Intermediation in Future Energy Markets: Innovative Product Design and Pricing

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Abstract

In order to mitigate the impacts of climate change, the international community envisages significant investments in electricity generation from renewable energy sources (RES). The integration of this decentralized and fluctuating type electricity generation poses several challenges to planning, operation, and economics of power systems. The established energy systems were originally designed for a centralized electricity generation that follows the uncontrolled but well predictable demand. However, for large shares of RES, relying only on the flexibility of the generation side would be economically inefficient. Furthermore, the environmental benefits of using RES would be depleted by additional carbon emissions from ramping highly flexible fossil-fueled power plants. An appealing alternative to facilitate the efficient integration of large shares of RES is to exploit the so far mainly passive demand side as an additional source of flexibility. The established centralized approaches can hardly handle the fine-grained and decentralized nature of demand side flexibility. Therefore, the intermediation between centralized control and decentralized demand will play a major role in future energy markets, which constitutes the overarching topic of this dissertation.

Typically electricity generation from RES is capital-intensive but has near zero marginal costs. On this account, novel services need to be offered in order to transmit the right economic signals. To this end, the concept of the differentiable good electricity is refined in this dissertation. Embedded into the so-called energy service, characteristics such as temporal and spatial price differentiation or the risk of interruption can be specified to differentiate the so far homogeneous good. Based on the morphological design theory a framework for the notion of energy services is established and subsequently implemented as a decision support system. This supports a systematic and structured product development process to design innovative energy services.

Such an innovative energy service is, e.g., the charging of electric vehicles in car parks, where prices are differentiated by job completion deadline. This allows the car park operator to control the aggregated load of all charging jobs to follow local RES generation. Based on this energy service the downstream activity of an intermediary is formally modeled as an optimization problem and evaluated by means of an empirical simulation experiment. The results provide insights on pricing policy and the value of demand side flexibility with regard to both the integration of local RES generation and operative profit optimization. In order to illustrate another innovative energy service the presented model is extended by the upstream activity of the intermediary. Household consumers are offered monetary incentives if they allow

the intermediary to control their appliances. The results indicate the cost saving potential from demand side flexibility for the intermediary's procurement of electricity. Beyond that, this model formulation constitutes the foundation for further examinations, e.g., to study the strategic behavior of intermediaries on real-time electricity markets that are prone to market power abuse due to low market liquidity.

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Contents

List of Figures

List of Tables

List of Abbreviations

CHP	Combined heat and power
ComEd	Commonwealth Edison
DDP	Deadline differentiated pricing
DLC	Direct load control
DR	Demand Response
DSM	Demand Side Management
DSO	Distribution system operator
DTW	Dynamic time warping
EEG	Erneuerbare Energien Gesetz (Renewable Energy Source Act)
EEX	European Energy Exchange
EU	European Union
EV	Electric vehicle
ICT	Information and communication technology
ISO	Independent system operator
kV	Kilovolt
kW	Kilowatt
kWh	Kilowatt-hour
kWp	Kilowatt-peak
LL	Lower level
MW	Megawatt
MWh	Megawatt-hour
OTC	Over-the-counter
PHEV	Plug-in hybrid electric vehicle
PV	Photovoltaic
RES	Renewable energy sources
RTP	Real-time pricing
SOC	State of charge
TOU	Time-of-use
TSO	Transmission system operator
UL	Upper level
V	Volt

Chapter 1

Introduction

Sustainability is one of the major concerns of today's world. At the Paris climate conference in December 2015, the international community agreed to keep the increase in global average temperature to 2°C above pre-industrial levels in order to mitigate the impacts of climate change. Being at the forefront of international efforts the European Union (EU) set itself ambitious goals to this end. Its member states committed to reduce greenhouse gas emissions by 20% until 2020 (EU Commission, 2010), by 40% until 2030 (EU Commission, 2014), and ultimately by 80-95% until 2050 (EU Commission, 2011) compared to 1990 levels. To achieve these goals the EU Energy Roadmap envisages "significant investments in [...] renewable energy." The German legislator embodied this in a separate "Renewable Energy Sources Act" (EEG): At least 80% of electricity consumption shall be produced from renewable energy sources (RES) by 2050 (§1 II 3 EEG 2017) supporting it with several incentives. Several other countries have taken similar actions (Notenboom et al., 2012).

RES integration poses several challenges to planning, operation, and economics of energy systems that were originally designed for centralized conventional and controllable energy generation (Perez-Arriaga et al., 2012; Bird et al., 2013). In contrast, energy generation from RES is distributed, volatile and intermittent and cannot offer the supply flexibility needed to guarantee grid stability by balancing demand and supply. Traditionally, utilities have treated the demand side as inelastic and renewable energy generation is seen as negative demand. To account for sudden changes in demand or forecast errors the required flexibility has historically been provided by conventional generation units, such as (limited available) pumped hydro storage, or (costly) gas-fired power plants (e.g. Ortega-Vazquez and Kirschen, 2010). However, for large shares of RES, relying only on the generation-side flexibility would require a large number of backup units, which is both economically inefficient and could hinder the environmental benefits of using RES (IEA, 2014). This affects the energy trilemma by endangering the energy system's efficiency that is determined by its reliability, sustainability, and costs.

An appealing alternative to facilitate the efficient integration of large shares of RES is to exploit the so far mainly passive demand side as an additional source of flexibility (Strbac, 2008; Schuller et al., 2015; Gärttner et al., 2016). Rather than assuming load being inelastic, demand can be shaped to follow supply. Demand Side Management (DSM) has been in focus of many researchers and the power industry lately (Strüker and van Dinther, 2012; Chua-Liang and Kirschen, 2009). The demand side can be shaped in two fundamentally different ways: either through direct load scheduling or by Demand Response (DR) that engages consumers to adapt their energy usage pattern by means of monetary or non-monetary incentives (Albadi and El-Saadany, 2008). Exploiting demand side flexibility improves economic outcomes compared to a "supply follows demand" paradigm but concurrently increases power system complexity — at least at first sight. From an infrastructural point of view it is the bidirectional communication between distributed actors and resources in the power system that becomes an essential prerequisite for this kind of applications. Therefore, the Smart Grid is rolled out nowadays to facilitate the activation of the demand side. In addition to that, concepts offering appropriate economic incentives encapsulated in attractive energy services need to be designed.

The fine-grained and decentralized nature of DSM calls for an intermediation between supply (generators, grid operators) and demand (consumers, businesses). Managing demand side flexibility is much more complex than the traditional generation capacity dispatch on the supply side. In case of direct load scheduling coordination of decentralized individuals is computationally expensive or in mass market DR applications avalanche effects can endanger grid stability (Ramchurn et al., 2012; Gottwalt et al., 2011). Intermediaries can better exploit flexibility as they can pool this potential and offer the net total on wholesale markets in a processable form (EU Commission, 2015b). Lately, the market has recognized this need: Municipal utilities and start-ups acting as intermediaries in the energy sector are increasingly emerging.

Even though the activation of the demand side is technically implemented nowadays, "engineering" a techno-economically evolved energy system is crucial to constitute a disruptive innovation to the energy sector (Roth, 2002). The market engineering framework proposed by Weinhardt et al. (2003) provides a principled approach to structure the economic transformation and isolate individual challenges in such a system. It helps to break down a market outcome into market structure, transacted objects, and actions of market participants.

In the case of an energy system the desired market outcome is a reliable, sustainable and economic power system. This pursuit is directly affected by actions and behavior of market participants embedded in a socio-economic and legal environment. Market structure and transaction objects (e.g., energy services) can nudge participant behavior, that are both the only directly controllable elements for intermediaries in the market environment. The market engineering discipline is complex and offers many fields of research because the cause-effect relationship between these controllable elements and the market outcome is indirect, e.g., due to to bounded rationality or cognitive biases of participant behavior (Bazerman and Neale, 1993).

The work at hand focuses on *transaction objects* from the point of view of market participants on the intermediation level assuming this to be a building block of future energy markets. The development of new transaction objects rather than the adaption of cautiously protected market structures by traditional energy utilities will play a major role for emerging intermediaries. A multitude of approaches in form of energy service products were and are to be designed in research and industry to tackle the aforementioned challenges. To this end, the main objective of this dissertation is to investigate the most important challenges intermediaries will face in the period of transformation towards future energy markets: (a) establishing a structured approach for the development of transactions objects, (b) understanding the agent behavior of the intermediaries' end-consumers, and finally (c) marketing the end consumers' flexibilities on wholesale markets.

1.1 Research Outline

The fundamental basis of this dissertation is the existence of infrastructure in the form of a Smart Grid that facilitates bidirectional communication between suppliers and consumers. This creates the opportunity to develop new product solutions in contrast to the former perception of electricity being a homogeneous good. Consequently, the first research question aims at defining the energy service concept and how to assist the product development process in a structured way.

Research Question 1 – Quality Differentiation

What characterizes the energy service concept and what is a structured way to design differentiated energy services?

The notion of "energy services" is specified and the concept of "quality differentiation" is presented building on existing literature and adapting its theories. Based on these foundations and the morphological design theory (Zwicky, 1967) design dimensions for energy services are explored. The morphological methodology is further extended to assist the product development process and illustrated by means of a prototypical decision support system.

Having established the fundamentals for the understanding and design of energy services, the following research questions instantiate a deep dive into the application of energy services in DR scenarios. A case in point is electric vehicle (EV) charging which is considered as a prime case of load flexibility (Goebel et al., 2014; Shao et al., 2011). Thereby, the deadline differentiated pricing scheme (Bitar and Low, 2012) is applied to an EV charging use case. A car park operator in the role of an intermediary offers the service of EV charging to end-consumers during their car park stay. The car park operator elicits demand side flexibility through deadline differentiated prices to match the emerging energy demand to local photovoltaic (PV) generation located on its rooftop. To this end, charging requests contributing flexibility are incentivized through energy price reductions subject to user-chosen charging completion deadlines.

The second research question investigates the value of flexibility in this setting.

Research Question 2 – Value of Flexibility

What is the value of EV charging flexibility and how should a deadline differentiated price menu be determined to optimally elicit it?

Focusing on the operational management of EV charging a stochastic mixed-integer optimization model is formulated and evaluated. Empirical driving profiles, real-world operational data from a car park, and recorded solar generation data provide a realistic input setting. The impact of customer flexibility on the car park operator profit is measured to determine the value of flexibility.

A car park operator's scheduling freedom increases the more fine-grained the price menu is. This, in turn, increases complexity for end-consumers since the number of options to choose from increases.

The third research question addresses the impact of simplifying the structure of the price menu on the operator profit.

Research Question 3 – Value of Complexity

What is the impact of reducing the price menu complexity on the intermediary's profits?

Electricity generation from PV panels can be very volatile and intermittent, especially on a local level. Hence, regional forecasts commonly deviate from the realized electricity generation. The following research question aims at answering this issue and examines whether demand side flexibility elicited through deadline differentiated pricing can mitigate PV forecast errors.

Research Question 4 – Mitigating Forecast Errors

To what extent can deadline differentiated pricing help mitigate PV forecast errors?

Instead of assuming perfect information on local PV generation, real-world forecasts from responsible transmission system operators are employed. These forecasts provide a general trend for regional PV generation but do not reflect local fluctuations. The mitigation potential is analyzed in terms of loss of profit compared to the perfect information scenario.

Car parks will be frequented by heterogeneous EV customers with varying requirements either regarding their energy demand or more fundamentally their economic valuation. Taking into account customer diversity instead of e.g. assuming homogeneity in theoretical models can have a major impact on real world applications. This effect is analyzed in the deadline differentiated pricing application case by examining the impact of different customer diversity models.

Research Question 5 – Modeling Customer Diversity

How do different customer diversity models impact the intermediary's profits?

The final part placed a stronger focus on the upstream activity of intermediaries. Relevant wholesale markets to procure end-consumers while leveraging their flexibility to counter RES volatility are day-ahead markets and real-time markets. End-consumers in this scenario are households providing shiftable loads at diverse disutility levels.

Research Question 6 – Wholesale Procurement

To what extent can a demand response intermediary benefit from consumers' household flexibility with respect to the wholesale procurement of electricity?

This research question is addressed by means of a three-stage bi-level electricity market model encompassing an intermediary interacting with both end-consumers on the downstream and a system operator on the upstream. The intermediary interacts with end-consumers to establish a long-term DR contract. To serve this demand the intermediary procures electricity from wholesale markets managed by the system operator. The results of several numerical simulations allow to quantify the value of flexibility under consideration of realistic wholesale procurement situations and the impacts of modeling end-consumer preferences on DR programs.

1.2 Structure of the Dissertation

The outline of this dissertation is illustrated in Figure 1.1. The remainder is divided into three parts. Part I establishes the foundations: Chapter 2 introduces the fundamentals of power systems and energy markets and applies the market engineering framework to the power sector. After developing a linked perspective on the notions of "energy service" and "quality differentiation" in Smart Grids in the first part of Chapter 3 the aforementioned three important challenges intermediaries are facing are investigated. The first challenge of developing transaction objects is addressed in this chapter by establishing an extended morphological approach and instantiating it in a prototypical decision support system.

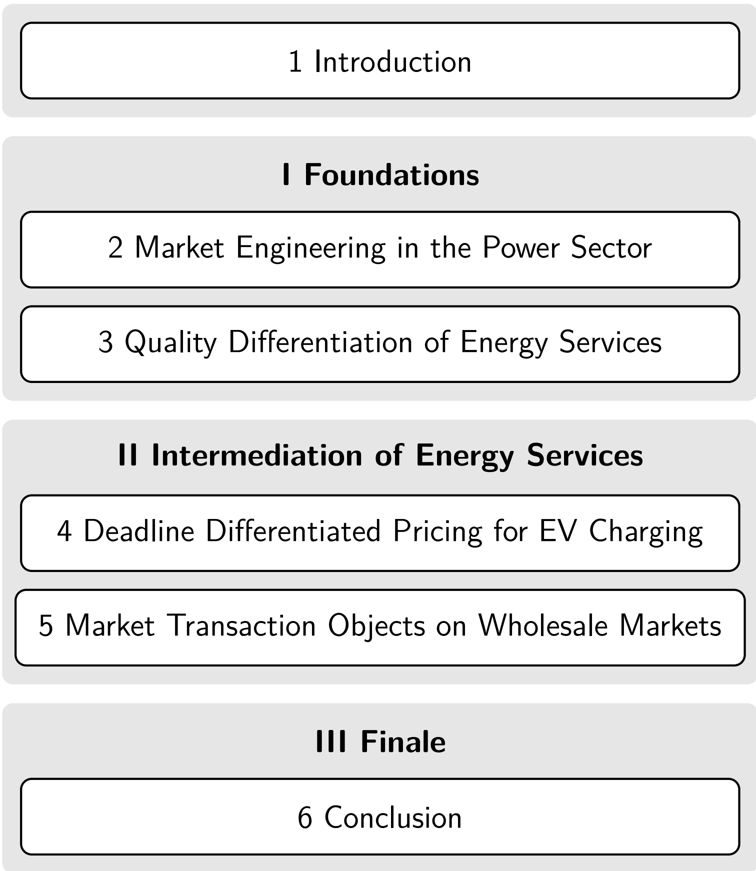

Figure 1.1: Structure of this work

Part II examines specific demand response energy services from the point of view of an intermediary. Chapter 4 introduces and applies the deadline differentiated pricing scheme on an EV charging use case by formulating a stochastic mixed-integer optimization problem. Hereby, the second challenge of understanding the agent behavior is investigated. Within Chapter 5 the upstream activity of an intermediary is taken into account additionally yielding a three-stage bi-level stochastic optimization problem. This addresses the intermediaries' third challenge of interacting with wholesale markets. Finally, Part III with Chapter 6 concludes by summarizing the key contributions of this dissertation and provides an outlook on open research questions.

Part I

Foundations

Chapter 2

Market Engineering in the Power Sector

THE industrialized world considers an operational electrical power system as a basic service. The economies and societies throughout the world rely on power systems for everyday operation. This is demonstrated by the effects of the very few historic outages, e.g., in New York in 1977 and 2003. The city-wide outage in 1977 resulted in looting, vandalism, and other disorders. In 2003 a regional two-day outage accounted for a cost of approximately six billion US dollars (Minkel, 2008). Therefore, it is no surprise that large-scale power systems are historically established in a hierarchical approach: Few centrally operated large power plants generated electricity that had to be transmitted to distribution nodes via high voltage and from there on via low voltage distribution grids to end consumers. In the 1990s environmental concerns and depleting fossil energy sources triggered the need to generate electricity from renewable energy sources. This poses several challenges to the centralized approach due to the distributed and volatile nature of renewable generators (Ramchurn et al., 2012).

This chapter first presents a concise overview of the historically established structure of the power system in Section 2.1. Section 2.2 provides a synopsis on the structure and characteristics of energy markets. Lastly, Section 2.3 closes this chapter by introducing and applying the market engineering framework (Weinhardt et al., 2003) to the energy market.

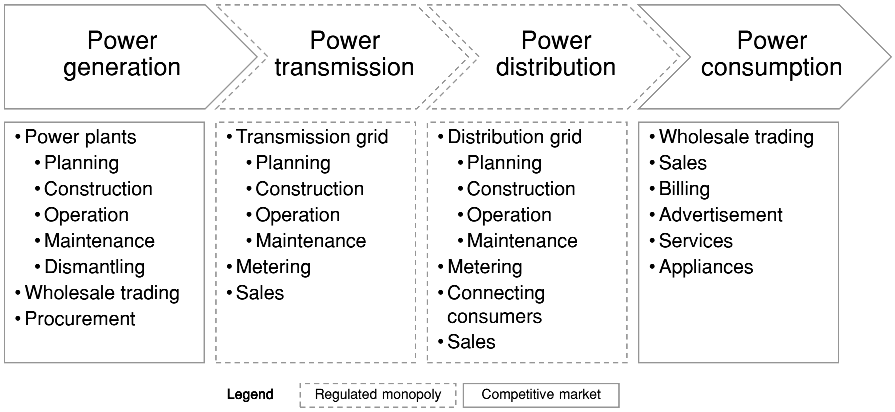

Figure 2.1: Structure of a conventional electricity value chain (based on Hoitsch et al., 2001).

2.1 Power System Fundamentals

The fundamental functions of an electricity value chain consist of generation, transmission, distribution and consumption of power as depicted in Figure 2.1. Before the liberalization of electricity markets that has been accomplished in all EU countries and others (Joskow, 2008b), utility companies were in charge of the whole value chain and thus vertically integrated. Even though the functions contain very heterogeneous tasks, an integration was beneficial for energy utilities due to the need for an unobstructed interplay between the elements of the value chain. In 1998 the liberalization in Germany forced the unbundling of utility companies: They had to separate the competitive functions — generation and sales — from grid operation, which is a natural monopoly (Train, 1991). Since then the markets for power transmission and distribution are regulated by the German Federal Network Agency (Jamasb and Pollitt, 2000).

2.1.1 Generation

As already noted mostly large-scale generators were historically constructed to secure the electricity provision of countries. The portfolio of generators is heterogeneous for different reasons: lowering the dependency from specific primary energy sources, increasing the operational flexibility due to various technical characteristics, and adapting to regional circumstances. Coal and nuclear power plants typically serve the base load as they have low marginal costs, but high ramping costs. On the other

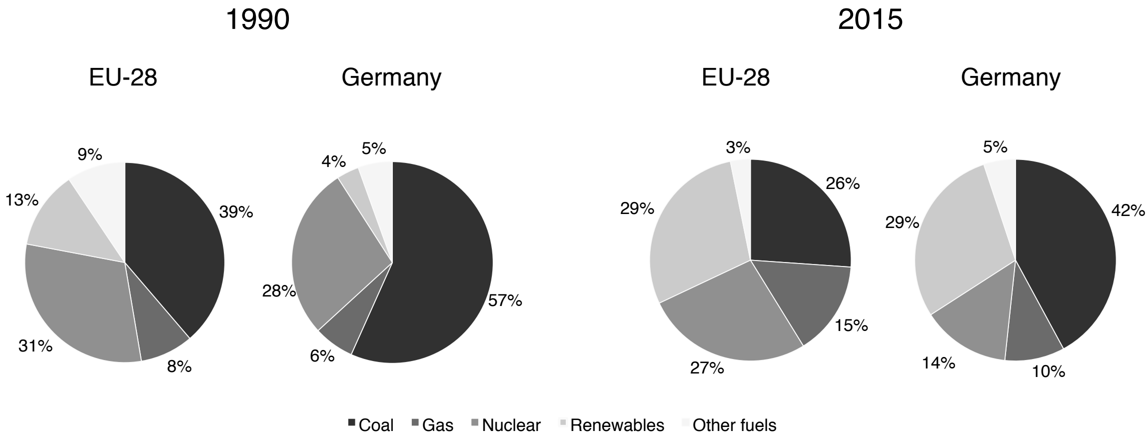

Figure 2.2: The evolution of electricity generation portfolios from 1990 to 2015 (based on Agora, 2016; AGEB, 2017; Eurostat, 2016b).

hand gas, pumped hydro, and in developing nations still common oil power plants have low investment and ramping costs and are therefore used to react to short-term state changes of the electricity system. Hence, portfolios differ around the world. This is not only due to energy-political reasons but also to diverse present conditions such as availability of fossil fuels.

Figure 2.2 depicts the evolution of the electricity generation portfolios and regional differences by means of a comparison of the portfolio of today's European Union countries and Germany. To date, fossil fuels are the dominating resource for electricity generation despite their carbon footprint and limited supply. After the Second World War, the idea of a peaceful use of nuclear energy in the form of nuclear power plants thrilled the fast-growing industry nations such as USA, Russia, France, and Japan. After the oil crisis of the 1970s at the latest, nuclear power was seen as the best long-term solution for a reliable power supply. Due to the major nuclear accidents 1986 in Tschernobyl and 2011 in Fukushima, as well as the unresolved problem of final storage, the broad public acceptance for nuclear power was lost and many countries decided to phase out of nuclear power generation. Enabled by critical research developments in alternative generation technologies, mostly wealthy nations bet on electricity generation from renewable energy sources as the long-term solution for a clean power supply. To this end, the EU countries have increased the share of electricity generation from RES to 29% by offering subsidies to the construction and operation of generation units.

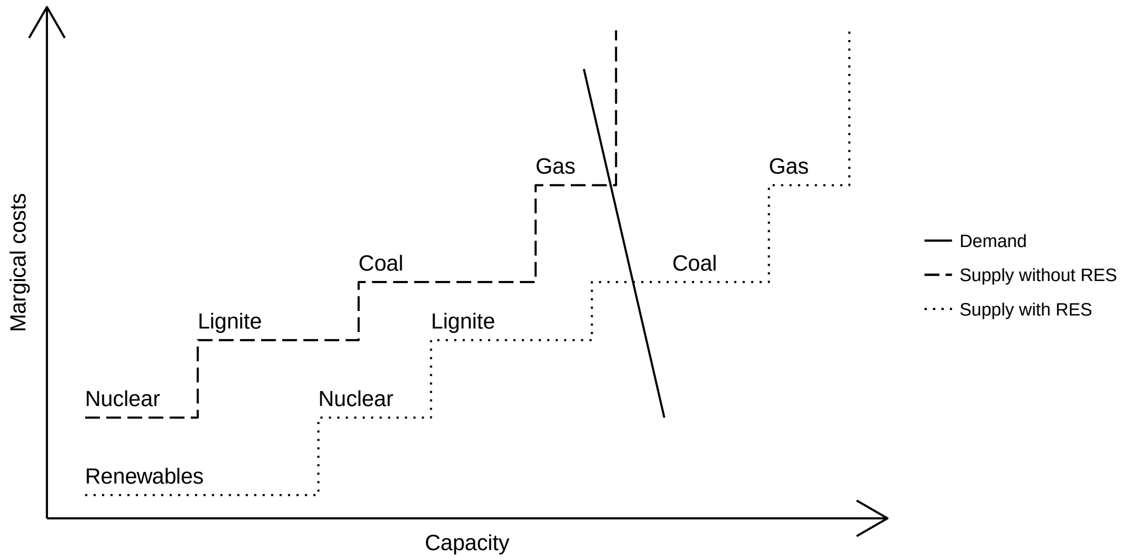

Figure 2.3: Merit order dipatch and effect

In contrast to conventional power plants, RES generation has near zero marginal costs and is always running but has a volatile generation pattern due to weather stochasticity and a low capacity utilization. Typically the dispatch of a generation portfolio follows the marginal cost structure that considers availability and ramping constraints yielding the merit order curve depicted in Figure 2.3 (Stoft, 2002). The intersection between the (typically inflexible and therefore steep) demand curve and the supply curve is the market clearing price. The merit order effect describes the impact of generation portfolio development towards integrating renewables (Sensfuß et al., 2008). Since renewables have near zero marginal costs the original merit order is shifted to the right. Assuming an unchanged demand curve the market clearing price decreases the more renewables are integrated into the power system.

Currently, generation from RES is constantly growing worldwide. Due to the stochastic nature of renewables flexible generation capacity is needed to balance times of low wind or photovoltaic power generation. Gas power plants are flexible enough to mitigate the volatility of renewables. Unfortunately, price spikes that are needed to amortize the capacity investments of these generators occur less often due to the merit order effect: Coal power plants are recently most of the time the market clearing price setters. This “missing money problem” (Joskow, 2008a) can not stimulate investments for flexible generators and has even led to several power plant shut downs in Germany according to the German Federal Network Agency (Bundesnetzagentur and Bundeskartellamt, 2016, p. 52). This problem is further compounded by political decisions such as feed-in tariffs and investment rebates for renewable generators (Haas et al., 2004). Economists are discussing whether the common energy-only markets will fail to massively integrate renewables and thus new market designs need to be established that can better incentivize capacity provision (Cramton and Ockenfels, 2012). In 2015, Germany decided to stick to the energy-only market design and encouraged the industry to find innovative solutions to react flexibly to short-term changes of the generation side (BMWi, 2015). This is the central topic if this dissertation.

2.1.2 Transmission and Distribution

The transmission and distribution grid structure logically follows the historically centralized power system to deliver electricity from a low number of large-scale generators to a multitude of widespread consumers. Transmission lines transport electricity over long distances from generators to substations. To limit the power loss to a minimum the electricity transport is carried out on extra high voltage on either 220 or 380 kilovolts (kV) overhead, undersea, or underground (El-Hawary, 2008).[1] The substations, being the point of transition from transmission to distribution grid, transform electricity to lower voltage levels and distribute it to consumers. The distribution grid is divided into three different levels: high voltage (35-110 kV), medium voltage (10-30 kV), and finally low voltage (230-400 V) (Brunekreeft et al., 2015). Large consumers, e.g., industrial companies, obtain electricity from medium or even high voltage levels, while small consumers, typically households, are connected to the low voltage level.

In Germany, the power grid is managed by the transmission system operators (TSO) and the distribution system operators (DSO), respectively. They are responsible for grid operation, maintenance, stability, and reliability. DSOs are in addition responsible to connect new consumers and small generators to the grid. These may be households, industrial consumers, or RES generators. The N-1 criterion, that only applies to the transmission grid, requires a redundant system setup (Schwab, 2009).

[1] The reported voltage numbers apply for Germany and most of Europe. Some countries might employ deviating voltage levels for their transmission and distribution grids.

Table 2.1: Circuit length and other characteristics of the German electricity grid in 2015 (Bundesnetzagentur and Bundeskartellamt, 2016).

	TSO	DSO	Total
System operators (number)	4	817	821
Total circuit length (km)	36,001	1,780,856	1,816,857
Extra high voltage	35,610	360	35,970
High voltage	391	96,267	96,658
Medium voltage	0	511,164	511,164
Low voltage	0	1,173,065	1,173,065

Since electricity grids require high investment costs and rather low operating costs, TSOs and DSOs are considered natural monopolies (Train, 1991) and are therefore regulated by the German Federal Network Agency (Jamasb and Pollitt, 2000). In Europe, the system operators usually own the grid whereas, e.g., in the USA independent system operators (ISO) only operate the grid. Brunekreeft et al. (2005) argue that the separation of ownership and operation is a more flexible solution to react to possible changes in the market area.

Before the liberalization in Germany, the energy sector was dominated by only four large utilities: RWE, E.ON, Vattenfall, and EnBW. Large enterprises were in favor because large-scale generators and the power grid require high investments. This grid partitioning remained with regards to the TSOs whereby unbundling forced the utilities to found new companies that were subsequently mostly sold to foreign shareholders: Amprion, Tennet TSO, 50Hertz Transmission, and TransnetBW. While the TSO unbundling according to Directive 2009/72/EG requires a strict separation of organizations, the DSO unbundling is less restrictive. In contrast to the German TSO market, Table 2.1 shows that in the distribution grid more than 800 DSOs exist that manage approximately 500 times more circuit length than the TSOs (Bundesnetzagentur and Bundeskartellamt, 2016).

As already mentioned the structure of the power system originates from the idea of centralized, large-scale electricity generation. However, RES generators that currently constitute the main part of generation expansion are small and decentralized. Therefore, it is the task of the DSOs to feed-in generation from RES at the low and medium voltage level. Obviously in case of more generation than demand in a grid region the direction of power flow changes. A bidirectional power flow in combination with uncertain and fluctuating renewable generation poses a challenge for the distribution grid. The volatility in grid expansion planning suggests that DSOs in Germany are still in the progress to understand how to cope with this issue: While the DSOs reported in 2014 to invest 6.6bn Euros in future grid expansions they corrected this number to 9.3bn Euros one year later. In 2015, expenditures for redispatch measures and curtailment of renewable output to ensure grid stability nearly tripled compared to 2014 to a total of 890m Euros (Bundesnetzagentur and Bundeskartellamt, 2016). These numbers document the currently present potential for unused flexibility that could be exploited by introducing demand side management measures. Obviously, this potential has an upward tendency because the ratio of electricity generation from RES will further increase. In particular, the work presented in Chapters 4 and 5 suggest energy services that address the above-outlined challenges.

2.1.3 Consumption

Electricity is the third largest source of final energy consumption in Germany. In 2015 electricity accounted for 20.8% of final energy consumption following fuel with 29% and gas with 25.1% (BMWi, 2017). Figure 2.4 depicts the development of energy sources since 1990. Fuel oil, coal, and lignite mainly used for space heating decreased from 31.6% in 1990 to 12.8% in 2015. Environmental aspects driving alternative methods for space heating as well as temporally increased oil prices are possible reasons for that development. Meanwhile, gas and electricity consumption increased moderately from 37% in 1990 to 45.9% in 2015. It can be expected that the importance of electricity increases significantly in the next decades. The irresistible market penetration of electric vehicles will cause a substantial energy source shift from fuel towards electricity increasing the importance of the power sector in general and in particular for the sake of climate goals.

