. Following this reasoning, all approaches allow desired consumption at any time (*BM*), except for the load curtailment options ($-$). This is a disadvantage and not compatible with today's expectations of reliable power supply almost independently from the type of load.

Comfort level The comfort level is a transcription for the safety distance kept from minimum required user limits. The spontaneous mobility in the EV case serves as proxy for this criterion. Therefore, *UC* serves as a benchmark scenario, since it always ensures consumption as early as possible (*BM*). All other approaches lead to small differences in the average SOC in the given parameter instances ($\circ$). However, the comfort level also heavily depends on the parametrization.

Desired supply utilization The uncoordinated approach does not incentivize load shifts to desired supply (e.g., low-cost, RES) at all ($-$). All other approaches incorporate incentives to shift load into periods with low-cost wholesale prices. Obviously, the *SB* coordination serves as a benchmark in terms of desired supply utilization (*BM*). However, given the individual information base, *SLC* and *SLP* can limit loads, even if it is not necessary in

[30] The Swiss grid planning impact study, which is presented in the next section, includes these other loads in the analysis.

terms of aggregate load (○). In contrast, *DLP* and *DLC* influence demand only if it is necessary due to aggregate infrastructure limits (+).

Efficiency/Fairness The efficiency or fairness criterion is more weakly defined in this case and combines several aspects of the other criteria. Basically, it rates whether the coordination approach is able to differentiate between low and high load valuation. This means that in time slots with capacity constraints preferably demand with high valuation is served. *UC*, *SB*, *SLC* and *DLC* cannot distinguish between different valuations for demand in capacity-constrained time slots (−). For *UC* and *SB*, this is because capacity is not considered at all. *SLC* and *DLC* are forms of direct control and therefore could integrate different valuations in forms of static contracts only (i.e., only low valuation loads that can cope with curtailment will accept these approaches). *SLP* adds the dynamic pricing of load and therefore leads to prudent usage of high load levels. However, *SLP* still focuses on own load only and does not lead to shifts of unnecessary loads with low valuation in comparison to other consumers in times of high infrastructure utilization (○). This target is achieved by *DLP* only. Given the right setup, *DLP* incentivizes load shifting in times of high aggregate load and thus tries to ensure efficient use of infrastructure in combination with supply-based incentives (+).

	Coordination					
Criterion	*UC*	*SB*	*SLC*	*DLC*	*SLP*	*DLP*
Communication complexity	*BM*	+	+	○	+	−
Tariff complexity	*BM*	+	○	−	○	−
Infrastructure limit protection	○	−	*BM*	*BM*	+	+
Consumption guarantee	*BM*	*BM*	−	−	*BM*	*BM*
Comfort level	*BM*	○	○	○	○	○
Desired supply utilization	−	*BM*	○	+	○	+
Efficiency/Fairness	−	−	−	−	○	+

Table 4.8: Qualitative comparison of load coordination approaches

Summarizing the comparison, the load-pricing approaches — especially *DLP* — seem a promising alternative to load curtailment contracts, since control remains at the customers' level. The main obstacles are potential challenges in customer acceptance as well as the lack of a smart grid infrastructure that is necessary to overcome tariff and communication complexity.

4.4 Swiss Grid Planning Impact Case Study

As the electrification of individual mobility connects the transportation sector to the power system, also influences on power grid planning are discussed. This section studies the impact of EV charging loads on the Swiss high-voltage grid under different EV penetration and pricing scenarios. It is an adapted and extended version of our working paper on the grid impact of electric vehicles in Switzerland (Salah et al., 2013). Similar to the simulations before, the respective individual peak load induced by a typical commuter car depends on the technical specifications of the charging spot and the vehicle. A typical commuter car in Switzerland covers a distance of approximately 18,000 kilometers/year and therefore increases the consumption of electric energy by approximately 2,700 kWh which is more than the yearly average consumption of a single person household.[31]

4.4.1 Swiss Grid Planning

The typical planning horizons for power grids are in the order of decades due to grid assets' long service life. EVs may create new and unexpected load patterns with potentially high simultaneity factors due to commuter traffic, which needs to be considered in grid planning activities. Our study extends one influence factor in BKW's target grid planning project 2040 which aims at modeling possible scenarios in order to estimate future grid load and power flows to plan future grid development. BKW periodically plans the future grid structure on a long-term basis. The current project is titled "Zielnetzplanung 2040". A scenario-based approach is used to evaluate contingencies for technological changes similar to other grid planning studies (see Mobasheri et al., 1989).

In recent years, different aspects of EV impact on power systems have been investigated by electrical engineers and energy economists. However, existing publications mainly deal with high-level estimates of consumption, physical impact at specific locations or issues in distribution grids (see Section 4.2.3). This section complements existing research by focusing on high-voltage grids using real data for grid capacity and utilization, spot prices and mobility behavior in a Swiss case study. The grid load and capacity utilization at high-voltage substation level in the BKW grid region (Figure 4.15) are the focus of this analysis. Given the mentioned real-data input parameters, we model and analyze the impact of different charging coordination scenarios and market penetration levels on substation capacity utilization. The overall objective is to understand the

[31] These proportions differ somewhat from the US situation mentioned before (Data source: http://www.bfe.admin.ch/themen/00526/00541/00542/00630/index.html?lang=en&dossier_id=00765)

Figure 4.15: BKW's grid service region in Switzerland

long-term impact of EV charging load on the grid — an important aspect in grid planning.

Using data from the Bern region in Switzerland, the study tackles the following research questions with the goal of supporting grid planning for the next 20 to 30 years:[32]

- What is the influence of EV charging on substation capacity utilization in high-voltage grids at different EV penetration levels?
- What is the potential influence of variable price-based EV charging coordination on substation capacity utilization in high-voltage grids given price-responsive EV charging agents?
- What is the potential influence of *DLP* pricing in this practical grid expansion planning setting?

4.4.2 Swiss Grid and Mobility Data

In order to estimate the load impact from EV charging activity on the BKW high-voltage grid in the Bern area, the model builds on different real sets of data. These model elements and input data sources are illustrated in Figure 4.16. Vehicle data (1) consists of technical data concerning battery capacity and power consumption which has an effect on the individual EV charging demand. The

[32] These specific research questions are added because the use of proprietary data required alignment of the content in this section.

power rating of charging systems (2) determines the minimum length of a charging procedure and the maximum instantaneous impact of an individual vehicle on the system. Another external input for the model is the electricity spot price Swissix (3) which serves as a baseline for a variable EV charging tariff. Technical specifications and locations of high-voltage substations in the BKW grid (4) are incorporated to account for regional differences in grid capacity. Given the forecast of every substation's load curve (5), all other loads are accounted for as well. By considering the market penetration and regional allocation of electric vehicles (6) we can map the effects of regional differences to corresponding substations. Swiss driving profiles (7) from the Swiss Federal Statistical Office (SFSO) are the main source for modeling driving behavior which governs the charging requirement for daily trips as well as the times during which charging procedures can take place.

Model element	**Data Source**
(1) EV technical data	OEM data
(2) Charging power	IEC 62196-1
(3) Electricity prices	Swissgrid, EPEX
(4) Grid infrastructure	BKW data
(5) Load curve forecasts	BKW data
(6) EV deployment	SFSO data
(7) Driving profiles	SFSO census

Figure 4.16: Model elements and data sources

Vehicle Technical Data

The model deviates from original car specifications and instead uses a fictitious vehicle with similar specifications as used to evaluate the different load coordination approaches in Section 4.2.1: 30 kWh battery capacity ($\overline{SOC}$) and a consumption of 0.15 kWh/km determining a maximum range of 200 km.

Charging Power

In this case study, we assume that by 2040 home and public charging stations at 11 kW will be widely available in Switzerland and vehicles will support three-phase charging. This charging speed determines the same maximum charging amount in one time slot as Parameter κ in Section 4.2.1.

Electricity Price

For the evaluation of the charging loads three pricing scenarios are applied — static pricing, SB pricing and DLP. The power price for end consumers in Switzerland comprises 40% generation, trade and marketing costs, 46% grid costs and 14% taxes and other dues.[33] For the static electricity price scenario, we can directly apply a price of 0.18 €/kWh to our model in the form of a flat tariff for EV charging. However, variable electricity prices are currently not yet readily available to retail customers. Therefore, the model uses a hypothetical SB tariff which assumes that the entire wholesale costs follow the Swissix spot market price. The DLP approach uses the SB price and adds a dynamic price component to account for the current system load. To increase the temporal resolution of the prices and increase the alignment with the driving profiles, the hourly exchange prices are linearly interpolated to obtain quarter-hourly prices. Let p_T denote the Swissix wholesale price in hour T and p_{T+1} the wholesale price in the subsequent hour $T+1$. The linearly interpolated price $p(t)$ in $t \in [T, T+1]$ is then given by:

$$p(t) = (T + 1 - t)p_T + (t - T)p_{T+1} \tag{4.24}$$

For example, if two subsequent hourly prices are 50.00 €/MWh and 60.00 €/MWh, we obtain in-between quarter-hourly prices of 52.50 €/MWh, 55.00 €/MWh, and 57.50 €/MWh. These prices are then fed back into the generation share by normalizing with the average price in 2010 and are then applied to the dynamic electricity tariff scenario. To ensure tractability of the approach, we use an exogenous price and in our model abstract from influencing feedback mechanisms on the electricity price. The potential development of future power prices and the influence of flexible loads are discussed in Section 4.5.1.

Grid Infrastructure

The power grid comprises different layers ranging from high-voltage transmission lines to low-voltage distribution grids. Relevant bottlenecks in the grid are the line limits and transformer capacities across different voltage levels. This case study focuses on the load at substations in the high-voltage grid of BKW. These substations comprise transformers between the high-voltage grids, that either run on 132 or 50 kV, and the connected medium-voltage grids, that operate at 16 kV, and further aggregate the load of end consumers in the low-voltage grid. Typical transformers have a capacity of 12.5, 25, or 40 MVA depending on the load profile in this region.

A substation is the topological node where we measure the load to calculate

[33] For further information, we refer to the association of Swiss electricity enterprises (http://www.strom.ch).

the capacity utilization. For the sake of simplicity, we abstract from the capacity utilization of overlying high-voltage lines, since this would require time-intensive load flow calculations. Thus, the utilization values reported correspond to transformer capacity and not to actual system capacity. Hence, the values are systematically too low, as transformer capacity may be higher than the feeding line limits. Initial calculations of the developed scenarios on the real BKW grid model show that the lines can be an important limiting factor. We use the (n-1)-capacity of all HV/MV transformers in each substation as 100% capacity on our model, i.e., half of the total capacity in the case of two equal transformers and two thirds in the case of three equal transformers.[34] This is a standard approach in high-voltage grid planning.

In Switzerland, 8 million people are supplied through approximately 250 substations with a transformer capacity of 40 MVA on average (BFE, 2010). In the area supplied by BKW and adjacent regions[35] there are 122 substations in total. 78 of these are completely or partly owned by BKW which supply approximately 350.000 people. Reasons for the deviation of people per substation ratio is that BKW supplies rural areas with a low residential density, while cities like Bern are supplied by other operators. For 59 of BKW's substations sufficient data was available to be able to generate an individual load curve forecast for each of them. Out of these 59 substations, the load forecasts of ten substations already exceeded today's transformer capacity in 2040 without additional EV charging loads which necessitates capacity investments to ensure reliable future operation. As the focus is on transformer substation requirements due to EV charging, we excluded these substations from our analysis. The remaining 49 substations (highlighted in Figure 4.17) are considered and serve as base for our model.

To capture the effect of EV charging on these substations we need to map municipalities (with their expected number of electric vehicles) to each substation. The location of the distribution grid stations[36] connected to substations determines which municipalities are supplied by which substations. The distribution of EV charging stations within the municipalities which are connected to the low voltage grid is not within the scope of our simulation. Our study focuses on the aggregate charging load which can be measured on the substations' level.

[34] For ease of exposition, this reference value is being referred to as "substation capacity", even though substations' switchgear can represent another limiting factor besides lines and transformers.

[35] Adjacent regions had to be examined in BKW's target grid planning project as they can influence BKW's grid.

[36] Distribution grid stations transform between medium voltage grids and low voltage grids.

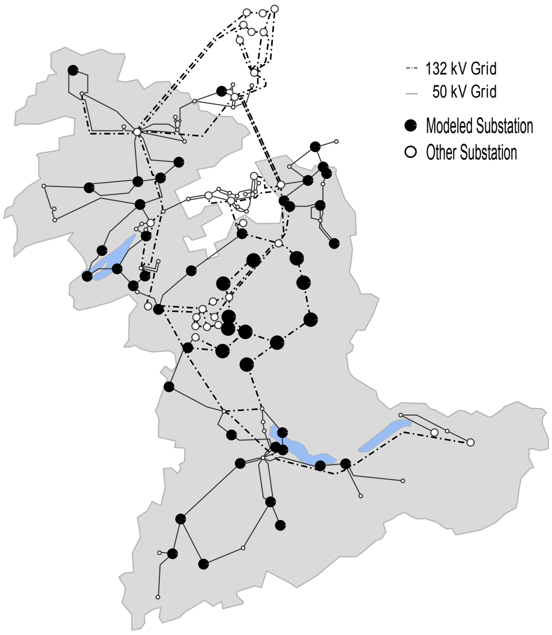


Figure 4.17: BKW high-voltage grid and (modeled) substations

Load Curve Forecasts

BKW forecasts the substations' load curves for the year 2040 within the target grid planning project. An extensive scenario analysis incorporated 18 drivers of electricity generation and consumption. More than 80 published studies were used to predict the future development of these drivers. Among the most influential drivers of consumption are economic growth, demographics, transportation and energy efficiency. The resulting forecasts are used to identify the substation load curves for 2040. To obtain the original load curves, the three peak load days of the year 2010 were selected along with the previous and following day. The average of these nine load curves serve as characteristic worst-case substation load curve for the year 2010. Based on this load curve the influence factors are added to obtain a forecast for the load curve of the year 2040.

Market Penetration and Vehicle Allocation

The market penetration of electric vehicles obviously has a high influence on the total load generated by their charging activity. The Swiss Federal Office of Energy presents possible market penetration of electric vehicles for the next 20 years in four different scenarios in its fact sheet (Bundesamt für Energie, 2010). These scenarios are complemented by an additional BKW scenario which was developed up to the year 2040 within BKW's target grid planning. The analysis is based on this scenario and assumes that in 2040 there will be 700,000 EVs in Switzerland. This number corresponds to 16% of all vehicles in Switzerland. We allocate the EVs to the substations of BKW in order to model their influence on substation load curves. An overview of the required input data and the combination is depicted in Figure 4.18.

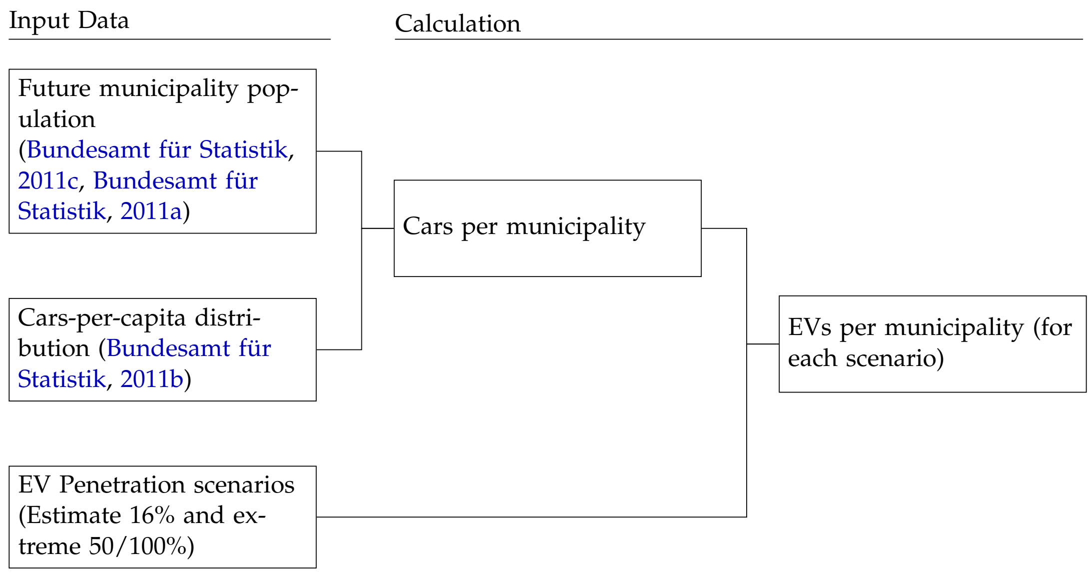


Figure 4.18: Mapping of different input data to derive EV distribution

The distribution of the electric vehicles in each municipality in Switzerland is estimated using current municipality population (Bundesamt für Statistik, 2011c) and future projections (Bundesamt für Statistik, 2011a) as well as the cars-per-capita ratio (Bundesamt für Statistik, 2011b). Subsequently, we estimate the number of passenger cars in each municipality in 2040. Assuming that the nationwide market penetration is identical across municipalities, we estimate the number of electric vehicles in each municipality as shown in Figure 4.19. As explained above, we can map each municipality to a substation in our grid model to directly derive the number of EVs per substation. Furthermore, we analyze more extreme penetration levels of 50% and 100% to see potential results for higher penetration rates. By increasing the EV penetration rate homogeneously across municipalities, we can identify the substations that will sooner reach their limit. These extreme scenarios help to demonstrate the potential impact of static and variable prices.

Driving Profiles

In order to model EV charging activity we need to know when the EVs are connected to a charging point. To this end, we use driving profiles that provide information about a car's location/status (e.g., at home, at work, driving) over time. The Swiss Federal Statistical Office (SFSO) has carried out a survey regarding the mobility behavior in Switzerland (Bundesamt für Statistik, 2007) which

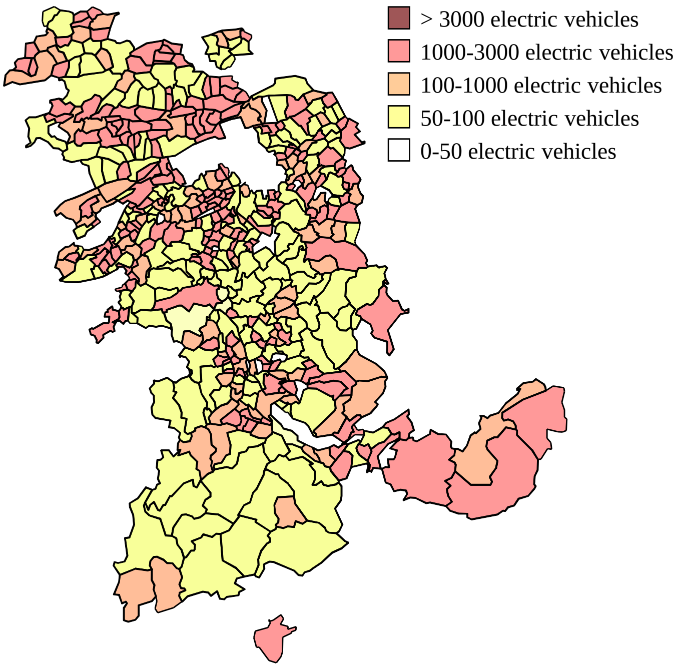


Figure 4.19: Estimated number of EVs per municipality in the relevant regions in 2040

serves as base data for our model. Members of 60,000 households were selected randomly and interviewed regarding their mobility behavior on the day before the interview day. We use the survey questions on trip timing, distances, type and means of transportation to extract raw trip data. Figure 4.20 depicts the distribution of the daily driving distances.

This trip data is wrapped in driving profiles that consist of the driving status, the distance driven, and the location of the car in a 15-minute resolution over the whole day. We use these driving profiles to model the EV charging requirements. Although these profiles are based on conventional vehicle trips, we apply them to build EV models — similar to the previous section — as changes in the driving behavior have to be expected only in the long-run (Oeltze et al., 2006). In order to allow for load shifts greater than one day, the driving profiles are extended to a period of one week by looping them. Of the initial set of 17,087 driving profiles, we had to remove 4.1% of the profiles, as they conflicted with certain model assumptions:[37]

- 1.3% of the profiles featured trips that exceeded the assumed EV range in

[37]This differs from the approximately 10% of driving profiles that had to be removed from the German Mobility Panel employee data in Section 4.3. Except for the difference of employees only in the German Mobility Panel to a mixed population here, the underlying reasons for the difference are not known. However, some differences may be due to the survey format. For example, SFSO data refers to the day before the interview, which clearly excludes trips and vacation times greater than one day. As depicted in Figure 4.20, the distribution is similar to typical mobility behavior.

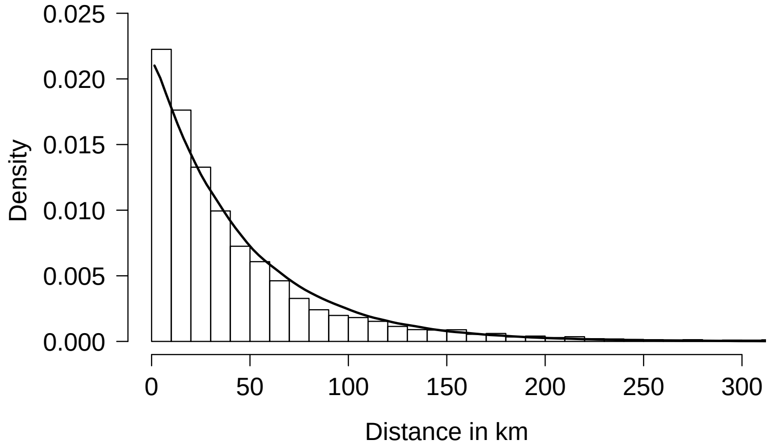


Figure 4.20: Distribution of daily driving distances in the SFSO mobility survey

a single trip

- 0.4% of the profiles featured trip sequences with insufficient recharge time and thus exceeded the assumed EV range
- 2.4% of the profiles did not terminate at the home location and were thus unable to fully restore battery capacity at the end as required for optimal EV charging

Given the limited size of the mobility survey compared with the EV penetration projection, we reused the set of driving profiles to generate the necessary input data. To maintain integrity with respect to the driving habits, the assignment of profiles to substation is based on the municipality type as provided by the SFSO (Schuler et al., 2005), i.e., only rural profiles are used in rural areas.