Households typically use electricity for space and water heating, work, e.g., cooling, motion, or information and communication, and lighting (Erdmann and Zweifel, 2016). Comparing the development of electricity consumption from Figure 2.4 with

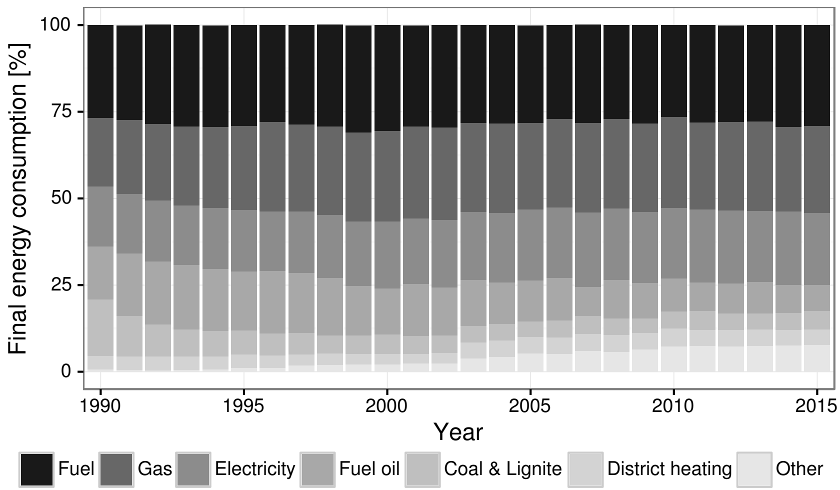

Figure 2.4: Final energy consumption divided by energy source from 1990 until 2015 (BMWi, 2017).

the German (DE) electricity price increase over the years depicted in Figure 2.5, the economic assumption of an inelastic demand for electricity particularly from households is evident. Based on this assumption synthetic load profiles were defined for different small- to medium-sized consumer types in households and industry. DSOs report the demand forecast, calculated with the help of these load profiles of connected consumers, to the supplying utilities that have to procure electricity accordingly.

Households that are connected on low voltage levels usually receive a simple electricity tariff consisting of a fixed connection fee and a constant rate per kilowatt-hour (kWh). Industrial consumers, usually connected to the medium voltage level, pay a connection fee as a function of maximum load of a billing period. Larger consumers can be equipped with an advanced metering infrastructure in order to individually optimize the procurement of electricity.

Fueled by the constant operation state of nuclear power plants the simplest form of time-of-use tariffs (TOU) was introduced in the 60s mainly addressing storage water heaters (Torriti et al., 2010). Having a (high) daytime rate and a (low) nighttime rate, the start of the nighttime rate is typically signaled via ripple control to appliances. Due to the nuclear power phase-out, this early form of DR hast lost its importance. Other types of demand response have not yet been established for

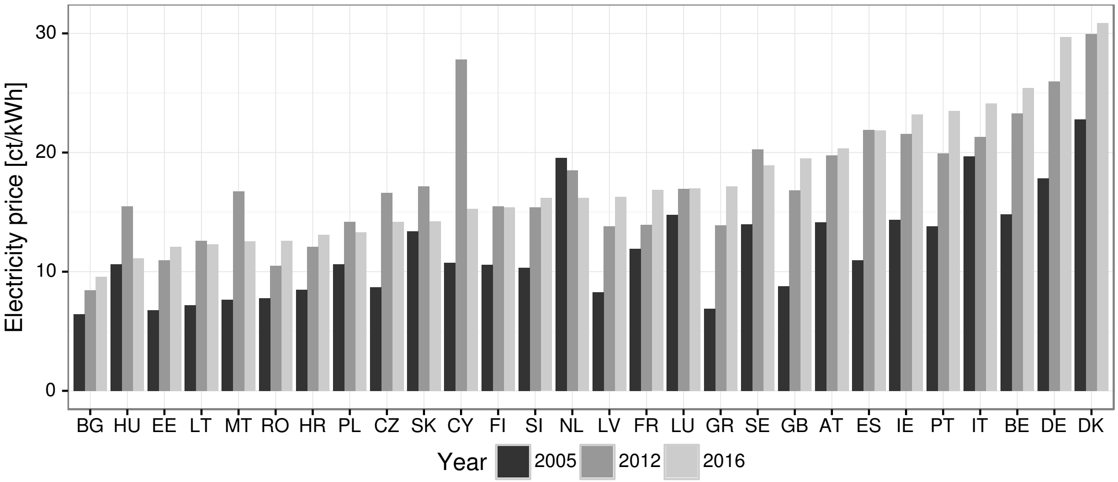

Figure 2.5: Average electricity price for a medium-sized household in EU-28 countries in 2005, 2012, and 2016 in Eurocent per kWh (Eurostat, 2016a).

households in Germany. Even though research on incentivization of electricity usage adaptations started in the 1980s (Schweppe et al., 1988) and was intensified lately due to the market penetration of RES generation (Strbac, 2008), implementation in the real world is still reluctant. However, the roll-out of smart meters (§21, EnWG) sets the infrastructural requirements for the introduction of DR products. This is elucidated in detail in Chapter 3.

Figure 2.5 depicts a comparison of electricity prices for households between the EU-28 countries and its development over the last years. Apart from a few exceptions, electricity price increased substantially in all countries in the EU due to increased commodity prices and subsidies for RES generators. Prices differ significantly between EU countries: E.g., in Denmark a medium-sized household paid more than three times as much as in Bulgaria in 2016. Germany has the second highest prices for electricity with 29.7 ct/kWh (Eurostat, 2016a).

The development of the composition of the electricity price in Germany is illustrated in Figure 2.6. The costs for generation, transmission, and sales were the dominating driver for changes in the electricity price until 2009. Since then, these costs were stable and even dropped in the last five years due to the merit order effect of RES generation that was explained in Section 2.1.1. However, the merit order effect is only based on the marginal costs. RES generation has high investment costs

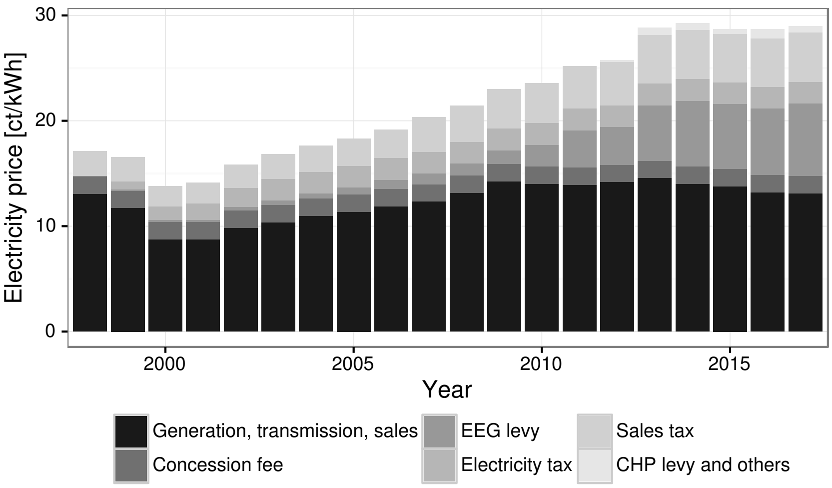

Figure 2.6: Composition of the average German electricity price for a medium-sized household from 1998 until 2017 in Eurocent per kWh (BDEW, 2017).

compared to their expected electricity output. This leads to higher full costs for RES generation compared to conventional generation[2]. To reduce risks for investors and ease the market integration of RES generators, the German legislator introduced a fixed feed-in remuneration. It is paid to RES generation owners and financed through the EEG levy by consumers. Since this EEG levy is proportional to the share of RES generation, it continuously increased up to nearly 25% of the total electricity price in 2017. Therefore, since 2009 the EEG levy has been the dominating driver for the development of the electricity price. It is expected that from 2023 onwards the EEG levy will decrease due to the phase-out of remunerations for early built generators and lower feed-in remunerations for later built generators (Graichen et al., 2015).

2.2 Energy Market Structure

Electricity is assumed to be a homogeneous good for traders since wholesale buyers are typically neither interested in the generator type nor the seller's identity. However, it can not be treated like other commodities since it cannot be stored without high losses or costs. Electricity can be exchanged via different distribution channels that differ in time of exchange, settlement, and pricing mechanism eventually yield-

[2]Due to reduced production costs, RES generators, particularly PV panels, recently reached full costs that undercut the full costs of a couple of conventional generators (TAZ, 2015).

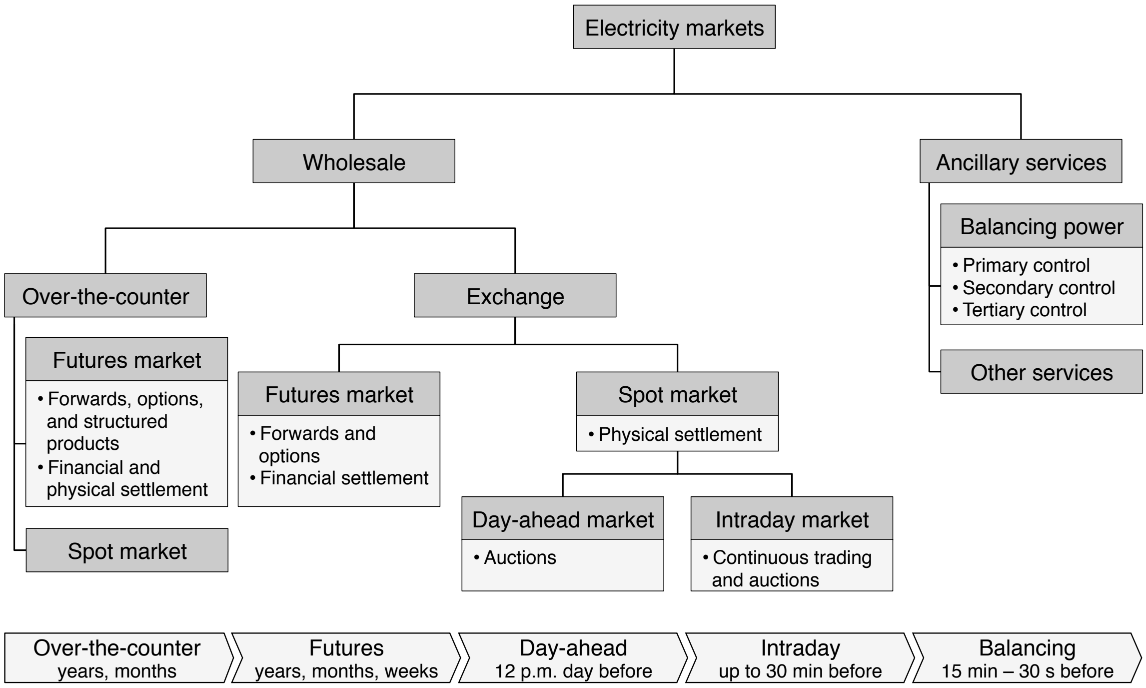

Figure 2.7: Structure of the German electricity market and traded products with their corresponding time frame (Judith et al., 2011).

ing different prices. Figure 2.7 gives an overview of available distribution channels for electricity trading in Germany. While platforms for ancillary services mainly address the short-term needs of TSOs, wholesale markets cover mainly long- and medium-term and to some extent short-term products. Wholesale markets are organized in bilateral, so-called over-the-counter (OTC) trading and exchange markets (e.g., the European Energy Exchange) that are usually interconnected between each other. An alternative to this structure is the pool market model that is currently present in few countries. In contrast to exchange markets, pool markets are centrally organized and require all trades to be executed on this market platform. It originates from the strictly regulated market architectures for vertically integrated utilities and therefore has disadvantages regarding competitiveness (Ockenfels et al., 2008).

Most generated electricity in Germany is traded OTC: In 2015 OTC brokers reported[3] a traded volume of 5,724 TWh, while only 1,247 TWh were traded on

[3]Due to the decentralized nature of OTC trading, accurate monitoring is impossible. Only a subset of all OTC brokers reported traded volumes to Bundesnetzagentur and Bundeskartellamt (2016). In addition to brokered trades, OTC trades can as well be executed directly between parties. For 2010 Bundesnetzagentur and Bundeskartellamt (2011) provides an estimation of

exchanges in the German-Austrian market region (Bundesnetzagentur and Bundeskartellamt, 2016). Ockenfels et al. (2008) point out that the advantages of bilateral trading come particularly into effect at futures market where transaction speed is neglectable. Therefore, centralized bilateral trading and centralized exchange markets typically coexist (Stoft, 2002). The following subsections introduce each market type.

2.2.1 Over-the-Counter

OTC contracts are non-anonymous, bilateral, non-standardized trades between wholesale entities and possibly supported by brokers. Since no central market exists, trading happens over undefined communication means, e.g., telephone and not on a physical trading floor. Thus, it is not listed on an exchange. Generally, risk of default is existent in contrary to exchanges but can be hedged by clearing banks. The overwhelming bulk of electricity is traded years in advance (up to six years) via OTC contracts due to the high flexibility in terms of products offered and often lower prices compared to exchange markets (Rademaekers et al., 2008; Lijesen, 2007).

Due to the nature of OTC trades, mostly every type of trade is possible: short-term contracts via a spot market, long-term contracts via a futures market, financial or physical settlement. If traders agree on a financial instead of a physical settlement, a cash settlement (difference between the forward price and the spot market price) is carried out between parties at an agreed fixed date. Historically, OTC trading was mainly settled physically as most market participants were generators and large consumers. Recently, many speculators have participated on OTC markets increasing the importance of financial settlement (Judith et al., 2011). Financial settlement is particularly chosen in case of a long-term contract, while on the spot market physical settlement still dominates. Popular long-term products are quarterly or yearly time bands of a specific amount of electricity.

the total volumes of OTC trades (10,670 TWh) and trades on exchanges (678 TWh). Therefore, it can be assumed, that the total volumes of OTC trades in 2015 are far higher.

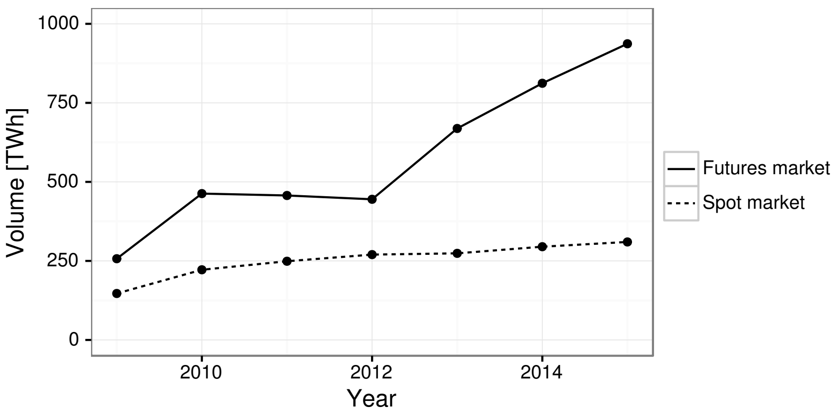

Figure 2.8: Comparison of the traded volumes on exchange futures and spot markets from 2009 until 2015 in the market region of Germany and Austria (Bundesnetzagentur and Bundeskartellamt, 2016).

2.2.2 Exchange

In contrast to OTC contracts, on exchanges, standardized products are traded anonymously and free of default risk. The European Energy Exchange (EEX) manages the exchange for electricity in the joint market region of Germany and Austria. While the German futures market is directly operated by the EEX, the spot market is handled by its 50% subsidiary EPEX SPOT and to a small degree by the Austrian EXAA. Settlement on the spot market is solely physical, whereas on the futures market it is mainly financial.

In Figure 2.8 the traded volumes on futures and spot markets is depicted. The traded volume on the futures market exceeds the electricity generation because financial settlement allows to trade electricity multiple times. In all reported years more volume is traded on the futures market than on the spot market. Even though the gap increased in the last years, spot markets have an important reference function to evaluate arbitrage situations in a competitive environment. Traders usually only accept bilateral trades if they believe that this trade is more advantageous than selling or buying at the spot market (Ockenfels et al., 2008). In addition, the spot market directly affects the dispatch of power plants.

On futures markets, forwards and options are traded continuously and mainly financially. In continuous auctions, each incoming bid is checked and matched if possible or otherwise entered in an order book that is ordered by price and time for a later match (Madlener and Kaufmann, 2002). Therefore, settled contract prices can differ between transactions. Due dates for tradeable month, quarter, and year products can be up to ten months, eleven quarters, and six years in case of forwards or five months, six quarters, and three years in case of options after the trade, respectively.

The purpose of these products is for both generators and distributors to hedge against price risks that are present on spot markets due to the low storability of electricity. Besides these participants, a large number of the market participants is constituted by speculators. They are mainly interested to benefit from volatility and differing market expectations. In 2015 more than one third of the market participants at the EEX were financial service institutes or banks. This explains the popularity of financial settlement (Bundesnetzagentur and Bundeskartellamt, 2016). The interaction of mainly financially interested parties with futures markets increases the trading volume and is therefore important to ensure a high market liquidity.

At the spot market in Germany products can be traded day-ahead or with shorter lead times (intraday trading). The most common products that can be traded are hourly contracts, standardized block contracts, and individual combinations of hourly contracts. Typical block contracts are "baseload" (a full day), "peakload" (from 8 a.m. until 8 p.m.), and "off-peak" contracts (all other non-peak hours of a day). In addition to that, quarter hours can be traded intraday, which is an important product to complement the typical ramps of RES generation that incur mostly during morning and evening hours. Day-ahead products are traded within call auctions, while intraday products were purely traded in continuous auction until 2014 (Madlener and Kaufmann, 2002). In December 2014 the EPEX SPOT introduced an opening call auction for the intraday[4] market taking into account the development of RES generation. This step should increase market liquidity[5] of the intraday market by concentrating the trades to one moment of the day. Figure 2.9 compares the traded volumes on the EPEX SPOT market platform. Even though this data might signify a remarkably higher importance of the day-ahead market,

[4]The word "intraday" might be misleading because the intraday opening auction takes place on the day before the products are delivered. However, the word "intraday" is used as a synonym for quarter-hour products in the trading jargon, which justifies the confusing wording.

[5]This issue is further addressed in Chapter 5.

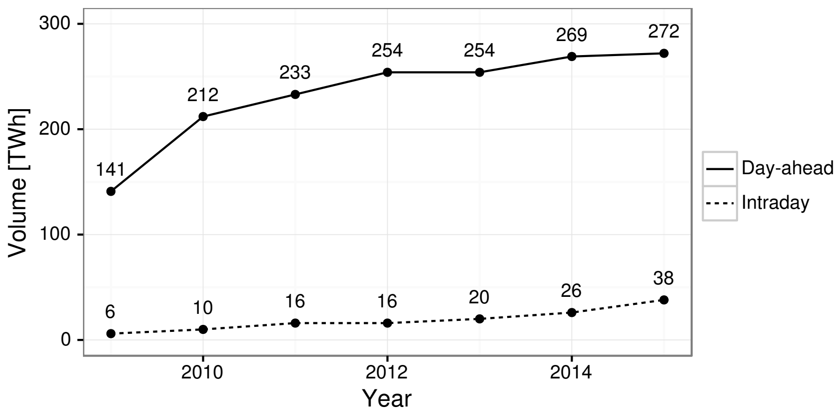

Figure 2.9: Comparison of the traded volumes on spot markets from 2009 until 2015 in the market region of Germany and Austria (Bundesnetzagentur and Bundeskartellamt, 2016).

the intraday market is crucial for an efficient market integration of RES generation (Grimm, Ockenfels, and Zöttl, Grimm et al.). The introduction of the intraday auction supported a volume growth of approximately 50% from 2014 to 2015.

The day-ahead auction is a double-sided, sealed-bid, uniform price auction that takes place at 12 p.m. every day. Until then, bids need to be transmitted from market participants to the market platform. The bids consist of up to 200 price-volume combinations between -3,000 up to 3,000 Euro/Megawatt-hour (MWh) for each product. After the auction closes, all bids are aggregated into linear interpolated[6] demand and supply curves for each hour of the day (Judith et al., 2011). Applying the uniform pricing rule (Madlener and Kaufmann, 2002), the intersection of both curves (compare Figure 2.3) yields the market clearing price that is published approximately 1 hour later. This bid matching ignores constraints from block bids or grid limitations. Therefore, block bids are eliminated if the average market price is not suitable and price calculation is repeated until all remaining block bids can be fulfilled. Afterwards, generators calculate the dispatch of their generating units and transmit it until 2:30 p.m. to the responsible TSO. Subsequently, the TSO performs load flow calculations based on these dispatches to identify possible congestions in the transmission grid and eventually instructs redispatch measures. Remunerations for redispatch measures that are paid for ramping-up and -down

[6]Other markets use additional rules for the price determination in case of multiple price levels at the intersection.

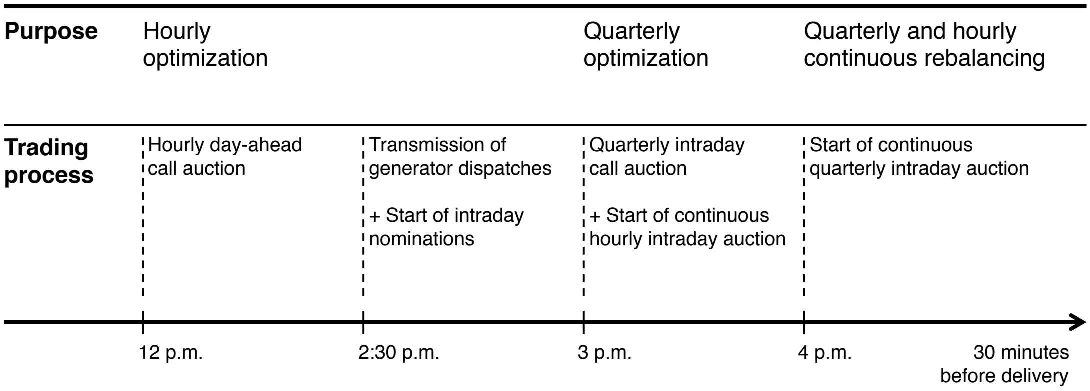

Figure 2.10: Overview of trading processes at the spot market in Germany based on illustrations of EPEX (2017).

of affected generators are determined by the German Federal Network Agency in an adequate manner. However, the remuneration calculations are currently under investigation (BNA, 2015).

The intraday market consists of several components. Figure 2.10 depicts the chronological context of these components with the aforementioned day-ahead trading. After the day-ahead auction that determined the reference market price, at 3 p.m. the continuous auction of hourly products starts and simultaneously the intraday opening call auction for quarter-hour products takes place. This call auction works similar to the day-ahead auction but offers a reduced set of products. Market participants can only transmit bids on 96 single quarter-hour products of a day. Due to the low trade volume and less product complexity, calculating the market clearing prices is usually finished after approximately 10 minutes. From 4 p.m. onwards the quarter-hour products can be traded continuously in single form, standardized blocks, or individual blocks until 30 minutes before delivery. In contrast to call auctions, in continuous auctions market participants have access to an open order book and bids are checked and matched — if possible immediately — using the pas-as-bid pricing rule (Madlener and Kaufmann, 2002). If bids can not be executed immediately they are entered into the order book. The order book lists all bids that could not yet be matched. They are ranked primarily by price and secondarily by time.

2.2.3 Ancillary Services

Short-term imbalances between demand and supply, e.g., due to inaccurate forecasts or unforeseen events, are addressed by different types of ancillary services. Besides the central ancillary service of *balancing power*, that will be explained in detail in the next paragraphs, many other services such as voltage control services or power system stabilizers are important to ensure a reliable power system. *Voltage control services*, e.g., offered from generators by producing or absorbing reactive power while producing active power, are used to maintain a defined voltage band. *Power system stabilizers* adjust the output of generators to dampen oscillations. Thus, they increase the amount of power that can be transmitted through the grid. In case of an imminent system fault, *intertrip schemes* automatically disconnect generators and loads to maintain system stability. Despite these measures, power system collapses can occur. In these rare events, generators with *black-start capabilities*, e.g., hydropower plants or diesel generators, are crucial to restore the power system (Kirschen and Strbac, 2004).

Balancing power is managed by TSOs based on measuring the frequency in its control zone that consists of multiple balancing groups. If demand and supply are not balanced, firstly kinetic energy is used to neutralize the imbalance. This limited available kinetic energy comes unselectively and automatically from all connected flywheel mass. In case of a power deficit, flywheels are slowed down to release kinetic energy and in case of a power surplus, flywheels are accelerated to store kinetic energy. Obviously, the release and storing of kinetic energy changes the rotation speed and, therefore, induces a difference in frequency. In order to comply with technical quality standards of the power supply, balancing power is utilized and triggered by these frequency deviations (Consentec, 2014). Therefore, TSOs demand both positive and negative balancing power in case the power system has a power deficit or a power surplus. Balancing power can be distinguished based on its activation time. In Germany, three different quality types of balancing power have been established: primary control reserve, secondary control reserve, and tertiary or minute reserve (Klobasa, 2010). Consentec (2014) provides a detailed description for these balancing power types:

- *Primary control reserve* facilitates a fast stabilization of the frequency after an incident. For the sake of an efficient operability, it is activated automatically and decentrally by frequency deviations. This takes place in a solidary manner regardless of control zones[7]. Offering primary control reserve requires a full activation in less than 30 seconds. Possible generators that can offer this type of balancing power are hydraulic and thermal large power plants. Due to low storage capacities, primary control reserve needs to be replaced rapidly.

- *Secondary control reserve* is activated automatically but in contrast to primary control reserve in a selective manner. Therefore, it is only activated in the control zone responsible for the incident. By means of a power-frequency control, the TSO continuously calculates the discrepancy between target and actual power transmission to interconnected control zones. According to that, the TSO requests secondary control reserve directly from power plants based on a merit order of activation costs. Secondary control reserve is activated until primary control reserve is fully deactivated and restored. Typically thermal and pumped-storage power plants that can be activated in less than 5 minutes can offer secondary control reserve.

- *Tertiary (minute) reserve* is utilized in cases of a long-running system failure, e.g., a power plant outage. Requirements to qualify for tertiary reserve are rather low since the maximum activation time is 15 minutes and execution is not automatic. Instead, the activation is requested via a central platform based on a merit order list. Gas turbines, demand flexibility, or biomass power plants can offer tertiary reserve. Recently, small generators that struggle in meeting the prequalification requirements started offering tertiary reserve based on the idea of virtual power plants Mashhour and Moghaddas-Tafreshi (2011); Lombardi et al. (2009).

Following §6 I StromNZV TSOs are obligated to procure balancing power through a shared anonymous tender across control zones that is implemented on the Internet platform `www.regelleistung.net`. Tenders for primary and secondary control reserve are executed weekly and for tertiary reserve daily. To participate in tenders, potential bidders need to prequalify their units with the responsible TSO. Bidders

[7]Therefore, transmission grid capacities need to be reserved to guarantee provision of primary control reserve from other control zones.

compete in a pay-as-bid call auction based on a demand rate. Winning bids, determined by the merit order of demand rates, receive their indicated demand rate. In case of secondary control and tertiary reserve, a bid additionally includes the specification of an energy rate. These reserve types are scheduled by ascending energy rate, that is paid out in case of activation (Swider, 2008).

On a monthly basis, TSOs financially settle their costs for balancing power. Symmetrical prices for balancing energy are calculated historically for each quarter hour accounting for all incurred expenses for balancing power. Balancing groups that are part of a TSO's control zone pay or receive these prices based on deviations from their previously forecasted target power balance (Consentec, 2014). In the last years, cost for balancing power increased dramatically and reached one billion euro in Germany 2015 (SPON, 2016; Welt, 2016). The growing market penetration of renewables will increase the amount of uncontrollable generators in the German power system. Therefore, the need for balancing power will further increase in the next years. However, the introduction of the opening call auction for the intraday market reduced the market volume for minute reserve in 2016. Demand side flexibility could meet at least part of this need if the balancing mechanism design was modified (Stadler, 2008; Koliou et al., 2014) in order to reduce costs for the expensive provision of balancing power.

2.3 Applying the Market Engineering Framework

Markets are the basis of our economies as they offer a platform for the allocation and distribution of goods or services. According to Weinhardt and Gimpel (2007), a market is defined as follows:

> Definition 1 – Market
>
> *"A market is a set of humanly devised rules that structure the interaction and exchange of information by self-interested participants in order to carry out exchange transactions at a relatively low cost." (Weinhardt and Gimpel, 2007)*

The design of markets has been of great interest for economists. Theoretical literature dates back to the 1960s (e.g., Vickrey, 1961; Gale and Shapley, 1962) that laid the groundwork for practical applications in the 1990s (e.g. McMillan, 1994; Roth and Peranson, 1999). Especially in case of electricity markets, a good design of markets is important due to the high complementarity between tradeable services, e.g., generation, transmission, and ancillary services (Roth, 2002). The market engineering framework proposed by Weinhardt et al. (2003) provides a principle structure that supports achieving a good market design. They define market engineering as follows:

Definition 2 – Market Engineering

"Market engineering is the process of consciously setting up or re-structuring market mechanisms and market infrastructure in order to make it an effective and efficient means for carrying out negotiations and exchange transactions." (Weinhardt and Gimpel, 2007)

In contrast to traditional market design approaches, the market engineering framework takes a holistic view on markets. The market design itself, as referred to, e.g., by Roth (2002), only represents one element of the market engineering framework that is explained in detail in Section 2.3.1. Generally, markets originate from two main sources: conscious design and undirected evolution (Smith, 2003a). Since details can matter (Roth and Ockenfels, 2002) and determine success or failure of a — especially electronic — market, Weinhardt and Gimpel (2007) propose a conscious design approach based on a five-stage process as depicted in Figure 2.11. Existing markets should be maintained by iterating this process in order to ensure that the market design adapts to changes in its environment.

The market engineering process is based on the typical waterfall model from software engineering. The environmental analysis is the first stage of this process. By means of surveys, interviews, and reviews in present literature, the market engineer should become aware of stakeholders, legal and social frameworks, and market segments. A thorough characterization of the environment provides the input for the

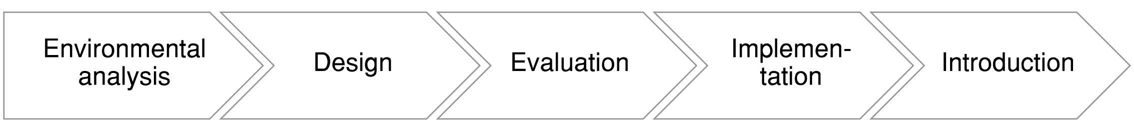

Figure 2.11: Market engineering process (based on Weinhardt and Gimpel, 2007).

design stage. In that stage, the market engineering framework is employed. The design of a market is chosen to lead to a specific market objective. Methods from the field of mechanism design are applied during this stage. Even though the process is based on the waterfall model, there is usually a frequent exchange between results from the design and the evaluation stage. Design ideas are theoretically modeled and simulated or empirically analyzed for the sake of evaluation. Subsequently, changes in the design are required implying a stage back in the process. Before implementation, an intensive testing with stakeholders based on a prototype can be examined to assess whether the desired behavior achieved by the market design. Finally, the market design is implemented electronically or even physically and subsequently introduced by training participants and advertising its launch.

2.3.1 Market Engineering Framework

The pivotal elements of a market are outlined by the market engineering framework that is depicted in Figure 2.12. It is a static view on a market that should be kept in mind by a market engineer. Some of these elements are directly modifiable by the market engineer, e.g., the whole market structure and the transaction objects. Others can hardly be influenced, e.g., the agent behavior and socio-economic and legal environment or, in case of the market outcome, can only indirectly be affected. The latter is the final result of a market that usually plays a central role in the discipline of market engineering.

A market is embedded into a *socio-economic and legal environment*. It determines the cultural background and norms of market participants that have an effect on their behavior. Besides, existing national or international law can be a constraint for the choice of transaction objects that can be offered or specific market structure elements. Both can be treated as external parameters to the market engineer that can evolve over time. Although, legal frameworks or political goals are sometimes influenced to some extent through lobbying of large companies.

The ultimate goal of a market engineer is to generate a specific *market outcome*. In contrast to the engineering of products, a market engineer can not define the quality directly (Weinhardt et al., 2003). Instead, the market outcome is the sum of all elements in the market engineering framework but mostly affected by the market

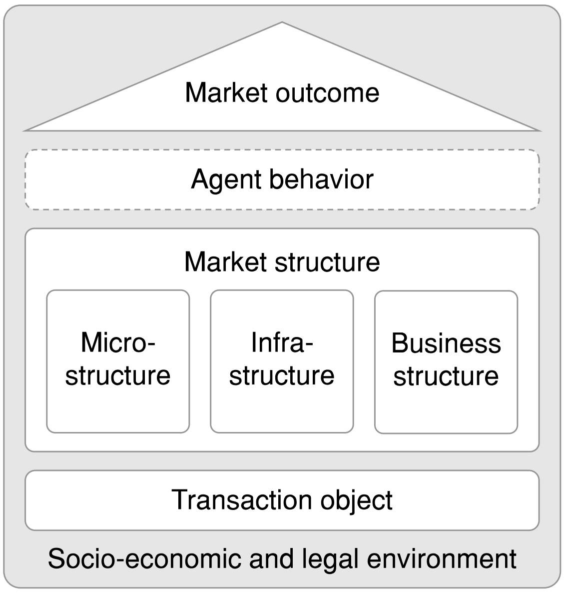

Figure 2.12: Market engineering framework (based on Weinhardt et al., 2003).

participant's behavior on a given market structure. Typically a market engineer wants to design a market that is accepted and used by market participants addressed by key measures such as market activity or liquidity. However, measuring the market outcome is difficult because it is often multi-dimensional and depends on the context, as Maskin (2008) remarked in his Nobel prize lecture.

Agent behavior is the reason why market engineering is a complex discipline: There is no direct cause-effect relationship between the designed market structure and the market outcome (Weinhardt and Gimpel, 2007). A common fundament to implicate a given behavior, e.g., towards the desired market outcome, is an incentive compatible mechanism (Hurwicz, 1973). In contrast to the abstraction in game-theoretic models, agent behavior in real world is biased by bounded rationality (Bazerman and Neale, 1993) and therefore difficult to predict. In the market engineering framework it is treated as an exogenous factor of a market that is not perfectly known to the market engineer (Weinhardt et al., 2003). Since it plays an important role in a market by directly affecting the market outcome, it should be anticipated as good as possible by means of experimental methods. After understanding agent behavior it can be formally represented by analytic methods to be able to estimate reactions to specific market elements.

The *market structure* is one element that can directly be formed by a market engineer. It consists of the microstructure, the infrastructure, and the business structure. The *microstructure* deals with the market mechanism that is usually seen as the central element of market design (Smith, 2003b). For instance, in case of auctions, the bidding language is defined within this element. A robust and reliable *infrastructure* is the basis for communication between market participants and the market. Due to the increasing importance of electronic markets, this element is often reduced to the information technology aspects even though physical markets are addressed as well. This element has particularly driven by the developments in the financial market industry, e.g., by the increasing demand for high-frequency trading. Lastly, the *business structure* defines the business model of a market provider. It comprises setting fees for admission to the market and transactions, that can both be critical with respect to agent behavior. These three elements cannot be designed separately as there is a strong interdependency among them Weinhardt and Gimpel (2007).

Finally, the *transaction object* deals with the resources that are to be allocated on the market. This resource can be a good, a service, or even a right or certificate. It is the central object that is sold and bought on markets and therefore entitles the existence of a market.

2.3.2 The Energy Trilemma

In order to apply the market engineering framework to the energy market, a market engineer should start with specifying the desired market outcome. Usually, the efficiency of an energy market is assessed along three dimensions: ecologic sustainability, economic efficiency, and supply security. Since these dimensions are competing against each other, Sautter et al. (2009) refer to them as the "energy trilemma"[8] that is depicted in Figure 2.13. For instance, coal power plants produce electricity at low cost and are usually reliable but generate high emissions. Therefore, a trade-off between these dimensions needs to be made in terms of energy policy and investment decisions. Currently, supply security is a hard constraint in the energy policy while compromises are accepted in terms of sustainability and costs.

The *supply security* is mainly determined by three factors (compare Section 2.1):

[8] In Germany, the energy trilemma is called "Energiepolitisches Zieldreieck".

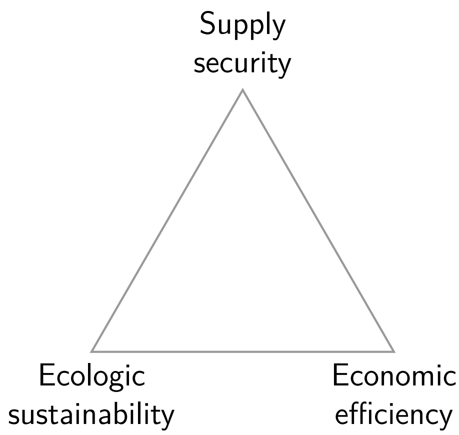

Figure 2.13: The energy trilemma

generation adequacy, transmission capacity, and distribution capacity. Generation adequacy is currently not critical in Germany because many conventional power plants are in reserve due to the construction of new RES generators. However, external effects can put the generation adequacy at risk, as happened in France in 2016: Due to a design flaw and the high dependency on affected nuclear power plants, France was prone to power cuts in the winter (Reuters, 2016). In contrast, transmission capacities are scarce in Germany, especially between Northern Germany with a surplus of electricity from offshore wind power plants and Southern Germany that has more demand than (RES) supply. However that is not a threat to supply security, as in cases of overloaded transmission lines, conventional power plants can generate enough electricity to supply the South. Most of the time the distribution capacities are the reason for a reduced supply security, e.g., local blackouts or voltage band deviations. As the N-1 criterion does not apply to the distribution grid, lightning strokes, outages of outdated transformers, or damages to lines from constructions can cause such events.

The *economic efficiency* considers costs for capacities, e.g., generators and the grid infrastructure, and marginal costs, e.g. fuel for generators. Even though market prices have fallen on wholesale markets that mainly represent marginal costs, the end consumer prices have increased recently (compare Figure 2.5). This is because the investment in RES generators is subsidized through end consumer prices, while RES generators have nearly no marginal costs. Obviously, this is a situation, where the both dimensions economic efficiency and ecologic sustainability clash and trade-offs are actively made by policy makers.

Ecologic sustainability is endangered by carbon emissions from fossil power plants, by the radiation of uranium that fuels nuclear power plants, by land usage from generation sites and overhead lines, and by water contamination from underground or undersea lines. Ecologic sustainability needs to be cared for from two perspectives: From a long-term perspective, the investment in generation and grid capacities needs to consider sustainability factors, which is already taken care of by the German policy maker. These investments only pay off if the short-term perspective is considered: It is important to ensure, that the intermittent RES generation is consumed, e.g., by flexible loads, which is the main topic of this dissertation.

Recently the integration of all stakeholder interests, e.g., citizens, has been discussed particularly in Germany. The so-called "not in my backyard" attitude delayed the construction of wind power plants and transmission lines (DIE ZEIT, 2014). Therefore, the energy trilemma is sometimes expanded by the dimension of "social acceptance" to a rectangle. However, this dimension has not broadly been adopted as an additional dimension but rather as a soft criterion that needs to be taken care of at planning stage. Legitimation of such large projects has not yet and should not become grassroots democratic (Schröter, 2016).

2.3.3 Engineering the Energy Market

Historically, the power system and market regime were designed for centralized generators run by monopolists. Recent and future developments in the power sector call for an adaption, as depicted in the previous sections of Chapter 2. Legislators and market participants have lately reacted to these developments. This is discussed in the following and supplemented by corresponding research activities focusing on the German energy market particularly from an intermediation perspective. Since the market outcome has already been discussed in detail in Section 2.3.2, it is left out in this section.

Socio-Economic and Legal Environment

The EU set itself ambitious goals to reduce greenhouse gas emissions by 20% until 2020 (EU Commission, 2010) in order to reduce global warming. These emissions should be reduced gradually by ultimately 80-95% until 2050 (EU Commission, 2011) while the electricity should play a major role to achieve that. To this end, electricity generation should be generated by nearly 100% in 2050. Several actions were taken by the EU to achieve the challenging goals. In 2005 the EU emissions trading system was introduced by setting a cap on the overall emissions but leaving the task of allocating the emission allowances to a market. Probably due to an oversupply of emission rights, prices for certificates decreased dramatically undermining the incentive to reduce carbon emissions. At least 50% of the money raised from these certificates should be invested into projects to increase energy efficiency or improve climate protection (EU Commission, 2016). Besides, the EU passed a regulation[9] in 2014 that sets an average carbon emission target for new passenger cars to 130 gram carbon dioxide per kilometer that will be reduced to 95 gram in 2020. Car makers have added new car models to their fleets — partially electric vehicles — in order to conform with this regulation that is binding for all EU nations.

Recently the EU started the consultation phase for a new market design ensuring that innovative companies and reliable intermediaries across Europe can compete against established utilities (EU Commission, 2015a). They should be incentivized to utilize new technology and focus on consumers to develop and deploy new products and services. Additionally, it should be ensured that electricity markets — especially long-term markets — are open to all market participants, namely providers for flexible demand and new energy services to effectively signal what and where to invest. In 2015, the German government established its vision of an "electricity market 2.0" (BMWi, 2015). It clearly dissociates from the idea of a capacity market and instead strengthens long-term market signals to finance investments. Besides, a new design of the grid fees is considered to allow for market-based demand side management.

This concise overview of the German socio-economic and legal environment reveals the opportunities for intermediaries and new energy services in the fields of demand response in the future energy market. However, it can be expected that legal frameworks will be adapted frequently and therefore companies should prepare to be flexible with regards to regulations.

[9]Regulation (EU) No. 333/2014

Agent Behavior

The top-down architecture of the power system and the homogeneity of electricity rubbed off on the utilities' knowledge about their customers. Customers were only seen as homogeneous power consumers without caring for their characteristics. However, a proper assessment of their behavior is important to be able to design energy services and market structures that induce the desired market outcome. Especially if the demand side should become flexible it is important to understand how to stimulate consumers.

Current research suggests demand response programs that rely on monetary incentives, e.g., for load shifting (Albadi and El-Saadany, 2008; Strbac, 2008). Monetary incentives can be program based or ultimately price based (Albadi and El-Saadany, 2007). User behavior can be influenced by setting up appropriate graphical user interfaces, e.g., depicting a market. Such a hidden market user interface can reduce the complexities of a real market and support consumer participation (Seuken et al., 2010). Taking on the idea of sharing economy (Hawlitschek et al., 2016), peer-to-peer platforms for virtually transacting, e.g., PV electricity (Liu et al., 2015) have become business models of interest (buzzn, 2017). Implementing this idea on the blockchain technology that became popular with the virtual currency "Bitcoin" gained interest in the power sector (LO3, 2017). Recently, gamification approaches became increasingly popular to promote energy efficiency or even load shifting (Gnauk et al., 2012; Grossberg et al., 2015), but has been applied as well beyond the power sector (Deterding et al., 2011; Huotari and Hamari, 2012). These approaches could be promising in the power sector, particularly when considering the society's willingness to accept additional costs for the sake of sustainability (Borchers et al., 2007).

This work mainly focuses on the idea of monetary incentives triggering agent behavior. While Section 4 assumes consumer rationality, Section 5 will further discuss and apply the concept of bounded rationality (Simon, 1955).

Market Structure

The market structure of the power sector has already seen dramatic changes throughout the world due to the liberalization of energy markets (Joskow, 2008b). Policy makers in Germany (BMWi, 2015) and the EU (EU Commission, 2015a) call for new market structures to facilitate the energy transition. Within the loosened expectable legal boundaries new market structures could enhance the market opportunities for intermediaries offering innovative energy services.

The downstream microstructure in the power sector has been dominated by fixed power supply contracts. The upstream market activity has focused on the allocation of electricity products. In order to enhance the integration of RES electricity, the microstructure should be adapted to include the trade of flexibility. An obvious approach to activate the demand side is passing price signals from wholesale markets to end consumers. Recently, new companies have emerged in Germany offering new price mechanisms to customers, e.g., variable prices (NEXT Kraftwerke, 2017) or even a flat fee regardless of usage (beegy, 2017; innogy, 2017). Turning the view on research, Ramchurn et al. (2011) present a decentralized agent-based mechanism that reduces efforts for consumers by automation technology while tackling the danger of avalanche effects (Gottwalt et al., 2011). Samadi et al. (2012) propose to model user preferences and energy consumption patterns as user-specific utility functions and optimize the aggregation of all utility functions. They show that both consumers and suppliers would benefit from such a pricing mechanism. Turning the view on flexibility products, (Dauer et al., 2015) design a bidding language to allocate load flexibility from aggregators and consumers. They show that load flexibility auction could reduce costs for balancing power emerging from the increased share of RES generation. Lamparter et al. (2010) propose a mechanism that efficiently elicits truthful preferences and constraints of consumers and suppliers. Based on a highly flexible market platform an optimal solution for the overall system is determined.

The physical infrastructure that is available in the current power system ensured a reliable grid operation in the top-down architecture that is recently being adapted. The gradually rolled-out Smart Grid is a fundamental and critical infrastructure that enables communication with consumers (Sioshansi, 2011). This communication must be secured by both hardware-based and software-based firewalls and encryption mechanisms (Metke and Ekl, 2010; Moslehi and Kumar, 2010) to guarantee a reliable grid operation further on. Since smart meters measure the household consumption in real-time and at fine granularity, it is possible to extract complex usage patterns (Molina-Markham et al., 2010) or even identify single appliances by disaggregating the consumption data (Parson et al., 2012). Therefore, it is inevitable to encrypt (Mármol et al., 2012) or aggregate (Efthymiou and Kalogridis, 2010) individual measurements to preserve privacy. In order to reduce deployment obstacles for smart appliances industry standards for a proper interoperability are required (Gungor et al., 2011).

The business structure of a wholesale market usually consists of fixed access fees and transactions fees for the trading itself. Quality differentiation with respect to the connection type to the market can be realized via service levels. For instance, the EEX in Germany offers three different qualities of connection: “internet”, “virtual private network”, and “leased line”. Obviously, this fee structure is designed for full-time wholesale traders. Either intermediaries need to represent small consumers or new business structures to run these wholesale markets are necessary. Asmus (2010) discusses several possible business structures for the future and envisions two possible scenarios: Either utilities will become purely “smart energy integrators” by offering to operate the energy delivery and an information network or they will become “energy service utilities” and sell applications of energy, e.g., heat or lighting. The latter scenario will be further discussed in Chapter 3. As already mentioned, several aggregating companies have emerged in Germany (e.g., Next Kraftwerke, beegy, or Lumenaza) usually combining revenue streams from hardware, e.g., communication infrastructure or PV panels, and a profit-share from trading activities with demand side capacities.

Transaction Objects

Often, market engineering focuses on the market structure (cf. Gimpel et al., 2008) even though market engineers can design transaction objects as well. Especially in the power sector, where market structures are either cautiously protected by powerful utilities or regulated, emerging companies should concentrate on offering new transaction objects. Since the power sector was liberalized not long ago, a great deal of hidden potential can be elicited by new product offerings.

Innovating the transaction object in case of the power sector has its limits because per se electricity is a homogeneous good. However, Schweppe et al. (1988) propose a differentiation by time and location, even though the technical properties such as voltage and frequency are quasi-equal. He et al. (2013) examine different contract types with regards to their ability to engage consumers in demand response. They conclude that a variety of contract types is necessary for demand response to be appealing to a variety of consumers. In Chapter 3 a structured product development process for transaction objects will be presented including a further discussion of related literature.

Being a potentially the largest future single-application consumer, specialized transaction objects for EV charging should be considered. Sioshansi (2012) compares different tariff types by their potential to reduce generation costs and emissions. The results show that real-time pricing performs worst due to the inability of linear prices to signal convex generator costs and instead suggests to offer rebates to consumers to delay a charging job. Comparable to the latter tariff concept, the BMW Charge-Forward program offers a one-time payment to EV owners who accept occasional charging delays that can manually be declined reducing the payment (BMW, 2017). In Chapter 4 this concept is further examined and discussed.

Chapter 3

Quality Differentiation of Energy Services

Currently, system stability is primarily ensured by supply side operations, in particular load balancing through conventional generators and system reserves (see Section 2.2.3). This traditional control approach may become increasingly uneconomical and unreliable due to uncertainty of intermittent renewable energy sources and decommissioning of conventional power plants. The increase of intermittent renewable energy sources on the supply side effectively decreases the share of controllable elements in the power system. The arising imbalance can be compensated through activation of the so far mainly passive demand side. The Smart Grid enables bidirectional communication between distributed actors and resources in the power system. It meets the infrastructural requirement to activate the demand side and is rolled out nowadays. In addition to that, concepts offering appropriate economic incentives need to be designed.[1]

However, these economic incentives need to be embedded in attractive service offerings corresponding to the individual application scenarios for different customer groups. This, in turn, requires the development of new products and services and considerations about the appropriate market environment. Fundamentally, these service offerings need to pave the way towards a value-oriented pricing paradigm instead of relying on the current marginal-cost-based assessment for the value of

[1] Please note that this chapter builds on a previously published research paper in Energy Policy (Salah et al., 2017) and previously published conference papers (Schuller et al., 2015; Flath et al., 2015).

electricity. Marginal-cost-pricing will fail in the long-run if power systems are increasingly governed by zero-marginal-cost generation with high output volatility.

The objective of this chapter is to characterize the corresponding energy service concept and to provide a structured approach to design energy service products for end customers under consideration of the key product characteristics. To this end, the morphological approach following Zwicky (1967) is adapted to explore design dimensions for energy services encompassing the four categories of risk, pricing options, infrastructural requirements and product properties.

First, the notion of energy services is specified by building on and adapting existing definitions of this term in Section 3.1. Additionally, previous work regarding product differentiation in the electricity sector and more general in the service sector is considered. From these foundations the methodology built on Zwicky's framework is derived in Section 3.2. Section 3.3 presents the morphological box for energy services while Section 3.4 elaborates on interdependencies between design options and the complexity related to energy service features. Furthermore, the method is illustrated by characterizing real-world service configurations and a prototypical decision support system for service designers. Section 3.5 concludes and discusses policy implications for regulators to support the process of advancing energy services.

3.1 Related Work

This section revisits existing definitions of energy services and looks into general service design properties to guide the morphological approach for service innovation in the energy domain.

3.1.1 Energy Services

The term energy service has different meanings in literature. These meanings can be classified into three main streams: Understanding the classic business of utilities as a service, planning, installation and financing of small power plants (e.g., photovoltaic power plants) and services enabled by the use of energy.

Hill (1977, p. 317) defines a good as "a physical object which is appropriable and, therefore, transferable between economic units". In contrast, "one economic unit performing some activity for the benefit of another" and thereby changing the condition of a person or a good is the idea of a service (Hill, 1977, p. 318). In line with this reasoning, Kloubert (2000) identifies two components in the classic core offering of utilities: The energy carrier (e.g., coal, gas) itself is a typical good. Transmitting this good in a possibly modified form to customers adds the characteristics of a service. Utility companies extend the so-called dual core offering by auxiliary services such as metering, consumption optimization, and emergency services.

Following Vine (2005), energy services consist of developing, installing and funding multi-year projects that enhance the energy efficiency or load reduction of customer facilities. Especially in the US, the literature employs the term "ESCO" (energy service company) to refer to this definition (Dayton et al., 1998; Goldman et al., 2005; Satchwell, 2010; Vine et al., 1999). This is in line with the notion of energy services as defined by Rosmanith et al. (2007) and the EU Directive 2006/32/EC: An energy service is "the physical benefit, utility or good derived from a combination of energy with energy efficient technology and/or with action, which may include the operations, maintenance and control necessary to deliver the service, which is delivered on the basis of a contract and in normal circumstances has proven to lead to verifiable and measurable or estimable energy efficiency improvement and/or primary energy savings."[2]

In contrast to Vine's and Hill's understanding, Sorrell (2007) focuses on the service itself: "Energy service contracting involves the outsourcing of one or more energy-related services to a third party". This includes, e.g., basic services like hot water supply or more sophisticated service offerings, such as illumination levels, room temperatures etc. Seizing the three-stage-framework of offering a service due to Kloubert (2000), Sorrell adds the result stage — transforming energy to something valuable for the customer — to the first two stages. These consist of (1) setting up infrastructures and procuring primary energy carriers and (2) producing and transmitting the energy, which is the base for the following considerations.

Building on Sorrell's definition, in this work, energy services are understood as services that are facilitated by energy, in particular for energy-intensive applications, offered on the mass market. This notion introduces a new facet that facilitates to provide a value-based assessment of the utilization of energy that is differentiated by

[2] Article 3(e), Directive 2006/32/EC of the European Parliament and of the council

the end-use application. In turn, this enables new options to harness demand side flexibility potentials which are of great importance in future energy systems with large shares of intermittent generation sources (IEA, 2014).

3.1.2 Product Differentiation in the Power Sector

Electricity is typically considered a homogeneous good. Therefore, product differentiation has mainly concentrated on dynamic pricing so far (Tan and Varaiya, 1993). Real-time pricing (RTP) and other variable pricing schemes are well-known and studied examples (Albadi and El-Saadany, 2008; Woo et al., 2014; Borenstein, 2005). Direct load control (DLC) is another way to manage the balance of demand and supply. In DLC programs utilities offer incentives to customers in exchange for accepting pre-specified curtailment options (Albadi and El-Saadany, 2008). Both approaches induce uncertainty and complexity for individual customers that can be reduced by automation technology (Dütschke and Paetz, 2013). Further work concentrates on differentiation of electricity with regard to conventional attributes like the generation source (Kaenzig et al., 2013). Recently, the willingness to pay for green generation options has been extensively studied (Roe et al., 2001; Borchers et al., 2007; Yoo and Kwak, 2009; Hansla et al., 2008). Depending on the scenario, most studies find a higher willingness to pay for electricity from renewable sources.

Other network-based industries, e.g., telecommunication, evolved in a comparable way (Rinaldi, 2004). Deregulation of the telecommunication market induced competition which forced the development of innovative and heterogeneous products to account for individual customer needs (Kenyon and Cheliotis, 2001). In analogy to that, product differentiation in the electricity sector should not only concentrate on pricing but also consider different customer usage scenarios. The ongoing implementation of smart grids forms the technical basis for this development (Woo et al., 2014). This way, the (physically) homogeneous good electricity becomes a differentiable transaction object in economic terms (Weinhardt et al., 2003).

3.1.3 Product Differentiation in the Service Sector

Since the notion of energy services builds on the service concept, differentiation can, in particular, be attained by a variation of service quality attributes. Service quality has been subject to extensive research mainly building on top of quality indicators established in the SERVQUAL framework (Parasuraman et al., 1988). This framework focuses on "traditional" services performed by humans, e.g., in stores, banks, or other businesses. The relevant service quality dimensions include the perception of *tangibles*, *reliability*, *responsiveness*, *assurance*, and *empathy*. Some of these concepts are also applicable to energy services but have a different facet in their implementation. Tangibles, for example, are not as relevant or cannot be influenced, as well as empathy, and to some extent assurance, since the service is delivered through a device or appliance according to clearly defined technical specifications.

Parasuraman et al. (2005) have also put forward an important modification of the SERVQUAL concept to reflect the rise of electronic or e-services. The E-S-QUAL framework incorporates insights from numerous studies employing the Theory of Planned Behavior (TPB) and the Technology Acceptance Model (TAM). Its objective is to measure the "extent to which a website facilitates efficient and effective shopping, purchasing, and delivery." The general attitude towards the technological means that deliver a service can also be of importance for the energy services depicted later, since they rely on technical interfaces too. However, the focus of this work is to first define and characterize differentiation concepts, rather than assessing a particular implementation of one. The following main indicators employed in E-S-QUAL measure the quality of a service: reliability (correct technical function of a site), responsiveness (low latency and fast customer support), access (easy and timely), flexibility (choice of payment, shipping etc; rather referred to the delivery process), ease of navigation, efficiency (simple and effective usage design), assurance/trust (reputation of the site), security/privacy (data security level of the provider), price knowledge (price determination transparency during the purchasing process), site aesthetics, customization/personalization (user profiles).

Several of these indicators are directly applicable to energy service evaluation, in particular *assurance/trust* and *security/privacy*. Others like reliability and responsiveness can be adapted in a straightforward manner: The *reliability* of an energy service is intrinsically connected to the appliance that provides the service. Its reliability will typically be governed by the availability of energy to the appliance. The *responsiveness* dimension depends on user service quality expectations and behavior, e.g., frequency and required immediateness of service delivery. This plays a crucial role in Section 3.3.

Service access, flexibility, and efficiency require a nuanced interpretation in the energy domain: *Access*, for instance, may be restricted due to technical constraints (e.g., insufficient fuse capacity), or because the respective infrastructure (e.g., smart meter) is unavailable. *Flexibility* is employed differently in this work (see Section 3.3.1). The *efficiency* of an energy service is the energy consumption relative to a similar service. Naturally, most of the other dimensions also play a role for energy services when they are marketed or controlled. Furthermore, future energy services can be attributed to the e-service domain as well. This is because such novel services are enabled by the smart grid information and communication technology (ICT) layer extending standard grids. Consequently, the e-service dimensions apply as well and do not require a specific domain adaptation.

3.2 Methodology Fundamentals

This section aims at approaching energy service design in a methodical fashion. Therefore, it is linked with economics literature on quality differentiated products and the morphological design theory established by Zwicky (1948). In a nutshell, the economic framing illustrates the fundamental potential of energy service differentiation and thus establishes the answers to the "why" energy service innovation is required. Conversely, the morphological theory provides a structured approach for design processes and thus facilitates a better understanding of "how" service innovation can be managed in an effective manner.

3.2.1 Economics of Quality Differentiation

At the economic core of offering energy services stands the idea of companies exercising price discrimination between customers to extract profit. This subsection provides a concise overview of the subject matter while for an in-depth treatise the extensive industrial organization literature in this field is recommended (e.g., Varian, 1989; Tirole, 1988). The standard definition of Pigouvian price discrimination considers perfect price discrimination (first-degree), direct price discrimination based on observable customer characteristics (third-degree) and indirect price discrimination based on customer self-selection (second-degree). Highly customized energy services facilitate second-degree price discrimination.[3] Product differentiation through versioning is the key building block for this approach. To proceed, it is helpful to establish additional concepts:

- *Differentiated products:* The products in an industry are differentiated if customers consider them as (close but) imperfect substitutes.
- *Vertically differentiated products:* A vertically differentiated product space is characterized by a common preference ordering of the product offerings across customers.[4]
- *Horizontally differentiated products:* In a horizontally differentiated product space the consumers do not agree on the preference ordering.[5]

In the following, options of establishing quality discrimination in electricity provision through distinct energy service offerings are explored. These differentiation options allow for both vertical (e.g., reliability level) and horizontal differentiation (time-of-use brackets) of electricity products.

Product Differentiation in Power Systems Electricity is a fundamentally homogeneous good characterized by relevant physical properties (e.g., voltage or current). After all, it was this standardization that paved the way for the electrical age. Consequently, there is no such thing as differentiated electricity. However, product differentiation is enabled by wrapping the homogeneous commodity in a service offering that is marketing "energy services" instead of a commodity. This reflects the simple observation that "an end use device *uses* electric energy to provide a *service* to the customer" (Schweppe et al., 1989). It is this service which customers ultimately benefit from and which explains their willingness to pay. This differentiated view on electricity consumption paves the way for different forms of product differentiation

[3]Naturally, third-degree price discrimination also applies when targeting clearly identifiable segments such as industrial customers or residential customers with special equipment such as PV generation, electric vehicles or micro-CHP heating.

[4]If all products sell for the same price, all consumers choose the same product (the one with the highest quality).

[5]If all products are sold at the same price the optimal choice depends on the particular consumer.

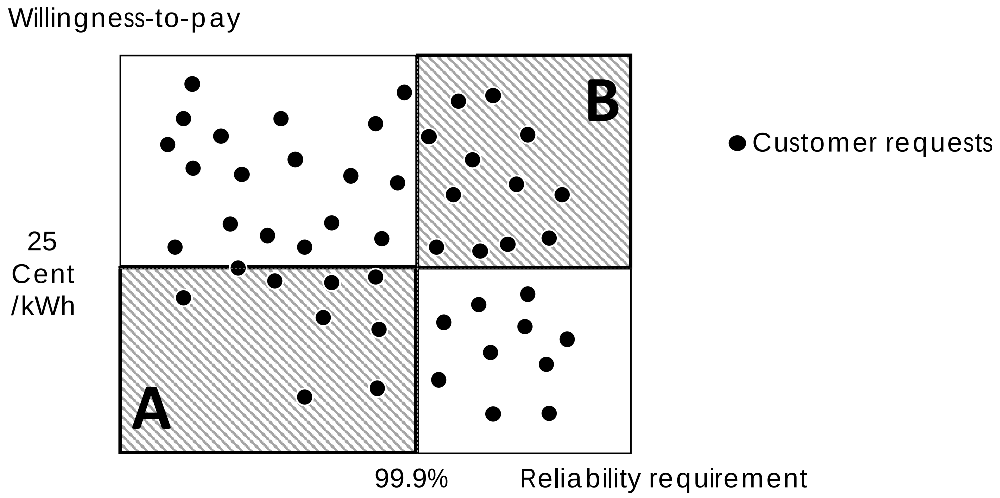

Figure 3.1: A stylized model of energy service differentation

through establishing various quality of service classes, e.g., time of service delivery or reliability guarantees.

A Stylized Example The canonical example for product differentiation of energy services is due to Chao and Wilson (1987) and reflects a reliability-price trade-off. A simplified version to illustrate the potential of increased efficiency by virtue of differentiated energy services is presented in the following. It is assumed that there are just two dimensions that customers care about when selecting an energy service offering—price and service reliability. The customer population is heterogeneous with respect to their quality requirements and their willingness-to-pay. Such a stylized market is illustrated in Figure 3.1. Often, an energy provider may offer a single homogeneous and hence non-differentiated product to this customer population. In the figure, this example product is shown with a 99.9% reliability level at a price of 25 cent/kWh. Only the customers in the top-left quadrant will consume this service. Customers in the right quadrants require a higher service quality, whereas customers in the bottom quadrants are priced out of the market.

While this may be the profit-maximizing *single* service offering for the provider, it is obvious that it simultaneously leads to inefficient over- and underprovision of quality. Consequently, differentiated service offerings (e.g., high reliability-high price, low reliability-low price) can increase allocative efficiency. The customer pools that the supplier potentially reaches are labeled A and B — the former group is interested in less costly offers with lower reliability guarantees, the latter group is willing to pay a premium for higher reliability.

3.2.2 Morphological Analysis

The morphological approach is a creativity technique for developing different designs for a certain artifact. It facilitates both surveying the problem area as well as the generation of concrete solution approaches. Morphological analysis is due to Zwicky who summarized the approach as a *structured analysis of systems* (Zwicky, 1948). While historically rooted in engineering and the design of physical products, the method has also spread into the service design domain. For example, Lay et al. (2009) apply morphological analysis to explore service-oriented business models in the business-to-business context. Similarly, Aurich et al. (2010) develop service offerings for industrial goods. Recent contributions use the technique to develop service offerings for electric vehicle ecosystems (Kley et al., 2011; Stryja et al., 2015).

First, one compiles a comprehensive list of design dimensions (*parameters*) describing generic aspects of the analyzed system. Subsequently, one needs to identify concrete design options (*elements*) for each parameter. The following stylized example illustrates this idea: When designing an office chair important parameters could be upholstery, frame, height adjustment, and backrest. The upholstery can consist of the elements leather, cotton, or plastic. The design elements for the frame are column, tripod, or quadpod. There may be no height adjustment, one with discrete levels, or a continuous adjustment. Finally, the back rest can be absent, fixed, or retractable. This information is arranged in matrix form — the so-called *morphological box* (Zwicky, 1967) — with parameters as rows and elements as columns. By selecting one element per parameter (one matrix cell per row) one can recombine design options to create distinct solution instances. Finally, one needs to evaluate the individual solution candidates to determine the final choice(s).