4.4.3 Results for Grid Planning

Using the model described above, we can evaluate the impact of EV charging loads on the substations in the BKW grid. We first look at the static electricity rate scenario with different penetration levels and corresponding simple charging behavior. Subsequently, we investigate the effect of smart charging in the variable rate *SB* scenario for different electricity price curves. Finally, we evaluate the same external price weeks with a *DLP* approach for each substation.

Static Rate Scenario

In the first scenario we analyze the impact of electric vehicles under current linear electricity rate conditions. Electric vehicles constitute a new power consumer that was supplied by fossil fuels so far. As generically demonstrated in the last sections, there is a risk that peak loads could rise by uncoordinated EV charging, and an extension of power grids would be required. Specifically in the evening hours new peaks are expected because of charging activity occurring when commuters return home. Under a static price (flat tariff for EV charging) there are no financial incentives for shifting the charging load, and hence the uncoordinated charging *UC* is applicable in this case.

The distribution of the substations peak loads with different EV market penetration levels is presented in Figure 4.21. The substation count (y-axis) denotes the number of substations with a specific peak load (x-axis). A peak load is the highest utilization ratio of all 15-minute intervals of a week at one specific substation. With an expected market penetration of 16%, none of the analyzed substations will be overloaded. However, we can identify a slight increase of peak loads. For a market penetration of 50% we find one substation that will be overloaded. At 100% penetration the number of overloaded substations increases to three.

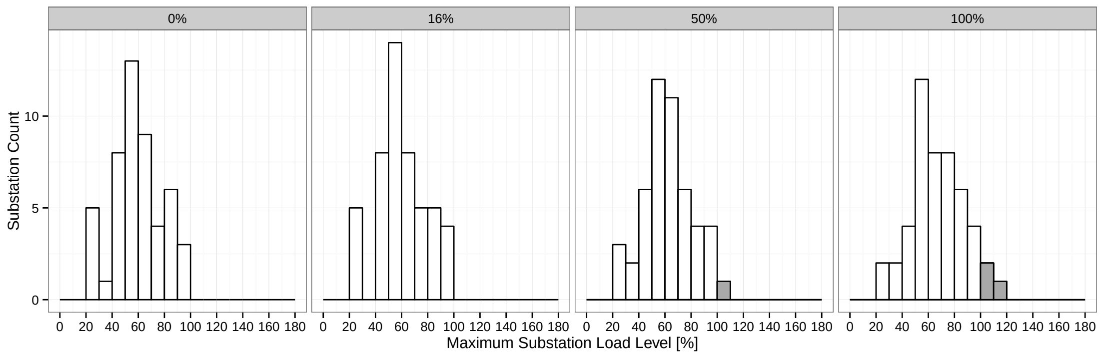


Figure 4.21: Substation peak load distribution with uncoordinated charging *UC* for different EV market penetration levels (N=49)

With the estimated progress of market penetration of EVs, we can expect that none of the substations will be overloaded until the year 2040. Thus, load clustering due to similar driving habits does not have a large impact on peak loads of BKW substations at a market penetration of 16%. At higher EV penetration levels, overload situations become more likely but still remain limited in both number as well as magnitude.

Variable Rate Scenario

In order to tap into EV charging flexibility, vehicle owners need to be offered incentives that promote charging during times of low generation costs or to balance fluctuating generation from renewable energy sources. To analyze this setting, we apply the exemplary variable rate described in Section 4.4.2 to reflect the wholesale market price in charging costs. This incentive results in an *SB* charging coordination based on the Swissix price.

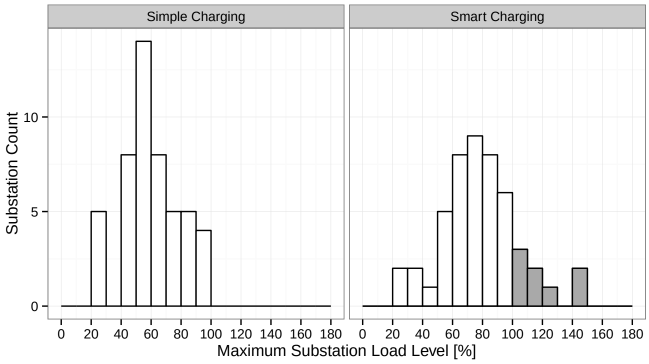


Figure 4.22: Substation peak load distribution under simple and smart charging for 16% market penetration (N=49)

Figure 4.22 shows that at a market penetration of 16% many substations are already overloaded under *SB* price-coordinated charging. Furthermore, reaching utilization levels of 150%, these overloads are more significant than the ones under simple *UC* charging with 100% penetration. The strong shift of the histogram towards higher peak loads is a result of price differences over the week. Due to the financial incentives, price-sensitive EV agents will charge their batteries at times of low electricity prices. The depicted histograms are based on the Swissix prices of the third calendar week 2010. However, the observed effects are robust to variations of the underlying price vector. In total we evaluated 12 different price weeks in 2010 that are depicted in Figure 4.23 — four example weeks for each season: summer, winter and transition.

Besides the aggregate view of all substations, it is also illustrative to look at the substations individually. Figure 4.24 provides anonymized utilization boxplots based on smart charging of all 12 simulated weeks for each substation. The solid line illustrates the peak utilization of each substation without EV charging loads. The diverse outcomes per substation reflect the multitude of real input data for the simulation. Some substations will be more challenged by upcoming EV charging loads. The underlying reasons for this heterogeneity are diverse, e.g., rural or urban areas, mobility behavior, EV distribution. Furthermore, this analysis provides some guidance on which substations will be suited for economic coordination of charging loads (overloads arising mostly from EV charg-

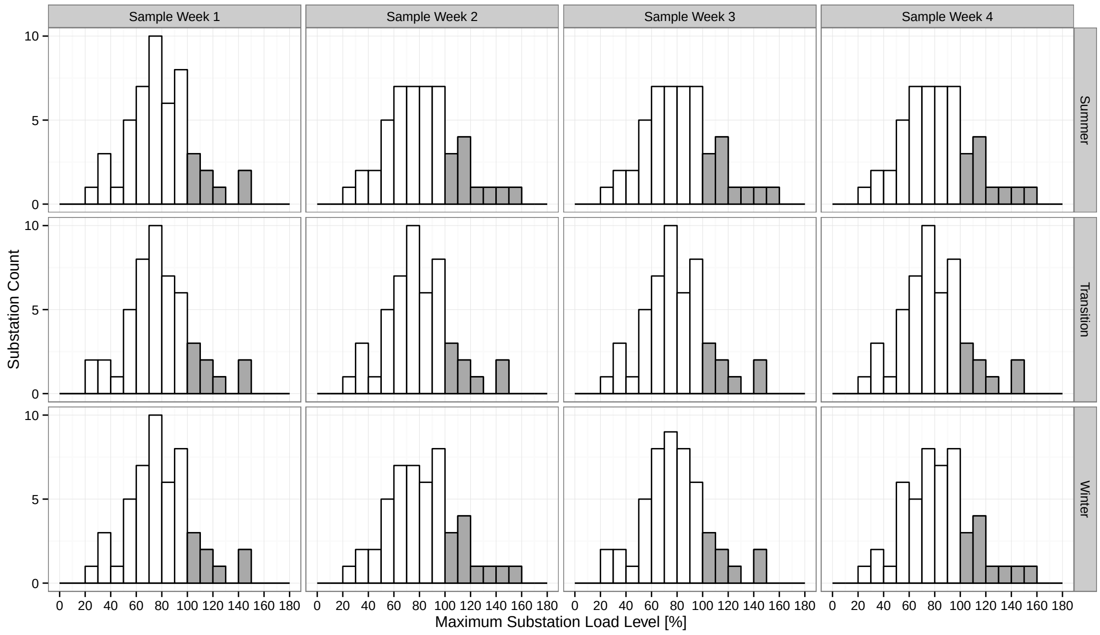


Figure 4.23: Substation peak loads with optimal smart charging for sample weeks in summer, transition and winter period under 16% market penetration (N=49)

ing), and which substations will most likely require capacity upgrades (high utilization levels even without electric vehicles).

DLP Scenario

Due to the resulting overloads of the variable *SB* coordination, we apply a *DLP* coordination to analyze the potential overload mitigation effect. Unlike the example with *Home* and *Work* locations in Section 4.3.1, *DLP* is set up at each substation in the BKW grid. The parametrization is the same as in Section 4.3.1 with $\xi = 3$ and the limit price based on the median of the external price of the respective week. As expected, *DLP* coordination succeeds in shifting EV charging load into times with lower grid utilization. Across all substations, the maximum capacity is never exceeded given 16% EV market penetration in the 12 example weeks simulated (Figure 4.25). The *DLP* approach 'allows' increasing peak loads caused by EV charging at substations with lower maximum utilization. In contrast, substations with high maximum utilization do not experience higher peak loads through EV charging under *DLP*. Nevertheless, as mentioned before, substations with high utilization even if no additional load from EVs is considered most likely will require capacity upgrades.

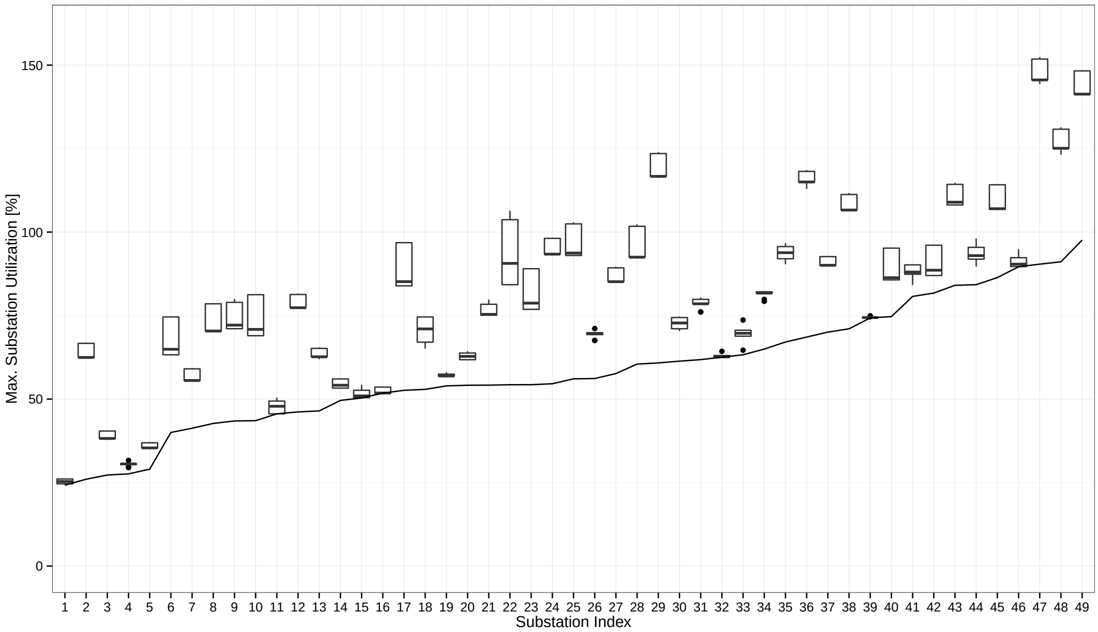


Figure 4.24: Boxplots for substation peak load distribution per substation with *SB* smart charging (based on 12 simulation weeks)

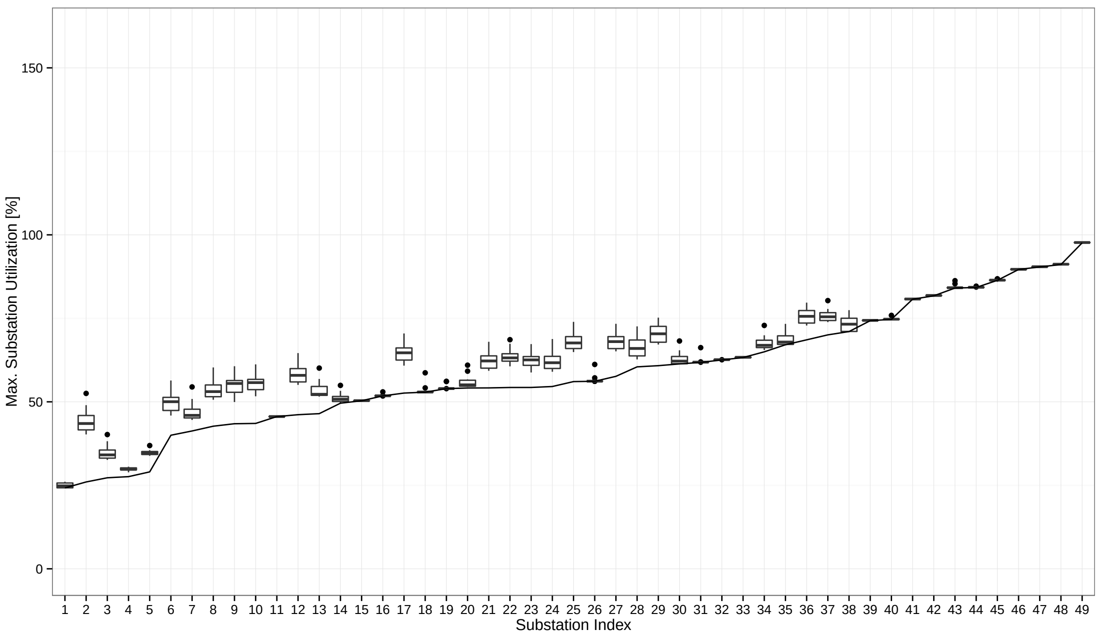


Figure 4.25: Boxplots for substation peak load distribution per substation with *DLP* smart charging (based on 12 simulation weeks)

4.4.4 Conclusion of Swiss Grid Planning Example

In our model for the EV impact on BKW's grid we find that under today's conditions with static electricity rates and an EV market penetration of 16% there is no risk of overloads on high-voltage substation level. However, under higher market shares of 50%, EV charging may lead to overloads at some locations without coordination. If regulatory conditions allow the use of variable electricity prices and consumers react on these prices to minimize mobility cost, substation overloads would already occur at a market penetration level of 16%. Thus both increasing EV penetration levels as well as coordination based on exogenous market prices may in the long run cause grid problems. The detected overloads can effectively be mitigated by adding a local load-based price component (DLP) which incentivizes the shift of charging loads into periods with lower local utilization.

These results signify three things:

(i) Price incentives can activate significant load flexibility with respect to electric vehicle charging.

(ii) Exogenous prices based on system-wide electricity wholesale prices give rise to strong over-coordination effects which may challenge local grid infrastructure limits not only on the low-voltage level but also in high-voltage distribution grids.

(iii) Capacity investments or grid-conscious EV charging coordination are required to guarantee adherence to substation utilization thresholds at high EV penetration levels.

Balancing an economically efficient use of low-cost supply for EV charging with additional grid costs will require the joint attention of regulators, researchers, grid operators, and generators while at the same time taking into account customer needs.

4.5 Conclusion of Local Load Coordination

The analyzed local load coordination approaches demonstrate potential to influence future grid operation and planning. The following section discusses the results, summarizes the findings, and provides an outlook of possible future research. This is an amended version of the discussion in our working paper Salah et al. (2013) an contains parts of Flath et al. (2013).

4.5.1 Discussion

The modeled approaches of local load coordination have limitations mainly concerning assumptions on modeled components and individual behaviour. The main limitations are discussed in the following.

Tariff Complexity

As noted before, spatial pricing schemes have been demonstrated to improve system efficiency while at the same time increasing the pricing complexity that customers are faced with. First, the discussed tariffs (e.g., *SLP*, *DLP*) are currently not realistic on a household level. Specifically, the complex tariffs require a full smart grid roll-out as well as real-time access to load and billing data. In addition, the regulator would need to allow one actor to charge dynamic fees based on the local system state. Given the deregulation to foster competition, a grid area is typically served by several electricity retailers in most countries. Therefore, the grid operator is suited to undertake this task as a form of his grid operation duties. So far, there is no intended introduction of such dynamic local grid fees. Even if the technical and regulatory issues are resolved, consumers need to accept highly variable tariffs or load curtailment for the implementation of the discussed load coordination mechanisms. Dütschke and Paetz (2013) find that consumers prefer simple over complex tariffs and that demand automation is needed to tap consumers' flexibility. However, EV charging constitutes an additional and flexible load which may facilitate the introduction and serve as a reference case for load coordination approaches as well as more complex tariffs, since it is separable from other loads through designated charging stations.

Full Price Responsiveness

Furthermore, the load clustering and coordination results, given a variable price vector, are based on fully price-responsive EV owners with perfect knowledge of future market prices. Unquestionably, these are benchmark results for the effects of price-responsive EV charging on the power system while still assuring given mobility patterns. In general, load flexibility in field trials is only limited as mentioned before. Faruqui and Sergici (2010) review 15 residential dynamic pricing studies and report mean peak reductions of 4-44%, depending on rate design. They find an especially high impact of dynamic pricing if supported by enabling technologies such as automated air conditioning. However, these studies are based on residential demand which includes load types that are less shiftable (e.g., entertainment, cooking). In contrast, EV loads are easily shiftable without or with only a minor loss in mobility comfort. Therefore, high load flexibility seems to be possible in the presence of appropriate incentives and technical support for EV owners (e.g., intuitive interfaces and automated charging systems). Smart charging of EVs offers higher benefits than other load management approaches due to large charging energy amounts. In the future, variable pricing can be applied to other flexible loads as well (e.g., distributed storage, heating and cooling appliances) to leverage demand side flexibility. Another aspect may be the flexibility in mobility patterns, as this thesis assumes invariant mobility needs. As mentioned by Sioshansi (2012), consumers may change their driving patterns when they get used to variable tariffs. In addition, the examples assume that the entire consumer population is in the same tariff. In real applications, a variety of different tariffs will be offered to consumers. Thus, consumers with a preference for higher quality of service may select different tariffs. Consequently, the load coordination effects presented may be valid for parts of the total consumer base only. Different behaviour based on heuristic EV charging strategies and only limited knowledge is discussed in our papers Flath et al. (2012) and Flath et al. (2013).

Exogenous Price Vectors

In all instances of our model we assume an exogenous price vector. Depending on the scenario, the variability and the spread between highest and lowest price are different. However, it should be noted, that for the analysis of substation utilization, the absolute level of the dynamic prices is not essential. Price variability is crucial, as optimal charging leverages these price differentials to determine charging schedules. In the case of completely flat price curves, these load coordination incentives vanish. This approach implicitly assumes that wholesale prices remain unaffected by the EV loads. This is clearly a limiting assumption, as concentrated charging loads may induce system-wide load increases which should impact wholesale prices. Other publications focus on different aspects of load influence on wholesale prices. Boisvert et al. (2002) find in the NYISO zone that the supply curve is "hockey-stick shaped" with prices exponentially increasing in load. Whereas, Li and Flynn (2006) analyze 13 different power markets and find that the relationship between price and load differ significantly. Nyamdash and Denny (2013) investigate the influence of storage deployment on wholesale prices in a unit commitment model. They find a reduction in fuel cost but an increase in the average electricity price of the simulated power system.

Using Swissix prices as an example, a price-load relationship becomes evident. The effect greatly varies, even when controlling for season and day type as illustrated by the large price differences present at each load level in Figure 4.26. Both increasing amounts of intermittent generation and increased load flexibility (a result of large-scale electrification of individual transport served by renewable energy sources) will further distort the load-price relationship. Therefore, a stable and meaningful wholesale price model based on aggregate load is not

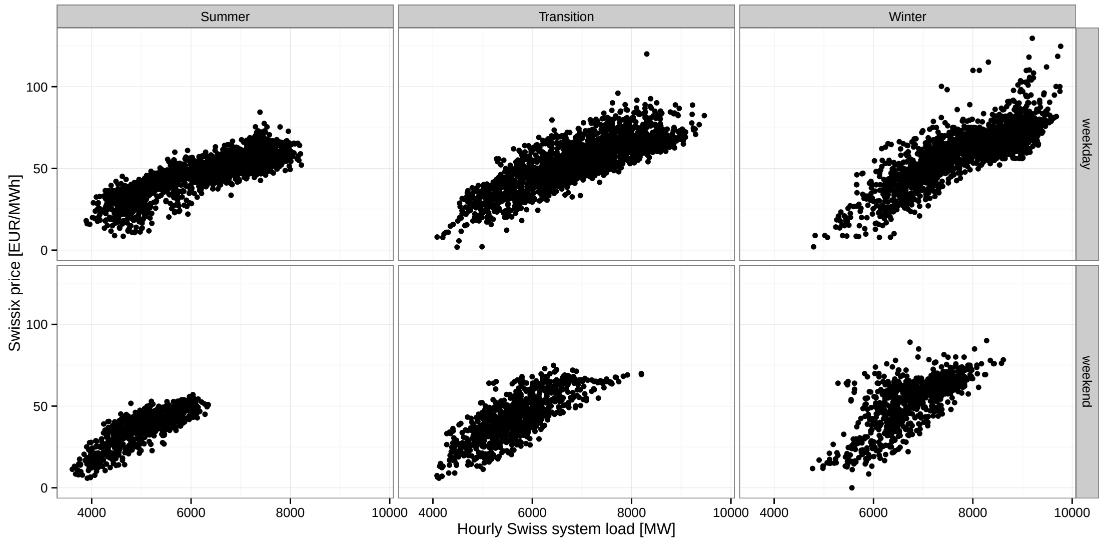


Figure 4.26: Swissix price and Swiss total system load in 2010

available. For this reason, we avoid implementing an arbitrary model and keep prices as an exogenous and invariant input. The wholesale prices used as input thus mainly serve to capture possible price dynamics. Other stochastic price vectors will likely yield very similar results concerning the more frequent occurrence of substation overloads. Still, the wholesale price effect of large-scale EV integration (and other flexible loads) offers interesting opportunities for future research.