It should be noted that the option space exhibits combinatorial growth in parameters and elements with the gross number of solution options obtaining as $\prod_{p \in P} |E(p)|$. In the example, there are $3^4 = 81$ design options for the chair. To limit this solution space explosion, one should search for interdependencies between different elements from different parameters which facilitate reducing the solution space. In the chair example, a reasonable assumption is that height adjustment is only available for the case of a column frame. This reduces the number of possible solutions to 45. This observation relates to the two-stage product-line selection problem where in the first stage infeasible configurations and dominant features are removed to improve the performance of the subsequent optimization (Schön, 2010).

3.3 A Morphological Box for Smart Grid Services

In the past, product differentiation in the energy service sector was somewhat neglected due to both a lack of need as well as inadequate technological capabilities given the absence of ICT. In the following, a morphological box is constructed for designing differentiated energy service offerings (see Figure 3.2). The morphological approach facilitates a more systematic identification of design options for transaction objects in future retail energy services. Design parameters are grouped into four categories — risk, pricing, infrastructure, and product properties. Similar to the approach described by Kley et al. (2011), effectively four distinct morphological boxes are obtained to be able to map different service characteristics. These individual boxes are further described and, subsequently, interdependencies between them are explored.

3.3.1 Risk Parameters

The design elements in the first category enable the service provider to reduce, interrupt, or shift the amount of delivered energy services and therefore transfer the respective risks to the customer. Reducing the up-time requirement for specific energy services potentially reduces overall system costs by increasing demand side flexibility. In practice, an unlimited risk is unusual because it can result in a complete execution stop. A reasonable service offering should therefore usually include any type of risk limitation.

Risk in *quantity* addresses the paradigm of load curtailment. If the risk is limited, it results in a partial execution of the energy service. Similarly, the service provider

<table>
<tr><th></th><th>Parameter</th><th colspan="12">Design Elements</th></tr>
<tr><td rowspan="3">Α - Risk</td><td>Quantity</td><td colspan="4">None</td><td colspan="4">Limited (partial execution)</td><td colspan="4">Unlimited</td></tr>
<tr><td>Interruption</td><td colspan="4">None</td><td colspan="4">Limited (frequency, duration)</td><td colspan="4">Unlimited</td></tr>
<tr><td>Time of delivery</td><td colspan="4">None</td><td colspan="4">Limited (deadline)</td><td colspan="4">Unlimited</td></tr>
<tr><td rowspan="5">Β - Pricing</td><td>Change announcement</td><td colspan="4">None</td><td colspan="4">With lead time</td><td colspan="4">Instantaneous</td></tr>
<tr><td>Calculation concept</td><td colspan="4">Flat</td><td colspan="4">Linear</td><td colspan="4">Non-linear</td></tr>
<tr><td>Calculation unit</td><td colspan="4">None</td><td colspan="4">Energy based</td><td colspan="4">Service purpose based</td></tr>
<tr><td>Temporal differentiation</td><td colspan="6">Static</td><td colspan="6">Variable</td></tr>
<tr><td>Spatial differentiation</td><td colspan="4">Uniform</td><td colspan="4">Roaming</td><td colspan="4">Nodal</td></tr>
<tr><td rowspan="3">Γ - Infra-structure</td><td>Metering</td><td colspan="3">None</td><td colspan="3">Cumulative</td><td colspan="3">Peak</td><td colspan="3">Continuous</td></tr>
<tr><td>Communication</td><td colspan="4">None</td><td colspan="4">Unidirectional</td><td colspan="4">Bidirectional</td></tr>
<tr><td>Automation</td><td colspan="3">None</td><td colspan="3">Timer switch</td><td colspan="3">Threshold</td><td colspan="3">Bid agent</td></tr>
<tr><td rowspan="3">Δ - Product properties</td><td>Energy source</td><td colspan="4">None</td><td colspan="4">Energy balance</td><td colspan="4">Power balance</td></tr>
<tr><td>Power profile</td><td colspan="4">Fully fixed</td><td colspan="4">Energy fixed</td><td colspan="4">Fully variable</td></tr>
<tr><td>Power quality</td><td colspan="6">None</td><td colspan="6">Yes</td></tr>
</table>

Figure 3.2: Overview of the morphological design options

could *interrupt* an already started energy service in a limited manner in terms of frequency and duration of the interruption occurrences. For instance in BMW's first pilot stage of the *ChargeForward* program(BMW, 2017) customers received up to $1,540 per year if they allowed interruptions of their charging processes for up to one hour. To account for the load shifting paradigm that directly addresses the volatile character of renewable energy generation, an energy service can be uncertain about its *time of delivery*. Service providers can guarantee their consumers to fulfill the energy service until a specified deadline instead of immediately executing the service. In accordance with Chao and Wilson (1987) the three risk parameters are closely related as they converge in their extremes: Reducing the quantity to zero is equal to an unlimited interruption or shift in time of delivery.

3.3.2 Pricing Parameters

The second group of parameters addresses well-known differentiation features for current standard electricity products and their design elements for the energy service concept.

Prices of energy services can be uncertain depending on the employed pricing concept. Therefore, besides having no *change announcements*, service providers can announce changes with a predefined lead time or, in the most complex case, as real-time prices in the short-term or potentially even instantaneous. Beside price changes, the *calculation concept* defines how an energy service is assessed in economic terms. The design elements included are flat, linear and non-linear price calculation concepts. The calculation concept refers in particular to every additional or marginal unit of a service. In this case, a flat concept imposes a fixed fee (again disregarding the variable usage) that is only limited by the technical line limits to supply the service device and the ability to actually use the energy service. Every individual can only consume a certain amount of a service since the outside options or other requirements of daily life usually oppose its continuous and unlimited use. Nevertheless, since energy has to be produced, this concept is diminishing energy efficiency efforts and will most likely only play a role when excess renewable supply is available. Linear calculation concepts relate to the price per unit consumed and are well-known from traditional electricity rates. Finally, non-linear pricing can address, e.g., shortage situations by imposing non-constant marginal costs of service provision. Thereby, higher usage intensity (e.g., fast EV charging — 20 kWh in 30 min) results in higher service fees than lower usage intensity (slow charging — 20 kWh in 3 h), independent of the total amount.

As mentioned before, energy services can, in particular, be differentiated from "traditional" energy provision by virtue of the *calculation unit*. Thereby, usage payments are no longer based on energy consumption (i.e., kWh) but rather a service purpose-based metric. For electric vehicles, this is, e.g., the usage time or the distance driven. For an air-conditioning service, one could imagine some service level related to lighting and HVAC performance in an office building. This type of contracting will only be plausible if a service provider installs the service equipment, e.g., a car-sharing operator (LeVine et al., 2014) or an energy service company offering performance contracting (Davis, 2012). This way device efficiency is not a user decision and the service provider can appropriately calculate the business case.

Further differentiation parameters can be temporal and spatial differentiation. Prices that have no *temporal differentiation* are static and do not depend on the time of service delivery. For variable prices, the underlying price menu may be static (time-of-use pricing) or dynamic (RTP). This is reflected by the corresponding choice of the *change announcement* parameter. *Spatial differentiation* captures that different regions can have specific demand and supply features or network limitations which need to be accounted for in the price, as is currently discussed in the form of nodal pricing schemes. In contrast to this regional differentiation, roaming allows customers to use a service at predefined locations for the same (roaming) price. Finally, the most straight forward design element is a uniform price for the energy service.

3.3.3 Infrastructure Parameters

Novel price and risk elements in a smart grid service offering will often entail corresponding infrastructure requirements which in turn may become part of the service bundle themselves. These will primarily include metering, communication, and control devices which are supplied by service providers to their contracted customers. This is analogous to the telecommunication sector where cell phones, routers, or modems are often provided for the duration of the contract.

Concerning *metering* equipment, simple service offerings may be realized using legacy Ferraris meters which facilitate only cumulative meter readings. A first extension of metering capabilities was historically established using dual meters for different time periods (e.g., night vs day) or usage classes (e.g., interruptible vs non-interruptible). Additional measurement of peak power is widely used for large industrial customers to penalize power spikes. The recent introduction of smart meters allows quasi-continuous metering with arbitrary granularity. Still, in most commercial realizations so far suppliers opt for 15 min metering intervals.

Historically, meters are offline and cannot directly communicate with suppliers. However, *communication* capabilities can augment the metering infrastructure for novel service approaches. Unidirectional communication channels allow service providers to push price updates to customers. Going one step further, bidirectional communication enables customers to actively communicate with the service provider. These customer messages may specify current availability requirements or transmit market orders.

Finally, customers may install device *automation* to improve the interaction with novel service offerings. This way automation can help reduce the perceived complexity of these services. Automation options range from simple timed or threshold-based switches (e.g., maximum payments) to pro-active bid agents adapting to observed and predicted user behavior.

3.3.4 Product Property Parameters

This group of characteristics introduces specific product category parameters. Following the guiding example of services for electric loads, candidate parameters include the energy source (primary energy), the possibility to alter the power profile, and power quality features.

Currently, electricity is mostly differentiated for marketing purposes by the primary energy source that is converted to electricity in the respective plant type. Utilities hereby guarantee the energy balance from a specific energy source for the demand of the customer. This is one of the two design options that emphasize this product property. Well-known examples for differentiation by *energy source* are green energy products. The other design option enhances this idea by guaranteeing the power balance with a specific energy source. This incorporates a more direct coupling of the energy service with the current availability of electricity from a specific type of generator. In general, the energy source parameter is added to an energy service by explicitly defining a specific power plant (e.g., wind turbine) or a group of power plants that virtually supplies the energy service in either of the above-mentioned shapes. As a consequence, this can imply an increased risk of service availability if the energy source is unavailable.

The second parameter contains the ability to alter the *power profile*. Following the taxonomy of Petersen et al. (2013) design elements are established in line with their notion of *bakery*, *batteries*, and *buckets*. The bakery is representative for appliances with a fully fixed power profile. Batteries allow an alteration of the (energy fixed) power profile as long as a target energy level is eventually met. An EV charging service is a perfect match for this group. Fully variable characterize the bucket class facilitating any load shape and any total energy amount. An example for the bucket class is heat pumps, relaxing not only the power but also the energy constraint in the given time frame. Ideally, the service provider can perform these power profile alterations without affecting the energy service delivered by the appliances.

The final, more technical parameter is *power quality*. This refers to physical characteristics of electrical power which particularly addresses the needs of commercial and industrial customers. To allow for a general classification this characteristic has binary design elements. For instance, customers could require a guaranteed voltage interval for their energy service, that can be assured by voltage regulated distribution transformers. Or the customer's electrical consumers generate an abnormal amount of reactive power that needs to be compensated by the service provider to support overload local grids.

3.4 Use Cases for the Morphological Box

Since its theoretical solution space is rather big possibilities to assist future product designers will be presented in the following. After introducing a formalization needed for the consecutive steps, interdependencies between design elements are discussed in Section 3.4.1 and a way to describe them mathematically is presented. With the creation of diversified products, complexity for the end consumers becomes an important topic. After discussing product complexity in Section 3.4.2 introduce a complexity scoring rule as an extension of the morphological box is introduced. Finally, the functionality of the proposed morphological box is illustrated by mapping exemplary energy services to it (Section 3.4.3) as well as presenting a prototypical decision support system for service designers (Section 3.4.4).

For the following discussions, a formalization of the morphological box from Section 3.3 is proposed. As indicated in Figure 3.2 energy services can be described by instantiating each parameter with a specific design element. For ease of exposition, an instantiation of the morphological box can be represented by means of binary matrices

$$A = \begin{pmatrix} \alpha_{1,1} & \cdots & \alpha_{1,n} \\ \vdots & \ddots & \vdots \\ \alpha_{m,1} & \cdots & \alpha_{m,n} \end{pmatrix}, B = \begin{pmatrix} \cdots \end{pmatrix}, \Gamma = \begin{pmatrix} \cdots \end{pmatrix}, \Delta = \begin{pmatrix} \cdots \end{pmatrix}. \tag{3.1}$$

Rows reflect design parameters and columns represent the corresponding design elements. If a design option is chosen, the respective binary variable is one and all other design option variables associated with the characteristic are zero. Clearly, for any valid configuration, all row sums must equal one.

3.4.1 Interdependencies Between Design Options

As discussed in Section 3.3 there are interdependencies between specific sets of design options. Determining those is key to increase computational efficiency of the product design problem. In the following a way of handling their occurrences is presented to simplify the process of designing energy services by reducing the theoretical solution space (compare Section 3.2). The intention is *not* to present a complete enumeration of interdependencies but rather to show that mathematical expressions can describe invalid combinations of design options based on illustrative examples.

Most interdependencies exist between either risk (A) or pricing (B) parameters and infrastructure (Γ) parameters. If for example one designs an energy service including temporal differentiation with variable rate periods, necessary metering equipment needs to be considered: Evidently, such a rate scheme will require continuous metering for correct billing. This is the simplest form of interdependency and can be formulated as follows:

$$\underbrace{\beta_{4,2}}_{\text{variable temporal differentiation}} \leq \underbrace{\gamma_{1,4}}_{\text{continuous metering}} . \tag{3.2}$$

The inequality formulation provides the flexibility to choose non-necessary infrastructure, e.g., to preemptively install sophisticated metering for possible future usage.

In the design phase, it is also possible to formulate more complex relations. For example, any type of risk limitation requires interactions between the service provider and the customer. Depending on the use case the customer's willingness to take risks might change, which he or she should communicate to the service provider. Vice versa, during service delivery the provider needs to inform an appliance about when to start, pause or stop. In this case, the infrastructure has to support bidirectional communication:

$$\underbrace{\max(\alpha_{1,2}, \alpha_{2,2}, \alpha_{3,2})}_{\text{limited risk of any } A\text{-parameter}} \leq \underbrace{\gamma_{2,3}}_{\text{bidirectional communication}} . \tag{3.3}$$

It should be noted that for unlimited risk unidirectional communication is sufficient as the service provider only has to signal service interruptions to the consumer without confirmation from the customer side. Following Equation (3.3) this can be expressed as follows:

$$\underbrace{\max(\alpha_{1,3}, \alpha_{2,3}, \alpha_{3,3})}_{\text{unlimited risk of any } A\text{-parameter}} \leq \underbrace{\gamma_{2,2}}_{\substack{\text{unidirectional}\\ \text{communication}}} + \underbrace{\gamma_{2,3}}_{\substack{\text{bidirectional}\\ \text{communication}}} . \tag{3.4}$$

Lastly, there exists a group of interdependencies where one (or more) design elements require the existence of multiple other design elements. In case designing an energy service with price changes that is either announced with a lead time or even instantaneous, it is necessary to meter its usage properly and of course to communicate these changes to the customer. On the other hand tariffs without an explicit change announcement, as in the case of TOU pricing, do not require communication and are therefore excluded in the following constraint:

$$\underbrace{\beta_{1,2} + \beta_{1,3}}_{\substack{\text{price changes with lead}\\ \text{time or instantaneous}}} \leq \min\left(\underbrace{\gamma_{1,4}}_{\substack{\text{continuous}\\ \text{metering}}} , \underbrace{\gamma_{2,2} + \gamma_{2,3}}_{\substack{\text{uni- or bidirectional}\\ \text{communication}}} \right) . \tag{3.5}$$

As illustrated above, most interdependencies of energy service parameters refer to infrastructure. Still, there do exist interdependencies that are not motivated by infrastructural requirements. For instance, determining a specific (renewable) energy source $\delta_{1,3}$ implicates an unlimited interruption risk of the energy service $\alpha_{2,3}$ (compare Section 3.3.4):

$$\underbrace{\delta_{1,3}}_{\substack{\text{power balanced energy}\\ \text{source (here: green)}}} \leq \underbrace{\alpha_{2,3}}_{\substack{\text{unlimited}\\ \text{interruption risk}}} . \tag{3.6}$$

3.4.2 Complexity of Energy Services

As electricity products are becoming more refined to reflect a changing generation market the complexity of such tariffs is another dimension to be considered. In this work *complexity* is understood as the perceived cognitive strain experienced by (potential) users of such a tariff and the ensuing difficulty of assessing their energy costs, rather than the technical challenge of its implementation (cf. Layer et al., 2017). Chao and Wilson (1987) already observed, that "a practical difficulty with spot pricing is that the sample space may be so complex that it would be impossible to implement the spot price in every contingency." Note that this is primarily a contracting dimension and not a risk aversion phenomenon. Consequently, isolating complexity from risk aversion is essential.

To this end, complexity analyses require an assessment of users' satisfaction with a tariff or their purchase behavior. In an early study Goett et al. (2000) discovered small businesses' considerable preference for fixed electricity rates as compared to the more complex TOU pricing, which is, in turn, preferred to RTP. However, it remains unclear if this preference is really a consequence of cognitive strain or of risk aversion. Dütschke and Paetz (2013) extend this conclusion to private users who are skeptic towards more dynamic tariffs but may reconsider after additional experience with such tariffs. Employing an extensive conjoint analysis, Gerpott and Paukert (2013) meanwhile find the incentive size of smart tariffs to be a more important determinant of users' tariff choice rather than the granularity of temporal differentiation or the lead time. In an extensive empirical study with a sample size of 664 participants, Layer et al. (2017) determine increasing dynamics as a fundamental driver of perceived complexity. Communication of subscription rebates in percentages is not found to have a significant impact. Furthermore, the authors find evidence, that increased complexity leads to an overestimation of costs. Therefore, it may have a detrimental effect when it comes to choosing such tariffs (cf. Homburg et al., 2014).

In essence, tariff complexity negatively influences customer acceptance of an energy service and this should be considered when applying the morphological box for energy service design (cf. Section 3.4.4). In the morphological design approach, perceived complexity arises from individual design choices. Each design option $x_{i,j}$ in the morphological boxes $X \in \{A, B, \Gamma, \Delta\}$ can contribute to the perceived complexity of an energy service. To express these scores complexity matrices need to be defined analogously to the design matrices from Equation (3.1):

$$C^X = \begin{pmatrix} c^X_{1,1} & \cdots & c^X_{1,n} \\ \vdots & \ddots & \vdots \\ c^X_{m,1} & \cdots & c^X_{m,n} \end{pmatrix}, \quad \forall X \in \{A, B, \Gamma, \Delta\}\,. \tag{3.7}$$

Using ratio scales for the individual weights facilitates the calculation of an aggregate complexity score of a given energy service. Multiplying a given energy service's morphological matrices for each design category with the corresponding transposed complexity matrices yields a square matrix per design category. The traces of these matrices (sum of diagonal elements) are then the category complexity scores of the given service design configuration. The sum of all the category traces can, in turn, be interpreted as a measure of the total complexity of a specified energy service:

$$Complexity(\text{Energy Service}) = \sum_X tr(X \cdot \left(C^X\right)^T), \quad \forall X \in \{A, B, \Gamma, \Delta\}\,. \tag{3.8}$$

The linear structure of the complexity score proposed above is meant for illustration purposes. One can easily imagine a convex function of the total sum or a category score to reflect complexity complementarity. Similarly, the highest individual complexity score could determine the total score.

Clearly, any meaningful evaluation of the complexity score will critically hinge on the measurement of each design option's relative contribution to perceived complexity. Measuring these values will be challenging and potentially subjective. However, for a relative comparison of multiple service configurations under the same complexity premises, the ratio scales can be relaxed to interval scales. Eventually, the outlined method can help support service marketing activities by providing the foundation to estimate user response to a tariff created.

3.4.3 Exemplary Products

To demonstrate the application and suitability of the morphological approach illustrative examples of differentiated energy service products are presented in this section.

Interruptible Load

As a first example, an interruptible electricity service is chosen as studied by Oren (2013) that was first implemented by Southern California Edison and several other utilities in the 1980s and has since been further refined (Jazayeri et al., 2005). In such an energy service the utility may interrupt power supply to the customer in response to cost considerations due to unexpected demand spikes or in times of imminent system imbalance. In a particular implementation presented in Oren (2013, Fig. 1) the service provider compensates a customer for both guaranteeing to be able to interrupt the load and for each time of actually executing the interruption. The number of periods of interruptions is limited to a specific number of times and hours per year.

$$A = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{pmatrix}, B = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}, \Gamma = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix}, \Delta = \begin{pmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}. \tag{3.9}$$

The matrices in Eq. (3.9) reflect the formal description of this energy service[6]. It carries only a limited interruption risk, both in duration and frequency. Pricing is non-linear since a reward for each interruption is added to the traditional linear and static energy rate. There is no temporal or spatial differentiation. Metering can be implemented in the classic cumulative manner, while in practice an additional interruption switch can be installed.

On the one hand, the customer can manually respond to a signal of the utility as implemented by the Electric Reliability Council of Texas (Jazayeri et al., 2005). On the other hand, the utility can access the switch remotely by means of an unidirectional communication channel as implemented by Minnesota Power (Minnesota Power, 2012). As suggested in Section 3.4.1 customers should be able to dynamically

[6]Note that zeros shown greyed out in Eq. (3.9) to (3.12) are preset as these design options are undefined (see Figure 3.2).

change the risk limit through a bidirectional communication channel. In contrast to the introductory example, both latter implementations have a simple linear calculation concept ($\beta_{2,2} = 1$).

Real-time Electricity Pricing

Conveying scarcity by means of price signals is another option to achieve system-wide power balance. Real-time pricing was first studied by Vickrey (1971) and later applied to electricity in the 1980s (Schweppe et al., 1989). Advocates argue for the long-run efficiency gains of real-time pricing (Borenstein, 2005) compared to static prices even though electricity demand is rather inelastic. Besides the ability to reduce peak demand cost-effectively, economists claim that real-time prices would mitigate market power and reduce price volatility on wholesale markets.

Real-time pricing programs were first introduced in the early 1990s and already counted more than 70 offerings in the 2000s (Barbose et al., 2004). In these — mostly voluntary — programs, retail customers must pay prices that vary over short time intervals (e.g., hourly) and are published a day or less in advance by utilities. An advanced and puristic program is offered by the utility Commonwealth Edison (ComEd) in Illinois[7]. ComEd simply passes along the average hourly market price with no mark-up to customers who can thus even partake in negative prices.

$$A = \begin{pmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}, B = \begin{pmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{pmatrix}, \Gamma = \begin{pmatrix} 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix}, \Delta = \begin{pmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}. \tag{3.10}$$

The matrices in Eq. (3.10) show the formal representation of the morphological box for real-time pricing. Customers do not carry any risk of service quality or availability since pricing aspects address the risk component. In the ComEd example, temporally variable prices are quoted instantaneously. Other programs, on the other hand, might have a lead time. Real-time pricing necessitates continuous metering which

[7] `https://hourlypricing.comed.com/`

is one of the biggest obstacles for its market launch (Costello, 2004). Additionally, most programs include a form of unidirectional communication to push prices to the metering system.

Deadline Differentiated Pricing for EV Charging

This service product example captures more complexity and thus explores further options in energy service design. In particular, the deadline differentiated pricing (DDP) approach is applied to an electric vehicle charging service that is further described in Chapter 4. Under DDP, energy services are differentiated by the latest time of service delivery. To compensate delayed service execution, the service provider offers discounts to consumers. Consumer rebates are increasing in the demand flexibility offered, i.e. a longer accepted delay until completion of the charging job.

$$A = \begin{pmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}, B = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{pmatrix}, \Gamma = \begin{pmatrix} 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix}, \Delta = \begin{pmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}. \tag{3.11}$$

Following the parameters and design elements in Figure 3.2 the DDP energy service can be formally described by the matrices in Eq. (3.11). This energy service entails no quantity risk, but a limited, in this case, deadline-induced, risk for the particular time of delivery. Since to date, most electric vehicles reject arbitrary power profiles or even interruptions, the energy service features no interruption risk and a fully fixed power profile ($\delta_{2,1} = 1$). The service provider announces price changes at latest at the time of arrival at the car park and therefore with lead time. The calculation concept is linear, while the calculation unit will typically be charging energy. Price levels are subject to change depending on grid and generation conditions. A given charging service will typically be location-bound (e.g., a given parking complex) and hence does not facilitate spatial differentiation.

Continuous metering is necessary to facilitate DDP due to possible price changes.

Likewise, bidirectional communication will be required to exchange and confirm price information. Besides the physical connection between grid and vehicle, the charging process is automated according to the established specifications with service delivery being terminated as soon as the agreed charging level is reached. Finally, the electricity properties will typically exclude both differentiation by energy source and extended power quality requirements.

Bitar and Low (2012), Nayyar et al. (2014) and Chen et al. (2015) present generalized versions of this energy service that abstracts from the EV charging context. In these cases restrictions on interruption ($\alpha_{2,2} = 1$) and power profile alteration ($\delta_{2,3} = 1$) of contracted loads are loosened.

Local Energy Market

Unlike regular tariff relationships where suppliers and customers agree on conditions for several transactions, local energy markets are characterized by repeated spot transactions with allocation and prices arising from bids and asks of market participants. Consequently, a sizable share of system risk is transferred to the demand side — either in the form of price risk (guaranteed delivery may be risky in the presence of price spikes) or quantity risk (limit prices curtail price risk but may lead to non-execution).

In the 1980s the seminal work on optimal spot pricing (Schweppe et al., 1981; Schweppe, 1988) conceptualized local energy markets as an advanced form of energy service intermediation. Diverse research projects (e.g., Hammerstrom et al., 2007; Giordano et al., 2013) showcased prototypical implementations. A wide-scale adoption of smart grids will create the technological basis for establishing energy marketplaces outside of small-scale experimental settings. Consequently, recent research in energy and computational economics has revisited the design challenges embedded in creating and rolling out such local energy markets (Ketter et al., 2013; Lund et al., 2012; Ströhle and Flath, 2016) or how to adapt them to specific scenarios like electric vehicle charging (De Craemer and Deconinck, 2012; Dauer et al., 2013).

$$A = \begin{pmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}, B = \begin{pmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}, \Gamma = \begin{pmatrix} 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}, \Delta = \begin{pmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}. \quad (3.12)$$

Again, the morphological approach can help to characterize this energy service. A market with limit orders on (partial) service completion is assumed, i.e. customers specify the maximum price which they are willing to pay for a tendered energy service (fragment). If prices exceed this reservation limit orders will not be executed resulting in unlimited quantity risk. This unlimited quantity risk also corresponds to unlimited delivery time risk. In this market setup, there is no interruption risk of an individual market transaction. However, repeated transactions are uncertain to be repeatedly allocated leading to a limited amount of interruption risk.

Price changes are instantaneous after each market clearing with a linear relationship between price and energy. Prices vary over time and apply only to the given marketplace. As noted above, local energy markets have significant infrastructure requirements. Continuous metering and bi-directional communication are necessary to facilitate and monitor market transactions. At the same time, customers will most likely be relying on trading agents to pursue their energy trading activity (Vytelingum et al., 2010; Gottwalt et al., 2011). Finally, local marketplaces will need sufficient market liquidity to be successful. Consequently, commoditized energy services with minimal specifications should be traded (Ströhle and Flath, 2016).

3.4.4 Prototypical Decision Support System

The above formalization of the morphological box lends itself to facilitating a decision support system for energy service designers. Such a system should guide practitioners by dynamically restricting design choices according to feasibility constraints and thereby improves the focus of the product development process. To illustrate this idea a prototype for such a decision support system was implemented using Microsoft Excel and Visual Basic (left side of Figure 3.3). Users can interactively select service design elements in the morphological box. Furthermore, they can specify a maximum complexity level for the final energy service. After any decision, the system dynamically updates dependencies arising from this decision, updates the current complexity level, and restricts future choices in accordance with dependencies and remaining complexity "budget."

The right side of Figure 3.3 illustrates the system functionality by means of two exemplary user journeys through the tool. The upper branch highlights the effect of interdependencies between design elements: After selecting "limited quantity risk (partial execution)" the system disables the "no communication" and "unidirectional communication" infrastructure design elements and automatically sets the only remaining infrastructure design element "bidirectional communication". Furthermore, after choosing to use a renewable energy source on a "power balance" level, in which case an unlimited interruption risk is inherent (compare Equation (3.6)), the parameter "interruption risk" is fixed to "unlimited". Besides, both choices deplete a minor part of the complexity allowance.

The lower branch demonstrates the effect of the energy service complexity limit. Selecting "variable temporal differentiation" of the price induces the deactivation of both design elements "non-linear calculation concept" and "fully variable" because selecting one of them would exceed the previously set maximum complexity. Furthermore, an interdependency occurs fixing the design element "continuous metering" in accordance with Eq. (3.2). After selecting "nodal pricing" the maximum complexity level is reached. Therefore, the tool deactivates all other complexity driving design elements. It should be noted that complexity weights are exemplary in this case.

These user journeys illustrate how decision support systems for energy service design can utilize the morphological box. The presented prototype focuses on reducing the choice through constraint and interdependency propagation. A proper implementation in practice should also consider the benefit side of the various design elements (additional profits or cost reductions) to help in determining the most beneficial service offering. To that end, the system should be connected with other corporate information systems (CRM, ERP) and augmented by suitable benefit-assessment-components, e.g., a simulation tool as presented by Gottwalt et al. (2011).

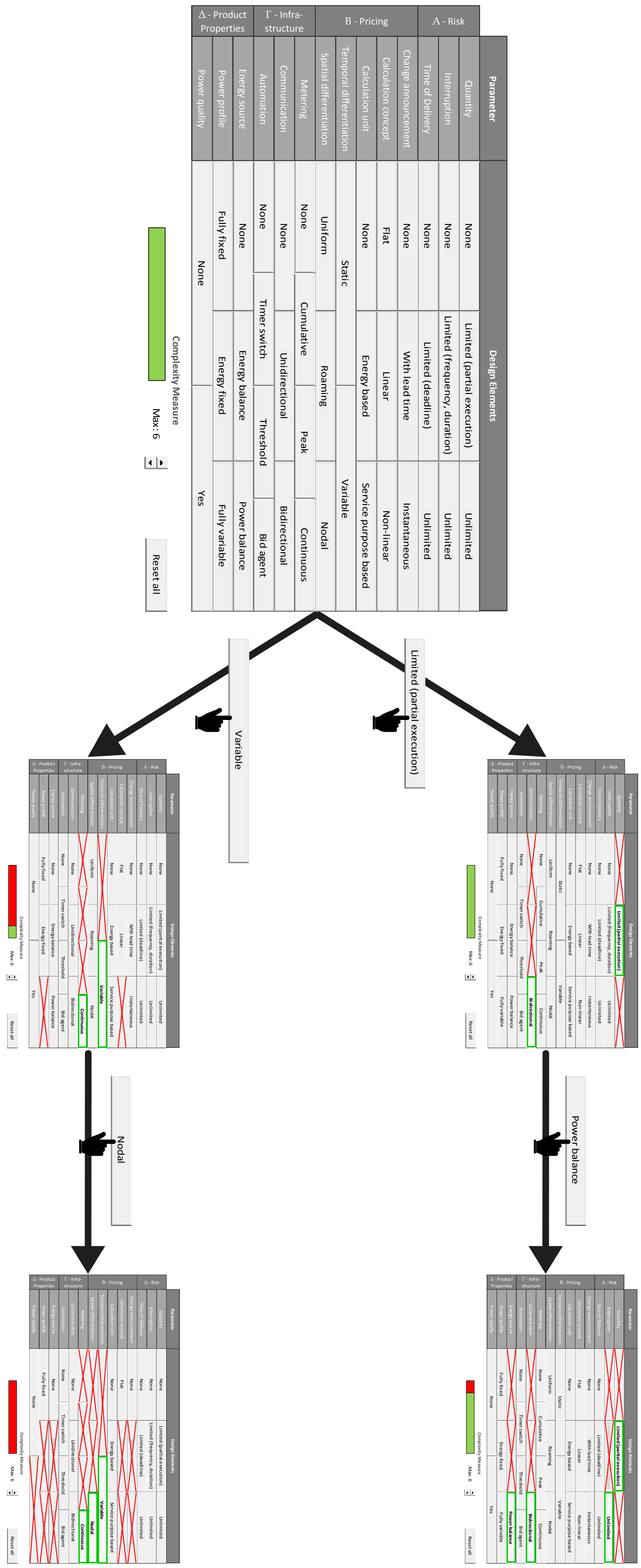

Figure 3.3: User journey through a prototypical decision support system

3.5 Discussion

Energy services play a central role to empower the currently mostly passive demand side. This demand side activation is crucial to cope with the risk that arises from a growing share of electricity supply from intermittent renewable energy sources (Papaefthymiou and Dragoon, 2016). Utility companies have started to increase efforts for product development that addresses the new situation in the power system, but there is still a lack of experience and effective methods and tools to support this development (Richter, 2013).

The work presented in this chapter is a first step to guide the structured design of energy services. It proposes a systematic and standardized way to address different product characteristics and their design options, with a particular focus on differentiation options with respect to quality of service attributes. This way, new and innovative combinations of service design options can support activating the flexibility potential of the demand side in a Smart Grid environment and ameliorate some of the supply risk inherent to intermittent generation.

Pricing options for these (new) energy service products were illustrated which improves setting the correct incentives for a desired customer behavior. In addition, infrastructural needs and additional product properties which depend on the specific use case were outlined. The constructed morphological box thereafter was applied by modeling exemplary reference energy service products. How the morphological approach can be formalized by means of a mathematical programming formulation was furthermore discussed: Formally describing interdependencies between product design elements increases efficiency by removing incompatible design options. Additionally, a complexity measure was introduced which facilitates assessing potential adoption obstacles for end customers. Finally, the theoretical concepts are illustrated by means of a prototypical decision support system for service designers.

The economic viability of cost-based electricity pricing with respect to generation adequacy is lively debated in the face of growing renewable generation shares. So far, the debate has mainly focused on supply side initiatives, e.g., the establishment of capacity markets (Boute, 2012; Browne et al., 2015; Hall, 2014). However, near zero variable costs also call for a value-based pricing of energy services as a new paradigm. To this end, pricing should be determined by individual customers' valuation for particular service characteristics. Quality-based energy service product differentiation facilitates efficient customer self-selection in response to a change in product characteristics. This enables better participation of numerous flexible loads which jointly can help to stabilize the power system (Gottwalt et al., 2016). The micro-transactions arising from these micro-flexibilities are facilitated by ICT capabilities offered in smart grid environments. The central idea is to (partially) limit supply security by means of active, demand-side risk sharing to stabilize supply security in the long term. Note that such an approach may loosen the current barriers between grids and energy markets in unbundled markets (Greening, 2010).

While it may take some more time until extreme RES penetration scenarios are realized, power markets and infrastructures will have to prepare for these challenges in advance (Mathiesen et al., 2011). Consequently, regulators must pave the way for an environment where a flexible demand side can choose from a richer set of differentiated energy services. This requires establishing a technological infrastructure that enables such a shift. These smart grid platforms must be non-discriminatory and equally accessible for established and new actors to allow for efficient competition. Similarly, some basic energy service with predefined quality characteristics should still be offered for those customers unable or unwilling to respond to quality differentiated energy service products. To foster this kind of innovation, regulators may need to adopt a more tolerant regulation regime and thus lower the barriers for new market entrants.

The telecommunication sector developed in an analogous way to the energy sector after liberalization (Hertzog, 2010; Smith, 2012). Telecommunication companies with varying scope (full service operators and niche players) have emerged to account for the customers' different valuations for service quality. Both the range of service quality differentiation options and the robust adaption of the regulatory frame in the telecommunication sector should inspire the energy sector (Bourreau and Doğan, 2001). One of the ideas that needs further investigation with respect to its implications in the energy service sector is flat rate pricing. A theoretically unconstrained energy consumption for a particular service could be envisioned while only a fixed, consumption-independent rate is paid. At the same time, the quality of supply or in particular the availability of energy from an intermittent source can be a quality differentiation characteristic that only allows flexible consumers (or appliances) to utilize this flat rate energy service. Further work must thus be dedicated to the comparison between the telecommunication and energy sector.

This work elaborated that product differentiation is important to retain economic viability of power systems dominated by renewable energy sources while focusing on the conceptual side of service innovation. However, going forward, the economic viability as well as suitable regulatory frameworks have to be evaluated and designed. Therefore, future work should seek to better understand the costs and benefits of individual design options. This will facilitate a proper service design optimization as envisioned in Section 3.4.

Introducing interactive decision support systems as illustrated in Section 3.4.4 will allow product designers to focus on creative aspects rather than thinking about formal limitations and interdependencies. To help practitioners transfer the ideas of this chapter into industry applications the prototypical decision support system needs to be expanded and adapted to specific use cases. Ideally, the tool should allow designers to start by developing and parameterizing the morphological box and specify interdependencies in a higher level description language.

Another key question is how fast and to what extent service providers can face customers with product differentiation of an originally homogeneous good. Surveys and experimental approaches are needed to assess customer acceptance and to develop robust estimates of the complexity scores introduced in Section 3.4.2. Additionally, customer risk aversion will influence the acceptance of energy services designed with the aforementioned methodology. To formulate promising business cases, practitioners would benefit from a way to take the risk preferences of specific customer groups into account.

Part II

Intermediation of Energy Services

Chapter 4

Deadline Differentiated Pricing for EV Charging

Electric vehicles are one of the most important options to enable sustainable individual mobility given that the electricity used to charge EVs originates from renewable energy sources. Concurrently, EV charging is considered to be a crucial part of demand side flexibility in future smart grids (Shao et al., 2011). Additional charging infrastructure is planned to be installed at public parking locations (German National Platform for Electric Mobility, 2015) in order to reduce range anxiety and to increase the availability of EVs to respond to fluctuations in the power grid. Car parks then constitute new load clusters that aggregate the demand of a considerable number of vehicles. To harness the potential of load flexibility in terms of time (temporal flexibility), it is necessary to understand and govern the heterogeneous charging behavior of EV users. It is constrained by many varying parameters, e.g., energy demand, parking duration, and monetary valuation. Price incentives are one major mechanism to exploit the heterogeneous flexibility potential. Furthermore, understanding the habits and the economic behavior of EV owners makes it possible to optimize the utilization of local fluctuating renewable energy generators like PV systems. These local generators can be installed on, or in proximity to the new load clusters to reduce the impact on the distribution grid (Salah et al., 2015) and thus address the objective to facilitate sustainable individual mobility.[1]

[1]Please note that parts of this chapter build on previously published research papers (Salah and Flath, 2016; Salah, Schuller, and Weinhardt, 2016; Salah, Schuller, Maurer, and Weinhardt, 2016)

In this chapter, a scenario is examined in which heterogeneous EV users charge their vehicles at a public car park. Users reveal their flexibility by indicating upfront their parking duration. This allows the car park operator to schedule EV charging activity in accordance with local generation from PV panels on the car park rooftop at zero marginal costs. Alternatively, the vehicles can be charged by using costly conventional generation acquired from the grid. To ensure truthful revelation of the drivers' departure time, a car park operator offers a DDP scheme to EV users following Bitar and Low (2012). DDP follows the assumption of rational EV customers who aim for the cheapest option to charge their EV as long as their parking behavior stays unaffected. Hence, lower charging prices are offered for customers that are willing to provide a higher level of temporal flexibility by interrupting or shifting their charging processes. Only considering charging fees (i.e. parking per se is assumed to be an independent problem), the car park operator needs to determine a profit-maximizing price menu under uncertainty with respect to customer preferences and generation availability.

The focus of this chapter is the operational management of EV charging in car parks with integrated PV generation. Investment costs, e.g. for PV installations are not considered. A simulation based analysis is performed that incorporates the formulation and evaluation of a stochastic mixed-integer optimization model. It is instantiated with mostly empirical input data to obtain realistic conditions for the following assessment: EV customers are modeled based on the following data sets: empirical driving profiles from the representative German mobility panel (Zumkeller et al., 2011), real-world data from an operational car park in southern Germany, and PV generation data from installed PV panels in southern Germany. Besides a central examination, this work establishes the foundations for the implementation of an energy informatics decision support artifact that integrates existing demand side flexibility of EVs.

The remainder of this chapter is structured as follows: The next section is further evaluating existing work in the area of demand side management and customer modeling in EV charging management. In Section 4.2, the stochastic optimization problem is introduced and formalized. Empirical data used to derive answers to research questions and the standard scenario instantiation are presented in Section 4.3. Section 4.4 examines the car park charging case from a general point of view and derives answers regarding the value of information and complexity. After examining to what extent DDP is able to mitigate RES uncertainty in Section 4.5 the impact of customer diversity is explored in Section 4.6. Section 4.7 concludes and summarizes future research opportunities.

4.1 Related Work

This section revisits existing concepts for demand side management and incentive mechanisms to activate it. Furthermore, implementations of these concepts in the field of charging coordination of electric vehicles are highlighted.

4.1.1 Demand Side Management and Pricing

In California, the integration of renewables requires doubling the load-following capacity following recent studies (CAISO, 2010). This will significantly raise electricity cost and diminish the net carbon benefit from RES (Ortega-Vazquez and Kirschen, 2010; Meyn et al., 2010). The central concepts of the smart grid, DR and DSM, are crucial to deeply integrate RES by supplying zero-emission regulation services considering the broad acknowledgment in recent research (Callaway and Hiskens, 2011; Cochran et al., 2014; Juul et al., 2015; Meyn et al., 2015; Palensky and Dietrich, 2011; Siano, 2014; Subramanian et al., 2013). However, proper assessments of its value and research on minimum marketable flexibility levels are still limited.

Information technology alleviates one of the major flaws of electricity markets: It enables the demand side to react in a dynamic fashion to changes in the supply situation (Strbac, 2008; Strüker and van Dinther, 2012). Following Albadi and El-Saadany (2007), DR can be categorized into incentive-based programs and price-based programs. Incentive-based approaches are common for large industrial customers and often involve direct load control of large loads at the customer site. This traditional approach has been extended by market-oriented DR programs that allow customers to participate in demand bidding on the respective markets (Chua-Liang and Kirschen, 2009). Small customers, e.g. the commercial and residential sector, in turn, would rather participate in a price-based program that includes different levels of dynamic prices, starting with simple two-staged time-of-use tariffs, extending up to real-time prices based on the wholesale development situation (Albadi and El-Saadany, 2008). The applicability of price-based programs may be endangered by herding effects if not explicitly taken care of (Flath and Gottwalt, 2016). The approach discussed in this Chapter builds on the notion of dynamic pricing with a special focus on local generation.

4.1.2 Charging Coordination of Electric Vehicles

EV charging is considered as a prime case of load flexibility (Shao et al., 2011; Goebel et al., 2014). Therefore, charging coordination of EVs received considerable attention of scholars in recent years. Most literature focuses on aspects of efficient grid integration, e.g., Acha et al. (2010); Caramanis and Foster (2009); Fan (2012); Green II et al. (2011), and on the assessment of economic implications in different market environments, cf. Flath et al. (2014); Grahn and Soder (2011). Other scholars assess the potential to balance renewable energy (Galus and Andersson, 2011) and to reduce the operative carbon footprint of charging (Schuller et al., 2015).

Different architectures for coordination and control of EV demand have been proposed (Schuller, 2015). Most approaches rely on centralized (hierarchical) coordination mechanisms in order to integrate EVs in DSM programs. Hierarchical mechanisms are prominent particularly in the context of commercial EV fleets. Eisel et al. (2015) investigate the economic effects of ICT-mediated DR programs for EV car sharing fleets. They find that demand side flexibility could further improve the operative costs of EVs in fleet applications. In addition to the mediation of DR programs, information systems have also been employed to support planning decisions for the optimal deployment of charging infrastructure (Wagner et al., 2014).

Car parks can be seen as local EV charging aggregators, which can employ renewable energy sources like PV to satisfy the demand requirements of contracted EVs. Ma and Mohammed (2014), e.g., investigate a plug-in hybrid electric vehicle (PHEV) car park with 75 kilowatt-peak (kWp) PV capacity and a fuzzy logic price determination algorithm considering RES generation and grid supply costs. However, customers are only modeled w.r.t. their arrival and departure times, not with respect to their economic preferences. Steuer et al. (2014) investigate a car park scenario but remain limited to the economic assessment under the current German regulation regime instead of evaluating the options to activate EV demand side flexibility. Further work from Chen et al. (2013) also proposes online deadline oriented scheduling for parking garages but does not consider renewable energy in the coordination objective. In addition, the service level assumed for customers is different (the operator has to compensate unserved load) than in this Chapter's work, where customers with an insufficient valuation are not served. Sánchez-Martín and Sánchez (2011) consider a parking garage scenario for 50 PHEVs and EVs and develop a charging heuristic that minimizes the share of unserved vehicle load given grid connection capacity constraints. They do not consider renewable energy generation and only purchase electricity from the grid in a simple two-part tariff. Recalde Melo et al. (2014), in turn, consider a car park in Singapore under different charging strategies and compare the effects on the total costs of the car park operator. Wagner et al. (2013) investigate the economic profitability of EV fleets for the provision of frequency regulation in the case of Germany. They find that negative regulation — offering to draw energy from the grid e.g. in situations where supply is greater than demand — can be profitable for an EV aggregator. Despite the similar investigation scenarios, no work in literature addresses the economic preferences to the extent that will be presented in the following sections.

This work extends existing centralized approaches to assess the demand side flexibility of EVs in a car park or fleet environment. The addressed gap includes the consideration of local PV generation and the combination with a variable pricing scheme while considering heterogeneous economic preferences of EV customers. In particular, an easy to use, robust economic incentive scheme is implemented considering different sources of uncertainty.

4.2 Model Formulation

The generic workflow of a simulation analysis is illustrated in Figure 4.1. First of all the external data sources need to be wrapped to generate simulation sample sets (see Section 4.3). After defining parameter instances for each scenario the model, which is defined in this section, is can be optimized and validated. Optimization and validation are executed based on two independently generated data sets: a

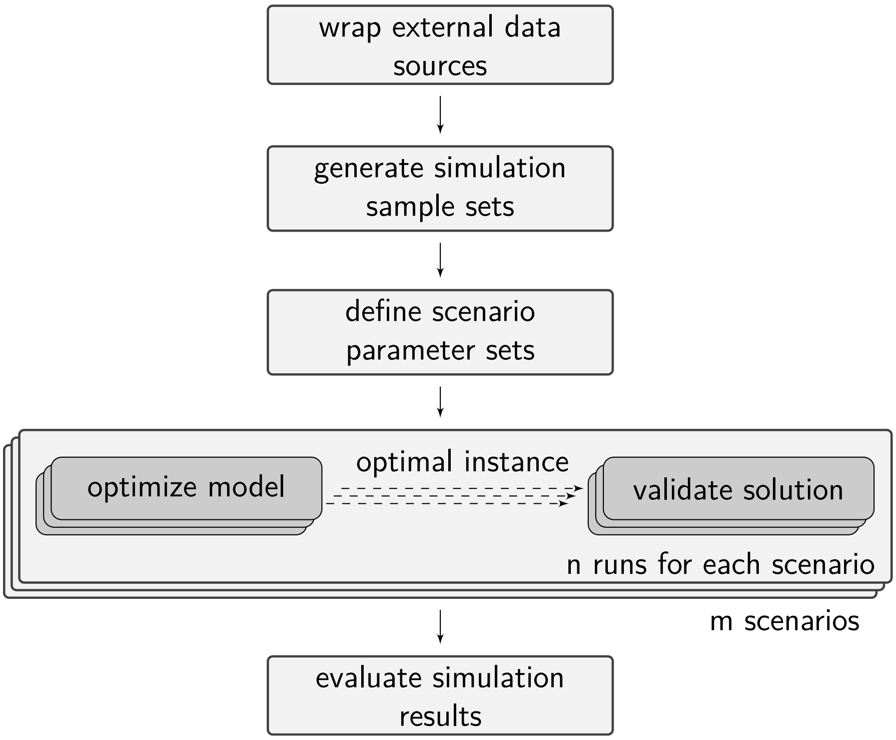

Figure 4.1: Program workflow

training sample and a validation sample. Each scenario passes multiple[2] runs to control for data coincidences. Lastly the obtained simulation results are evaluated (see Sections 4.4 ff.).

As noted in the introduction of this Chapter, the proposed model is based on (Bitar and Low, 2012) by adopting their notion of DDP. This paradigm is illustrated in Figure 4.2: Flexible demand, a set of deferrable loads, is scheduled to cost-efficiently match a given supply portfolio consisting of volatile, free of cost renewable generation and conventional backup generation. To incentivize the revelation of customer departure times, the operator quotes deadline differentiated prices, i.e. each possible delivery time has a specific price.

This pricing regime is cast to an EV car park scenario which is a natural fit.[3] Besides the concrete instantiation, the original model is extended by allowing for price menus with a limited number of price levels. The latter allows to explore the

[2]If not further specified, the number of runs is 100 .

[3]Bitar and Low (2012) note, that deadline differentiated pricing "would naturally complement the proliferation of plug-in electric vehicles in the US transportation fleet."

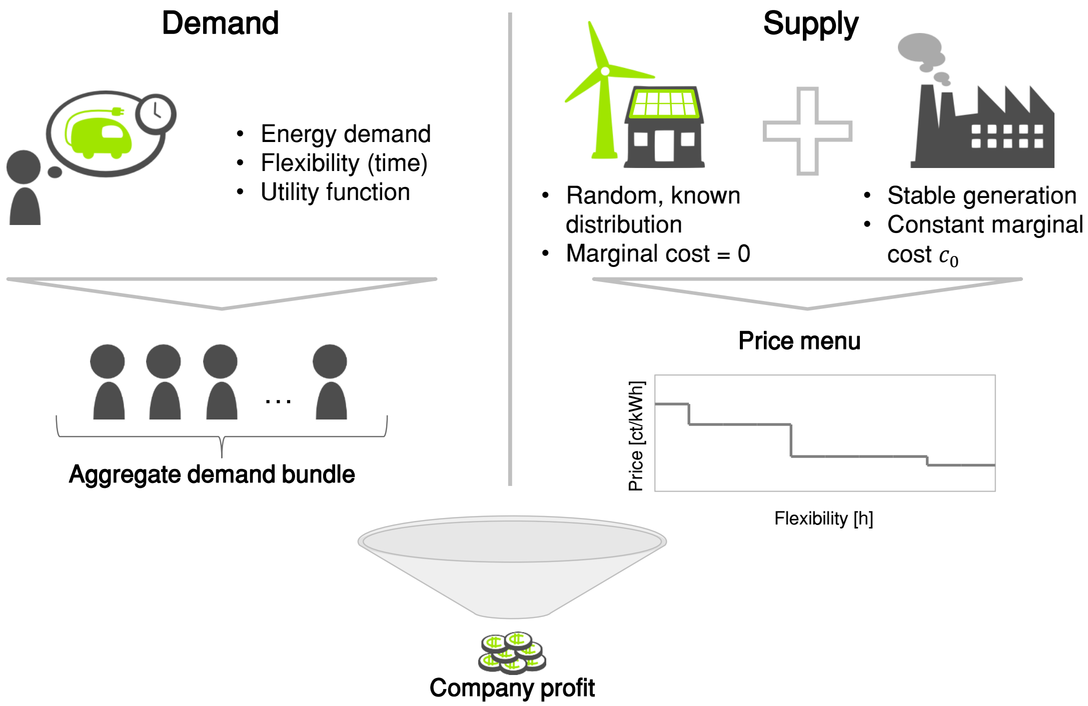

Figure 4.2: Scenario overview

value of varying tariff granularity levels (Watson et al., 2010) and e.g. to isolate the minimal, binary case flexible vs. inflexible.

The model's constraints can be grouped into three parts: The price menu constraints, the customer decision constraints, and the dispatch constraints. Formally, the customer decision is a separate optimization problem for each customer that maximizes the consumer surplus while choosing the amount of energy charged and the extent of flexibility provided. It will be shown that this optimization problem can be expressed with linear constraint terms. Hence, it can be integrated into the car park operators maximization problem. To limit the notational burden, first, the deterministic model is presented and afterwards the stochastic extension is introduced. The complete stochastic program is provided in Appendix A. Table 4.1 provides an overview of the sets, variables, and parameters used in this model.

4.2.1 Price Menu

The price menu is at the heart of deadline differentiated pricing. It connects flexibility offered by the customers with the electricity price they have to pay. Here,

Table 4.1: Model decision variables, parameters, and sets

Decision variable		**Unit**	**Domain**
Price at flexibility level f	p_f	ct/kWh	$\mathbb{R}_0^+$
Discount from p_f to p_{f+1}	Δ_f	ct/kWh	$\mathbb{R}_0^+$
Price jump from p_f to p_{f+1}	j_f		binary
Buy decision of c for $e_{c,f}$	$\delta_{c,f}$		binary
Maximum consumer surplus of c	u_c^{max}	ct	$\mathbb{R}_0^+$
Latest possible start of charging loads in t of customer segment $C_{a,f}$	$\sigma_{a,f,t}$		binary
Charging load of customer c	$\lambda_{c,t}$	kWh	$[0,\lambda^{max}]$
Energy bought in time slot t	η_t^g	kWh	$\mathbb{R}_0^+$
Parameter			
Maximum number of price levels	J^{max}		$\mathbb{N}$
Minimum extent of a price jump	Δ^{min}	ct/kWh	$\mathbb{R}_0^+$
Energy demand of c at flexibility level f	$e_{c,f}$	kWh	$\mathbb{R}_0^+$
Arrival time slot of c	a_c		$\mathbb{N}_0$
Max. flexibility of c	$\bar{f}_c$		$\mathbb{N}_0$
Min. charging duration of c	$\bar{t}_c^\lambda$		$\mathbb{N}_0$
Parking duration of c	d_c		$\mathbb{N}_0$
Max. charging amount per time slot	λ^{max}	kWh	$\mathbb{R}_0^+$
PV generation in t	η_t^p	kWh	$\mathbb{R}_0^+$
Conventional energy cost in t	c_t	ct/kWh	$\mathbb{R}_0^+$
Weight for scenario s	w_s		$\mathbb{R}_0^+$
Sets			
Arrival time slot	$a \in A$		
Temporal flexibility	$f \in F$		
Time slot	$t \in T$		
Customers with identical a and f	$c \in C_{a,f}$		
Scenario	$s \in S$		

flexibility offered by a customer opens the possibility to the car park operator to defer her load by a specific duration.

The array $[p_0, p_1, ..., p_n]$ represents the price menu for a set F of n different durations of flexibility. In this work, flexibility is understood as the possibility to defer load by a specific duration. The standard time interval is set to 15 minutes.[4] To preserve incentive compatibility with respect to flexibility reports, the price menu needs to be strictly decreasing in flexibility (Bitar and Xu, 2013). For reasons of practical applicability, the set of permitted price-flexibility-pairs needs to be restricted. To this end, the number of assignable prices is limited by adopting the rate jump specification presented by Flath (2014):

$$p_f = p_{f-1} - \Delta_{f-1}\,, \qquad \forall f \in F_{>0} \tag{4.1}$$

$$\Delta_{f-1} \leq j_{f-1} \cdot \xi\,, \qquad \forall f \in F_{>0} \tag{4.2}$$

$$\sum_{f=0}^{n-1} j_f \leq J^{max} - 1\,. \tag{4.3}$$

Here, Δ_{f-1} specifies the extent of jumps between adjacent price levels. The maximum number of price levels is given by J^{max} and ξ denotes a sufficiently large positive number. Equation (4.1) ensures that the price level p_f is consistent with p_{f-1} and jump amount Δ_{f-1}. Equation (4.2) enforces Δ_{f-1} to be zero if there is no jump. Equation (4.3) ensures the maximum number of jumps.

To enhance customer friendliness a minimum jump amount can be set to obtain perceivable price differences. This is implemented by the constraint

$$\Delta_{f-1} \geq j_{f-1} \cdot \Delta^{min}\,, \qquad \forall f \in F_{>0}\,, \tag{4.4}$$

where Δ^{min} is the minimum jump amount.

Besides limiting the number of price levels, a restriction on the time resolution of the price menu is introduced. This is accompanied by coarser intervals for flexibility reports over the underlying quarter-hourly time model.[5] Therefore a subset of price

[4] Consequently, p_0 denotes the energy price without flexibility, p_1 for a flexibility of 15 minutes, and p_n for a flexibility of $n \times 15$ minutes.

[5] This is done for reasons of practical applicability as well as to limit computational complexity leading to a more limited price menu.

jump variables j_f is disabled:

$$j_{f-1} = 0\,, \qquad \forall f \in F_{>0} \cap f \bmod \rho > 0\,, \tag{4.5}$$

where ρ is the time resolution parameter for the price menu — here: every ρ-th quarter a price jump is permitted.

4.2.2 Customer Decision

As noted earlier the customer decision formally reflects a separate optimization problem and therefore after integrating it into the car park operator's problem the whole model would result in a bi-level problem. Before explaining how to (linearly) integrate it, the customer's lower level problem is defined separately first.

A customer's objective is to maximize her consumer surplus

$$\max_{d} \mathcal{P}^{\mathrm{LL}} = \sum_{f \in F} U_c\left(e_{c,f}\right) - p_f \cdot e_{c,f}\,, \qquad \forall c \in C\,, \tag{4.6}$$

where $U_c(e_{c,f})$ is the customer's utility from energy amount $e_{c,f}$ and $p_f \cdot e_{c,f}$ are her expenses. To transform Equation (4.6) into a linear formulation, the utility function needs to be examined in more detail. Previous research on deadline-differentiated pricing assumes that customers' utility functions are strictly concave and continuous (Bitar and Low, 2012). Under these assumptions, it follows that the first order optimality condition $\nabla U_c(e^*_c) = p$ is a sufficient condition for a maximum, while meeting the requirement to be insertable as a linear expression into the upper level problem.

However, the strict concavity assumption on utility functions is not appropriate for the car park case. A natural way to determine the utility function is to employ costs for an outside option, i.e., the alternative to EV charging at the car park. EV drivers normally have the ability to charge their vehicle, e.g., at home. So, a good way to estimate a customer's utility for EV charging at a car park in this case is the energy rate she pays at home to charge her EV. As the battery has a predefined capacity, her utility function grows linearly until E kWh and stays constant beyond since the battery cannot be overcharged. Hence, the relevant interval is $0 \le x \le E$. Accounting for payments the consumer surplus is obtained as depicted in Figure 4.3.

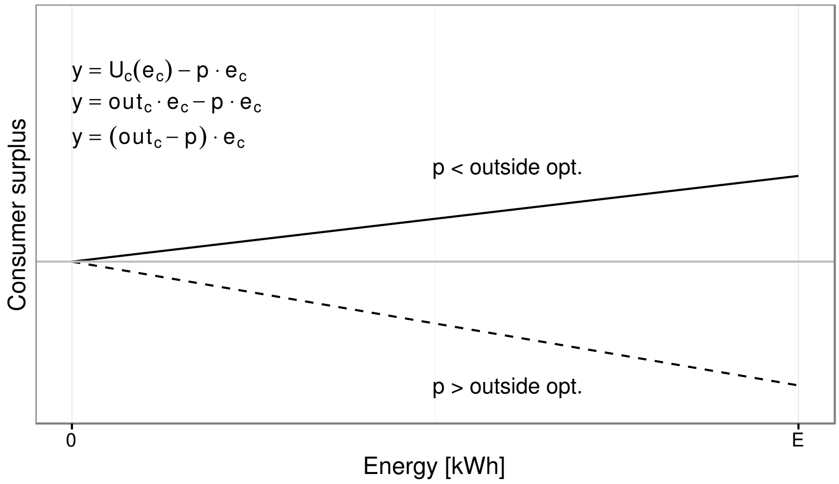

Figure 4.3: Exemplary consumer surplus functions of car park customers

The consumer surplus functions can exhibit two distinct shapes based on the difference between the price and the slope of the customer's utility function. As both price and utility function are (piecewise) linear, the resulting consumer surplus function is as well. To determine the optimum, it is sufficient to compare the interval boundaries of the consumer surplus function due to its monotonicity. Each consumer surplus function of this structure has at the most two edges: $x = 0$ and $x = E$. By introducing the binary variable $\delta_{c,f}$ reflecting the customer's decision to request an ahead known amount of energy $e_{c,f}$ (here: E) at flexibility level f, the customer maximization problem (4.6) can be reformulated to

$$\max_{\delta} \mathcal{P}^{\mathrm{LL}} = \sum_{f} \left(U_c \left(\delta_{c,f} \cdot e_{c,f} \right) - p_f \cdot \delta_{c,f} \cdot e_{c,f} \right) , \qquad \forall c \in C. \tag{4.7}$$

As the price menu is monotonically decreasing in the flexibility level, a customer will quote her total demand at her maximum flexibility $\bar{f}_c$ which is

$$\bar{f}_c = \underbrace{d_c}_{\text{Parking duration}} - \underbrace{t_c^{\bar{\lambda}}}_{\text{Min. charging duration}} , \tag{4.8}$$

while

$$t_c^{\bar{\lambda}} = \left\lceil \frac{e_{c,f}}{\lambda^{max}} \right\rceil \tag{4.9}$$

calculates the minimum required charging duration. Hence, Equation (4.7) can be reduced[6] to

$$\max_{\delta} \mathcal{P}^{\mathrm{LL}} = U_c(\delta_c \cdot e_c) - p_{\bar{f}_c} \cdot \delta_c \cdot e_c \,, \qquad \forall c \in C \,. \tag{4.10}$$

Since the maximization problem has been reduced to a comparison of two discrete values, Equation (4.10) can then be replaced by the following constraints assuming $U_c(0) = 0$:

$$u_c^{max} \geq U_c\left(e_c\right) - p_{\bar{f}_c} \cdot e_c \,, \qquad \forall c \in C \tag{4.11}$$

$$u_c^{max} \leq \delta_c \cdot \Big(U_c\left(e_c\right) - p_{\bar{f}_c} \cdot e_c\Big) \,, \qquad \forall c \in C \,. \tag{4.12}$$

The new continuous variable $u_c^{max} \geq 0$ reflects the customer's maximum attainable consumer surplus. Equation (4.11) ensures u_c^{max} to be greater or equal to the consumer surplus in case $\delta_c = 1$. The customer only has to decide whether or not she purchases the amount E. Equation (4.12) ensures that δ_c takes the correct value to represent the customer's optimal decision. If purchasing E has a negative consumer surplus, u_c^{max} is zero due to its non-negativity constraint and fulfilling Equation (4.12) is only possible with $\delta_c = 0$. Otherwise u_c^{max} takes the value of consumer surplus for purchasing E and therefore Equation (4.12) forces $\delta_c = 1$.

One may notice, that the term $p_{\bar{f}_c} \cdot \delta_c$ is non-linear as both factors are decision variables. Since this is a multiplication of one binary and one continuous variable, the term $p_{\bar{f}_c} \cdot \delta_c$ can be replaced by a new continuous variable y and linearized by the following additional constraints $\forall c \in C$ in accordance with Bisschop (2012, p. 84):

$$\begin{aligned} & y \leq p^{max} \cdot \delta_c \\ & y \leq p_{\bar{f}_c} \\ & y \geq p_{\bar{f}_c} - p^{max} \cdot (1 - \delta_c) \\ & y \geq 0 \,. \end{aligned}$$

while $p_{\bar{f}_c}$ is bounded by zero and a constant p^{max}. To increase comprehensibility the

[6]For ease of exposition, $e_{c,\bar{f}_c}$ and $\delta_{c,\bar{f}_c}$ are replaced by e_c and δ_c from now on.

term $p_{\bar{f}_c} \cdot \delta_c$ is maintained in this Chapter and only replaced in the implementation.