Power System Modeling

The impact of EV charging loads on transformer utilization in the grid is a relevant example in this thesis. This is an important step to understand opportunities and risks of flexible loads, but it is at the same time a simplification of the complex power system. To identify other effects and constraints (e.g., losses, line utilization, voltage drops), more detailed data and power flow analyses are necessary. The presented model assumes EV charging to be dynamic and all other influence factors to be static. New technologies (e.g., battery storage, home automation) and the development of decentralized generation units (e.g., solar, CHP) should be included to generalize the model and to obtain more robust simulation results. In addition, the model may be further detailed by considering geographical differences in vehicle penetration (see Saarenpää et al., 2013) or long-term changes in mobility behavior.

4.5.2 Summary and Outlook

The presented local load coordination approaches show interesting potential even when considering the discussed limitations. This section summarizes the main contributions and implications and gives an outlook on potential next steps.

Contribution and Implications

Variable electricity rates are considered an important option to coordinate consumption behavior in smart grids — in the case of EVs, their charging activity. However, the discussion around variable tariffs to shift loads so far has mostly ignored arising grid issues. Introducing variable tariffs that merely focus on incentives for low-cost or renewable generation will lead to a significant increase of peak loads in times of low prices given price-sensitive consumers (Gottwalt et al., 2011). To match these load increases substantial grid investments will be required. These may diminish the welfare gains expected from dynamic electricity pricing.

Therefore, the possibility and potentials of incentives based on adaptive pricing of local capacity or individual load levels need to be explored in the future. Specifically, if dynamic prices are offered to end consumers, the grid limitations have to be accounted for. Load coordination to increase the utilization of available capacity is an alternative to grid investments. This may pose a regulatory challenge in unbundled electricity markets, as marketing activities need to account for grid operations. Which load coordination approach is suitable in a specific application heavily depends on the load type and especially the service that is provided. Not only the flexibility is important for load coordination but the robustness to risks or consequences of small deviations as well. The results presented in this chapter underline the potential of load coordination. In combination with increasing home automation and awareness for power system challenges, existing loads may become more flexible as well. Not only does the potential have to be incorporated in grid control opportunities — such as ancillary services — but at the same time grid expansion and planning may need to be adjusted, based on local consumer population characteristics.

Opportunities for Future Research

There are various possible extensions or modifications of the model used for evaluating the load coordination approaches — in the input variables, the coordination approaches, and the resulting implications. For example, the potentials analyzed in this chapter do not include V2G services. Nevertheless, model extensions are straightforward. Resulting loads from the model on substation level can be used for load flow calculations, determining impact on power lines. In fact, initial calculations of the developed scenarios on the real BKW grid model show that already at a penetration level of 16% the lines can be an important limiting factor. Another natural next step is to model the implications of EV charging on other voltage levels or different high-voltage power grids to compare results. Moreover, some model assumptions may warrant closer attention to ensure robust results. So far, the model abstracts from battery specifications or different charging patterns which could affect battery ageing. As mentioned above, another strong assumption is the full knowledge of future mobility patterns and prices assumed in the optimal charging strategy. Finally, the model needs to be incorporated and aligned with other modeling efforts to support the major restructuring of the power system. For example, the integration with models of generation capacity development including the local, intermittent supply would allow for a combined analysis of dynamic supply and dynamic demand on different grid levels. In addition, the real potential of the different load coordination approaches needs to be investigated, e.g., consumer acceptance of these approaches for different services or the role of DSOs in future grid operation and planning.

Chapter 5

Transmission Grid Cost Allocation and Investment

Expected changes in electric power supply and demand impact future power grids. On the one hand, the shift from fossil fuel-based generation to renewable energy sources (RES) leads to more intermittent supply. On the other hand, demand profiles are expected to change, since new smart grid technologies enable flexibility in consumption of electricity and provide a basis for more diversified energy tariffs and services.

In addition to these changes in supply and demand patterns, there is also a locational shift of generation, since RES generators are typically not built at the same locations as existing fossil fuel plants. This relocation of generation capacity poses additional challenges for the historically grown grid infrastructure. Massive grid infrastructure investments are necessary and grid expansion actions are undertaken in different forms internationally.[1] Regulators have to consider both grid investments and other measures such as influencing the siting of new generators to achieve reliable electricity supply and define an efficient trade-off. In cases with high investment costs or extensive land consumption, project duration and public opinion are of major concern.[2] The allocation of grid investment costs fuels public discussions, as these costs are enormous and the beneficiaries are often not clearly identifiable, with some parties even being at a disadvantage. In essence, the individual goals of economic efficiency and common 'fairness' are difficult to achieve simultaneously. This chapter is motivated by recent discussions on rising energy prices, investment into grid infrastructure (e.g., new HVDC lines), siting of new RES generators as well as transmission pricing and cost allocation policies (e.g., Transmission

[1] e.g., UK http://www.nationalgrid.com/uk/Electricity/MajorProjects/, USA http://www.tresamigasllc.com/

[2] See German Grid Development Plan Consultation http://www.netzentwicklungsplan.de/sites/default/files/NEP_2012/Factsheet.pdf and UK National Grid Undergrounding Consultation http://www.nationalgrid.com/uk/Electricity/UndergroundingConsultation/

Pricing Methodology Review in New Zealand[3]). A full grid expansion to avoid any congestion at all allows location-independent perfect competition among generators but may not be the best solution in all cases.[4] As noted by Knieps (2013): "the extension of network capacities to such a degree that congestion disappears would result in overinvestment and cannot be considered a socially optimal solution."

An example for the locational changes of supply centers with the need for high investments into the transmission grid is the German *Energiewende*. Figure 5.1 depicts the suggested infrastructure investments of the four TSOs into the transmission grid in Germany until 2032. Part of these investments are 4 HVDC lines which connect regions in the wind-rich North of Germany with major load centers in the South. Mainly due to a massive increase of wind generation in the North, the TSOs expect a necessary investment into HVDC transmission capacity over 3,100 km with an estimated cost of € 27 bn without cabling (50Hertz Transmission GmbH et al., 2012). After a consultation process the regulator approved 3 of these HVDC lines and other projects to be pursued (BNetzA, 2012). Recently, the updated preliminary recommendation of the TSOs expects even higher required transmission capacity (50Hertz Transmission GmbH et al., 2013).

These major investments motivate the following questions: Are the investments efficient? Who pays for the investments? Neuhoff et al. (2008) provide an analysis of a similar situation in the UK, where the best wind resources are in Scotland. Their model shows that a more distributed investment into wind generation might be beneficial for three reasons: matching local demand with local supply reduces losses, less wind capacity curtailment due to less transmission constraint situations, and a less concentrated investment into wind capacity leads to a less volatile generation pattern in total. In the example of Germany, differences in grid cost for household consumers exist in the current system already. Figure 5.2 depicts the differences in grid charges for households (BNetzA, 2011). Households in the eastern part of Germany pay higher grid charges than in the Southwest. According to the regulator, these differences are caused by high investments into grid capacity in the 1990s and overall lower consumption in comparison to grid size (BNetzA, 2011).

Obviously, different types of grid cost allocation may lead to seemingly '*un-*

[3]See http://www.ea.govt.nz/our-work/consultations/priority-projects/tpm-issues-oct12/ for the currently ongoing consultation for the transmission pricing methodology review.

[4]The assumption of sufficient grid capacity with no congestion is also called *'copper-plate'* (see Brunekreeft et al., 2005).

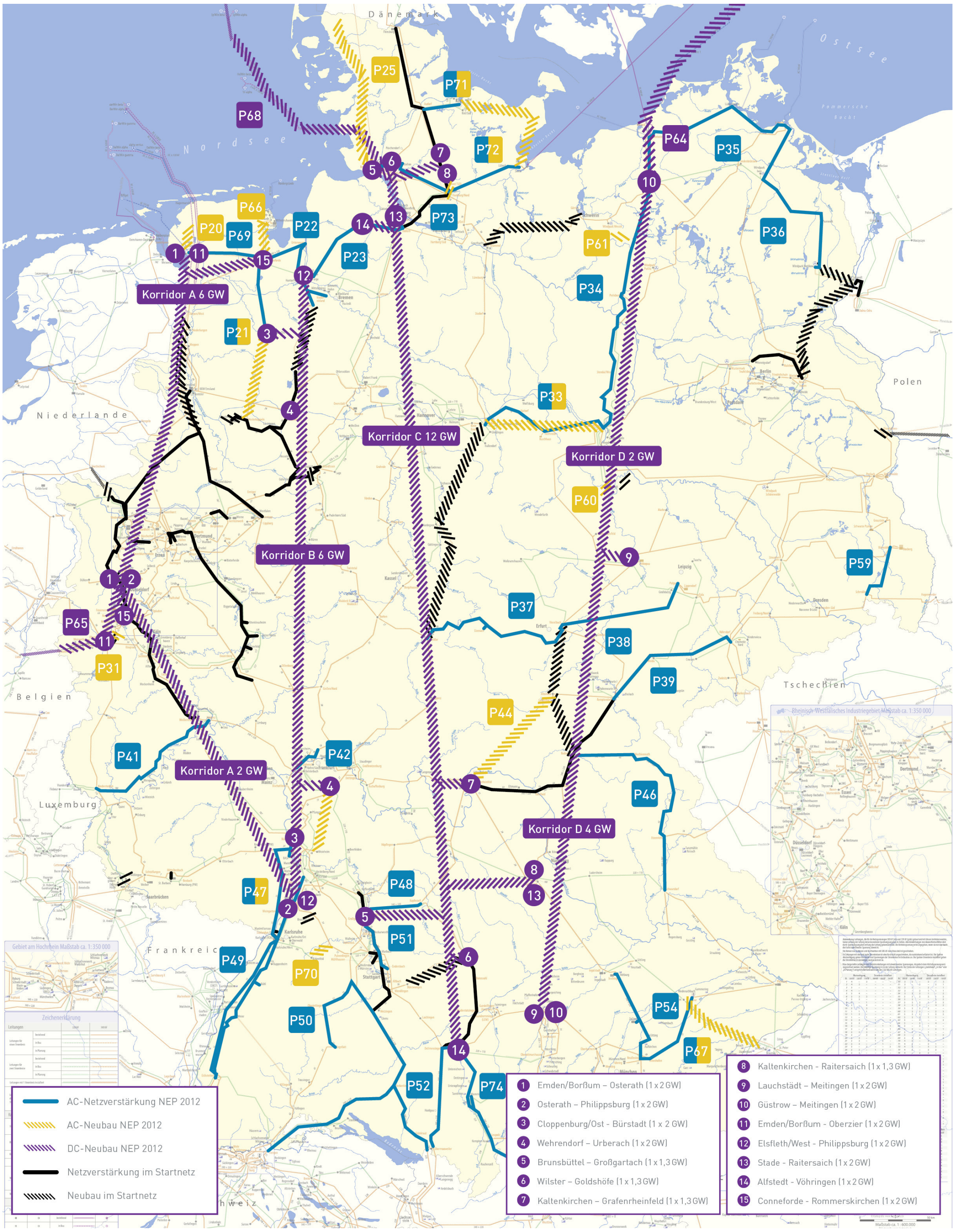


Figure 5.1: Suggested grid expansion projects in the lead scenario of the German Grid Development Plan 2012 (50Hertz Transmission GmbH et al., 2012)

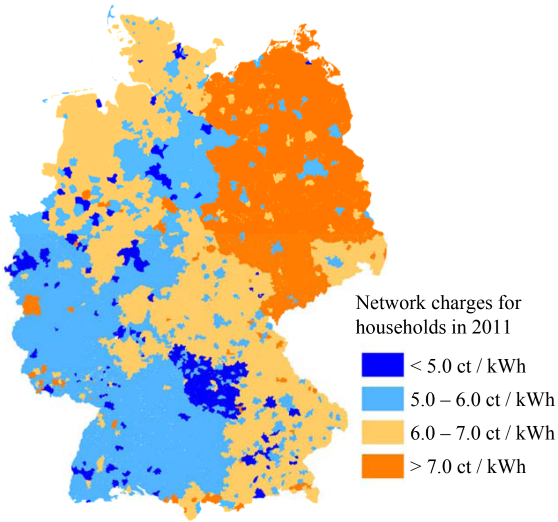


Figure 5.2: Locational differences in grid charges for households in Germany 2011 (BNetzA, 2011)

fair' outcomes. For example, one strange outcome may be that consumers who have no benefit bear a large share of the grid cost. Consumers in the eastern part of Germany, where a large share of the low-cost wind generation is located, may have to pay a major share of investments. This would increase the cost differences due to the building of new lines. However, in the German example, the final course is not yet set. In the context of this thesis, we contacted the German regulator (Bundesnetzagentur) in late November 2012 to find out who will pay for the investments into the transmission grid until 2032. So far, the questions are officially unanswered in written form. In informal phone calls the *Bundesnetzagentur* mentioned that a final answer is not yet possible, which may indicate that there may be room for changes in the regulatory regime.

Incentivizing local generation and consumption by charging direct beneficiaries of grid investments for grid cost may be a different approach to addressing upcoming grid challenges. The variety in cost allocation schemes under different regulatory regimes underlines the arising complexity which leads to public discussion and experts' consultations for regulatory advice. This chapter analyzes different cost allocation and pricing regimes in a simple network model. Focusing on the economic behavior and implications on consumer and total welfare, it simplifies the modeled entities as much as possible, abstracting from rich power system modeling aspects. Important questions to be analyzed are the influence of different cost allocation and pricing options on welfare as well as the corresponding investments in transmission and generation assets under different regulatory regimes.

This chapter is also an extension of own publications and working papers.

Specifically, Sections 5.2 – 5.5 are reproductions and extensions of our paper Ilg et al. (2012) and the results presented here are currently incorporated in the working paper *Investment and Grid Cost Allocation*.

5.1 Transmission Pricing and Cost Allocation Foundations

In most countries, integrated utilities have been in charge of electricity supply for end consumers, and pricing of separate functions has not been in focus. A vertically integrated monopolist utility is inherently incentivized to find a cost-optimal mix of transmission and generation assets. Deregulation in the power sector has led to an unbundling of tasks and often separate entities: generation, transmission, and local distribution. This development in combination with the need for investment fed the discussion on the siting of generators, locational pricing, and cost allocation of grid investments.

The literature on transmission pricing is mostly applicable to these questions and focuses on short-term operation as well as long-term cost recovery in some forms with locational differences. Due to lack of electricity storage and transmission capacity constraints, pricing needs to avoid congestion in the short run. Since electricity cannot be routed, topics like loop flows and ancillary services require unique approaches and limit the applicability of solutions from other network industries. At the same time, the high investment costs of transmission systems and generation plants require stable and long-term pricing to guide investment decisions and ensure the recovery of sunk cost. This section provides an introduction to the objectives, theory and dimensions of transmission cost allocation as well as related economic models to the approaches presented in this chapter.

5.1.1 Objectives of Electricity Transmission Pricing

Transmission pricing is complex and has to respect different aspects and incentives in order to lead to a preferred or intended outcome. Green (1997) provides an international comparison on transmission pricing and names six guiding principles for transmission pricing regarding economic efficiency and political implementation, which since then have been widely accepted by other authors: "The prices should:

- promote the efficient day-to-day operation of the bulk power market;
- signal locational advantages for investment in generation and demand;
- signal the need for investment in the transmission system;

- compensate the owners of existing transmission assets;
- be simple and transparent; and
- be politically implementable."

Also, Brunekreeft et al. (2005) name five points which should ideally be encouraged by network charges:

- "the efficient short-run use of the network (dispatch order and congestion management);
- efficient investment in expanding the network;
- efficient signals to guide investment decisions by generation and load (where and at what scale to locate and with what choice of technology — baseload, peaking, etc.)
- fairness and political feasibility;
- cost recovery."

Other authors formulate or list similar principles in other ways (e.g., Hunt and Shuttleworth, 1993; Oren et al., 2002; Pérez-Arriaga and Smeers, 2003). On the one hand, some of these requirements can be grouped into 'soft' implementability requirements of fairness, simplicity and political feasibility. On the other hand, there are some 'hard' economic facts and incentives that need to be considered to foster an efficient outcome. Namely, these are short-term efficient operation as well as long-term efficient investment and remuneration of all participating actors.

5.1.2 Transmission Cost Theory and Dimensions

This section briefly describes the different costs incurred by transmission and provides an introduction into theoretical cost allocation dimensions. Finally, international differences in cost allocation are presented to highlight the variety of existing regulatory regimes. The goal is to provide an overview and literature references for further details of the discussed topics.

Transmission Cost Types

From a TSO perspective, two different types of transmission costs can be distinguished: connection cost and network infrastructure cost (Madrigal and Stoft, 2012). Connection costs occur when a new consumer or generator needs to be connected to the transmission grid. Policies allocate different parts of the connection costs to individual actors. This ranges from super-shallow policies, where all grid expansions and network upgrades are borne by the TSO, to deep policies, where the individual actor has to also bear upgrade costs in the transmission grid (Madrigal and Stoft, 2012; Barth et al., 2008). As long as these costs can be assigned to a single consumer or generator — which is typically the case for shallow costs — they are not within scope of this chapter. These 'dedicated facility' costs are easily allocatable to a single generator or consumer (Pérez-Arriaga and Smeers, 2003). The deep connection policies are more difficult, since it is not a trivial task to assign deep connection costs, e.g., to a single generator due to the nature of dynamic usage and varying power flows. The network infrastructure costs cover the remaining transmission grid costs, and comprise mainly investment costs and costs of operation which typically include maintenance, losses, congestion, and ancillary services (Madrigal and Stoft, 2012).

One possibility for short-term cost recovery often discussed is the nodal or locational marginal pricing (LMP) approach, which leads to different locational prices in case of congestion. This results in short-run efficient outcomes and also generates congestion revenues.[5] Major publications agree that it is unlikely or even impossible to achieve full cost recovery by marginal pricing (Brunekreeft et al., 2005; Pérez-Arriaga et al., 1995; Pérez-Arriaga and Smeers, 2003). Therefore, even in an LMP system, the remaining costs still need to be allocated. Similarly, Knieps (2013) notes that cost recovery is an important question in transmission pricing, due to economies of scale in transmission investment. In line with the cost allocation white paper of Baldick et al. (2007), we agree that short run congestion costs, LMPs, and redispatch costs are important but beyond the scope of this chapter. Hence, this chapter's focus is limited to capital or investment cost allocation and recovery in the long-term.

Generic Alternatives for Transmission Cost Allocation

For cost recovery the main question is whether the cost should be allocated to generators or consumers. In existing literature this is often discussed as the G-charge/-component for generation and the L-charge/-component for load (Brunekreeft et al., 2005; von Hirschhausen et al., 2012). One generally desired

[5] A critique mentioned in Leuthold et al. (2008) is that a large number of nodal prices is seen as too complex by some researches, and therefore zonal prices may be a compromise. However, the zonal approach is also strongly criticized by Hogan (1999), due to the fact that nodal pricing would lead to zones with similar prices if there is no difference between nodes. However, Hogan (1999) also mentions that the focus of his argument is short-term congestion management. Finally, the magnitude of impact is again discussed by Oren (1998). For more details on nodal and zonal pricing as well as where the concepts are applied, Leuthold et al. (2008) provide further information.

principle is the following: beneficiaries or those who cause the grid cost, should pay (see Pérez-Arriaga and Smeers, 2003). However, beneficiaries are very difficult to identify in an interconnected power grid and often change over time.

In addition to the cost allocation to different stakeholders, the calculation method for transmission charges is another dimension. An important factor is whether cost allocation should be uniform or differentiated. One possible type is differentiation by location of generation or consumption.

Madrigal and Stoft (2012) provide an overview of network infrastructure pricing methodologies. Shirmohammadi and Gorenstin (1996) name similar paradigms for calculation of transmission charges based on actual cost. They identify three different transmission pricing paradigms:

- Under a *postage stamp* model all transmission users pay the same rate pro rata, independent from individual benefit or cost causality, e.g., for consumers based on total consumption (energy-based) or maximum demand (capacity-based) (Madrigal and Stoft, 2012). A small deviation is a *license plate* fee which is a regionally differentiated postage stamp rate (Brunekreeft et al., 2005).

- *Usage-based* methods on the other hand attempt to charge grid users in relation to their actual use of the infrastructure. Madrigal and Stoft (2012) further divide these methods into flow-based and MW-mile calculations. The latter also incorporate distances for rate calculations in addition to caused flows.[6] As mentioned before, the definition of usage-based can be extremely complex in interconnected power grids.

- *Combined* pricing approaches are a blend of postage-stamp and usage-based methods.

In summary, the discussion on who is to be charged for the usage of the transmission system is spanned by two extremes: socialization vs. beneficiary pays (PJM, 2010). In the case of socialization, grid costs are split independently from benefits with the main argument that every stakeholder benefits from the reliability provided by the transmission grid. By contrast, under 'beneficiary pays' the costs are allocated to the stakeholders who benefit the most (e.g., by usage of capacity or low electricity prices). One has to note, that if the benefits are widely distributed, a beneficiary-pays scheme might result in in the same cost allocation as socialization (MIT, 2011). Obviously, it is a challenging task for regulators to create conditions and rules for transmission cost allocation that fulfill all objectives mentioned in the previous section

[6] For more details on distances and the difference between geographical and electric distance please refer to Pérez-Arriaga and Smeers (2003).

International Examples and Approaches

In reality, grid costs in most countries are financed by several different charges (e.g., connection charges, postage stamp charges per kWh). There is no common and agreed guideline or model that defines how much each actor needs to pay for transmission.

The differences in regulatory regimes are already pronounced, even for the connection costs that seem 'easy to allocate', such as super-shallow cost. All cost allocation methods from super-shallow to deep are applied in different countries (see Madrigal and Stoft, 2012). The same applies for the European Union (von Hirschhausen et al., 2012). A detailed overview also demonstrates that even in the EU, the included cost parts in transmission tariffs vary to a great extent, e.g., losses, different system services (ENTSO-E, 2012b). These publications also show that none of the concepts of postage-stamp and usage-based pricing have been globally accepted so far (see Madrigal and Stoft, 2012).

Also, the cost allocation to generation or load is implemented differently, even within a single country, e.g., different ISO regions in the U.S. (PJM, 2010). The same applies for the European Union where around half of the member states allocate all transmission cost to load/consumers (PJM, 2010). The other half also allocates varying shares of the cost to generators. A regularly updated overview on who pays transmission is provided by the European Network of Transmission System Operators for Electricity (ENTSO-E, 2011, 2012b).

Several regulators recently attempt to improve cost allocation schemes to match their specific situation and promote efficient as well as 'fair' outcomes (e.g., FERC in the US, Electricity Authority in New Zealand). For example, Order 1000 by the US Federal Energy Regulatory Commission (FERC) tries to address these questions by allocating costs to beneficiaries:[7] "The regional and inter-regional cost allocation methods each must adhere to six regional and interregional cost allocation principles:

- costs must be allocated in a way that is roughly commensurate with benefits;
- there must be no involuntary allocation of costs to non-beneficiaries;
- a benefit to cost threshold ratio cannot exceed 1.25;
- costs must be allocated solely within the transmission planning region or pair of regions unless those outside the region or pair of regions voluntarily assume costs;

[7] Source: `http://www.ferc.gov/whats-new/comm-meet/2012/051712/E-1.pdf` (p. 395)

- there must be a transparent method for determining benefits and identifying beneficiaries; and
- there may be different methods for different types of transmission facilities."

Olson (2012) provides an interesting interpretation of the Order 1000 and discovers that it is still complex to allocate grid cost 'fairly' even if the order uses the word 'fair' 32 times. Another example is the transmission pricing scheme in New Zealand which has been subject to discussions and changes several times in the last years (Electricity Authority, 2012). In contrast, other countries still apply a socialization of large shares of grid investment cost.

Since this section cannot fully analyze and discuss all regulatory approaches, only some selected cases on transmission cost allocation are presented. First, LMP is not only used by the often mentioned example of PJM, but also by other U.S. ISOs and in other countries, e.g., New Zealand, Argentina (Frontier Economics, 2009). Zonal approaches are used in the UK and also in other countries such as Australia (National Grid, 2013; Frontier Economics, 2009; Ault et al., 2007). In Germany, transmission injection pricing for generation nodes is prohibited by regulation (Knieps, 2013). A real example demonstrates the influence of cost allocation methods on actual investment and also on social welfare: The Arizona Commission rejected a transmission line the cost of which would have had to be borne by Arizona ratepayers, whereas California customers would have benefited from supply at lower cost (Baldick et al., 2007).

The different approaches and recent discussions show that there is currently no generally accepted optimal approach. This is why we evaluate different scenarios where grid costs are paid by either generators or consumers. Olmos and Pérez-Arriaga (2009) summarize the current situation accurately: "There is no universal consensus on the most adequate regulatory approach for transmission investment, access, and pricing." Or as Green (1997) puts it: "None of the authors claims that they have 'the' right answer, and it probably does not exist. All we can do is learn from each others' experience, and hope for incremental improvements."

5.1.3 Related Work on Transmission Pricing and Cost Allocation

This section provides an overview of related work to the models applied in this chapter. These models analyze the influence of different transmission cost allocation regimes in a static scenario with existing assets and in a dynamic scenario where a generator still can invest into capacity. Hence, publications that analyze different transmission pricing approaches as well as competition in spatial grid models are briefly summarized to show complementary approaches to the ones used in this chapter. Since each publication tackles various relevant modeling dimensions, they are presented only briefly to avoid repetitions of the same sources. The relevant aspects of each publication for the models applied in this chapter are summarized in Table 5.1.

Overviews

Some publications offer overviews with a focus on different aspects in spatial electricity markets. Green (1997) serves as a good introduction into the topic, raises the main questions on welfare, incentives as well as implementability and gives an overview of the international experience. Ventosa et al. (2005) provide an overview on electricity market modeling trends and split the models into optimization, equilibrium, and simulation models. Similar to Ventosa et al. (2005), this chapter focuses "for brevity's sake" and presents only a selection of models, i.e., a large share of literature that deals with nodal pricing and operational models is left out. However, Hsu (1997) provides a good overview of short-term transmission pricing literature. He also points out the unresolved challenges with long-term cost allocation and incentives. Smeers (1997) discusses the potential of different competition equilibrium models in restructured gas and electricity markets. Finally, Kagiannas et al. (2004) contribute a review of generation planning methods under competition.

Competition

Competition in spatial models is analyzed by a multitude of models — the following selection matches the topics addressed in this chapter. Borenstein et al. (2000) employ a two-node model with one dominating supplier at each node and constrained grid capacity. Using Cournot competition they show that modest additions to transmission capacity can yield large social benefits. In addition, they discuss opportunities to extend their model and apply it to the Californian electricity market to find that strategic congestion may be an important issue. Wei and Smeers (1999) model a spatial oligopolistic Cournot competition among generators with regulated transmission prices. They apply two transmission pricing regimes — namely average-cost and marginal-cost pricing — to a four node simulation representing European countries and find that average-cost pricing yields lower supply but higher profits.

In a three-node Cournot model with loop flows, Cardell et al. (1997) find that market power may also be exerted by increasing outputs to congest transmission lines. Hobbs (1986) analyzes short-run spatial price equilibria in an oligopolistic deregulated power market with the use of different models. He applies the

Nash-Bertrand and a limit price model to upstate New York. The comparison of prices, profits, and social welfare to a regulated prices regime shows that consumers experience different price effects based on their location.

Investment

Investment and expansion are often analyzed in publications using several stages. Aflaki and Netessine (2012) present a paper on strategic investment into RES. They use an investment and a generation stage, however, grid investment or cost allocation is not in focus. Joskow and Tirole (2005) analyze merchant transmission investment in detail and incorporate several dimensions to obtain more realistic models. They demonstrate — also using simple economic two-node models — that merchant transmission investment may lead to inefficiencies, e.g., when market power influences nodal prices or lumpiness of investment lead to over- or under-investment. Chao and Wilson (2012) analyze electricity transmission and generation investments in three models: efficient coordination, merchant transmission investment, and sequential coordination. They find substantial differences in welfare, prices and investments between efficient regulated and merchant investment and suggest their model as a tool for transmission planners to evaluate different situations and regimes. They state that when the efficiency losses of self-financed (injection fees and congestion charges) investments are small, it might be advantageous due to the avoidance of cost allocation discussions. Murphy and Smeers (2005) investigate different generation investment models also including a two-stage Cournot model but use a single node to avoid transmission challenges. Sauma and Oren (2006) as well as Sauma and Oren (2007) propose a 3-period model for investment and Cournot competition. The periods are transmission planning followed by generation investment and finally an energy spot market. They investigate the influence of transmission investment on social welfare and find that different targets — namely maximization of social welfare, minimization of market power, and maximization of consumer or producer surplus — may all lead to different grid expansion plans. Van der Weijde and Hobbs (2012) evaluate transmission investment for renewable energy sources under uncertainty using a stochastic two-stage optimization model. They apply their model to the UK transmission system and analyze the value of information and the cost of ignoring uncertainty.

Allocation and Cost Recovery

Other publications deal specifically with the challenge of cost allocation and recovery in different settings. Rubio-Odériz and Pérez-Arriaga (2000) analyze different allocation methods to recover remaining costs of the transmission service that are not paid by marginal pricing. This "complimentary charge" is allocated by three approaches: "marginal participation factor", "mean participation factor", and "benefit factors". In their comparison of the methods they consider benefit factors as the best concept based on the criteria efficiency, objectivity and simplicity. However, they also raise serious implementation problems due to the complexity of benefit identification. Rious et al. (2009) employ an average participation tariff in addition to nodal pricing which allocates cost to generators based on their total use of the network and improves coordination between generation and transmission investments significantly. Similarly, Olmos and Pérez-Arriaga (2009) present an approach which is meant to accompany nodal prices to recover full cost. Their approach socializes the unused fraction of a line and tries to allocate the remaining cost based on the expected incremental use of the line by each generator and each load. However, they also mention the challenge that these transmission charges need to be determined and published before the generation investment decision. This is a non-trivial task and the optimality of the results can only be analyzed ex-post, when investment decisions have already been influenced. Joskow and Tirole (2000) investigate the effects of the allocation of physical and financial transmission rights in a congested network — first with a simple two-node model and then they expand it to a model with loop flows. This paper does not focus on cost recovery, it is mentioned here due to the description of the simple grid model.

Practical Examples

Finally, some publications discuss transmission pricing and cost allocation in practical examples. The following three papers give a notion of the differences between theoretical concepts and real-life implementations. Philpott and Hoang (2010) analyze a scheme based on auctioning physical flow rights as alternative to the allocation of HVDC cost to South Island generators in NZ. Ault et al. (2007) model the investment cost-related zonal pricing approach in the UK and find that it is suitable in the future if some issues are resolved that affect some actors, e.g., the effect of distributed generation and the re-zoning in some areas. Dietrich et al. (2009) show for the German market that an integration of grid conditions leads to a different siting of power plants and a social welfare gain in comparison to the current situation with no locational signals.

Reference	Industry model					Pricing			Regulatory regime			Additional features				Key notions
	Monopoly	Duopoly	Oligopoly	Perfect comp.	Other	Nodal	Uniform	Other	Socialized	Beneficiary pays	Other	Demand elasticity	Intermittent supply	Full cost recovery	Dynamic investment	
Aflaki and Netessine (2012)	✓	✓						✓			✓		✓	✓	✓	Analysis of investment into RES and conventional generation under vertical integration and market competition. They find that due to intermittency of supply, market liberalization may not promote efficient generation investments.
Borenstein et al. (2000)		✓				✓				(✓)	(✓)	(✓)				Two-node Cournot model with constrained transmission capacity and Bertrand extension. They find that transmission expansion mitigates market power and reduces prices.
Cardell et al. (1997)			✓			✓				(✓)	(✓)	✓				Spatial three-node Cournot model with loop flows that yields the result that market power may also be exerted by increasing outputs to block transmission.
Chao and Wilson (2012)			✓			✓			✓	✓	✓	✓			✓	Three-node Cournot model with two transmission lines to study efficient transmission and generation planning. Costs are allocated to consumers in three ways: socialized, beneficiary pays, and market-based. The authors state that when the efficiency losses of a self-financed investments (injection fees and congestion charges) are small, it might be advantageous due to the avoidance of cost allocation discussions.
Hobbs (1986)			✓					✓		✓	✓	(✓)			(✓)	Model of Bertrand competition and limit-pricing in spatial electricity markets. The comparison to a price regulation model shows that consumers experience different price effects by location.
Joskow and Tirole (2000)	✓		(✓)			✓				(✓)	(✓)	✓				Two- and Three-node model to analyze the influence of transmission right allocation on a congested network. They find that physical and financial transmission rights can increase market power of generators and consumers.
Joskow and Tirole (2005)				(✓)		✓				(✓)	(✓)				✓	A merchant transmission investment is expanded to incorporate realistic attributes in transmission, e.g., market power. The authors find that merchant transmission investment yields inefficiencies given these attributes.
Murphy and Smeers (2005)		✓		(✓)							✓	✓			✓	Single node model which investigates generation investment and perfect competition as well as simultaneous and two-stage cournot competition.

Reference	Industry model					Pricing			Regulatory regime			Additional features				Key notions
	Monopoly	Duopoly	Oligopoly	Perfect comp.	Other	Nodal	Uniform	Other	Socialized	Beneficiary pays	Other	Demand elasticity	Intermittent supply	Full cost recovery	Dynamic investment	
Olmos and Pérez-Arriaga (2009)						(✓)		✓		(✓)				✓		Analysis of transmission charge designs to recover grid cost and guide siting decisions. The application to the Spanish power system shows the expected result that exporting regions pay higher transmission charges.
Rious et al. (2009)				(✓)	✓	(✓)		✓		(✓)					✓	Two-node model with nodal pricing and an average participation tariff to send long-term signals. The authors find that an implementation of a locational network tariff is more important for efficient siting of generation capacity than the implementation of nodal pricing.
Rubio-Odériz and Pérez-Arriaga (2000)					✓			✓		(✓)	(✓)			✓		Analysis of three different network cost allocation methods with application to the Spanish market.
Sauma and Oren (2006), Sauma and Oren (2007)			✓			✓			(✓)	(✓)		✓			✓	Cournot competition to evaluate the influence of transmission investment on social welfare with three periods: transmission planning, generation investment and market operation. Expansion plans differ largely dependent on the optimization target.
Van der Weijde and Hobbs (2012)					✓			✓			✓				✓	Two-stage stochastic optimization model that minimizes total cost consisting of transmission investment as well as investment and operation of generation under uncertainty.
Wei and Smeers (1999)			✓					(✓)		(✓)		✓		(✓)	✓	Spatial Cournot with regulated transmission prices (average and marginal) charged to generators. Average-cost pricing yields lower supply but higher profits than marginal-cost pricing.

Table 5.1: Summary of selected contributions on transmission grid pricing and cost allocation models

This chapter extends prior research on grid or transmission pricing and cost allocation by investigating cost allocation and local price differentiation simultaneously. The use of price discrimination raises again the question of what is *fairness*. As discussed in the beginning, one may argue that electricity is a commodity product and all types of differentiation are per se *unfair*. However, this thesis rather follows the argumentation that *fair* prices can also be differentiated, e.g., by time or location especially in order to yield an efficient outcome. This corresponds to the notion that current uniform pricing regimes are not per se *fair* in terms of grid cost allocation (Faruqui, 2010). Different regulatory cost allocation regimes are compared with respect to their impacts on total and consumer welfare. The intention is to present the modeling assumptions from an economic point of view and to allow the reader to judge applicability and limitations of the presented model.

5.2 Grid Cost Allocation and Competition - A Microeconomic Analysis

A simple analytical network model with a three-step time structure serves as the base to investigate different alternatives for transmission grid cost allocation. A previous version of the model has been published published in our paper Ilg et al. (2012). This basic model abstracts from physical reality and is intended to guide the discussion on the economic implications with respect to welfare distribution as well as implications on investment behavior. In the following, the model and decision structure are described in general. Subsequently, the model is instantiated twice — first to analyze welfare distribution with preexisting investments and second to analyze investment behavior into new grid and generation capacity.

5.2.1 Basic Stylized Grid Model

We assume an unbundled power market with the functions generation and transmission performed by legally and commercially separated entities. The basis is a simple two-node grid model (nodes L and H) with heterogeneous conditions for generation of electricity similar to Joskow and Tirole (2000, 2005). At each location (node), we model one generator and one consumer population. The locations are interconnected by a transmission infrastructure (i.e., a single transmission line or a more complex transmission grid) operated by a TSO O as depicted in Figure 5.3. For the consumer populations at each location $D_j, j \in \{L, H\}$ it is not relevant whether these are actually individual end consumers (households or industry), distributors, or retailers, since the latter simply serve as load aggregators. Independent generator populations $G_i, i \in \{L, H\}$ serve the demand as suppliers either directly at their location or via the transmission grid infrastructure. Both locations feature sufficient natural resources to serve total demand if sufficient generation capacity is built.

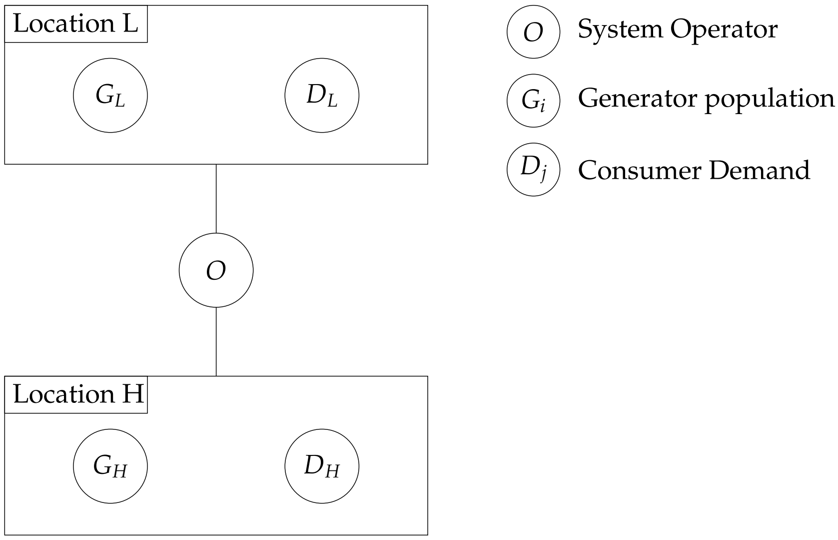


Figure 5.3: Basic model overview

Grid costs are imposed on different participants depending on the regulatory regime. Consumers are assumed to be price takers, i.e., demand is perfectly inelastic. In the following, two different instances of this basic model are used to analyze locational competition and investment behavior with different conditions for generation and investment efficiency, respectively.

5.2.2 Generic Timing and Decision Structure

Our basic model is applied using different assumptions and scenarios to investigate competition and investment behavior. We split the analysis into two parts, since the model instances strongly depend on the question to be answered. The reason for this is the sequence of decisions we assume in context of the transmission investment and operation:

- Step 1: Regulatory environment decision
- Step 2: Investment decision into generation capacity at both locations
- Step 3: Revenue generation through electricity dispatch and pricing

All decisions in competition and investments are based on full knowledge of the regulatory environment. Without existing generation and transmission infrastructure assets, the participating actors decide on their investments based on the regulatory environment. Subsequently, the actors compete on the market and try to maximize their profit under the given regulatory regime. Obviously, actors incorporate the third stage of revenue generation into their investment decision. To this end, we first analyze step 3, to understand the behavior of participants given a preexisting infrastructure. This is comparable to a static case where generators and the transmission grid are already existing — which is true for large parts of most power systems. Step 2 on the other hand represents a dynamic decision on new investments into generation and transmission capacity.

The following sections provide a description of the two different model instances we use to analyze step 2 and 3. First, step 3 with competitive dispatch and pricing is investigated under different regulatory regimes. Based on these results, the investment stage in step 2 is discussed. In the classification of Ventosa et al. (2005) step 3 is modeled as an equilibrium model whereas we use an optimization model for one generator in step 2.

5.3 Grid and Energy Pricing with Preexisting Investments

This section is an amended version of our publication Ilg et al. (2012), with modifications regarding the focus of the regulatory scenarios and extensions to account for uneven consumer population splits. Instead of emphasizing the locational price differentiation, we mainly focus on the allocation of grid cost. One major assumption in this section is that generators at each location and the connecting transmission grid are preexisting. First, the market and institutional scenarios that we want to analyze with our model are presented as described by Smeers (1997). Based on Smeers (1997), the market scenario defines the main design parts of our model such as number and behavior of participants, structure of the industry and hypotheses about competition. Obviously, the basic parts of the market scenario are already defined by the basic grid model (Section 5.2.1). Subsequently, we describe the institutional scenarios that are defined as the regulatory environment set by public authorities which influences the market.

5.3.1 Market Scenario and Behavior of Participants

Our model analyzes the competition between two generating firms at different locations. Generators are independent entities and do not cooperate, i.e., they compete at both locations to maximize individual profit. Extending the basic grid model, the generators G_L at location L produce at constant marginal cost of MC_L per unit of energy, whereas the generators G_H produce at marginal cost MC_H (Figure 5.4).

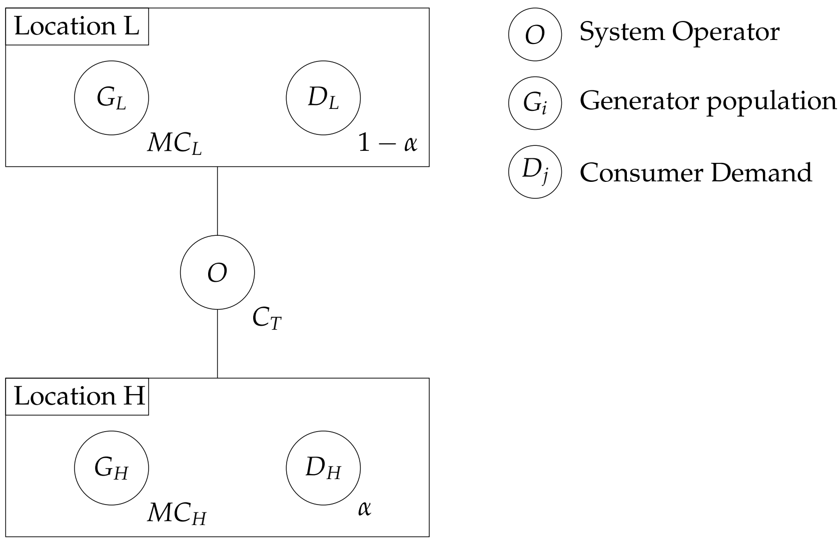


Figure 5.4: Model instance for grid pricing with preexisting investment

We focus on the case of cost asymmetry, that is generators differ in their marginal production costs, such that $MC_L < MC_H$. To reduce the notational burden we normalize MC_L to zero without loss of generality. Therefore, MC_H can be interpreted as the generation cost difference between the two locations. We assume generators behave competitively and maximize their profits by setting their prices strategically. Our model abstracts from physical constraints such that the generators are not limited by transmission or generation capacity.

For ease of exposition, we normalize the total demand in the model (i.e., the sum of both consumer population demands) to unity. However, the consumer distribution is variable across the two nodes. Parameter α defines the share of the consumer population at location H. Therefore, a consumer population share of $1-\alpha$ is situated at the low-cost location L. The additional assumption $1 > \alpha \geq 0.5$ ensures that the major share of total consumption is located at the high-cost location H. Each consumer population chooses its supplier purely price-based. If prices are identical, they randomly choose either one with equal probability.