In Section 4.2.1 the possibility to limit the number of price jumps was introduced. Therefore, the price menu is no longer strictly decreasing in flexibility. It is believed that at identical prices, customers prefer earlier energy delivery as this resonates with the aversion of low battery levels (Eberle and von Helmolt, 2010). To ensure this, energy demands are shifted to the shortest flexibility duration with the same price which is considered in the constraints introduced in the next section.

4.2.3 Dispatch

In order to serve the customers' demand for energy in the specified flexibility range while optimizing for the company's profit, the demand needs to be aggregated and subsequently matched with available energy generation. To this end, two additional temporal dimensions besides flexibility are necessary: Customers arrive at a particular time slot $a_c \in A$ and are accordingly seen as active jobs in a number of time slots $t \in T$ subject to a_c and $\bar{f}_c$. From a dispatch point of view customers arriving at the same time a and having the same flexibility f can be treated identical and are therefore grouped into customer segments $C_{a,f} \subset C$.

To dispatch energy to charging requests new variables need to be defined. The binary variable $\sigma_{a,f,t}$ signs the starting slot t of charging loads from all customers c of customer segment $C_{a,f}$ with identical arrival a_c and load shifting flexibility $\bar{f}_c$. Each charging process has exactly one latest possible starting point (4.13) which can only occur within the flexibility range after arrival (4.14):

$$\sum_{t \in T} \sigma_{a,f,t} = 1\,, \qquad \forall a \in A, \forall f \in F \tag{4.13}$$

$$\sum_{t \in T \setminus \{a,\ldots,a+f\}} \sigma_{a,f,t} = 0\,, \qquad \forall a \in A, \forall f \in F\,. \tag{4.14}$$

$\lambda_{c,t}$ carries the real valued charging loads in each time slot t of customer c. To ensure that the requested energy demand is met while the EV is connected — which is between arrival time slot a_c and departure time slot $a_c + d_c + 1$ for customer c —

obviously the following must apply:

$$\sum_{t=a_c}^{a_c+d_c+1} \lambda_{c,t} = \delta_c \cdot e_c \,, \qquad \forall c \in C \,. \tag{4.15}$$

To preserve incentive compatibility in the presence of limited price menus, demand will only arise at flexibility levels offered with a discount. E.g. if the operator sets no discount for providing one time slot of flexibility and a customer has a maximum flexibility of one time slot she would provide no flexibility since there is no incentive. Therefore, Equation (4.16) prevents from starting a charging process after a specific amount of flexibility time slots if the corresponding price jump does not exist. If there is *no* price jump j_{t-1} charging processes of customer group $C_{a,f}$ should not be started as late as t time slots after arrival a but instead at $t-1$ (or less) time slots after arrival a (cf. last paragraph of Section 4.2.2).

$$\sigma_{a,f,a+t} \leq j_{t-1} \,, \qquad \forall a \in A, \forall f \in F_{>0}, \forall t \in \{1, \dots, f\} \tag{4.16}$$

$$\sum_{\tau=a_c}^{t+\bar{t_c^\lambda}} \lambda_{c,\tau} \geq \sigma_{a,f,t} \cdot \delta_c \cdot e_c \,, \qquad \forall a \in A, \forall f \in F, \forall c \in C_{a,f}, \forall t \in T \,. \tag{4.17}$$

Equation (4.17) ensures that the requested energy for the particular flexibility level is allocated within the allowed time window. E.g., if $\sigma_{0,1,1} = 1$ and the minimum charging duration $\bar{t_c^\lambda} = 3$ the charging load variables need to allocate $\delta_c \cdot e_c$ units of energy within arrival $a_c = 0$ and (not including) time slot $(t + \bar{t_c^\lambda}) = (1+3) = 4$. The non-linearity $\sigma_{a,f,t} \cdot \delta_c$ in Equation (4.17) is typically already dissolved by mathematical solvers during model construction since a multiplication of two binary variables can easier be handled than a linearization of one binary and one continuous variable as shown in the last subsection.

Finally, allocation commitments need to be covered by generation dispatch:

$$\sum_{c \in C} \lambda_{c,t} \leq \eta_t^p + \eta_t^g \,, \qquad \forall t \in T \,. \tag{4.18}$$

where η_t^p denotes the local renewable energy supply and η_t^g denotes the (residual) energy procured from conventional sources via the grid.

4.2.4 Objective Function

The company's goal is to maximize profits by determining an optimal price menu as well as specifying corresponding dispatch policies. Profits are realized as revenues (selling energy to EVs at the prices specified in the price menu) minus costs for conventional generation:

$$\max_{p,\delta,\eta,\Delta,j,u,\sigma} \mathcal{P}^{\mathrm{UL}} = \sum_{c \in C} \left(p_{\bar{f}_c} \cdot \delta_c \cdot e_c \right) - \sum_{t \in T} \left(\eta_t^g \cdot c_t \right) . \tag{4.19}$$

The deterministic model is transformed into a stochastic model by optimizing over multiple (weighted) scenarios $s \in S$ with different sets of customer and generation data while only allowing to specify *one single* price menu for all scenarios. Therefore, the company has to define a price menu not knowing which of the scenarios will but only that any of the scenarios could occur with probability w_s:

$$\max_{p,\delta,\eta,\Delta,j,u,\sigma} \mathcal{P}^{\mathrm{UL}} = \sum_{s \in S} w_s \cdot \left(\sum_{c \in C} \left(p_{\bar{f}_{s,c}} \cdot \delta_{s,c} \cdot e_{s,c} \right) - \sum_{t \in T} \left(\eta_{s,t}^g \cdot c_{s,t} \right) \right) . \tag{4.20}$$

The complete stochastic model is provided in Appendix A. If not further specified the presented optimization problem is solved using the optimization solver Gurobi 5.6.3 with an optimality gap of 1 % between the solution's objective value and the best bound.

4.3 General Data and Application Scenario

In order to answer the proposed research questions simulations are conducted. To ensure the representativity the simulations are built on different real sets of data where applicable. Demand data (Section 4.3.1) consists of technical EV characteristics and driving / parking behavior and the customer's utility function. To account for realistic generation data (Section 4.3.2) measured power signals of a PV panel are used.

4.3.1 Demand Data

Relevant EV characteristics for the model proposed in the last section are *electricity consumption*, *battery capacity*, and *charging speed*. To this end, original car specifications of a Nissan Leaf with 24 kWh battery capacity (equivalent to the maximum battery state of charge $\overline{SOC}$) and a consumption of 0.18 kWh/km determining a maximum range of 133 km are used. A charging speed limitation of 11 kilowatt (kW) is considered, as nowadays charging stations with at least 11 kW are widely available[7]. Since direct current charging with higher charging powers requires additional and potentially more costly infrastructure, the focus is set on standard three phase alternating current charging.

In order to model EV charging activity in car parks, it is necessary to know their energy demand and time window of the car park stay. To this end, driving profiles providing information about a car's location or status (e.g., at home, at work, at shopping, driving) and distance traveled over time are used. The German Mobility Panel (Zumkeller et al., 2011), a representative survey of mobility behavior in Germany that is continuously recorded since 1997, provides necessary data for the aforementioned.[8] The survey data is wrapped in driving profiles that consist of driving status, distance driven and location of cars in a 15-minute resolution over a whole week. Overall 5079 driving profiles are available from this data source.

It is assumed that EV owners have access to a charger at home and therefore selected trips from the data source start at home and park for one of the following activities before they return home: shopping, leisure, work, or business trip. Since most trips of the attained driving profiles clearly undercut the battery capacity, it is assumed that EV owners do not charge their EVs every time they return home, which is, e.g., in line with the expected usage behavior of Opel Ampera-e.[9] To account for this, the starting state of charge (SOC_0) is set to 75 %. From the 5079 driving profiles, that describe car movement over a whole week each, 9488 individual trips could be identified that follow the above-mentioned structure (home - parking

[7]See `www.goingelectric.de/stromtankstellen/` for a comprehensive listing of fast charging stations.

[8]From MOP data the file "W" is selected. Data description and code plans are available at `mobilitaetspanel.ifv.kit.edu/english/92.php`

[9]`http://www.stern.de/auto/fahrberichte/opel-ampera-e-500-kilometer-reichweite--opels-elektroauto-fuer-jedermann-7235726.html`

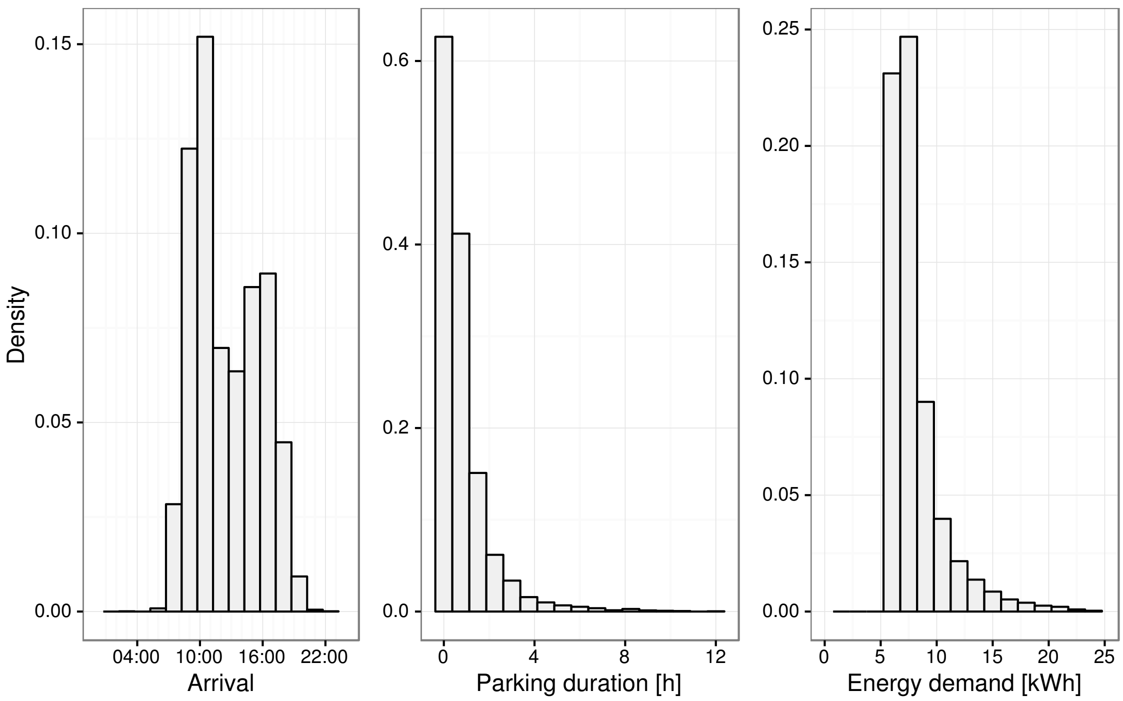

Figure 4.4: Derived trip data from the German Mobility Panel (Zumkeller et al., 2011)

- home) and are feasible with regards to the simulation length of 24 hours and range limitation of the assumed EV specifications. The relevant data derived from these trips representing the EV charging requirements in a car park are *time of arrival*, *parking duration*, and *energy demand*, depicted in Figure 4.4.

On average around 1000 customers per day visit the examined exemplary car park in the center of a major city in southern Germany. The left-hand side of Figure 4.5 shows that visits occur mainly during daytime. The German National Platform for Electric Mobility predicts that EVs will represent approximately 2.5 % of all passenger cars in Germany in 2020. Commuting from rural into urban areas with EVs will be one of the most common use cases (Nationale Plattform Elektromobilität, 2012). Since this type of commuters represent a large target group at the analyzed car park, an above-average EV customer share of 10 % is assumed which results in 100 EV customers per day.

For each of the 100 customers, one of the aforementioned extracted trips is sequentially and randomly drawn with replacement to represent a complete customer data set for a day. The random drawing is manipulated such that the parking duration

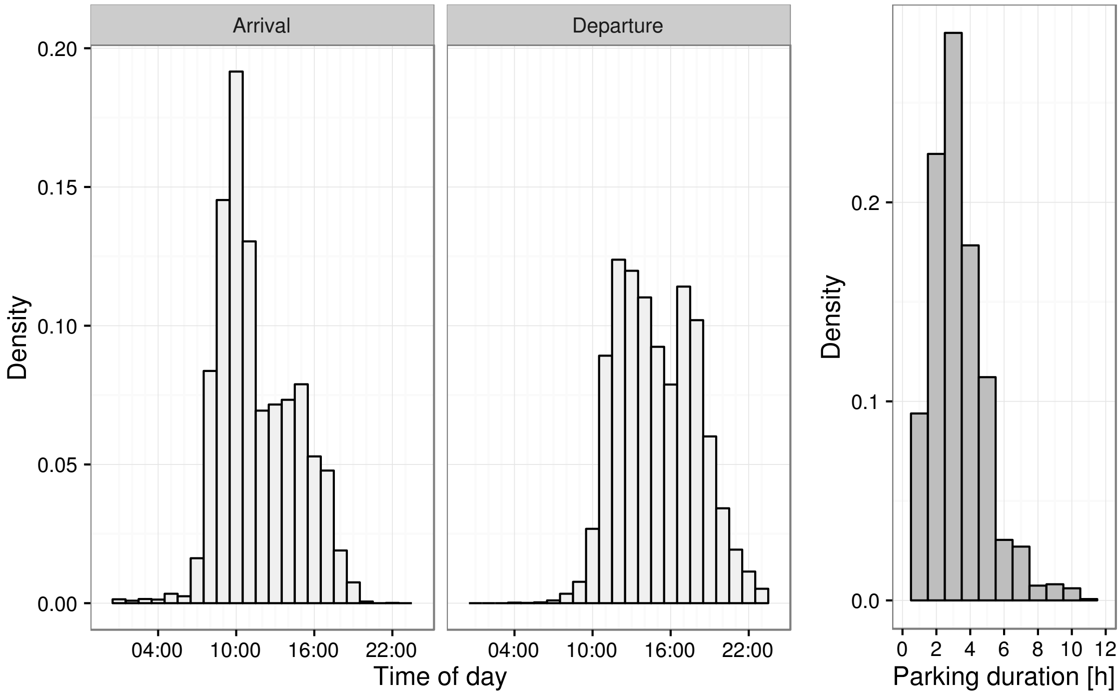

Figure 4.5: Distribution of empirical data on arrivals, departures and the corresponding parking duration

of a complete customer data set matches the parking duration distribution of the exemplary car park (compare parking duration data of Figure 4.5 with Figure 4.4). The process of generating complete customer data sets for an exemplary day is repeated 100 times to ensure statistical reliability. Besides, two separate data sets — a training and a validation data sample — are generated for the later analysis on imperfect demand information.

The right-hand side of Figure 4.5 reveals that the customer's average parking duration exceeds the necessary average EV charging time (3.5 hours vs. 45 minutes at 11 kW). This is an indicator that load shifting is a potentially promising use case in this application scenario. While the applied data source for driving profiles was recorded mainly with conventional combustion engine vehicle, they can still be used to create EV models (e.g., Metz and Doetsch, 2012; Schuller et al., 2014). Fundamental mobility needs can be considered to be fairly stable.

Finally, the customer utility function needs to be added to the customer data sets. Following Section 4.2.2, the utility function is parameterized with both the customer's individual energy demand and the cost for the outside option. The latter

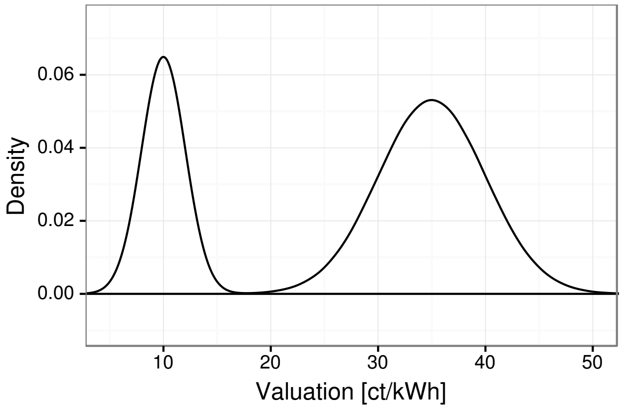

Figure 4.6: Bimodal distribution of the customers' cost for the outside option

parameter has a direct effect whether or not to charge at the car park given a specific price menu. The energy demand is $\overline{SOC} - SOC_t$, that is derived from the customer's attached trip data. Since it is assumed that EV owners own a charger at home they will therefore consider charging at home as their outside option that can be quantified with the household electricity rate.

To retain analytic tractability and in lieu of an appropriate data set the customers' household electricity rate (outside option) is assumed to be normally distributed with $\mu = 35$ ct/kWh and $\sigma = 5$ ct/kWh for two thirds of the population. It is assumed that the other third is equipped with PV panels at home supplying a major part of their charging energy at lower costs. The cost for the outside option of this customer group is modeled to be normally distributed with $\mu = 10$ ct/kWh and $\sigma = 2$ ct/kWh. In total a bimodal distribution is obtained (see Figure 4.6).[10] Each customer is assigned a randomly drawn cost for the outside option from this distribution.

4.3.2 Supply Data

Available energy at the car park consists of renewable energy generated by PV panels on the car park rooftop and conventional energy supplied by an energy provider. Measured data from an exemplary PV panel located in the South West of Germany are used to account for fluctuations in renewable energy generation. Figure 4.7 illustrates the potential influence: Generation data of three exemplary days in July

[10]Section 4.6 further investigates to what extent the customers' cost for the outside option affects the obtained results.

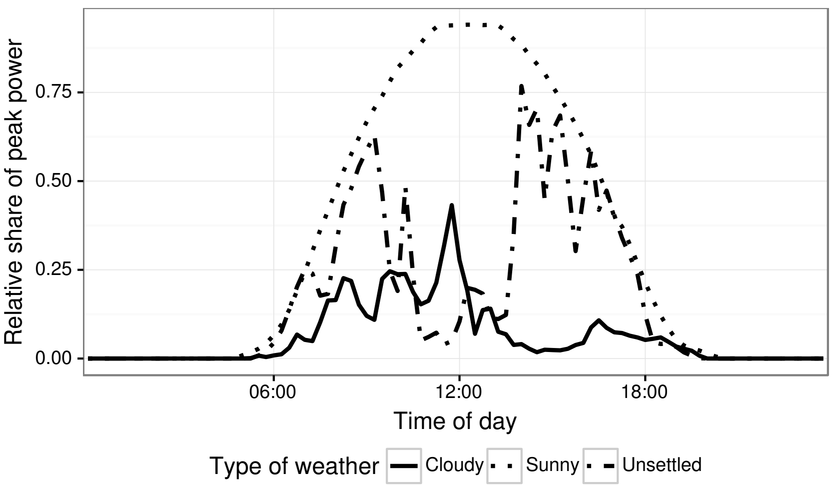

Figure 4.7: Chosen generation scenario data from exemplary days in July 2013

2013 with appropriate weather conditions were chosen to highlight the extent of deviations. If not further specified, the optimization is run over the selected *unsettled* weather condition scenario. This weather condition is common in Germany and challenging for the energy system due to the high volatility.

To obtain concrete energy values the dimension of the PV panels fitting on the car park rooftop needs to be determined. The examined car park has a usable, shadowless rooftop space of approximately 2000 square meters. Assuming a generation power density of 125 W_{peak}/m^2 (Steuer et al., 2014) PV panels of up to 250 kWp could be installed. A good balance between supply and demand in terms of provided energy over the whole year is achieved at 100 kWp, which is defined as the standard scenario.

In contrast, the conventional energy supplied by an energy provider is stable and unlimited but not free of charge. It is assumed that this energy can be procured by the operator at 30 ct/kWh, which — in case of no private PV energy supply — undercuts the average household electricity rate (compare Figure 4.6). This reflects reality since commercial or industrial customers consume higher quantities than private households which results in lower prices.

A complete overview of all parameters introduced in this and the previous subsection is depicted in Figure 4.8. The denoted values represent the base case scenario either based on empirical data or assumptions as aforementioned. These parameters are sequentially altered in the following subsections.

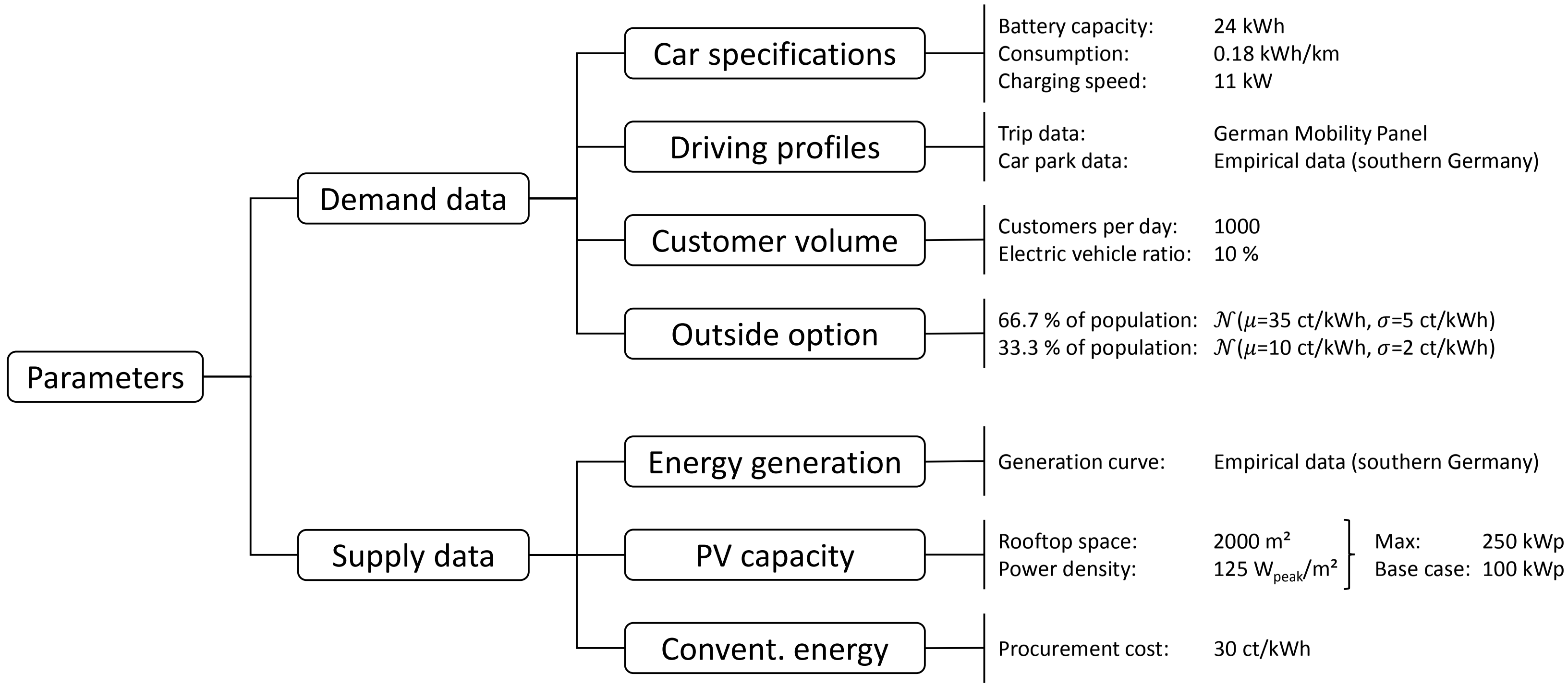

Figure 4.8: Overview of the most important parameters and assumptions for the base case scenario

4.4 General Results

Cyber-physical systems with ubiquitous sensor-actor infrastructures facilitate new planning paradigms. A case in point is pricing decisions: Novel dynamic and individual pricing schemes may enhance profitability by more effectively tapping into customer willingness-to-pay and by improving capacity utilization levels.

At first, Section 4.4.1 examines the capacity utilization topic with a sensitivity analysis of the model's supply side (see the lower part of Figure 4.8). The central aspect of this examination is the pricing scheme determination, since the determination of other decision variables, e.g., scheduling variables, is straight forward. Bitar and Low (2012) show that the earliest-deadline-first paradigm provides an optimal solution for the scheduling policy without requiring knowledge about the intermittent supply process.

While theoretic models allow the determination of "optimal" pricing schemes for sandbox situations, application to real cases is often impossible to be directly implemented due to computational or memory requirements. Yet, companies will still seek to exploit the available data in a near-optimal way. In big data analytics, dimension-reduction techniques are a standard approach to handle large data availability and extract as much information as possible. As a foundation, Section 4.4.2 investigates whether the pricing scheme determination in the car park EV charging application scenario follows a consistent learning process.

Companies generally deal with pricing decisions from two points of view to improve profitability: Both, increased product choice which leverages the degree of self-selection and increased knowledge about demand can improve profitability. This reasoning is explored in Section 4.4.3.

4.4.1 Supply-Side Sensitivity Analysis

The objective of this subsection is to examine the impact of the supply side on the optimal price determination. To perform this sensitivity analysis two parameters on the supply side are altered: The PV generation capacity that has a direct effect on the locally produced electricity η_t^p and the procurement cost for conventional electricity c_t. The range of values of these parameters are as follows:

- The PV generation capacity — being a scaling factor for the electricity generation η_t^p — is altered between 25 and 250 kWp with a step size of 5 kWp. This parameter range covers possible rooftop installations of the examined car park.

- The cost c_t for conventional electricity procured from the grid η_t^g is altered between 25 and 35 ct/kWh with a step size of 1 ct/kWh. In addition, extreme cases with 15, 20, 45 and 50 ct/kWh are selected. A static-in-time cost structure is assumed: $c_0 = c_1 = ... = c_{t_n}$.

Each of the latter two parameter setups is simulated 100 times in accordance with Figure 4.1 with varying customer data to guarantee statistical reliability. The respective parameter not in alteration is constant (c_t = 30 ct/kWh and 100 kWp for the PV generation capacity). To isolate effects a deviation from the base case scenario presented in Figure 4.8 is required resulting in the following parameter setup:

- Regarding the price menu setup, the most restrained case with only two price levels J^{max} is leveraged. Thereby, it is possible to differentiate the customer decision regarding the provision of flexibility in a binary way. The minimum extent of a price jump Δ_{min} is set to 0.1 ct/kWh to account for a realistic setting for the awareness of price differences.

- From the generation scenarios depicted in Figure 4.7 the "unsettled" scenario is chosen to instantiate η_t^p. It is a prototype for a challenging generation scenario.

- Perfect knowledge of demand (see the left side of Figure 4.2) is assumed yielding a theoretical benchmark.

Figure 4.9 shows the resulting optimal price menus averaged over the 100 reiterations for each simulated parameterization. If a customer chooses the normal price, she receives a charging service that starts immediately after plugging in the EV. To qualify for a reduced price, the customer must accept a possible shift in time for her requested charging service. The car park operator presets a specific duration that applies to all customers by which the charging service can be shifted at most. Even though the generation scenario is static, this duration may differ slightly from run to run. The price reduction is based on a qualification feature. Hence, the deadline differentiated pricing scheme can be used to segment customers. Since customer data is altered from run to run the change in needed duration for the reduced price is explained. The left-hand side of the figure represents the sensitivity analysis on the PV generation capacity while the procurement cost is fixed to 30 ct/kWh. Vice versa, on the right-hand side the PV generation capacity equals 100 kWp.

The prices chosen by the car park operator take values between approximately 29 and 37 ct/kWh. Comparing this value range with the distribution of the customer valuation determined by her outside option yields a first finding. Customers equipped with PV panels at home have a valuation for a charging service that is far below this price range. None of them will request a charging service from the car park operator. Since this holds in extreme scenarios with low procurement costs or a high PV generation capacity this cannot be explained by the cost structure of the car park operator. Instead, the absence of price discrimination causes this behavior. Providing charging services for this customer group would necessitate considerably lower prices resulting in a lower overall profit since revenues from the the other customer group would diminish.

In case of alteration of the PV generation capacity a logistic decrease of both the high and the low price can be identified. A decrease of prices is a measure to increase the volume of electricity sold to customers. The car park operator conducts this to allocate the produced electricity that would otherwise not generate any cash flow. The gradient moves towards zero after approximately 130 kWp because a saturation of profitable customers is reached. Further price decreases would increase the sold volume but not the profit following similar considerations as in the last paragraph. Based on the normally distributed valuation of customers the amount of gained additional customers through price decreases diminishes beyond 35 ct/kWh while the amount of lost profits increases exponentially.

The right-hand side of Figure 4.9 shows the effect of altering the procurement cost. Obviously, the car park operator sets the prices higher to reduce sales the more he has to pay for additional electricity procured from the grid. The dependency of both the normal and the reduced price from procurement cost is linear. The gradient is significantly lower than one because for a constant PV generation capacity of 100 kWp only a short proportion of the demand is covered by procured electricity (see

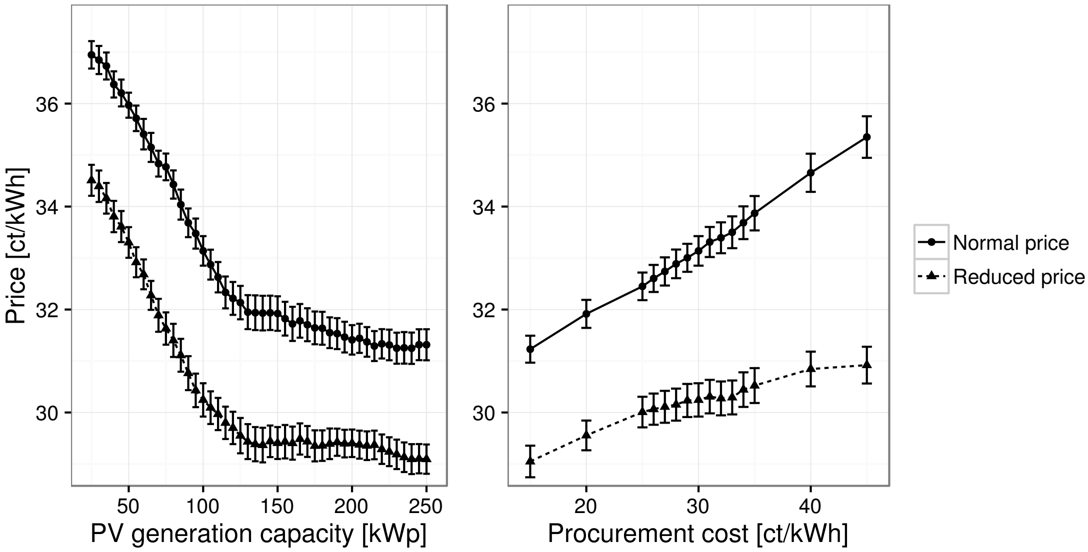

Figure 4.9: Supply-side parameter effects on deadline differentiated prices with two price levels ($J^{max} = 2$)[11]

Section 4.5 for more details).

The gradient of the normal price if substantially greater than the gradient of the reduced price. This difference is connected to the source of electricity used to supply the charging services. In case of the normal price, the associated charging services are supplied by procured electricity to a higher extent than the shiftable charging services that are associated with the reduced price. A greater proportion of the latter can be supplied by the intermittent but free of cost PV electricity. Hence, the reduced price is more independent from the procurement cost than the normal price.