A regulated TSO provides transmission services based on the constant calculatory grid cost C_T which incur per unit of energy transmitted from one location to the other. These constant grid costs or capital costs of transmission infrastructure are based on the assumption of an ideally sized grid (i.e., there is always enough and no excessive unused transmission capacity). Naturally, dynamic grid utilization is heavily dependent on load patterns and the generators' capacity factors. Abstracting from this complexity, we focus on static grid situations comparable to a long-term average analysis. This is similar to a regulated monopolist that is allowed to recover cost. Depending on the institutional scenario these grid costs are charged either to generation or demand.

5.3.2 Institutional Scenarios

We analyze four different regulatory regimes or scenarios (Figure 5.5). In this first part, we abstract from investment and focus on competition between preexisting generators under the different regulatory scenarios.

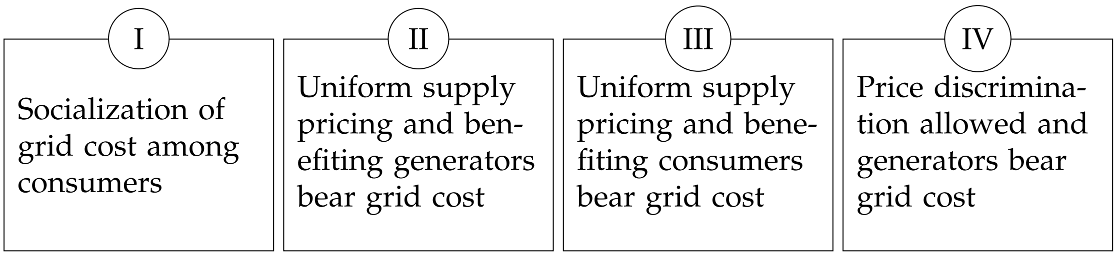


Figure 5.5: Institutional scenario overview with preexisting investments

Depending on the institutional scenario generators have to set uniform prices or are allowed to discriminate prices by consumer location. Prices of generator G_i at location j are represented as $p_i^j, i \in \{l, h\}, j \in \{L, H\}$, i.e. p_l^H is the price the low-cost generator is offering to consumers at the high-cost location H. In our reference Scenario I generators are not allowed to discriminate prices by location. All transmission and grid-related costs are socialized and allocated to consumers based on their share of total consumption independent of their location. This results in a market where generators set uniform prices for all consumers purely based on generation cost without taking into account transmission cost. In the subsequent scenarios we want to compare transmission pricing based on a simple beneficiary pays scheme. In Scenario II transmission costs are fully allocated to transmitting generators and in Scenario III to transmitting consumers, only based on total share of transmitted energy. Still, generators are not allowed to differentiate their price by customer location. However, the transmission cost allocation schemes may lead to differentiated total cost for consumers. The last Scenario IV analyzes the influence of price discrimination with cost allocation to beneficiaries.

5.3.3 Scenario I — Socialization of Grid Cost and Consumers Bear Grid Cost

The socialization of grid costs to customers based on their demand and independently of their location is a simple form of cost allocation. Since grid costs are merely added to the uniform price of generation, both consumer populations pay the same price per unit of energy, including transmission. Socialized grid costs have no influence on the price competition between the generators. Without the possibility of price discrimination, generators have to charge the same price at both locations. Therefore, we simplify the price notations as follows:

$$\begin{aligned} p_l^H &= p_l^L = p_l, \\ p_h^H &= p_h^L = p_h. \end{aligned} \tag{5.1}$$

Owing to the Bertrand-style competition with uniform prices, all demand will be allocated to the generator that offers the lowest price or split evenly in case of identical prices. The demand function for the generator L is

$$N_{G_L} = \begin{cases} 1 & \text{if } p_l < p_h \\ 0.5\alpha + 0.5(1-\alpha) & \text{if } p_l = p_h \\ 0 & \text{if } p_l > p_h \end{cases} \tag{5.2}$$

and respectively the opposite for generator H. Since identical prices would lead to split population, which in return would change total grid cost, we abstract from this special case in order to derive clear results. In addition, this outcome would be somehow artificial and unstable given the multitude of different generation technologies.

Based on this demand the profit functions of the generators are

$$\begin{aligned} \pi_L &= N_{G_L}(p_l - MC_L), \\ \pi_H &= N_{G_H}(p_h - MC_H). \end{aligned} \tag{5.3}$$

The resulting competition is a typical Bertrand competition based on the generation price. The generators will undercut prices as long as they are above marginal cost. Similar to Peeters and Strobel (2009), we define undercutting as the setting of lower prices to attract consumers from the opposite generator despite any additional cost such as transportation or transmission. Finally, low-cost generators will serve the whole market at a price slightly below marginal cost of the generators at the high-cost location. Then the high-cost generator can no longer undercut without making losses. This results in an equilibrium generation price for all consumers of

$$p_l^* = p_l^{*H} = p_l^{*L} = MC_H - \epsilon. \tag{5.4}$$

Given totally inelastic demand and marginal production cost of zero, and neglecting ϵ, the equilibrium profit functions of the generators are

$$\begin{aligned} \pi_L^* &= MC_H, \\ \pi_H^* &= 0. \end{aligned} \tag{5.5}$$

Both consumer populations have to pay the same end consumer price and additionally finance total grid cost αc_t which leads to the average consumer cost for their demand of

$$AVC_{D_L} = AVC_{D_H} = MC_H + \frac{\alpha C_T}{1} = MC_H + \alpha C_T \tag{5.6}$$

The socialization of grid cost results in the maximum grid infrastructure to serve $\alpha \geq 0.5$ of the total consumer population with low-cost generation. This result has two interesting facets. First, generators with higher cost cannot compete independently of grid cost levels. Second, consumers next to low-cost generation pay for the grid like the customers next to the high-cost generation without being beneficiaries of the transmission.

5.3.4 Scenario II — Benefiting Generators Bear Grid Cost

In the second scenario the transmission grid costs are fully allocated to the transmitting generators, and they still have to offer uniform prices to consumers (Equation 5.1). The competing generators have to take into account the expected grid cost for serving the whole market when setting their prices, which leads to the following profit functions

$$\begin{aligned} \pi_L &= N_{G_L}(p_l - MC_L) - \alpha C_T, \\ \pi_H &= N_{G_H}(p_h - MC_H) - (1-\alpha)C_T. \end{aligned} \tag{5.7}$$

Equilibrium prices result from the same undercutting competition as in Scenario I, with generators anticipating their share of grid cost when serving remote consumers. Depending on the transmission cost, the low-cost generator located next to the smaller consumer population might not have lower total marginal cost. Again, the generator with the lowest marginal cost will serve all consumers at the minimum price of the opposite generator. Given the transmission cost, minimum prices when serving all consumers are

$$\begin{aligned} \underline{p_l} &= MC_L + \alpha C_T = \alpha C_T, \\ \underline{p_h} &= MC_H + (1-\alpha)C_T. \end{aligned} \tag{5.8}$$

The resulting equilibrium prices depend on both the consumer population partition (α) and the locational difference in generation cost (MC_H). Excluding the possibility to split consumer populations evenly, we obtain two possible outcomes.

Case 1 — Low-cost generator captures market If $\underline{p_l} < \underline{p_h}$, the low-cost generator can serve the whole market. The condition can be converted into

$$\begin{aligned} \underline{p_l} &< \underline{p_h} \\ \alpha C_T &< MC_H + (1-\alpha)C_T \\ \frac{1}{2\alpha - 1} &> \frac{C_T}{MC_H} \end{aligned} \tag{5.9}$$

G_L will charge the other generator's minimum price minus an infinitesimal discount. Neglecting ϵ, the resulting price obtains:

$$p_l^* = MC_H + (1-\alpha)C_T \quad \text{if } \frac{1}{2\alpha - 1} > \frac{C_T}{MC_H} \tag{5.10}$$

Including generation and grid costs, the industry profits are

$$\begin{aligned} \pi_L^* &= (1-2\alpha)C_T + MC_H, \\ \pi_H^* &= 0. \end{aligned} \tag{5.11}$$

As the low-cost generator accounts for grid cost αMC_T when setting prices, the resulting prices are the average consumer cost: $AVC_{D_L} = AVC_{D_H} = p_l^* = MC_H + (1-\alpha)C_T$.

Case 2 — High-cost generator captures market In the opposite case $\underline{p_l} > \underline{p_h}$ the high-cost generator will capture the whole market. Thus, neglecting ϵ, the equilibrium price is

$$p_h^* = \alpha C_T \quad \text{if } \frac{1}{2\alpha - 1} < \frac{C_T}{MC_H}. \tag{5.12}$$

The resulting industry profits are

$$\begin{aligned} \pi_L^* &= 0, \\ \pi_H^* &= (2\alpha - 1)C_T - MC_H. \end{aligned} \tag{5.13}$$

Again, the grid cost $(1-\alpha)C_T$ are already included — the price represents the final average consumer cost: $AVC_{D_L} = AVC_{D_H} = p_h^* = \alpha C_T$.

Cases — Overview The condition $\frac{1}{2\alpha-1} < \frac{C_T}{MC_H}$ that determines the switch from case 1 to case 2 depending on the grid-to-generation-cost relation $\frac{C_T}{MC_H}$ is depicted in Figure 5.6. In the area above the depicted function G_H serves total demand — G_L otherwise in the area below. In both cases the total industry profit $\Pi^* = \pi_L^* + \pi_H^*$ is absorbed by a single company while network costs amount to

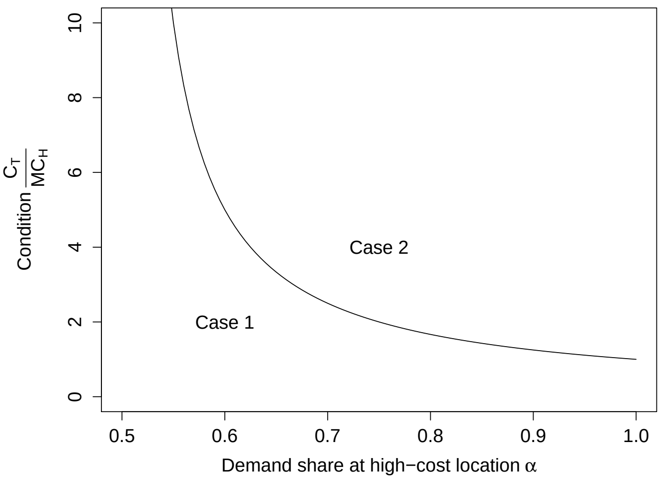


Figure 5.6: Characteristics of condition $\frac{1}{2\alpha-1}$ for different α

αC_T in Case 1 or $(1-\alpha)C_T$ in Case 2, respectively. Generators with higher cost can therefore compete if grid cost are high, generation cost difference is low and large share of population is at the high cost location.

5.3.5 Scenario III — Benefiting Consumers Bear Grid Cost

In the third scenario all grid costs are allocated to the consumers that use transmission capacity. Given the restriction to uniform pricing, consumers pay the same price per unit of energy but have to add transmission cost if buying from the opposite generator. That is, consumer demand D_L will always choose the less expensive option of $(p_l,\ p_h + C_T)$ and D_H will choose the less expensive options from $(p_l + C_T,\ p_h)$. In pure Bertrand competition, generator G_L faces the following demand function:

$$N_{G_l} = \begin{cases} 1 & \text{if } p_l < p_h - C_T \\ 0.5\alpha + 1 - \alpha & \text{if } p_l = p_h - C_T \\ 1-\alpha & \text{if } p_h + c_t > p_l > p_h - C_T \\ 0.5(1-\alpha) & \text{if } p_l = p_h + C_T \\ 0 & \text{if } p_l > p_h + C_T \end{cases} \tag{5.14}$$

while G_H always captures the remaining demand.

Therefore, generators need to consider expected grid cost for consumers when setting their uniform prices (Equation 5.1). With our assumptions $MC_H > MC_L = 0$ and $C_T > 0$, generator pool G_L is always able to capture its local consumer demand D_L; therefore the lower two lines of Equation 5.14 cannot occur, and the high-cost generator will never capture the whole market. With respect to consumer demand D_H we need to analyze two different cases.[8]

Case 1 — Market served by low-cost generator In the case of $C_T < MC_H$, the low-cost generator can capture the whole market due to a large generation cost difference (first line of Equation 5.14). The low-cost generator can profitably price the high-cost generator out of the market by setting a price at

$$p_l^* = MC_H - C_T - \epsilon \tag{5.15}$$

Neglecting the infinitesimal ϵ, the generators will generate a profit of

$$\begin{aligned} \pi_L^* &= MC_H - C_T, \\ \pi_H^* &= 0, \\ \Pi^* &= MC_H - C_T. \end{aligned} \tag{5.16}$$

Both consumer populations will buy at this price p_l^* from G_L. Additionally, the consumers at the high-cost location have to bear the grid cost of αC_T. Therefore, the average consumption costs for each demand population are

$$\begin{aligned} AVC_{D_L} &= MC_H - C_T, \\ AVC_{D_H} &= \frac{\alpha(MC_H - C_T) + \alpha C_T}{\alpha} = MC_H. \end{aligned} \tag{5.17}$$

The population at the low-cost location has lower average cost than consumers at the high-cost location: $AVC_{D_H} > AVC_{D_L}$.

Case 2 — Market split In the case of $C_T > MC_H$, each generator has a local cost advantage and could serve its local market profitably without connecting grid infrastructure. However, generators can leverage the threat of potential grid cost to realize higher prices at their local consumer pool. In such a case, a Nash-Bertrand equilibrium in pure price-strategies does not exist (Shy, 2001). However, Morgan and Shy (1996) propose the Undercut Proof Equilibrium as an alternative solution concept. According to Peeters and Strobel (2009), the rationale behind the UPE has some similar features as the Stackelberg sequential price setting process. Each generator assumes its own price as fixed and analyzes whether the opposite generator has an incentive to undercut in order to capture the whole market. In the UPE each generator sets the highest price possible without giving the opposite generator an incentive to undercut and capture the whole market. In detail that means G_L has to set the price p_l satisfying the

[8] Again, we abstract from analyzing the cases of $p_l = p_h - C_T$ to avoid fictitious results with split consumer pools and therefore differing grid cost.

following condition

$$\pi_{G_H} = (p_h - MC_H)\alpha \geq p_l - MC_H - (1-\alpha)MC_T. \tag{5.18}$$

Whereas G_H sets the price p_h subject to

$$\pi_{G_H} = p_l(1-\alpha) \geq p_h - \alpha MC_T. \tag{5.19}$$

This leads to the UPE prices of

$$\begin{aligned} p_l^* &= \frac{1-\alpha}{\alpha^2-\alpha+1}MC_H + C_T, \\ p_h^* &= \frac{(\alpha-1)^2}{\alpha^2-\alpha+1}MC_H + C_T. \end{aligned} \tag{5.20}$$

The characteristics of these UPE prices dependent on α are depicted in Figure 5.7. Obviously, the absolute price level depends on MC_H and C_T, however, the shape of the curves is invariant.

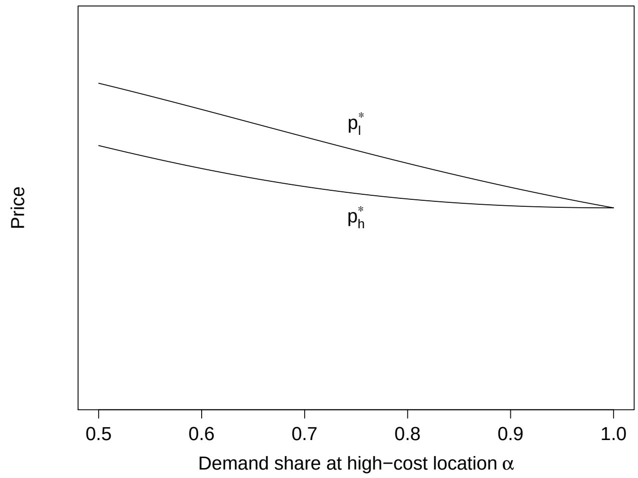


Figure 5.7: UPE consumer prices for different α with split market and without transmission

The equilibrium prices always fulfill the condition of $p_h^* < p_l^*$ with no transmission occurring that also means $p_h^* = AVC_{D_H} < AVC_{D_L} = p_l^*$. Therefore, consumers at the high-cost location are better off than consumers at the low-cost location (5.7). This is in contrast to an equilibrium in mixed strategies which predicts that lower prices are set by a generator with lower cost and smaller customer base (Peeters and Strobel, 2009) and also in contrast to a Hotelling location model (Shy, 2001). This special property of the UPE prices may have an influence on real or experimental competition cases (Peeters and Strobel, 2009). However, Shy (2001) notes that in some industries it is common for firms with a larger consumer base to sell at a lower price, e.g., discount stores.

Industry and firm profits are then given by local population share times equilibrium price minus the generation costs:

$$\begin{aligned}\pi_L^* &= \left(\frac{1-\alpha}{\alpha^2-\alpha+1}MC_H + C_T\right)(1-\alpha),\\ \pi_H^* &= \left(\frac{(\alpha-1)^2}{\alpha^2-\alpha+1}MC_H + C_T - MC_H\right)\alpha,\\ \Pi^* &= \frac{(1-2\alpha)}{\alpha^2-\alpha+1}MC_H + C_T.\end{aligned} \tag{5.21}$$

Cases — Overview In summary, the low-cost generator can serve the whole market if its cost advantage is large enough (Case 1). However, G_L has to compare the profit with the profit of a split market (Case 2) to decide whether it is better to serve all consumers or give up the remote customers in order to realize higher profits. Comparing Equation 5.16 and Equation 5.21, we can determine when it is optimal for G_L to serve the whole market or when it is optimal to forfeit the remote customers, respectively:

$$\begin{aligned} MC_H - C_T &> \left(\frac{1-\alpha}{\alpha^2-\alpha+1}MC_H + C_T\right)(1-\alpha)\\ \Leftrightarrow \frac{\alpha}{2-3\alpha+3\alpha^2-\alpha^3} &> \frac{C_T}{MC_H}\end{aligned} \tag{5.22}$$

The factor $\frac{\alpha}{2-3\alpha+3\alpha^2-\alpha^3}$ is strictly increasing in $\alpha \in [0.5; 1]$ and depicted in Figure 5.8. As long as the grid costs are sufficiently low in comparison to generation

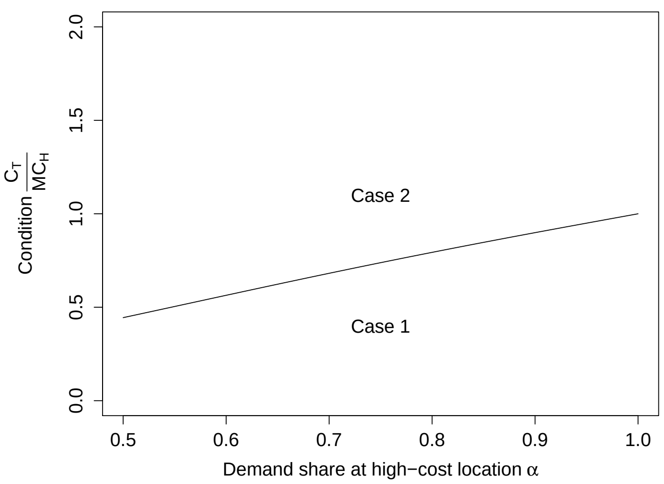


Figure 5.8: Characteristics of condition $\frac{\alpha}{2-3\alpha+3\alpha^2-\alpha^3}$ for different α

cost , G_L will serve the whole market (case 1). However, if the grid costs are sufficiently high, the low-cost generator will find it profitable to serve only its local customers in a split market to realize the higher UPE prices (case 2). In addition, the switch between the two cases depends on α. For small values of α, the low-cost generator tends to split the market already at lower grid cost.

This scenario has two interesting implications. First, in the case of a split market, the generators can utilize '*virtual*' grid cost as market protection and set higher prices. This means in a split market no grid infrastructure is necessary. However, the '*threat*' of grid pricing allows to set higher prices on the respective local market. Second, when the low-cost generator serves the whole market, consumers at the high-cost location as beneficiaries pay higher average end consumer prices.

5.3.6 Scenario IV — Price Discrimination and Generators Bear Grid Cost

In the final scenario generators are allowed to discriminate prices based on consumer location, i.e. there are four individual prices $p_l^H, p_l^L, p_h^H, p_h^L$ in the market. This price discrimination effectively separates the two markets. In this case we focus only on the option where transmitting generators have to cover transmission cost.[9] This results in differentiated end consumers prices per unit of energy, including transmission/grid cost. Similar to Scenario II, competing generators have to consider expected grid cost when setting prices. However, they can utilize grid cost to realize higher prices with their local consumer population.

Equilibrium prices result from undercutting competition in each market with generators anticipating their share of grid cost when serving remote consumers. Again, the generator with the lowest marginal cost will serve the consumers at the minimum price of the opposite generator. In this scenario minimum prices differ by location:

$$\begin{aligned}
\underline{p_l^L} &= MC_L = 0, \\
\underline{p_h^L} &= MC_H + C_T, \\
\underline{p_l^H} &= MC_L + C_T = C_T, \\
\underline{p_h^H} &= MC_H.
\end{aligned} \tag{5.23}$$

The resulting optimum prices do not depend on the relative consumer pool sizes (α and $1-\alpha$), since the markets are separated by price discrimination.

Given the assumption $MC_H > MC_L = 0$, the low-cost generator G_L can al-

[9] In Ilg et al. (2012), we demonstrate that individual welfare is independent of cost allocation in a price discrimination scenario.

ways capture the whole customer demand D_L by charging the minimal price $\underline{p_h^L}$ minus an infinitesimal discount:

$$p_l^{L*} = \underline{p_h^L} - \epsilon = MC_H + C_T - \epsilon \tag{5.24}$$

For the equilibrium in respect of consumer demand D_H we distinguish two cases similar to Scenario III. Depending on the grid and generation cost difference, low-cost generators serve the whole market if their cost advantage is sufficiently large or each consumer population is served by the local generator without transmission.

Case 1 — Market served by low-cost generator In the case of $C_T < MC_H$, the low-cost generator can capture consumer demand D_H due to a large generation cost difference by charging

$$p_l^{H*} = \underline{p_h^H} - \epsilon = MC_H - \epsilon \tag{5.25}$$

Total industry profit is generated by the low-cost generator alone:

$$\begin{aligned} &\pi_L^* = (1-\alpha)(MC_H + C_T) + \alpha MC_H - \alpha C_T = MC_H + (1-2\alpha)C_T, \\ &\pi_H^* = 0, \\ &\Pi^* = MC_H + (1-2\alpha)C_T. \end{aligned} \tag{5.26}$$

The average consumer costs are higher at the low-cost location

$$\begin{aligned} AVC_{D_L} &= p_l^{L*} = MC_H + C_T, \\ AVC_{D_H} &= p_l^{H*} = MC_H. \end{aligned} \tag{5.27}$$

Case 2 — Market split In the case of $C_T > MC_H$, the high-cost generator G_H has a local cost advantage and can serve its local market profitably leveraging the differentiating grid cost to realize higher prices by charging:

$$p_h^{H*} = \underline{p_l^H} - \epsilon = C_T - \epsilon \tag{5.28}$$

Total industry profit is split between both generators with no transmission cost:

$$\begin{aligned} \pi_L^* &= (1-\alpha)(MC_H + C_T), \\ \pi_H^* &= \alpha C_T, \\ \Pi^* &= (1-\alpha)MC_H + C_T. \end{aligned} \tag{5.29}$$

Similar to Case 1, the average consumer costs are higher at the low-cost location

$$
\begin{aligned}
AVC_{D_L} &= p_l^{L*} = MC_H + C_T, \\
AVC_{D_H} &= p_l^{H*} = C_T.
\end{aligned}
\tag{5.30}
$$

Cases — Overview For low grid cost C_T the generator G_L can profitably serve the whole market. As soon as $C_T > MC_H$ or $\frac{C_T}{MC_H} > 1$ respectively, the market is split independently of the consumer demand distribution. Figure 5.9 depicts the condition and the respective case per area. In both cases consumers at the low-

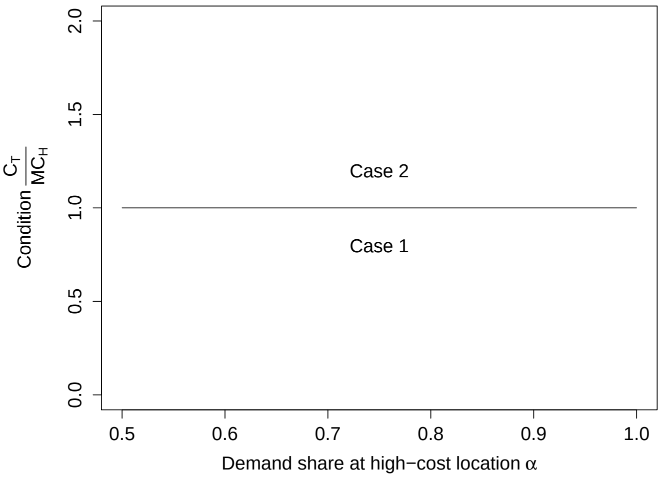


Figure 5.9: Characteristics of the switching condition in Scenario IV for different α

cost location face higher prices. Again, both generators can use 'virtual' grid cost as market protection and to set higher prices in a split market.

5.3.7 Comparison of Scenarios

In this section we compare the different scenarios with respect to their economic impact. More precisely, we compare the overall cost efficiency, firm profits and customer cost split by location. To obtain more compact expressions, we again drop the ϵ terms. Table 5.2 summarizes the results along the important dimensions. An important factor are the different conditions for $\frac{C_T}{MC_H}$ that determine the outcomes in each scenario. To this end, all conditional functions are plotted in Figure 5.10.

Cost Efficiency

The most obvious way to analyze allocative efficiency in our model is to calculate the total industry costs arising from grid and generation cost. A social planner would clearly minimize these costs to maximize social welfare. For $MC_L = 0$ the

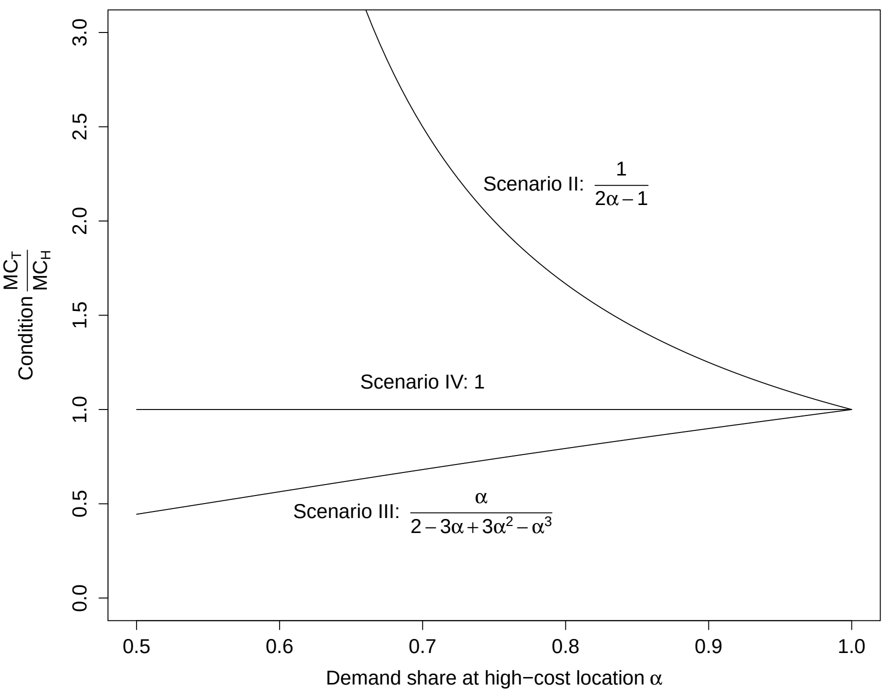


Figure 5.10: Characteristics of conditions for different α

Pricing		Uniform Pricing					Discriminatory Pricing	
Allocation Scenario		I Soc. cost	II Ben. Generators		III Ben. Consumers		IV Ben. Generators	
Demand served by		G_L	G_L	G_H	G_L	Split	G_L	Split
Condition		–	$\frac{C_T}{MC_H} < \frac{1}{2\alpha-1}$	$\frac{1}{2\alpha-1} < \frac{C_T}{MC_H}$	$\frac{C_T}{MC_H} < \frac{\alpha}{2-3\alpha+3\alpha^2-\alpha^3}$	$\frac{\alpha}{2-3\alpha+3\alpha^2-\alpha^3} < \frac{C_T}{MC_H}$	$\frac{C_T}{MC_H} < 1$	$1 < \frac{C_T}{MC_H}$
Total grid cost		αC_T	αC_T	$(1-\alpha)C_T$	αC_T	0	αC_T	0
Industry profit	Π^*	MC_H	$MC_H + (1-2\alpha)C_T$	$-MC_H + (2\alpha-1)C_T$	$MC_H - C_T$	$\frac{(1-2\alpha)}{\alpha^2-\alpha+1} MC_H + C_T$	$MC_H + (1-2\alpha)C_T$	$(1-\alpha)MC_H + C_T$
Generator	π_L^*	MC_H	$MC_H + (1-2\alpha)C_T$	0	$MC_H - C_T$	$\left(\frac{1-\alpha}{\alpha^2-\alpha+1} MC_H + C_T\right)(1-\alpha)$	$MC_H + (1-2\alpha)C_T$	$(1-\alpha)(MC_H + C_T)$
profits	π_H^*	0	0	$-MC_H + (2\alpha-1)C_T$	0	$\left(\frac{(\alpha-1)^2}{\alpha^2-\alpha+1} MC_H + C_T + MC_H\right)\alpha$	0	αC_T
Avg. consumer	AVC_{D_L}	$MC_H + \alpha C_T$	$MC_H + (1-\alpha)C_T$	αC_T	$MC_H - C_T$	$\frac{1-\alpha}{\alpha^2-\alpha+1} MC_H + C_T$	$MC_H + C_T$	$MC_H + C_T$
costs	AVC_{D_H}	$MC_H + \alpha C_T$	$MC_H + (1-\alpha)C_T$	αC_T	MC_H	$\frac{(\alpha-1)^2}{\alpha^2-\alpha+1} MC_H + C_T$	MC_H	C_T

Table 5.2: Competition scenario comparison with preexisting investment

cost-minimal schedule is readily determined: Demand D_L will always be served by generator G_L, while for demand D_H it depends on the proportion of C_T and MC_H. If $C_T > MC_H$ or noted differently $\frac{C_T}{MC_H} > 1$, demand D_H is optimally served by generator G_H. Otherwise it is optimal to serve the whole market with generator G_L. This threshold criterion is represented by the constant function $\frac{C_T}{MC_H} > 1$ in Figure 5.10.

From the analysis, we obtain that scenarios I and II cannot achieve this total cost optimum for $\frac{C_T}{MC_H} > 1$. This is because under the uniform pricing regime with socialized grid costs or generators bearing grid costs the optimal split allocation cannot be achieved. In Scenario II the market is always served by G_L until the whole market switches from G_L to G_H at the threshold level $\frac{C_T}{MC_H} > \frac{1}{2\alpha-1}$ due to Bertrand competition. Conversely, in Scenario III, generator G_L's incentive to sustain higher prices with the local demand for $\frac{C_T}{MC_H} > \frac{\alpha}{2-3\alpha+3\alpha^2-\alpha^3}$ yields a split outcome in cases where concentrated generation by generator G_L would be efficient. Finally, in Scenario IV, the cost-optimal allocation is always achieved.

Industry Profits

The comparison of industry profits — in this case it is defined as the total profits of both generators — is more complex and also depends on $\frac{C_T}{MC_H}$ and the demand distribution factor α. Figure 5.3 depicts the total industry profits for relevant realizations of C_T with fixed levels $M_H \in \{1, 2, 3\}$. The first result is that no Scenario is strictly dominating the other scenarios. However, for $\frac{C_T}{MC_H} < 1$, Scenario I with socialized grid cost yields the highest industry profits. In all other scenarios, total industry profits fall with a small but increasing C_T. As soon as the specific threshold condition as depicted in Figure 5.10 is reached, the total industry profit rises again. As mentioned before, this happens only at high levels of C_T and α in Scenario II. In this scenario, the total industry profit can surpass the Scenario I profits at unrealistically high C_T levels only. This is due to the inefficient centralized customer allocation. In contrast, the industry profit in Scenario IV with discriminatory pricing jumps to a dominating level as soon as $\frac{C_T}{MC_H} > 1$. This is clearly a result of both generators using their market power in their local market protected by high grid cost. Customer-borne grid pricing with uniform generation prices (Scenario III) yields more differential results: For low relative grid costs, $\frac{C_T}{MC_H} < \frac{\alpha}{2-3\alpha+3\alpha^2-\alpha^3}$, industry profits are strictly lower than in the other scenarios. Even with the switch to a split market, the profits do not immediately surpass the other scenarios. However, for high relative grid cost $\frac{C_T}{MC_H} >> 1$, this scenario leads to strongly increasing industry profits similar to Scenario IV and also surpassing Scenario I and II.

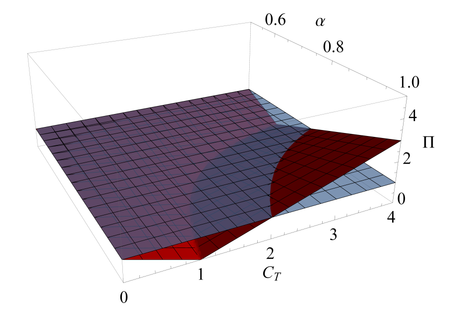
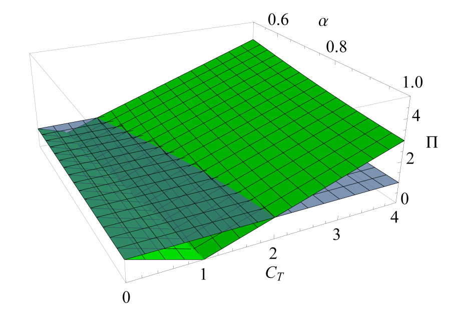
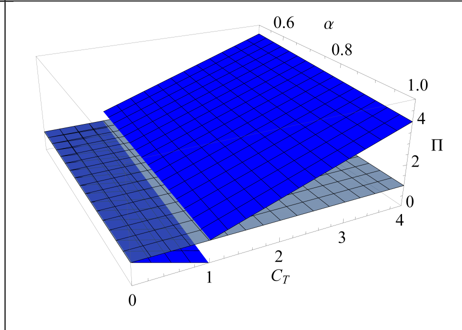
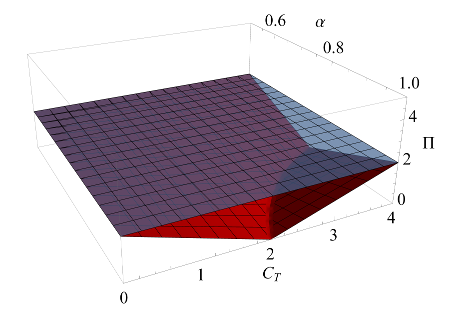
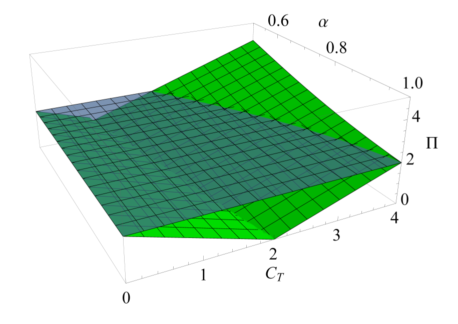
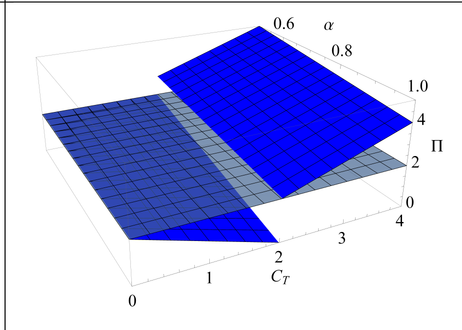
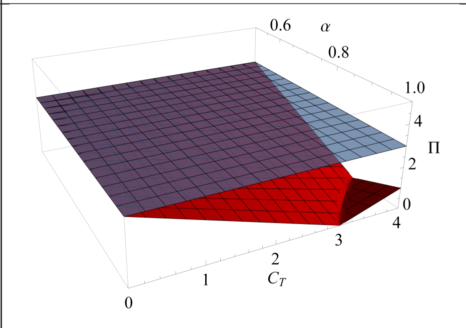
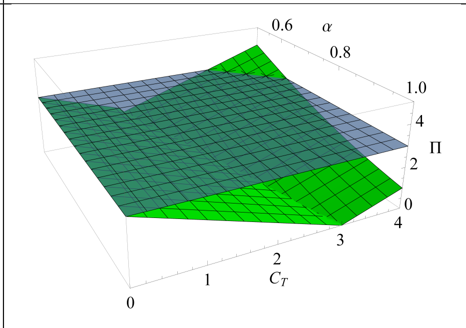
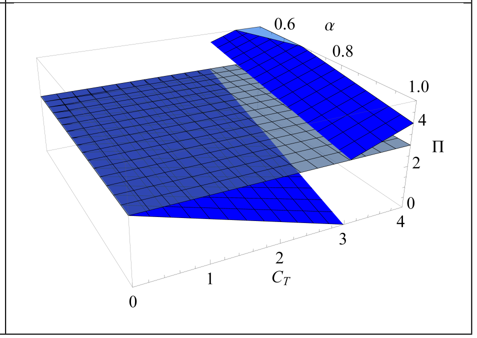
	Scenario II	**Scenario III**	**Scenario IV**
$MC_H = 1$			
$MC_H = 2$			
$MC_H = 3$			

Table 5.3: Industry profit of scenarios II, III and IV in comparison to the reference Scenario I given different levels of generation cost MC_H

Consumer Cost

Obviously, consumers' costs are to some extend complementary to the generation profits. However, especially their distribution is an important factor from a regulatory perspective. Hence, the first differentiating factor of all scenarios is whether final end consumer costs are equal or differentiated across the locations. To this end, Table 5.2 contains final consumer cost by location. Clearly, Scenario I and II result in final uniform end consumer cost by design. Given the Bertrand competition, a split market is also impossible in these scenarios. Interestingly, Scenario II results in strictly lower or equal consumer cost in comparison to Scenario I with socialized grid cost.

For Scenario III and IV, the large industry profits in a split market case as discussed above are reflected in the consumer cost. Given a split market, the final cost always contains the grid cost C_T which can be interpreted as the 'protection bonus' due to high grid cost. Furthermore, it is interesting to look at the locational consumer cost which differs by location in all cases of Scenario III and IV. In most cases consumer demand D_H is better off than consumer demand D_L. Given that the low-cost generator G_L is situated close to consumer demand D_L, this insight seems counter-intuitive. However, it results naturally from the possibility of product differentiation. Interestingly, this difference is most pronounced under the discriminatory pricing Scenario IV. Consumer demand D_L is only better off under Scenario III when benefiting generators bear grid cost and grid cost are low enough to fulfill the condition $\frac{C_T}{MC_H} < \frac{\alpha}{2-3\alpha+3\alpha^2-\alpha^3}$. That is, the optimal cost efficiency in Scenario IV and partly in Scenario III come at the cost of inter-population inequality and high industry profits in case of split markets without the need of grid infrastructure.

5.3.8 Conclusion on Grid Cost Allocation with Preexisting Investments

Unlike regulated or cost-based pricing, the presented framework allows the generator firms to select an optimal pricing strategy to maximize profits. Locational discriminatory pricing yields efficient outcomes with respect to total welfare. This cost-optimum is achieved at the expense of the consumers, with the generators being able to secure significant profits. However, if the cost difference between the generators is large compared to the grid cost, all scenarios achieve the same efficiency with the low-cost generator serving total demand. Considering typical cost structures in the electricity market this is a very relevant case.

Scenarios III and IV allow cost differences between the consumer populations. Casual reasoning might suggest that this could be beneficial for consumer demand D_L which is located next to the the low cost generation capacity. Due to product differentiation and strategic pricing, the converse is true in most cases with consumer demand D_H facing lower costs. Again, the case of high generation cost difference is special, yielding a unique result in Scenario III: Remote consumers pay more than local consumers.

Our model lends itself to future extensions. The Bertrand competition model may be replaced by alternative specifications like Cournot or Hotelling. This may shed light on the robustness of our results. In fact, Smeers (1997) notes that "the achieved equilibrium lies between the Cournot equilibrium and the Bertrand equilibrium. It is close to the Cournot equilibrium at peak time, when capacities are almost saturated and close to the Betrand equilibrium when there is significant excess capacity". Similarly, dropping the infinite capacity assumption or introducing richer cost functions (e.g., grid cost with economies of scale) allows the analysis of more complex situations. Finally, analysis of the investment location choices as discussed in the following may enhance our understanding of the interplay between network costs and investments.

5.4 Grid Cost Allocation and Investment

In this section we analyze the influence of different regulatory environments on generation investment decisions and the necessary transmission grid capacity. The results presented here are currently incorporated in the working paper *Investment and Grid Cost Allocation*. In our simple example we disregard competition and analyze the investment behavior of a single profit maximizing generation investor. As described in Section 5.2.2, the investment decision is based on full knowledge of the regulatory regime. Consequently, the generator invests in order to maximize his profit. The stylized grid model as presented in Section 5.2.1 with some additional assumptions serves as the basis for the following analyses. Similar to the competition model with preexisting investments in Section 5.3, we first describe the underlying market scenario and the analyzed institutional scenarios (Smeers, 1997).

Market Scenario

We assume that no generation capacity is existing before investment. This is a rather unusual assumption in real situations in the development of power systems. However, the shift to RES leads to significant changes in power systems including — in some cases — the replacement of a major share of the generation capacity. Hence, regarding grid cost allocation policy, regulators might think about treating new generators or specific types of generators differently to achieve efficient investments. The major difference between both locations in this model instance is the investment necessary to generate enough output to balance demand. In one location (L), lower investments are necessary to install new generators with a certain energy output g_L, whereas the second location (H) leads to higher investment for generators with an output g_H. To this end, we introduce two investment cost factors w_L and w_H with $w_L < w_H$ to account for differences in investment to achieve the same output (Figure 5.11).