Besides, this analysis gives a hint towards answering Research Question 2 from the customer point of view. The difference between the normal and the reduced price can be understood as the value the customer gains from offering her temporal flexibility. This relative discount is depicted on the left plot and its required flexibility on the right plot respectively in the following two figures. Figure 4.10 presents these key figures for the sensitivity analysis of the PV generation capacity, whereas Figure 4.12 does for the sensitivity analysis of the procurement cost.

The mean relative price discount ranges between 6 and 9 % ct/kWh of the normal

[11]If not further specified the following holds for all figures in this section: Error bars denote the 90 % two-sided confidence interval based on 100 observations for each visible data point.

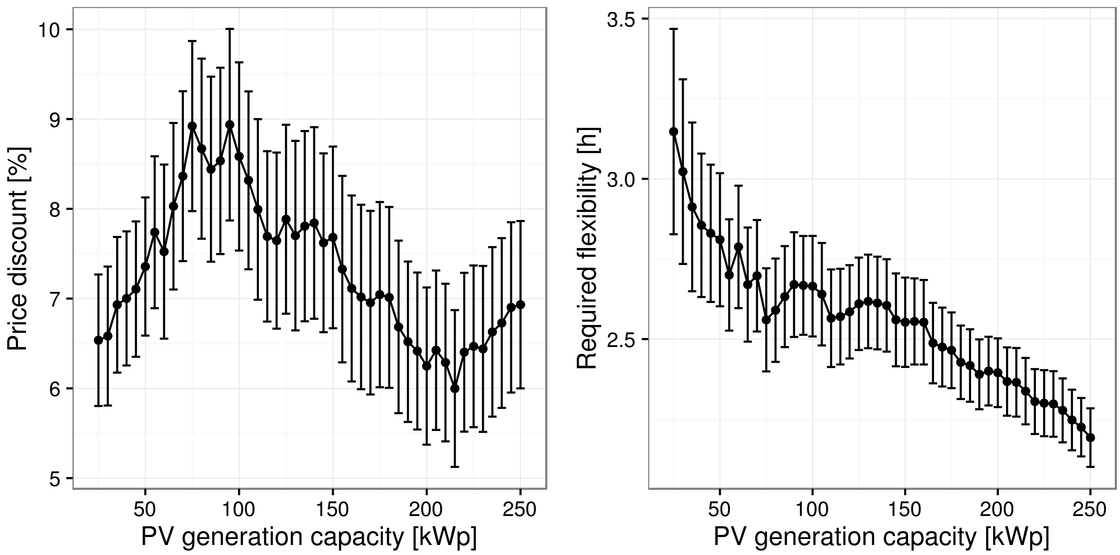

Figure 4.10: Effect of the car park operator's PV generation capacity on the relative discount and its required flexibility of deadline differentiated prices in a two price level setting ($J^{max} = 2$)

price for different PV generation capacities. Significant effects[12] of differences in the PV generation capacity on the relative price discount can only be observed between 60 and 120 kWp. This may be due to a good balance between demand and supply in this PV generation capacity region. A good balance exists, if neither the electricity generated from PV panels superimposes the demand or vice versa. In this situation temporal flexibility has a high value since shaping demand to the volatile PV generation is critical for profit maximization (see Figure 4.11). Therefore, the car park operator offers higher discounts to elicit more shiftable charging services. In a superimposition situation flexibility has a lower value because demand does not need to be shaped to be supplied by the free of cost PV electricity. The remaining price discount in superimposition situations exists due to customer segmentation reasons. A distinct group of customers with a low valuation can be addressed via the reduced price without lowering profits from normal price customers. Besides, lowering the required flexibility while maintaining the price levels is a measure to increase sales to match surplus of electricity generated from the increased PV capacity.

[12]A significant difference between two statistical populations exists if the mean value of one population is beyond the confidence interval of the other population at a specific significance level. For that, the populations represented by the analyzed samples are assumed to be normally distributed. This condition has been verified with the Shapiro-Wilk test.

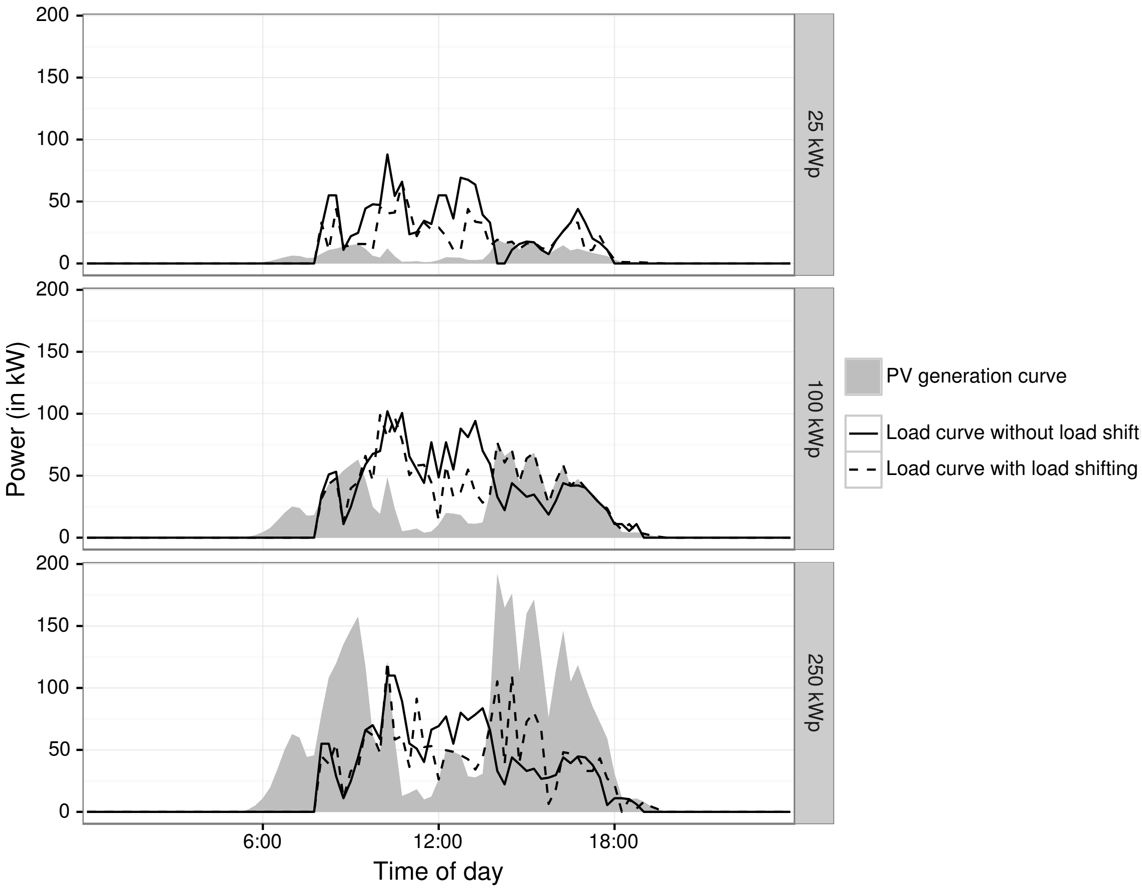

Figure 4.11: Detailed view on specific runs from selected parameter instances based on Figure 4.10 highlighting superimposition situations.

The impact of the PV generation capacity on the required flexibility to qualify for the reduced price is linear. Both the mean and its confidence interval width decrease with increasing capacity. The range of required flexibility is between 2 and 3.5 hours. This means that a charging service requested by a customer for the reduced price may be postponed for up to the required amount of temporal flexibility. Comparing the structure of this plot with the left-hand side of the figure points towards a counter-intuitive relation. One would expect the same structure for both key figures for the reason of load shaping. However, load shaping is not the driving factor for low or high PV generation capacities (cf. Figure 4.11). As before, customer segmentation might be of higher interest in these parameter ranges, indicated by the difference in confidence interval widths. By increasing the required flexibility, the number of possible customers that meet this requirement decreases. This is in line with less

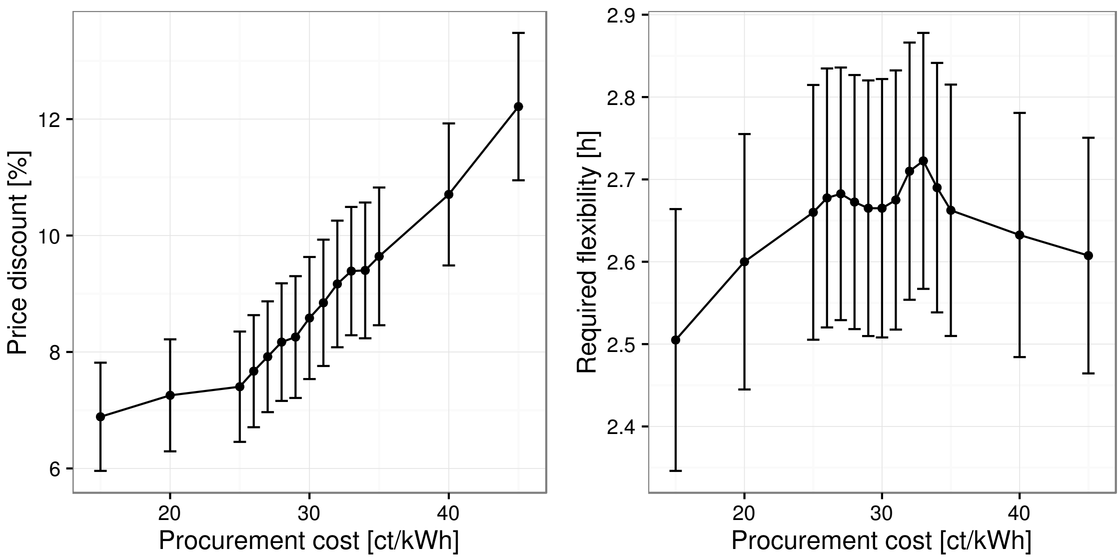

Figure 4.12: Effect of the car park operator's procurement cost for conventional energy on the discount and its required flexibility of deadline differentiated prices in a two price level setting ($J^{max} = 2$)

available free of cost PV electricity for low PV capacity parameter values. On the other hand, for high PV capacity parameter values, more customers can be supplied with free of cost PV electricity. Therefore, the required flexibility is reduced to increase sales.

These findings motivate another important aspect for a car park operator. Capacity planning for the PV generation and the installation capacity of charging points — directly affecting the potential number of customers per day — has to be done jointly for two reasons: First, the car park operator can draw more operative profits (ignoring investment costs at this point) the higher he sets the PV capacity and the number of charging points. Second, the non-rationality of consumers that induces entry barriers should be considered: Increasing the required amount of flexibility beyond a specific level by setting too low capacities for PV electricity generation could discourage customers to consume the reduced price charging service.

Finally, Figure 4.12 presents a deep dive into the effects of procurement costs. As already indicated in Figure 4.9 the price discount increases with the procurement cost. This effect is significant from 25 ct/kWh onwards. The constant price discount level at procurement costs between 15 and 25 ct/kWh points towards the previous findings. For the reason of customer segmentation, a price discount between 6 and 8 % is chosen that is independent of the analyzed supply-side parameters. On the other hand, the required flexibility does not depend significantly on procurement costs in the entire analyzed parameter range. From a theoretical point of view procurement costs mostly have an effect on the ratio from which energy source the demand is supplied. Therefore, the required flexibility should always be fairly stable if the procurement cost is significantly higher than the free of cost PV electricity. The decreasing trend for lower procurement costs indicates that flexibility becomes less important if costs for both energy sources converge.

This section already partly addressed Research Question 2. From the point of view of a customer, the difference between the normal price and the reduced price represents the value of flexibility. Depending on the concrete parameter setting, the value amounts to a range between 6 and 12 % of the price customers face for charging their EVs at a car park. It should be noted that this is only the value passed to the customer side and that the model considers a monopolist car park operator. Hence, the customers are offered minimal savings. These savings can be expected to be higher in a more competitive environment. The value that stays with the car park operator is highlighted in detail in Section 4.4.3. Secondly, to isolate supply-side effects the number of price levels has been limited to two. Removing this restriction will increase the value of flexibility since the possibilities to adapt to diverse customer properties increase. Across scenarios, the required flexibility can be fulfilled in most cases by the majority of customers when comparing it with the empirical parking duration distribution (Figure 4.5).

4.4.2 Consistency of Learning Process

The analysis conducted in the last section is based on perfect knowledge regarding demand yielding a theoretic benchmark. For the real-world implementation, it is unusual to assume perfect knowledge. Even with growing digitization it is unlikely that all demand data will be present to the car park operator to calculate an optimal price menu for a specific group of customers.[13] Instead, it can be assumed, that

[13]However, scheduling and purchasing of electricity can nearly be decided in real-time. Customers will have transmitted the critical information needed to conduct these operational actions (e.g., parking duration, battery SOC, ...)

companies will conduct market research to gain indications on valuation, customer volume etc. Depending on the extent of market research, knowledge of demand will be vague or more detailed.

In order to simulate this situation, two separate data sets have been constructed from the same distributions: a training and a validation data set. Each data set consists of 100 possible demand realizations of a day the car park operator could face in terms of each customer's valuation, energy demand, parking duration etc. Since both data sets are generated from the same distributions they would converge if the realizations were drawn endlessly. It is assumed that 100 is a sufficiently high number of realizations to approximate the conversion. Differing levels of demand knowledge can then be represented by defining the number of randomly drawn realizations from the training data set used for the stochastic optimization to determine one optimal price menu. The performance of the resulting price menu is subsequently determined by applying it to all possible realizations of the validation data set.

Whether a gain of information can be translated into better decisions of the car park operator depends on the consistency of the learning process. Here, the learning process is the determination of the price menu conducted by solving the stochastic optimization model presented in Section 4.2. Following Vapnik (1999) the model of learning consists of three components applicable to the price menu determination problem:

- A *generator* that independently draws a realization vector of customer data $\vec{x}$ from a fixed but unknown distribution $P(\vec{x})$.
- A *supervisor* returning the optimal price menu $\vec{p}$ for every realization vector $\vec{x}$ through a fixed but unknown function.
- A *learning machine* that implements a set of functions $f(\vec{x}, \alpha), \alpha \in A$ that return possible price menus.

The problem of learning is to choose the function that best predicts the supervisor's response. The discrepancy between the supervisor's response and the function's determined price menu provided by the learning machine can be measured by a loss function $L(\vec{p}, f(\vec{x}, \alpha))$. The goal is to find a function $f(\vec{x}, \alpha^*)$ that minimizes the expected value of the loss given the training data set. Following the empirical risk minimization induction principle, the learning process given the function $f(\vec{x}, \alpha^*)$ is consistent if the empirical expected value of the loss converges to the actual expected value of the loss.

Applying this concept to the car park operator problem allows identifying whether the constructed stochastic optimization problem — one specific function $f(\vec{x}, \alpha)$ — is a consistent learning process. If this is given one can be certain that feeding the problem with more training data improves decision making. The loss function can be formulated as the relative difference between the profits earned from a stochastically determined price menu and the profits earned from deterministically determined price menus being the theoretic optimums. Let $\hat{p}(X^t)$ be the stochastically determined optimal price menu based on the set X^t of realization vectors $\vec{x}^t$ from the training data set and $p^*(\vec{x}^t)$ be the deterministically determined optimal price menu based on one specific realization vector $\vec{x}^t$ from the training data set. Then, the empirical loss function is

$$L^{emp} = 1 - \frac{\sum\limits_{\vec{x}^t \in X^t} \Pi(\hat{p}(X^t), \vec{x}^t)}{\sum\limits_{\vec{x}^t \in X^t} \Pi(p^*(\vec{x}^t), \vec{x}^t)},$$

where $\Pi(p, \vec{x})$ is the car park operator profit that results from applying price menu p to the demand realization $\vec{x}$. Following Section 4.2.4 the stochastic problem equals the deterministic problem if only one scenario exists in the stochastic case. Subsequently, in that case $X^t = \{\vec{x}^t\}$ and hence $\hat{p}(X^t)$ will be equal to $p^*(\vec{x}^t)$ yielding $L^{emp} = 0$.

The actual loss function is formulated as follows:

$$L^{act} = 1 - \frac{\sum\limits_{\vec{x}^v \in X^v} \Pi(\hat{p}(X^t), \vec{x}^v)}{\sum\limits_{\vec{x}^v \in X^v} \Pi(p^*(\vec{x}^v), \vec{x}^v)},$$

where $\vec{x}^v \in X^v$ denotes a demand realization of the validation data set and $p^*(\vec{x}^v)$ is its deterministically determined optimal price menu. Hence, the denominator is again a theoretic benchmark for $\hat{p}(X^t)$ that is the same stochastically determined optimal price menu based on the set X^t as above. Since the training data set X^t and the validation data set X^v originate from the same distributions the gap between the empirical loss L^{emp} and the actual loss L^{act} should diminish for an increasing set X^t if the learning process is consistent.

As introduced earlier both the training data set and the validation data set consist of 100 demand realizations each. To avoid random effects each scenario run is repeated until all training data is utilized and each of these repetitions is validated with the available 100 realizations from the validation data set. E.g., for a 5 % demand knowledge scenario five of the 100 available realizations from the training data set are randomly chosen to instantiate the model. This procedure is repeated 20 times and each time the resulting optimal price menu is validated with the 100 available realizations from the validation data set. Figure 4.13 depicts the mean and its 99% confidence interval of the resulting empirical and actual losses for each demand knowledge scenario plotted on the horizontal axis. Seven instances of the deadline differentiated pricing scheme with differing numbers of price levels are simulated. They are grouped into price menus with one price level and price menus with multiple price levels. As price menus with one price level do not elicit the temporal flexibility they differ significantly from price menus with multiple price levels. Since computational expenses to perform the stochastic optimization increase with the sample size, simulations with demand knowledge up to a maximum of ten samples (each representing one possible realization) from the training data set were performed. Additionally, a time limit of 6000 seconds for each optimization is introduced due to the difficulty to prove optimality in certain situations.[14]

Both plots in Figure 4.13 show the same typical loss structure. The empirical loss increases with the demand knowledge while the actual loss decreases. Applying a demand knowledge of one sample from the training data set results in no empirical loss. With the belief that this one sample represents the population the car park operator calculates a solution that is optimal for that specific sample. Believing that only this realization can occur, no better solution exists and therefore the empirical loss equals zero. When the sample size increases the car park operator needs to determine one price menu that is adequate for any realization of the applied samples

[14]Analyzing the solving structure in a sample of difficult problems of this type shows that the optimal solution is usually found after 10 % of the overall optimization time. The following 90 % of the time the solver is searching for a bound to prove optimality. Therefore, calculated solutions of optimization problems canceled due to the time limit are most likely optimal but not proven.

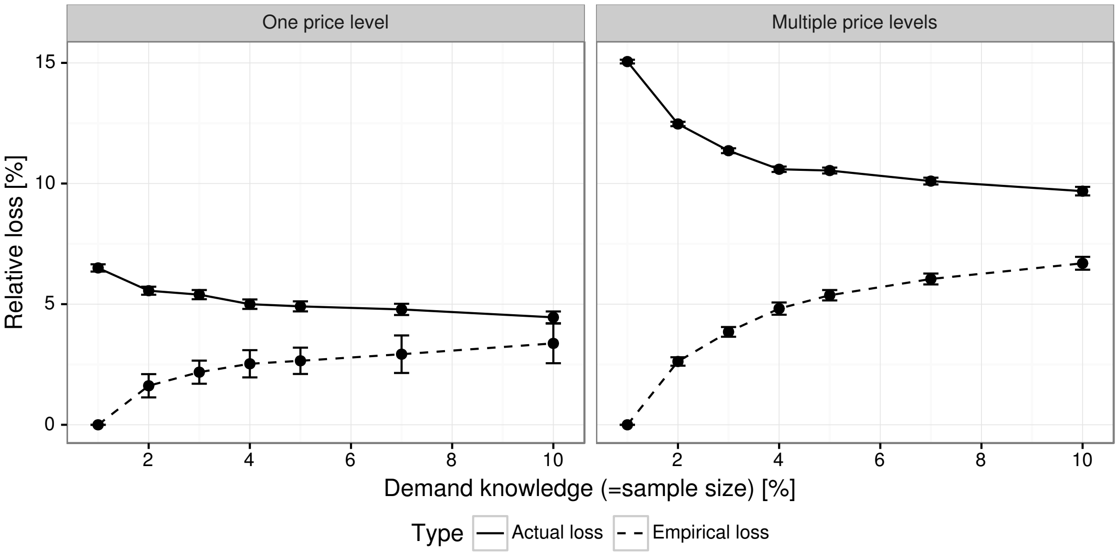

Figure 4.13: Convergence of the learning process regarding the company profit: Depicted are the mean losses and the corresponding 99% confidence interval split up into instantiations of deadline differentiated pricing with one price level and an aggregation of two to seven price levels.

since he believes that any of these samples could occur. Obviously, an optimized price menu for each sample (the theoretical optimum) would outperform this solution yielding an increased empirical loss. The actual loss curve behaves contrary to the empirical loss curve. The actual loss is high for small sample sizes because the calculated price menu is optimal for a small training sample but chances are high that this small sample deviates from a perfect representation of the complete validation population. The bigger the training sample size, the better the validation population is represented and therefore the actual loss decreases with demand knowledge. Both effects cause a decreasing difference between the empirical and the actual risk for a growing demand knowledge.

In both plots in Figure 4.13 the relative losses do not converge completely. This is related to limitations on both the convergence gap of the optimization solver and the sample size that can be processed. However, a convergence for higher sample sizes is evident which *confirms the consistency of the learning process.* This means that gathering more data to increase the demand knowledge and processing it is beneficial for a car park operator as it increases the decision quality to earn more profits. A price menu with only one price level converges faster than a price menu with multiple price levels. This behavior can be observed because in case of one price level fewer decision variables need to be determined. Therefore, fewer errors can be made compared to the multiple price levels where not only more levels but also the flexibility levels of price jumps need to be determined to meet the volatile supply profile. In addition, the overall converging loss level in case of multiple price levels is approximately twice as big as compared to price menus with one price level. Differences between price menus with multiple price levels are neglectable as indicated by the narrow confidence intervals.

These findings can explain why complex pricing schemes have not yet been introduced massively to retailing in the energy sector. More information and processing capabilities are needed to benefit from complex pricing schemes. Either these capabilities were not available or they were too expensive compared to the potential gain of applying these pricing schemes. This may change in the following decades due to several reasons: The information gathering becomes easier because improved big data approaches are being introduced. Information processing capabilities will continue to improve due to current developments in the hardware (CPU power) and software (dramatic solver improvements) industry. Lastly, the reason with probably the highest leverage is that with a higher RES ratio and lower flexible conventional supply the need for and the value of demand response applications increase.

4.4.3 Value of Information and Complexity

Before studying the value of information and the value of complexity it is important to understand the motivation for an aggregator to offer complex pricing schemes like deadline differentiated pricing. As already partly mentioned earlier, this pricing concept uses price discounts based on the offered flexibility

(a) to elicit the flexibility potential from customers to shift loads to times of PV production surplus,

(b) to skim as much customer valuation as possible by segmenting the customers,

(c) or to address different possible demand realizations in case of a deficit in market information.

Obviously, the original motivation of this work is to address **(a)**, while **(c)** is as well of interest regarding the real-world implementation where perfect information is not available. Being a consequence of pricing schemes that foster self-selection, **(b)** is analyzed in terms of the effect's magnitude but is not the focus of this work. Since all of these actions maximize the company profit, actions taken in the simulations using deadline differentiated pricing will always be the result of a mix of them. In order to evaluate which of these actions are dominant specific scenarios are defined and simulated as depicted in Figure 4.14 that isolate the above-mentioned motivations. The difference between these scenarios is based on fundamental settings regarding the rationality of customers and the car park operators knowledge about his demand.

Rationality Deviating from the base case scenario with *normal rationality* a *limited rationality* concept is implemented into the model. It intends that customers are truth-telling regarding their flexibility irrespective of price signals. Thereby motivation **(a)** to use deadline differentiated pricing is suppressed. Note that in the base case scenario customers only offer as much flexibility as needed to qualify for a lower price level. Therefore, Equation 4.16 is eliminated from the model allowing the charging to be shifted freely as long as the job is completed during the customer's stay. Additionally, since a price menu does not need to be incentive compatible if customers are truth-telling the restriction on the minimum jump amount is eliminated by setting $\Delta^{min} = -\infty$ deviating from the base case of 0.1 ct/kWh.

Knowledge Two types of knowledge about demand are assumed: One scenario without uncertainty at all and another with uncertainty. In the latter case, the car park operator knows five randomly drawn demand realizations from the training data set. The resulting price menu is validated with all 100 demand realizations from the validation data set. Thus, motivation **(c)** is suppressed in case of imperfect demand information. PV generation is assumed to be known.

Apart from that, deadline differentiated pricing is performed in different extents articulated by the number of price levels. Allowing one price level yields a simple pricing scheme without any discounts. Two price levels satisfy the lowest scaled version of a deadline differentiated pricing scheme, while five price levels offer a nearly full coordination freedom as shown later. Figure 4.14 shows the mean company profit

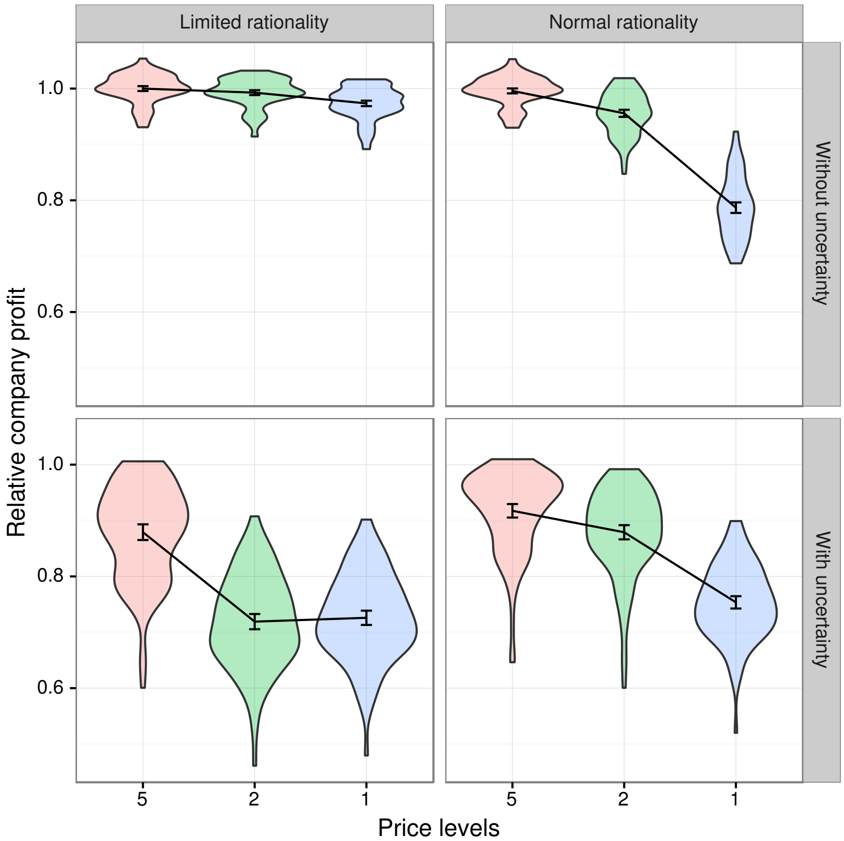

Figure 4.14: The effect of pricing capabilities under different rationality and knowledge settings. The average values are enriched by error bars and colored violins representing the confidence interval and the distribution respectively.

and its distribution depicted by colored violins. Values are relative to the mean company profit of the best case scenario with limited rationality, perfect knowledge, and five price levels. Each scenario data point is calculated based on simulation results from 100 demand realizations.

The upper-left quadrant shows the isolated effect of customer segmentation **(b)** on the company profit since both motivations **(a)** and **(c)** are suppressed in this scenario setting. The results show that a significant but minor segmentation effect exists. It yields a maximum profit increase of less than 3% (from blue to red). More than two thirds of this segmentation effect can be achieved with two price levels.

In the lower-left quadrant, the effect from **(c)** is added by introducing uncertainty to the model. Uncertainty decreases profits by approximately 25% in the simple pricing setting (blue). With a maximum coordination freedom (red) the profit loss from uncertainty is cut by half. Setting a two price levels menu (green) instead of a one price level menu has no significant effect. Since the effect from **(b)** is small in the upper-left quadrant effect and the only parameter that changes is the knowledge about demand most of the effect seen here is driven by **(c)**. This is based on the assumption that customer segmentation does not become more attractive under imperfect knowledge.

Overall a typical effect of imperfect knowledge can be observed: With uncertainty, the violins that depict the distribution of all observed company profits becomes longer and less concentrated. The impact of imperfect knowledge is lower in the normal rationality setting. In case of a maximum coordination freedom (red), it is approximately 4 % lower even though customers need to be incentivized to elicit their flexibility. This can be explained by an over-specification phenomenon. While the limited rationality case is performing better than the normal rationality case on the training sample that is used to obtain a price menu, this better performance diminishes when applying this price menu to the complete validation data set. Apparently, the customer segmentation exactly fits the price menu to specific customer segments that are not exactly matched in the validation data set while the flexibility elicitation is more robust.

Company profits do not differ significantly if comparing the results of limited and normal rationality in case of no uncertainty and full coordination freedom. That means, that the company is able to elicit the needed flexibilities to shift charging loads to match the generation pattern by monetarily incentivizing customers with a deadline differentiated pricing scheme with five price levels without loosing profits. Note that in the limited rationality case by definition all loads are fully flexible and in the normal rationality case price menus have to be monotone decreasing with flexibility to be incentive compatible. Using the deadline differentiated pricing concept yields a profit increase of up to 20% (from blue to red) in the normal rationality case, lowered slightly in case of imperfect knowledge. The profit gain is drastic even with only two price levels implying that the company can only partition between customers who want their charging jobs to be started immediately and customers who accept a limited load shift.

After understanding the basic impact of a deadline differentiated pricing scheme

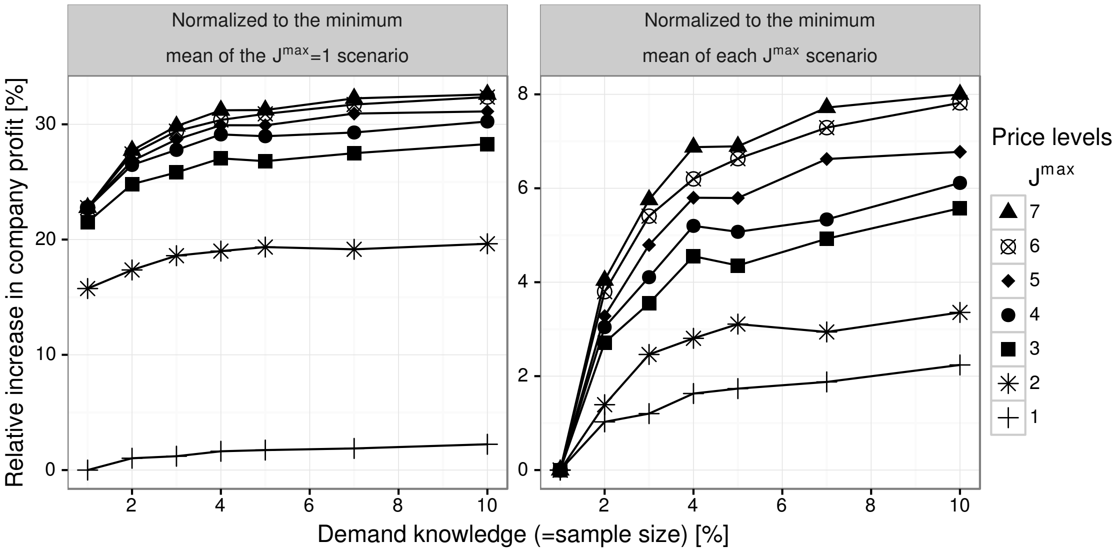

Figure 4.15: Average profit gains based on different demand knowledge and price menu settings.

the following analysis takes a deep dive into the impact of both information and complexity expressed by the simulation parameters demand knowledge and the number of allowed price levels J^{max}. Figure 4.15 is another representation of the simulation runs performed in Section 4.4.2 and at the same time a detailed view on the lower-right quadrant of Figure 4.14. Here, the company profits that can be realized with the validation population are presented. The applied price menus are determined based on differently-sized samples from the training data set depicted on the horizontal axis. The values of the left plot denote the relative increase in company profit compared to the simulation scenario with 1% demand knowledge and one price level representing the bottom line. On the right plot, each price menu scenario has its own bottom line: the average company profit obtained with a demand knowledge of 1% with the respective price levels setting. Therefore, Figure 4.15 expresses the profit gain from more information based on demand knowledge and in case of the left-hand side increased complexity through more price levels.