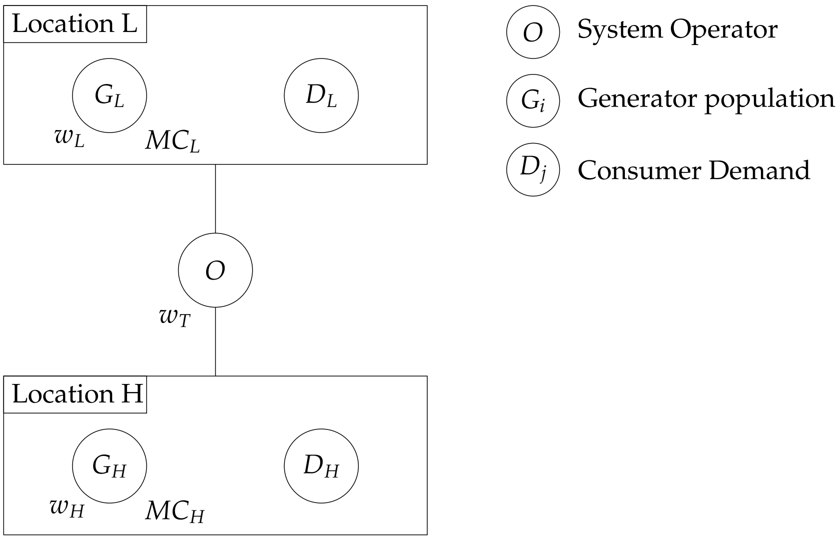


Figure 5.11: Model instance for grid cost allocation and investment

This means that investment cost I_L and I_H at the locations are depending on the generation capacity decision $g_i, i \in \{L, H\}$ and the investment factors:[10]

$$\begin{aligned} I_L &\equiv f(w_L, g_L), \\ I_H &\equiv f(w_H, g_H). \end{aligned} \tag{5.31}$$

In addition, we assume increasing marginal investment cost at both locations:

$$\begin{aligned} \frac{\partial I_L}{\partial g_L} &> 0, \\ \frac{\partial I_H}{\partial g_H} &> 0, \end{aligned} \tag{5.32}$$

Using wind power as an example, this investment type is comparable to wind farms at windy locations (L) and locations with less wind (H). The capacity factor of wind farms at location L is higher for the same capacity than at location H. In addition, the sites for wind parks at both locations are of different quality. First, wind farms are built at sites with the best capacity factor and least construction cost. Then, investment cost per output increases due to decreasing quality of sites at both locations. Once generation capacity is built at each location, all

[10]Similar to the previous chapter, we use a more compact notation throughout the chapter, e.g., $I_L(w_L, g_L)$.

generators produce at the same constant low marginal cost of $MC_L = MC_H$ per unit of energy. Without loss of generality we normalize $MC_L = MC_H = 0$ to reduce complexity of results. This assumption is based on the fact that maintenance costs are largely independent of energy output for renewable energy sources like wind or solar. For ease of calculation we do not use the consumer distribution factor α in this section. The demand of the consumer populations D_L and D_H at each location is represented by d_j with $j \in \{L, H\}$. Figure 5.11 provides an overview of the model instance.

Institutional Scenarios

With the model we aim to evaluate and compare different options for grid investment cost allocation and their influence on investment in spatially diverse electricity markets. The necessary grid investment cost T depends on the grid investment factor w_T as well as the locational distribution of demand and supply:

$$T \equiv f(w_T, d_H, d_L, g_H, g_L). \tag{5.33}$$

We analyze two different regulatory regimes or scenarios similar to scenarios I and II in the previous section. Both scenarios are summarized in Figure 5.12. We abstract from competition and focus on the investment policy of a single generation investor under the different regulatory scenarios. To this end, Scenarios III and IV from the previous section are not applicable due to the missing competition assumption. In our Scenario A, all transmission- and grid-related investment costs are socialized and allocated to consumers based on their share of total consumption, independently of their location. In Scenario B, grid costs are fully allocated to the transmitting generators. Hence, we assume transmission cost allocation based on a simple beneficiary pays scheme. In the following section, we generally describe the profit function and its sensitivity on different parameters. Afterwards, the impact of each regulatory regime on the profit and the investment decision is discussed in detail.

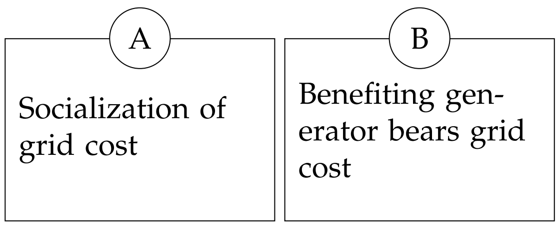


Figure 5.12: Institutional scenario overview for investment analysis

5.4.1 Generation Investor's Profit Function

An investor can optimally locate and size his generation capacity to maximize his profit. To this end, he has to consider both locations simultaneously and anticipate all revenues and cost. Given generation costs $MC_L = MC_H = 0$, the profit function is composed of five main parts:

- Revenue at location L: R_L
- Revenue at location H: R_H
- Investment cost for generation capacity at location L: I_L
- Investment cost for generation capacity at location H: I_H
- Transmission cost for transmission capacity: T

Since we assume demand to be inflexible, the amount of energy consumed and sold is fixed. Obviously, a single generating firm as a monopolist would charge infinitely high prices to maximize profit. We assume a price threshold where consumers stop consuming electric energy.[11] Consequently, the maximum revenue at each location (R_L, R_H) is fixed and the marginal revenue per unit of energy is constant up to the price threshold — with the generator always charging the maximum price. As long as marginal revenue is greater than marginal cost, the generator will serve all demand and invest in sufficient generation capacity.

The investment split between the two locations determines the investment cost, depends on w_i and g_i $i \in \{L, H\}$ and occurs as described above. We use simple quadratic functions to represent increasing total investments:

$$\begin{aligned} I_L &= w_L g_L^2, \\ I_H &= w_H g_H^2. \end{aligned} \tag{5.34}$$

This yields linear marginal investment cost:

$$\begin{aligned} \frac{\partial I_L}{\partial g_L} &= 2 w_L g_L, \\ \frac{\partial I_H}{\partial g_H} &= 2 w_H g_H. \end{aligned} \tag{5.35}$$

After the investment phase the generator serves consumer demand. Affected by the location of the generation capacity and the consumer demand, transmission infrastructure is necessary. Depending on the regulatory environment, the generation investor has to consider these costs or they are socialized across the

[11] In reality this could be a price where it is cheaper for consumers to switch to generating power on their own and stop buying from a central supplier.

consumer population. In our special case with inelastic demand, maximum consumer prices and total revenue are constant. This influences the investment behavior and a cost minimizing objective function is sufficient. The overall objective function of the generation investor is:

$$\min_{g_L, g_H} C = \underbrace{T(d_L, d_H, g_L, g_H, w_T)}_{\text{transmission cost}} + \underbrace{I(g_L, g_H, w_L, w_H)}_{\text{investment}}. \tag{5.36}$$

In addition to the basic assumptions, we note that under certainty investment in excess generation capacity would never occur. To this end, a simple condition ensures the balance that generation output equals demand:[12]

$$\sum_i g_i = \sum_i d_i, i \in \{L, H\}. \tag{5.37}$$

Obviously, generation output and demand are not constant in a practical setting. However, we abstract from this challenge and assume a sufficiently flexible system that can be approximated with constant demand and supply. In practical applications, this requires, for example, sufficient storage capacity at both locations.

To account for typical situations, we assume the majority of consumers and therefore the main load center to be at location H with higher investment cost , i.e. the sites for low-cost investment into generation are remote from load centers ($d_L < d_H$). Therefore, $\Delta d = d_H - d_L$ is strictly positive. In addition, we assume rational behavior — especially that the generation investor will always install enough generation at the low-cost location to serve the local demand ($g_L \geq d_L$). With the condition for the balance of generation and demand (Equation 5.37) we can derive the representations of necessary transmission capacity:

$$\begin{aligned} g_L + g_H &= d_L + d_H \\ g_L - d_L &= d_H - g_H \geq 0 \end{aligned}$$

Given these definitions, we can set up a model with increasing linear transmission investment cost depending on the discrepancy in demand and supply per location:

$$T(d_L, d_H, g_L, g_H, w_t) = (g_L - d_L)w_T = (d_H - g_H)w_T \tag{5.38}$$

The total generation investment cost in this scenario is the sum of investment at both locations (see Equation 5.34):

$$I(g_L, g_H) = w_L g_L^2 + w_H g_H^2.$$

[12] Another option may be to include a term which represents expected blackout cost dependent on supply-demand mismatches.

The defined terms induce varying impact on profits depending on the regulatory regime — which we will analyze in the following.

5.4.2 Scenario A — Socialization of Grid Cost

In this scenario with socialized grid cost, the generation investment decision is independent from grid investment, since the generator faces inelastic demand and consumers bear the grid cost. Thus, the transmission cost element in the generator's cost function is $T(d_L, d_H, g_L, g_H, w_T) = 0$ and the generator simply minimizes generation investment cost:

$$\min_{g_L, g_H} C = w_L g_L^2 + w_H g_H^2 \tag{5.39}$$

Generation investment will occur at the location with lowest marginal investment cost until total demand $d = d_L + d_H$ is served as long as marginal costs are below the consumer's reservation price threshold. With our assumption of linearly increasing marginal investment cost the generator will invest at both locations simultaneously, disregarding locational distribution of demand. Given the supply and demand Equation 5.37, we can calculate the optimal investment at each location for a given demand. The share of investment depends on the increasing marginal cost:

$$\begin{aligned}
C &= w_L (d - g_H)^2 + w_H g_H^2 \\
&= w_L d^2 - 2 w_L d g_H + w_L g_H^2 + w_H g_H^2 \\
\frac{\partial C}{\partial g_H} &= -2 w_L d + 2 w_L g_H^* + 2 w_H g_H^* \stackrel{!}{=} 0 \\
(w_H + w_L)\, g_H^* &= w_L d \\
g_H^* &= \frac{w_L d}{w_H + w_L}
\end{aligned}$$

Similarly, we obtain the optimal investment at the low-cost location as $g_L^* = \frac{w_H d}{w_H + w_L}$. As expected, the major investment into generation capacity occurs at the remote location with lower cost and a small share of total demand. Figure 5.13 illustrates how a given demand leads to a share of investment in generation capacity at each location and demonstrates that investment is independent of grid cost and consumer demand split. Notably, the necessary grid investment costs that are socialized obtain as $g_L^* - d_L = d_H - g_L^*$.

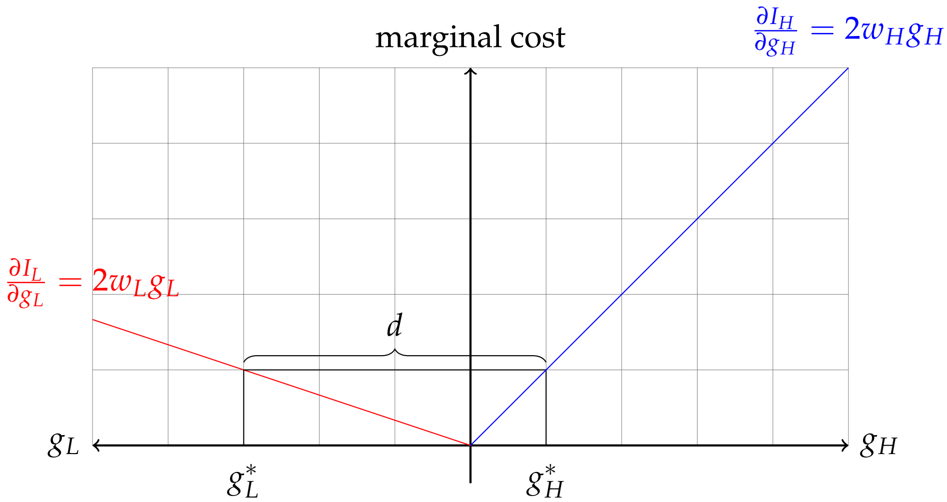


Figure 5.13: Investment Scenario A with socialized grid cost

5.4.3 Scenario B — Benefiting Generators Bear Grid Cost

In the second scenario, the benefiting generators bear the calculatory marginal grid investment cost. Given the single investor case, this means that the generation investor needs to factor in the expected grid cost $T \geq 0$ when deciding on the capacity investment locations. Hence, the grid costs remain in the cost minimization problem of Equation 5.36. Given $g_L = d - g_H$, we can eliminate g_L and simplify the cost function:

$$\begin{aligned} C &= (d_H - g_H)\, w_T + w_L g_L^2 + w_H g_H^2 \\ &= (d_H - g_H)\, w_T + w_L\, (d - g_H)^2 + w_H g_H^2 \\ &= (d_H - g_H)\, w_T + w_L \left(d^2 - 2dg_H + g_H^2\right) + w_H g_H^2 \\ &= d_H w_T - g_H w_T + w_L d^2 - 2w_L d g_H + w_L g_H^2 + w_H g_H^2 \end{aligned}$$

The optimal investment split requires minimization of these cost:

$$\begin{aligned} \frac{\partial C}{\partial g_H} &= -w_T - 2w_L d + 2w_L g_H^* + 2w_H g_H^* \stackrel{!}{=} 0 \\ (w_L + w_H)\, 2g_H^* &= 2w_L d + w_T \\ g_H^* &= \frac{w_L d + 0.5 w_T}{w_L + w_H} \end{aligned}$$

Similarly, we obtain the cost function depending on g_L by replacement of

$g_H = d - g_L$:

$$\begin{aligned}
C &= (g_L - d_L)\, w_T + w_L d_L^2 + w_H d_H^2 \\
&= (g_L - d_L)\, w_T + w_L g_L^2 + w_H \,(d - g_L)^2 \\
&= (g_L - d_L)\, w_T + w_L g_L^2 + w_H \left(d^2 - 2dg_L + g_L^2\right) \\
&= g_L w_T - d_L w_T + w_L g_L^2 + w_H d^2 - 2w_H d g_L + w_H g_L^2
\end{aligned}$$

And the optimal investment g_L^* at location L:

$$\begin{aligned}
\frac{\partial C}{\partial g_L} = w_T + 2w_L g_L^* - 2w_H d + 2w_H g_L^* &\overset{!}{=} 0 \\
(w_L + w_H)\, 2g_L^* &= 2w_H d - w_T \\
g_L^* &= \frac{w_H d - 0.5 w_T}{w_L + w_H}
\end{aligned}$$

In contrast to Scenario A, the generator considers transmission cost and invests more in generation at the high-cost location depending on grid cost w_T. Figure 5.14 illustrates how the grid cost influences the investment decision for an exemplary implementation of demand distribution and marginal cost. The costs at the low-cost location include the expected grid cost as soon as the local market is served and transmission to the high cost location is necessary.[13]

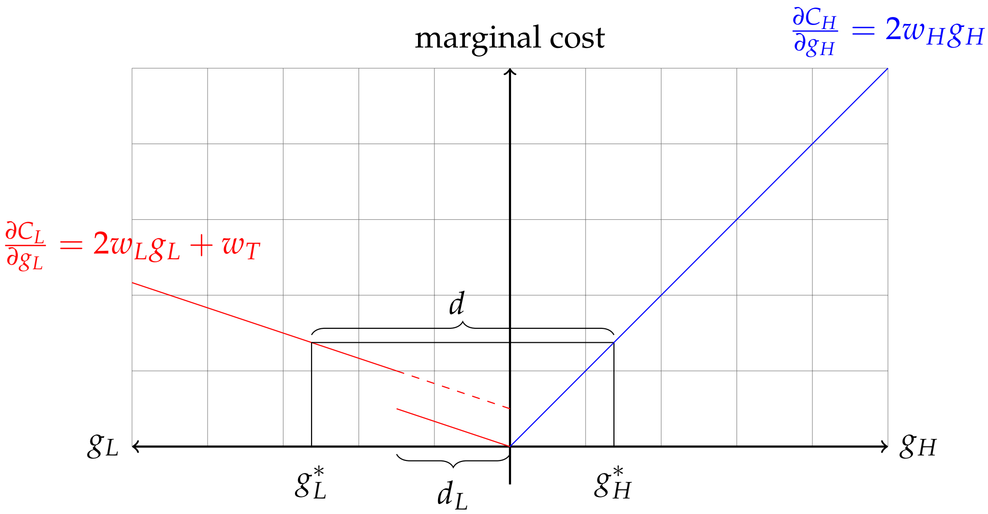


Figure 5.14: Investment Scenario B with generator bearing grid cost

[13]Given our assumption $g_L \geq d_L$ this is always the case for each additional capacity investment at the low-cost location.

5.4.4 Conclusion on Grid Cost Allocation and Investment

The simple analytical model shows the difference in investment decisions given the grid cost allocation regime. Table 5.4 summarizes the obtained optimal investment policies in dependence of the investment cost factors.

		Regulatory regime		
		Scenario A		Scenario B
Generation investment	g_L^*	$\frac{w_H d}{w_H+w_L}$	$>$	$\frac{w_H d-0.5w_T}{w_L+w_H}$
	g_H^*	$\frac{w_L d}{w_H+w_L}$	$<$	$\frac{w_L d+0.5w_T}{w_L+w_H}$

Table 5.4: Optimal locational generation investments given different transmission cost allocation policies

Given the socialization of transmission grid investment cost (Scenario A), the investing generator optimizes generation cost independently of location. Therefore a large share of total capacity investment occurs at location L with low-investment cost but also a smaller share of total demand. Hence, the model confirms that socialization reduces "the system's ability to promote investment in the best locations" (MIT, 2011). As Scenario B shows, the investor can already be incentivized to focus on overall more efficient generation capacity investments in this first investment step. In Scenario B he has to bear the grid investment cost which leads to lower generation investments at the low-cost location with small consumer demand. Consequently, less grid investment is necessary, since the generation investor trades grid investment off against generation investment.

These results are not restricted to the simple analytical model applied here. Knieps (2013) analyzes a richer model including variable infrastructure investments with "injection charges" for generators and "extraction prices" for consumers. He argues that with injection charges "incentives arise for the generators of renewable energy not only to focus on generation costs but also to choose the proper location of electricity generators, taking into account locational different injection charges" (Knieps, 2013). Another example is the recommendation of von Hirschhausen et al. (2012) to the European Commission to at least introduce a minimum grid price component that is charged to generators. Also, Madrigal and Stoft (2012) agree that if specific groups of renewable generators cause expansion cost, these generators should bear the cost. A practical example where different locational grid charges are used, is the zonal approach used in the UK. However, as also mentioned before, countries are using various transmission cost allocation schemes, which are even further differentiated, e.g., by type of consumption or voltage level.

5.5 Conclusion of Transmission Pricing and Cost Allocation

The multitude of alternatives to transmission pricing and cost allocation is also reflected in the regulatory practices in different countries as described in Section 5.1. The objectives are agreed on, but the practical implementation needs to pay attention to establishing the right incentives in the specific power sector which differ widely, e.g., in terms of liberalization, market power, generation technologies or grid topology. This is also reflected in the large number of research publications on transmission pricing and cost allocation as well as the expert consultations in different countries. In addition, the topic of who pays which share of the grid cost and on which calculatory base gains increasing importance due to several developments in major power markets:

- Locational shift of generation to remote locations requires grid investment for connection and transmission (e.g., offshore wind farms)
- Decreasing importance of marginal generation cost with rising shares of RES (e.g., wind, solar)
- Intermittent availability of RES with low capacity factors may lead to lower average grid utilization (see Table 2.1)
- Self-supplying consumers use grid less often and may absolve themselves from responsibility for socialized financing of grid assets
- Regulatory exemptions from grid charges for some consumers concentrate the cost burden on a smaller community (e.g., exemptions for large industry consumers in Germany)
- Increasing investment cost to realize future smarter grids and renew aging assets

To this end, the influence of pricing and cost allocation was analyzed in this chapter using a generic two-node model. First, the influence of cost allocation to benefiting generators or consumers on competition outcomes and behavior was analyzed. Second, the generation investment behavior was studied using different cost allocation regimes. Under the employed model assumptions, some interesting directions for future regulation can be discussed. Both model instances demonstrate possibilities to mitigate seemingly '*unfair*' grid cost allocations.

The first model shows that the allocation of grid cost influences the static competition outcome, e.g., in terms of efficiency and total end consumer prices. A socialization of grid cost may lead to high industry profits if transmission costs are low in comparison to generation cost differences. In addition, it demonstrates that generators can use transmission cost to exercise market power in local markets. And that consumers next to low-cost generation may be unintuitively exposed to higher prices than consumers at locations with higher marginal cost of generation. The model suggests one regulatory regime (out of four analyzed) which leads to an expected '*fair*' outcome under the assumption of low grid cost: When benefiting consumers — that are located remote from low-cost energy sources — bear the grid cost, the total prices paid by these consumers are higher as intuitively expected.

The second model targets the incentives for generation investors into capacity at different locations and analyzes the influence of cost allocation. It confirms and underlines that generators have little incentive to integrate transmission cost in their siting decision in a setting with socialized grid cost. This result is in line with Brunekreeft et al. (2005) who state that "in the absence of LMP, there is a strong case for a locational element to grid charges".

In summary, the models provide and describe opportunities for regulators to understand the incentives of the different actors given our model assumptions. First, the benefiting consumers need to be charged directly in order to create an environment where consumers who live in areas with low-cost generation actually pay less for their consumption. Second, the transmitting generators also need to face grid cost in order to create the incentives for them to allocate capacity efficiently in terms of grid and generation cost.

However, countries apply different regulatory regimes. One reason may be that the grid and competition model used here is extremely simplified and based on many assumptions. As mentioned before, the models may be adapted to be applicable for other research questions, for example, other competition models (e.g., Cournot, Hotelling), different cost functions (e.g., including economies of scale), or more complex grid representations. Another extension could tackle the hard assumption of inelastic demand which obviously enables the exert of market power. Bompard et al. (2007) state that a small increase in demand elasticity can mitigate market power enabled by constraints and leads to improved market outcomes. In addition, other factors increase the uncertainty of the results and may be analyzed in more detail, e.g, intermittent supply or stochastic demand. Overall, for specific power sectors and markets, the theories developed in the analytical models need to be verified in more realistic simulation models over time. These extensions go beyond the scope of this thesis, however, the literature review in the beginning of this chapter provides some links to other models.

Another important reason for various regulatory regimes are different targets and markets that regulators have to deal with as well as the possibilities and information they have to work with. For example, in complex power networks it is difficult to identify who is benefiting from a grid expansion, which can hinder precise cost allocation.[14] In addition, if grid costs account for a small fraction of total cost only and reliability and/or use of RES is most important, a socialization of grid cost among consumers might be seen as 'fair'. Also, applying differentiated grid charges can influence the level playing field for generators that is intended by investments for congestion-avoidance. Finally, the use of locations with low-cost generation condition might have political priority. Thus, despite the results in this chapter, there are various reasons why a regulator decides to socialize grid cost among all consumers or use an approach with zonal differences for demand and generation. For example, Baldick et al. (2011) recommend to change the UK cost allocation in a way that all existing grid costs (except for shallow connection cost) should be borne by consumers to enable the level playing field. However, in the same report they also recommend a "generation follows transmission" planning process and an efficient locational pricing scheme (Baldick et al., 2011). This would basically represent a centrally planned optimal grid expansion, where planned congestion costs yield to an optimal allocation of generation capacity. Indeed, the proposed theoretical "Optimal Charging Arrangement for Energy Transmission" (Baldick et al., 2011) seems a promising approach. In another publication, Baldick et al. (2007) provide a good statement on optimal planning: "As has been noted countless times in the past, there is virtually no transmission asset that has ever been built that has not been used in ways its planners and builders never anticipated." Leuthold et al. (2008) apply nodal pricing to the German network which serves as an example in this chapter. They find that nodal prices are more efficient than uniform pricing. However, they also state that the static nodal prices do not give incentives for efficient grid expansion.

In summary, the optimal decision on transmission pricing and cost allocation regulation depends on the specific situation and targets. However, given the increasing importance of grid cost mentioned above, the allocation of grid cost may be an important topic in challenged power systems. For that matter, one possible approach can be to charge some parts of the grid in a different way. One example are the costs of the HVDC connection in New Zealand which are allocated through separate charges (Electricity Authority, 2012). In line with Hogan (1998b), the allocation problems for existing transmission assets and grid expansion could be treated differently.

[14] It is even possible that an investment is counterproductive similar to the Braess paradox (Blumsack et al., 2007).

Chapter 6

Conclusion

This thesis focuses on the efficient use of power grid capacity and efficient investment into grid infrastructure on different voltage levels. More specifically, it analyzes different coordination mechanisms and incentives to achieve more efficient short-term operation and long-term investment behavior. The analyzed models have limitations and primarily serve as a guideline in specific cases. The specific discussion sections for the models on local infrastructure pricing (Section 4.5.1) and transmission grid cost allocation (Section 5.5) name the limitations and ideas for future extensions. This conclusion provides a summary of the main findings and implications of the discussed models. It finalizes with a more comprehensive overview of the potential solutions for challenges in future power systems and open questions in the transition to an efficient low-carbon power sector.

6.1 Summary

Major changes in power systems over the next decades pose challenges to existing power grids and require major infrastructure investments. These challenges are particularly complex in unbundled power markets where individual actors — generators, system operators, and consumers — need to be coordinated. Chapter 2 provides an overview of the characteristics for the major actors in the electricity supply chain and summarizes resulting challenges in physical operation and market design. Chapter 3 discusses coordination mechanisms and management options for each actor to react to bottlenecks in power grids, such as temporal or spatial load/supply shifting as well as capacity investments. Monetary incentives in the form of variable or even dynamic prices are discussed in more detail, based on theoretical potentials and frameworks. In addition, real-life implementations and promising recent developments are presented.

The local infrastructure coordination approaches analyzed in Chapter 4 specifically address the challenge of using existing distribution grids efficiently.

The example modeling of electric vehicles as flexible load demonstrates that a large scale introduction of variable prices based on variable supply (e.g., to incentivize consumption of RES) may lead to overloads in the distribution grid. However, these overloads can be mitigated through appropriate load coordination approaches. The investigated coordination approaches include a central planner, which serves as a benchmark, static and dynamic load curtailment as well as static and dynamic load pricing options. The load curtailment approaches can almost achieve the results of a central planner in terms of grid utilization and low-cost energy consumption with a relatively small impact on service quality. Furthermore, a main contribution of this thesis is the proposition and benchmarking of decentralized coordination approaches in form of dynamic load pricing which keep the individual decision at the consumer level. At the same time the approaches incentivize the use of low-cost supply (e.g., RES) while taking existing distribution grid limits into account. In the expected development to more decentralized and intermittent generation capacities, these ideas can help to ensure a reliable power system with efficient utilization of distribution grid capacity.

Different possible incentives on the transmission level are investigated in Chapter 5 using analytical microeconomic models. The models analyze the influence of different transmission infrastructure cost allocation regimes on competition and investment behavior of generators. It can be shown that cost allocation affects efficiency and '*fairness*' of the outcomes. The allocation of transmission grid cost can lead to opportunities for generators to secure significant profits at the expense of the consumers. In addition, the cost allocation regime can enable strategic pricing which results in seemingly '*unfair*' situations, i.e., consumers next to low-cost generation capacity face higher prices. Taking investment into new generation capacity into account, the model demonstrates that the typical socialization of grid cost can lead to inefficient investments and that a change in regulation to allocate grid cost to generators might foster efficiency. In summary, the results signify that all changes to regulatory regimes have to be thoroughly investigated in the light of the specific power market situation in order to yield positive or efficient results in total. As Green (2000) wisely put it: "Any change from existing systems is likely to produce winners and losers, and those who expect (rightly or wrongly) to be losers will have an incentive to oppose the changes. In the end, the results can depend as much on politics as on economics."

6.2 Outlook

The approaches discussed in this thesis add insights which emphasize the important role of the grid and may support efficiency in the transition to, as well as in the operation of, a low-carbon power sector. Recent newspaper articles demonstrate that grid investments and siting of new generation capacities receive increasing attention in political discussions in context of the *Energiewende*.[1] However, besides the topics discussed, there are still many open questions and numerous areas for further research that are either prerequisites for the success of the presented coordination approaches or stand independently alongside.

Complementary to the discussed topics, one major goal needs to be the advancement of efficient supply technologies, e.g., in storage, transmission, or generation. Similarly, or even more important is an efficiency increase in consumption. A simple raise of awareness for energy consumption can yield significant energy savings merely by switching off unnecessary equipment or investing in more energy-efficient equipment. To this end, rising power prices for end consumers (e.g., in Germany due to the *Energiewende*) might not only cause higher electricity bills but also yield very positive saving effects in the long run.

Smart grid technologies that improve the ability to monitor and control in real-time are actually prerequisites for the approaches presented in this thesis. While these technologies are already available today, their market penetration and use is hampered by missing incentives and limited user acceptance. When real-time data is widely available, research in energy informatics and economics can activate efficiency potentials in addition to a simple reduction of consumption. To foster this research, simulation frameworks and testbeds can be used to investigate how theoretical results can be realized in more practical settings. In addition to the overall setting, interaction with individual actors such as consumers, operators, and generators needs to be analyzed further. Open questions include, e.g., 'which type of of incentives (e.g., monetary or non-monetary) result in what kinds of effect?', 'What should the communication or interface between actors and systems look like to be accepted in terms of data security and to be efficient in terms of the outcome?', 'What kind of information on individual flexibility is most valuable?'. Answers to these questions can enable new services and business models in the future power sector. They may also overcome the roll-out issues and lead to a dissemination of smart grid

[1] See for example *Handelsblatt* on November 8, 2013 on the expectation that the transmission grid expansion in Germany will be more expensive than planned (`http://www.handelsblatt.com/politik/deutschland/energiewende-koalition-will-energiekosten-senken/9051802.html`).

technologies. In the special case of incentives for the efficient use of capacity and investment into power grid infrastructure, it is important to analyze the interaction of different incentives. Particularly when applying several coordination approaches in an interconnected grid they are not separate from each other but need to be checked for compatibility and mutual influences.

In addition to the technical aspects and user acceptance, other influencing factors need to be considered, e.g., legal issues, existing regulations, or resistance of individual stakeholders. Hence, the development of a consistent, integrated incentive and contract system is still a long way to go. The transition to another system needs some time and might require regulatory measures that are temporary only. One apparent example is the Renewable Energy Act in Germany: the necessity of modifications is widely agreed, but the detailed implementation is being severely discussed.

In summary, more flexibility combined with the right incentives can help to support power system transformations. However, there will be individual paths to a sustainable energy future as well as different detailed organizations — these paths remain to be seen.

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List of Abbreviations

AC	Alternating current
AMCIS	Americas Conference on Information Systems
ARegV	Anreizregulierungsverordnung — Incentive Regulation Ordinance
BDEW	Bundesverband der Energie- und Wasserwirtschaft — German Association of Energy and Water Industries
BEV	Battery electric vehicle
BKW	BKW FMB Energie AG — Swiss electric utility
BM	Benchmark
BMU	Bundesministerium für Umwelt, Naturschutz und Reaktorsicherheit — Federal Ministry for the Environment, Nature Conservation and Nuclear Safety
BMWi	Bundesministerium fÃ¼r Wirtschaft und Technologie — Federal Ministry of Economics and Technology
BNetzA	Bundesnetzagentur — Federal Network Agency
CCS	Carbon capture and storage
CHP	Combined heat and power
CWE	Central Western Europe
DC	Direct current
DG	Distributed generation
DLC	Dynamic load curtailment
DLP	Dynamic load pricing
DOE	Department of Energy
DR	Demand response
DSM	Demand side management
DSO	Distribution system operator
EEG	Erneuerbare-Energien-Gesetz — Renewable Energy Act
EEM	European Energy Market
EnLAG	Energieleitungsausbaugesetz — Energy Line Expansion Act
ENTSO-E	European Network of Transmission System Operators for Electricity
EnWG	Energiewirtschaftsgesetz — Energy Industry Act
EPEX	European Power Exchange

ERGEG	European Regulators' Group for Electricity and Gas
EU	European Union
EU ETS	European Union emission trading system
EV	Electric vehicle
FCEV	Fuel cell electric vehicle
FERC	Federal Energy Regulatory Commission
GHG	Greenhouse gas
GW	Gigawatt
HEV	Hybrid electric vehicle
HICSS	Hawaiian International Conference on System Sciences
HV	High-voltage
HVAC	Heating, ventilation, and air conditioning
HVDC	High-voltage direct current
ICE	Internal combustion engine
ICT	Information and communications technology
IEA	International Energy Agency
IEEE	Institute of Electrical and Electronics Engineers
ISGT	Innovative Smart Grid Technology
KAV	Konzessionsabgabenverordnung — Concession Fee Ordinance
KIT	Karlsruhe Institute of Technology
KW	Kilowatt
KWKG	Kraft-Wärme-Kopplungsgesetz — German Combined Heat and Power Act
LMP	Locational marginal pricing
MV	Medium-voltage
MVA	Megavolt ampere
MW	Megawatt
NYISO	New York Independent System Operator
OECD	Organisation for Economic Co-operation and Development
OECD	Organisation for Economic Co-operation and Development
OEM	Original equipment manufacturer
OPT	Optimal
OTC	Over-the-counter
PES	Power and Energy Society
PHEV	Plug-in hybrid electric vehicle
RES	Renewable energy sources
SAIDI	System Average Interruption Duration Index
SAIDI	System Average Interruption Duration Index
SB	Supply-based
SFSO	Swiss Federal Statistical Office

SLC	Static load curtailment
SLP	Static load pricing
SOC	State of charge
StromEinspG	Stromeinspeisungsgesetz — Electricity Feed Act
StromNEV	Stromnetzentgeltverordnung — Electricity Grid Charges Ordinance
SUV	Sport utility vehicle
SysStabV	Systemstabilitätsverordnung — System Stability Ordinance
TOU	Time of use
TSO	Transmission system operator
TW	Terawatt
UC	Uncoordinated
UNFCCC	United Nations Framework Convention on Climate Change
UPE	Undercut Proof Equilibrium
US	United States
V2G	Vehicle to grid
VAT	Value added tax
VDE	Verband der Elektrotechnik, Elektronik und Informationstechnik — Association for Electrical, Electronic and Information Technologies

Appendix

A Optimization program used for *SB*, *SLC*, *DLC*, *DLP*

Based on our paper Flath et al. (2013), we used the following optimization program for *SB*, *SLC*, *DLC*, and *DLP*:

```
int NbPeriods = ...;
float initSoc =...;
float maxSoc = ...;
float endSoc = ...;
range Periods = 1..NbPeriods;
float Capacity[Periods] = ...;
float Demand[Periods] = ...;
float Cost[Periods] = ...;

dvar float+ PosChargeamount[Periods];
dvar float+ Soc[Periods];

minimize
sum( t in Periods )
Cost[t]*PosChargeamount[t];

subject to {
forall(t in Periods )
ctNonNegativeSoc:
Soc[t] >= 0;

forall(t in Periods )
ctMaxSoc:
Soc[t] <= maxSoc;

forall( t in Periods )
ctChargeamount:
PosChargeamount[t] <= Capacity[t];

forall( t in 2..NbPeriods )
ctStorageConstraint:
  Soc[t] == Soc[t-1]+ PosChargeamount[t] - Demand[t];

ctInit:
  Soc[1] == initSoc + PosChargeamount [1] - Demand[1];

ctEnd:
  Soc[NbPeriods] >= endSoc;

};
```

B Optimization program used for SLP^{max}

Based on an amended version of the program in Flath (2013b), we used the following optimization program for SLP^{max}:

```
int NbPeriods = ...;
float initSoc =...;
float maxSoc = ...;
float endSoc = ...;
range Periods = 1..NbPeriods;
float Capacity[Periods] = ...;
float Demand[Periods] = ...;
float Cost[Periods] = ...;

dvar float+ PosChargeamount[Periods];
dvar float+ Soc[Periods];
dvar float+ maxLoad[Periods];

minimize
(sum( t in Periods ) Cost[t]*PosChargeamount[t])+1*maxLoad[NbPeriods]*maxLoad[NbPeriods];

subject to {
forall(t in Periods )
ctNonNegativeSoc:
Soc[t] >= 0;

forall(t in Periods )
ctMaxSoc:
Soc[t] <= maxSoc;

forall( t in Periods )
ctChargeamount:
PosChargeamount[t] <= Capacity[t];

forall( t in 2..NbPeriods )
ctStorageConstraint:
  Soc[t] == Soc[t-1]+ PosChargeamount[t] - Demand[t];

ctInit:
  Soc[1] == initSoc + PosChargeamount [1] - Demand[1];

ctEnd:
  Soc[NbPeriods] >= endSoc;

forall( t in 2..NbPeriods )
ctMaxLoadCarryOver:
maxLoad[t]>=maxLoad[t-1];

forall( t in Periods )
ctMaxLoadCurrentPeriod:
maxLoad[t]>=PosChargeamount[t];

};
```

C Optimization program used for SLP^t

Based on an amended version of the program in Flath (2013b), we used the following optimization program for SLP^t:

```
int NbPeriods = ...;
float initSoc =...;
float maxSoc = ...;
float endSoc = ...;
range Periods = 1..NbPeriods;
float Capacity[Periods] = ...;
float Demand[Periods] = ...;
float Cost[Periods] = ...;

dvar float+ PosChargeamount[Periods];
dvar float+ Soc[Periods];

minimize
sum( t in Periods )
(Cost[t]*PosChargeamount[t]+PosChargeamount[t]*PosChargeamount[t]*0.1);

subject to {
forall(t in Periods )
ctNonNegativeSoc:
Soc[t] >= 0;

forall(t in Periods )
ctMaxSoc:
Soc[t] <= maxSoc;

forall( t in Periods )
ctChargeamount:
PosChargeamount[t] <= Capacity[t];

forall( t in 2..NbPeriods )
ctStorageConstraint:
  Soc[t] == Soc[t-1]+ PosChargeamount[t] - Demand[t];

ctInit:
  Soc[1] == initSoc + PosChargeamount [1] - Demand[1];

ctEnd:
  Soc[NbPeriods] >= endSoc;

};
```

D Optimization program used for *OPT*

Further extensions of the previous programs result in the following optimization program for *OPT*:

```
int NbPeriods = ...;
int NbVehicles = ...;
float initSoc =...;
float maxSoc = ...;
float endSoc = ...;
float maxChargeAmount =...;
range Vehicles = 1..NbVehicles;
range Periods = 1..NbPeriods;
float ChargingPossibleH[Vehicles][Periods] = ...;
float ChargingPossibleW[Vehicles][Periods] = ...;
float Demand[Vehicles][Periods] = ...;
float Cost[Periods] = ...;

dvar float+ PosChargeamountH[Vehicles][Periods];
dvar float+ PosChargeamountW[Vehicles][Periods];
dvar float+ Soc[Vehicles][Periods];
dvar float+ TotalChargingH[Periods];
dvar float+ TotalChargingW[Periods];

minimize
sum( t in Periods )(
sum( n in Vehicles)(
Cost[t]*PosChargeamountH[n][t]+Cost[t]*PosChargeamountW[n][t]));

subject to {

forall(v in Vehicles)
ctInitStorage:
Soc[v][1] == initSoc + PosChargeamountH[v][1] + PosChargeamountW[v][1] - Demand[v][1];

forall(v in Vehicles, t in 2..NbPeriods )
ctStorageConstraint:
Soc[v][t] == Soc[v][t-1] + PosChargeamountH[v][t] + PosChargeamountW[v][t] - Demand[v][t];

forall(v in Vehicles, t in Periods )
ctChargeamountH:
PosChargeamountH[v][t] <= ChargingPossibleH[v][t]*maxChargeAmount;

forall(v in Vehicles, t in Periods )
ctChargeamount:
PosChargeamountW[v][t] <= ChargingPossibleW[v][t]*maxChargeAmount;

forall(v in Vehicles, t in Periods )
ctMaxSoc:
Soc[v][t] <= maxSoc;

forall(v in Vehicles)
ctEnd:
Soc[v][NbPeriods] == endSoc;

forall(v in Vehicles, t in Periods )
ctNonNegativeSoc:
Soc[v][t] >= 0;

forall(v in Vehicles,  t in Periods)
ctNonNegativeChargeamountH:
PosChargeamountH[v][t] >= 0;
```

```
forall(v in Vehicles,  t in Periods)
ctNonNegativeChargeamountW:
PosChargeamountW[v][t] >= 0;

forall(t in Periods )
ctTotalLoadH:
sum( n in Vehicles)(PosChargeamountH[n][t]) == TotalChargingH[t];

forall(t in Periods )
ctTotalLoadW:
sum( n in Vehicles)(PosChargeamountW[n][t]) == TotalChargingW[t];

forall(t in Periods )
ctMaxLoadH:
TotalChargingH[t] <= x;

forall(t in Periods )
ctMaxLoadW:
TotalChargingW[t] <= x;

};
```

E Comparison of Charging Coordination Outcomes at *Work* Location

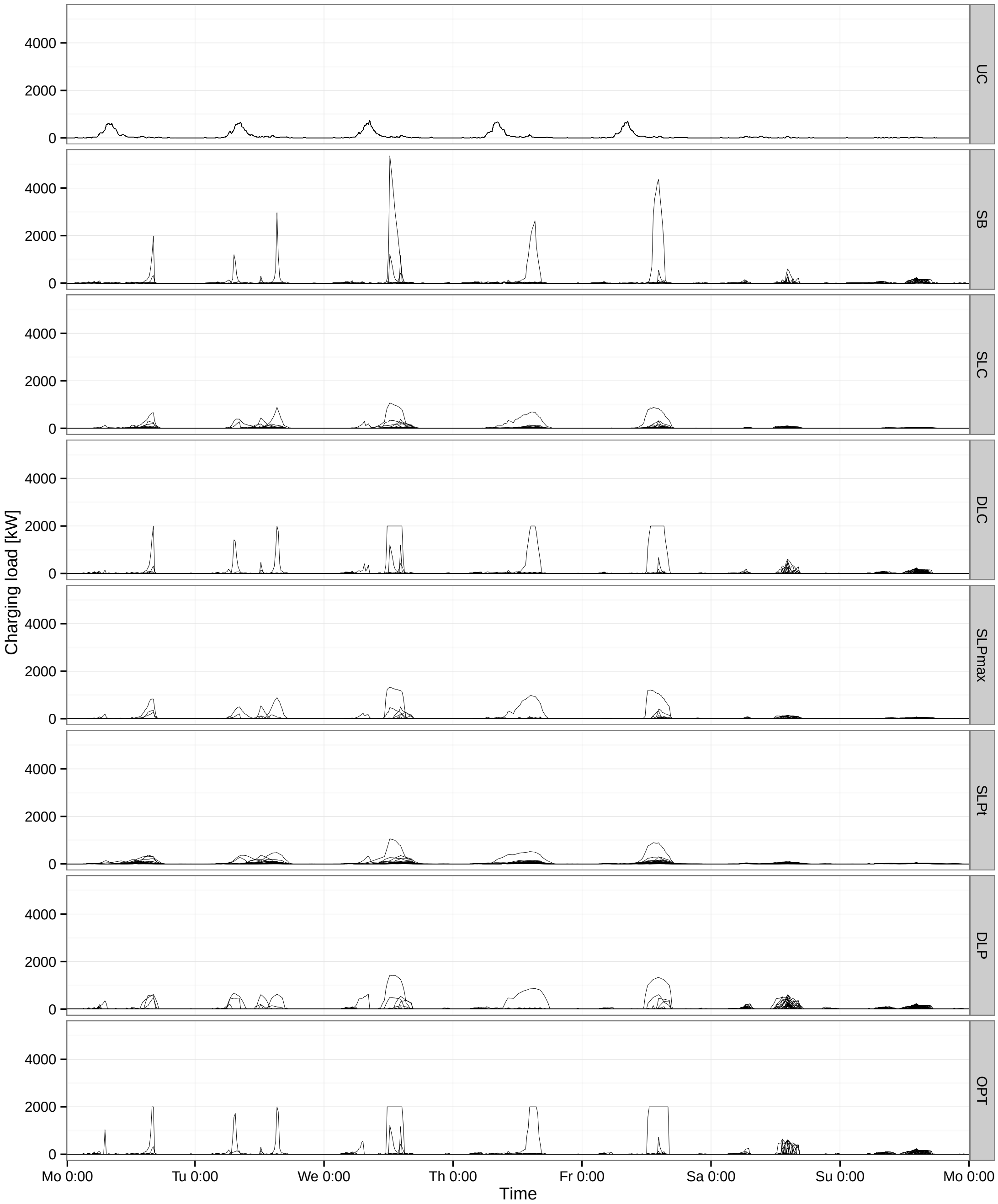

Figure E.1: Comparison of charging coordination outcomes at *work* over 52 weeks