From a theoretic point of view allowing more price levels should increase profits because the car park operator can elicit more load flexibility. The left-hand side of Figure 4.15 supports this hypothesis, even though contradicting corner cases are possible because price menus are determined based on a training sample and not on the validation population. Controlling the demand knowledge the effect of the maximum allowed number of price levels J^{max} can account for a profit increase up to 30%. The relative increase in company profit from one price menu to another price menu with an incrementally increased number of allowed price levels drops with more complex price menus. While the gaps between neighboring pairs of price menus with up to four price levels are notable, the profit increase with more price levels nearly diminish. In this model setup, profit gains from increased pricing complexity in low-to-medium complexity cases clearly outperform increased demand knowledge. For high complexity cases, this relation does not hold. Instead, for price menus with four up to seven price levels profit gains are higher from an increased demand knowledge than from an increased number of price levels. Turning the view to the right-hand side of Figure 4.15 it can be seen that the impact of the demand knowledge decreases with higher sample sizes in analogy to the aforementioned effect of the number of price levels. Controlling the number of price levels the effect of increased demand knowledge can account for a profit increase between 2 and 8%. Even though this figure seems to be low compared to the effect of price levels, comparing it with other industry standards puts it into perspective. E.g., revenue management in the airline industry increases revenues by 4 to 5% (Talluri and Van Ryzin, 2005, p. 10). The potential profit gain from an increased demand knowledge is driven by the number of price levels. It is somewhat logical that the potential from an increased coordination freedom can better be exploited with more available information. Another indicator that points towards this logic is that the yielded profits for $J^{max} \in \{4, 5, 6, 7\}$ are identical at a demand knowledge of 1% (see the left-hand side of Figure 4.15). A detailed examination of the resulting price menus reveals that in this case, the additionally available price levels remain unused in nearly all runs.

Figure 4.16 depicts a detailed view the price menu scenario with four price levels that exploits most of the coordination potential as shown above. The confidence intervals indicate that the demand knowledge improves profits significantly. Even though the gradient does not converge to zero, it is not recommended to apply a high amount of samples from the training data set. Besides emerging costs to gather training data in a real-world setting the computational expenditures grow exponentially. Considering this, a demand knowledge between 2 and 5% should be

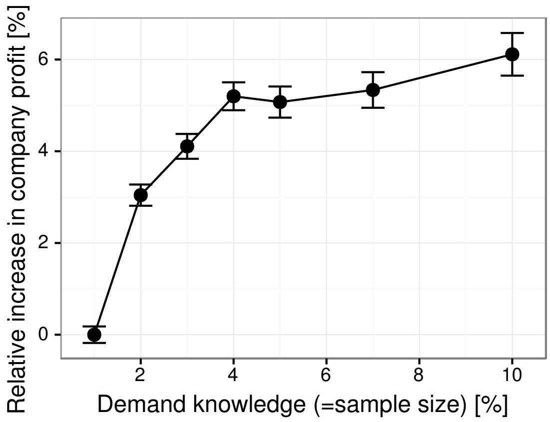

Figure 4.16: Average profit gains in the price menu scenario with four price levels based on different demand knowledge settings.

chosen depending on the concrete use case.

Another possibility to determine the amount of required information to calculate reliable price menus based on a limited set of training data is to measure the variability of price menus between different samples of the same size. In style of the stability requirement in stochastic optimization (Kaut and Wallace, 2007), demand knowledge is perfect if the resulting price menus are stable subject to sampling. Figure 4.17 depicts the highest and the lowest price levels of each price menu[15]. The reported values are standard errors of the amounts of the respective price levels and therefore adjusted for the number of simulated runs that differ due to the limited training data set[16]. Results show that the highest price is relatively stable and does not depend on the sample size. This explains the low dependency of the profit in a price menu setting with one price level from the demand knowledge (see Figure 4.15). Since the highest price does not require any flexibility from the customer it addresses the biggest proportion of the customers. Therefore, one sample already serves enough data to get a good estimate on the whole population's willingness-to-pay irrespective of the flexibility potential.

In contrast, the lowest price represents the price level that elicits most flexibility from the customers. Therefore, only a small proportion of the customers qualify for

[15]The price menu setting with one price level is left out for that analysis.

[16]To recall this natural limitation: With a demand knowledge of 1% 100 samples can be drawn while, e.g., with a demand knowledge of 5% only 20 samples can be drawn. The number of simulation runs therefore differ.

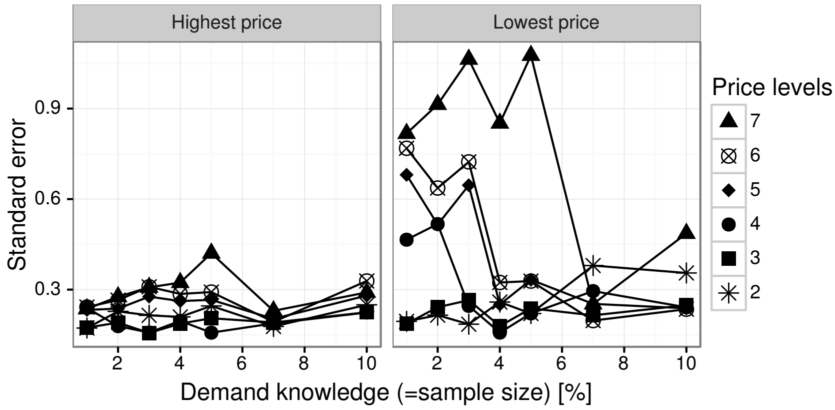

Figure 4.17: Standard error of the highest and lowest price of multi-price-level menues due to different demand knowledge settings.

this price level yielding a higher variability, at least for price menus with four or more price levels. The higher the number of price levels, the more demand knowledge is needed to reduce the variability of the lowest price of a price menu to a satisfying level. This is in line with the findings from Figure 4.15. An artifact that can be seen in Figure 4.17 are increasing standard errors with increasing demand knowledge in case of six or seven price levels up to a demand knowledge of 3%. As already mentioned there are situations where the maximum allowed number of price levels are not used because no customers exist in the employed training samples that could be further addressed by price incentives. In this case, the customers that are not already addressed by higher price levels have either a too low parking duration or willingness to pay, or they simply do not matter in relation to the preset optimality gap. Therefore, the variability first increases until a specific demand knowledge level at which all runs contain enough information so that setting the lowest price becomes a relevant decision variable for the sake of optimization.

4.5 Mitigating Renewable Energy Generation Uncertainty

As introduced earlier, EVs have the ability to make individual mobility sustainable. In order to leverage this potential, the electricity for EV charging needs to be provided by RES. The utilization of RES, e.g. wind power for charging can reduce lifetime carbon emissions of EVs by more than 75% compared to conventional vehicles (Helms et al., 2010). However, the volatility of this energy source poses several challenges.

As shown in the last section, through deadline differentiated pricing a car park operator can shape his load curve from EV chargings to follow a volatile supply pattern with the help of coordinating information systems. Another challenge that has not yet been addressed in this work is the difficulty to forecast the local generation curve of RES. In this work's application scenario this information is needed to determine suitable prices since the served demand should align with the quantity of costless, locally produced PV electricity. In case of a deadline differentiated pricing scheme not only the quantity but also the type of pattern of the generation curve influences the price determination, e.g., the minimum needed flexibility. To this end, this section investigates the following questions given the EV car park scenario comparing an instantiation of the deadline differentiated pricing scheme approach with a simple pricing approach:

- How sensitive is the company profit regarding PV generation forecast errors?
- Which share of EV charging demand is satisfied by PV energy in profit optimal scenarios?

After presenting the case study in Section 4.5.1 highlighting deviations from the base case (see Section 4.3) the above questions are evaluated in Section 4.5.2.

4.5.1 Case Study Description

Since the focus of this work is on the effects of forecast errors of PV generation, energy η^p generated by local PV installations is chosen to be the only stochastic variable. Figure 4.18 depicts the links between the two stages of this instantiation of the stochastic problem presented in Section 4.2. The price menu, decision variable of the first stage, is independent of specific realizations of the PV generation. The car park operator sets a price menu p based on a belief of possible realizations for the PV generation. Decision variables of the second stage — scheduling of jobs λ and purchasing missing energy η^g from the grid — are recourse variables, meaning that they are decided after the realization of the stochastic variable η^p is revealed.

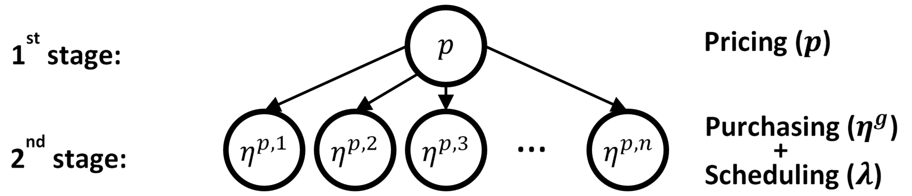

Figure 4.18: Deadline differentiated pricing as a two-stage stochastic problem.

For the analysis real-world meteorological data from the complete year 2013 is employed. Measured data from an exemplary PV panel located in the South West of Germany is used to represent each supply realization of the 365 days of the year 2013. The transmission system operator responsible for this region, Transnet BW (Schierenbeck et al., 2010), provides the corresponding forecast. This single forecast is assumed to represent the whole range of supply realizations of a day. Therefore, the car park operator determines the first stage decision variables based on the belief that this single forecast will be realized. The employed forecast data provides a general trend for the expected PV generation in the region but does not reflect local fluctuations in the availability of solar irradiation (see Figure 4.19). The car park's rooftop could accommodate PV panels of up to 250 kWp which could exceed the energy demand of 100 EV customers per day. Thus, scenarios with 20, 50, 100, 150, and 200 kWp are investigated.

Deviating from the base case scenario perfect knowledge of demand is assumed in this case study since the interest is focused on the effect of forecast errors regarding PV generation. Still, each day of the year is assigned a randomly chosen customer data realization from the training data set in order to balance any possible customer data effects.

Considering that customers have limited time to decide which price and shift duration to choose, the number of allowed price levels in a deadline differentiated price menu is limited. Obviously, this lowers profits for the car park operator, as customers will only offer the duration required to qualify for a cheaper price level. While this imposes a constraint on operator profits, its effects are minor. The simulation results in Section 4.4.3 have shown that allowing the car park operator to set four different price levels yields almost optimal profits. The minimum extent of a price jump Δ_{min} is set to 0.1 ct/kWh to account for a realistic setting for the awareness of price

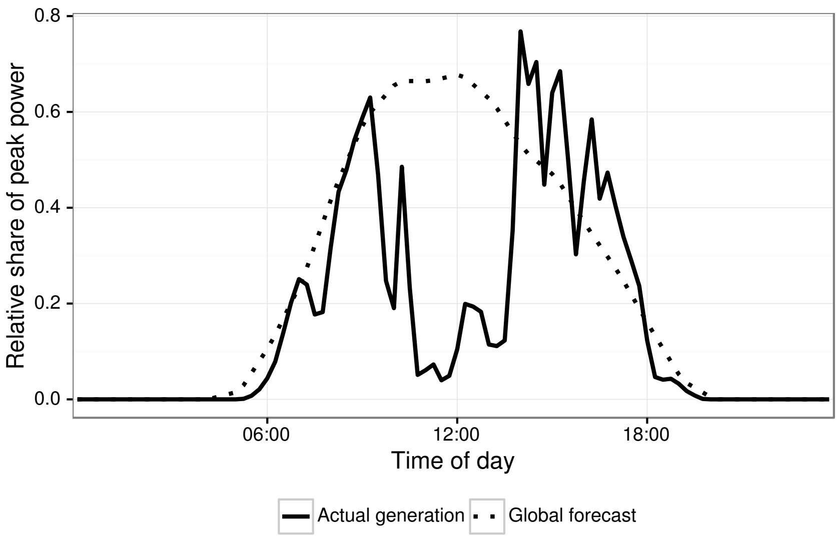

Figure 4.19: PV generation forecast and realization of an exemplary day in summer 2013.

differences. Hereafter, this instantiation is called DDP. As a benchmark scenario, a simple pricing approach is chosen that induces "as fast as possible" charging by omitting price incentives for job shifting. This is based on the current practice where fixed and mostly linear tariffs are employed for EV charging.

Besides the aforementioned deviations, all other parameters from the base case scenario presented in Section 4.3 hold.

4.5.2 Evaluating the Impact of RES Uncertainty

This section investigates to what extent the operator profit is affected by forecast errors of PV generation in DDP and simple pricing regimes. In addition, the impact of different generation capacities on profit and the ability to utilize local PV to satisfy EV charging demand is evaluated. For sake of statistical reliability, every day of the year 2013 is simulated and the resulting profits are compared. Since PV generation and customer data do differ from day to day, profits are normalized with a best case benchmark, which is DDP assuming perfect knowledge of the PV generation.

Operator Profit In the following, the effect of forecast errors and PV generation capacities on the operator profit is evaluated. Forecast errors are assessed by the dynamic time warping (DTW) distance (Berndt and Clifford, 1994). This error

Table 4.2: Comparison of the profit loss in different scenarios with the perfect knowledge benchmark.

	Photovoltaic peak power (kWp)				
Scenario	**20**	**50**	**100**	**150**	**200**
DDP	0.04%	1.09%	3.73%	4.15%	3.88%
Simple Pricing	7.85%	11.59%	15.08%	15.61%	15.77%

measure allows the comparison of time series while accounting for simple differences as time lags. In contrast to other common measures such as the mean absolute percentage error, DTW allows to better assess the relative similarity of compared time series. Applying other metrics (e.g. Euclidian distance) the reported relation is still consistent.

The results show that DDP reduces the profits losses from inaccurate PV forecasts in all investigated scenarios by at least 8% in relation to the simple pricing approach that does not elicit the customer's demand side flexibility (see Table 4.2). Excluding the 20 kWp case, that is later shown to be a too pessimistic capacity planning, the profit losses in the simple pricing approach are more than 4 times higher than DDP on average. Figure 4.20 shows the comparison between DDP and simple pricing and the resulting loss relative to the overall benchmark profit per day for all investigated scenarios. One dot represents the total profit loss generated in the respective pricing regime for one day. The plot thus allows an assessment of how well the applied pricing regime exploits the available demand flexibility of served EV customers. On the x-axis, the forecast error of that simulated day, expressed by the DTW distance, is depicted.

Both pricing regimes degrade in their performance in the forecast error. The highest sensitivity regarding the forecast error is observed at a capacity of 100 kWp expressed by the slope of the trend line. At this capacity, a substantial part of the available EV charging demand can be covered in an efficient manner. At further capacity increases forecast errors do not affect the profit loss as much since PV energy is generated in excess on many days. This is in line with the findings in Section 4.4.1, where the highest discounts are offered at 100 kWp signaling a good

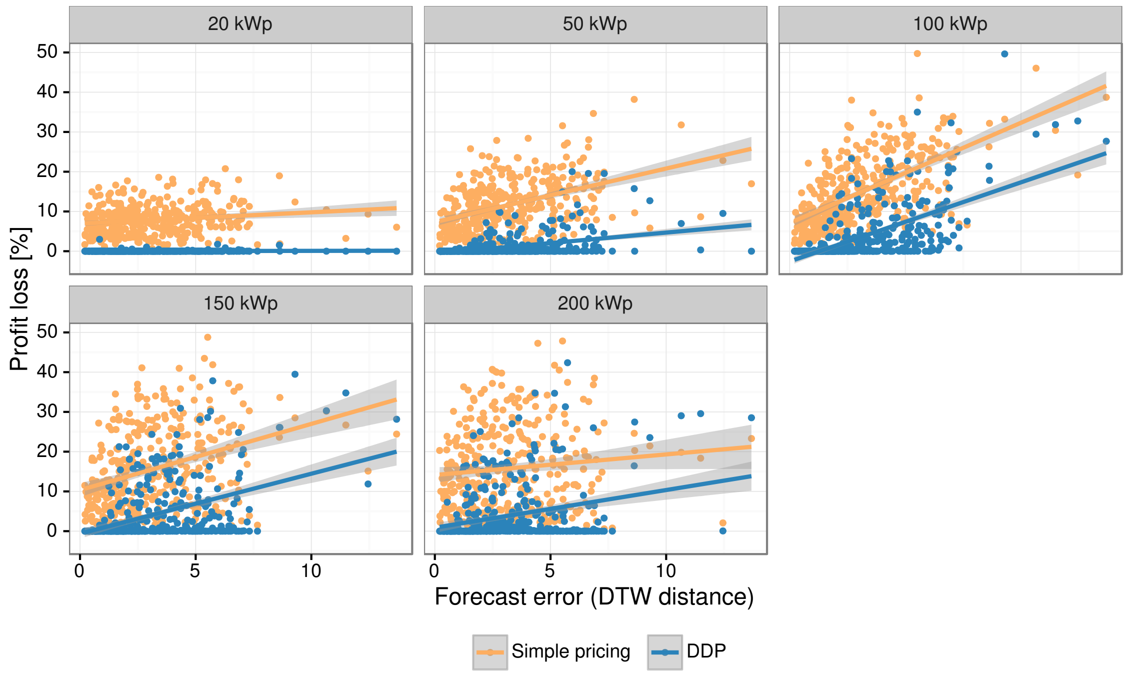

Figure 4.20: Effect of forecast errors on optimal profits per day in different scenarios. Shaded area represents the standard error of the linear trend in the respective pricing regime.

demand-supply-balance. Similarly, for smaller capacities, energy demand exceeds PV generation which leads to low forecast error effects. In the 20 and 50 kWp scenarios, simple pricing is more sensitive to forecast errors than DDP, which is surprising since setting prices with DDP generally requires more information. Simple pricing is mainly interested in the overall produced amount of energy to know how many customers to serve and therefore what price to set. In contrast, DDP additionally needs to know what length of flexibility is needed to bridge generation gaps. The ability of DDP to react to forecast errors by rescheduling loads apparently outweighs this.

With increasing PV capacity this advantage diminishes. Job shifting becomes less important since the PV generation exceeds energy demand on many days. At 200 kWp simple pricing appears to be less dependent on forecast errors than DDP, but this effect is not statistically supported.

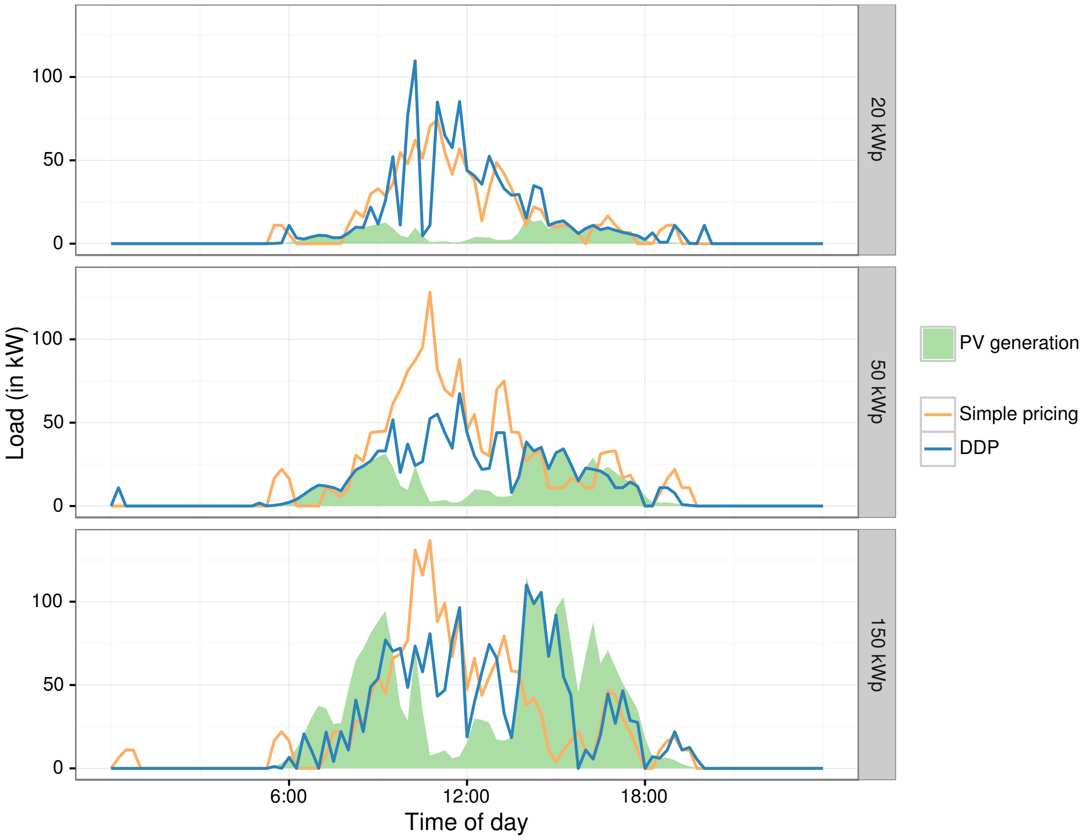

Figure 4.21: Load curves on the example day in summer in different generation scenarios.

Load Shape Characteristics The effect of different pricing regimes on the load shape of the EV chargings in a car park is depicted in Figure 4.21. One can observe that simple pricing leads to similar, non-responsive load shapes that are mainly driven by the arrival time at the car park (see Figure 4.5). Differences in the load shape in the same pricing regime are due to the differing number of customers served in every scenario and to slight deviations in the resulting schedule that is determined by the optimization procedure.

At 20 kWp (79 kWh electricity from PV generated on this day) both DDP and simple pricing lead to a quite similar load pattern and met demand (307 kWh at DDP vs. 296 kWh at simple pricing). The only difference is the slight shifting of the EV charging load from the generation minimum on midday to the two generation shoulders. For higher capacities, this phenomenon is more accentuated.

For 50 kWp (198 kWh electricity from PV generated on this day), the peak in the

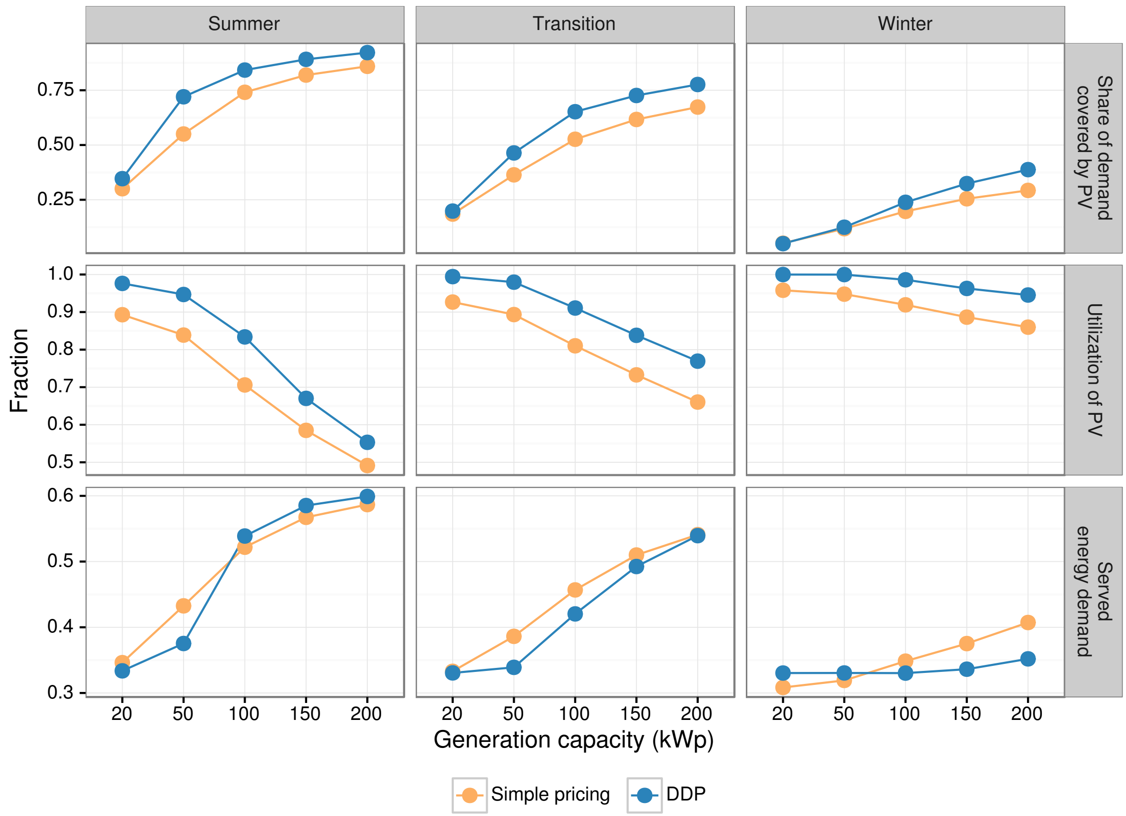

Figure 4.22: Season type differentiated overview of generation scenarios depicted regarding the share of EV charging demand covered by PV, share of utilized energy, and share of served energy demand.

low generation times is reduced by DDP resulting in lower served demand (320 kWh at DDP vs. 474 kWh at simple pricing). In the 150 kWp case (594 kWh electricity from PV generated on this day), DDP clearly shifts EV charging load from the initial arrival time to the afternoon hours where PV generation is more abundant while similarly meeting demand (557 kWh at DDP vs. 550 kWh at simple pricing). The resemblance in the morning hours with the load shape induced by simple pricing can be explained by constrained customers that do not offer enough flexibility to make use of the second generation maximum and are thus served directly at the beginning of their stay.

Renewable Energy Utilization The scenarios investigated differ in their ability to effectively utilize the available renewable energy. Figure 4.22 shows the results with respect to share of EV charging demand covered by PV generation, the relative utilization of the generated electricity, and the energy demand share that is being served overall. The results are faceted with respect to different seasons of a year that range from summer days with the highest generation over transition days that can have high energy production but also an increased variation in their generation pattern up to winter days that exhibit an overall low availability of PV energy. It can be observed, that DDP increases the share of EV charging demand that is covered by PV in every scenario. DDP has the highest improvement potential on summer days in the 50 kWp scenario where it increases the EV charging demand share served by RES by 30%. The overall utilized share of PV energy decreases in generation capacity. DDP always has a higher RES utilization rate than simple pricing due to the possibility to shift jobs to times of high RES generation. In most scenarios, simple pricing serves a higher share of customers at the expense of procuring energy from the grid which reduces the potential profit and sustainability gain respectively. DDP, in turn, can accommodate more customers only when considerable amounts of PV energy are available.

4.6 Exploring the Impact of Electric Vehicle Customer Diversity

In order to harness the flexibility potential of EV charging loads, it is necessary to understand how to influence the charging behavior of EV users. EV charging in car parks with integrated PV generation will constitute new substantial load clusters in the near future. These car parks will be frequented by heterogeneous EV customers who have varying requirements for their energy demand, but also an individual economic valuation to cover this demand. This heterogeneity can be addressed by price incentives, e.g., offered through the investigated deadline differentiated pricing scheme. Furthermore, understanding the habits and the economic behavior of EV owners facilitates to optimize the utilization of local fluctuating renewable energy generators like PV systems. In particular, the limiting assumption regarding the customer valuation introduced in Section 4.3.1 is relaxed, allowing to analyze the impact of different economic valuation models. Additionally, different levels of timely flexibility, expressed by the parking duration in the car park are considered. To contribute to the existing body of work this section presents answers to the following question regarding the EV car park case under a deadline differentiated pricing scheme:

- What is the quantified effect of different utility diversity models on the company profit?
- What is the quantified effect of different car park types expressed through deviating parking durations on the company profit?

After presenting the case study in Section 4.6.1 highlighting deviations from the base case scenario (see Section 4.3) the above questions are evaluated in Section 4.6.2.

4.6.1 Case Study Description

Recapping Section 4.3.1, the utility function of EV owners is determined by their outside option to EV charging in a car park. As noted in Section 4.2.2 the cost of the outside option directly affects the customer's decision to charge at the car park given a specific price menu. EV owners will consider charging at home as their outside option as they most probably have a home charging station. Tapping into the concept of heterogeneity each customer outside option is sampled from a normal distribution fitted to the home electricity rate in the aforementioned base case scenario. Since structural influences of the customer's outside option are investigated in this section, several statistical distributions to model the diversity of customers' charging cost at home are chosen. Besides considering a homogeneous modeling (each customer has a valuation of 35 ct/kWh), heterogeneous customer bases are modeled based on a uniform and a normal distribution both with the parameters $\mu = 35$ ct/kWh and $\sigma = 5$ ct/kWh as shown in Fig. 4.23.

Additionally, the influence of different parameter specifications within the heterogeneous models is investigated. To this end, additional customer sets are generated by varying the standard deviation in the normal distribution and the uniform distribution of the outside option from $\sigma = 1$ to $\sigma = 20$ ct/kWh.

The customer data is complemented by time specifications regarding the stay at the car park and energy demands. Both, the arrival times and energy demands are

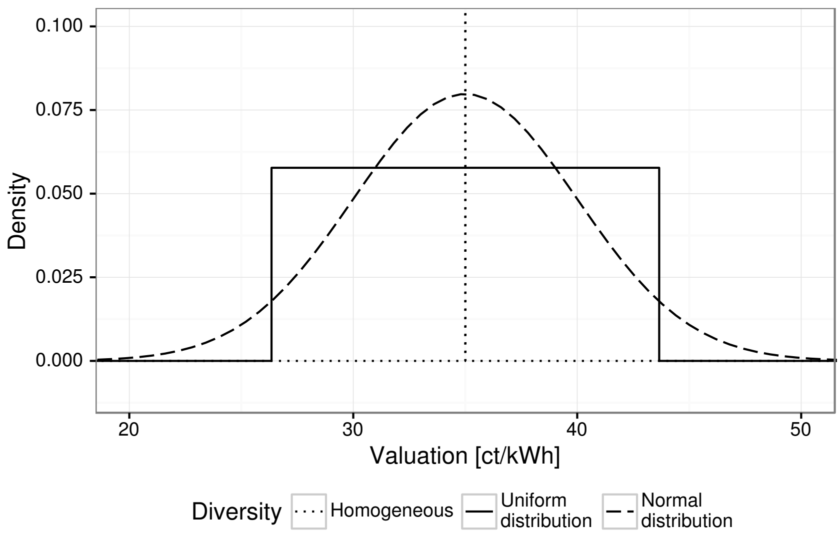

Figure 4.23: Distribution scenarios of customers' outside option for EV charging.

derived from the German mobility panel (Zumkeller et al., 2011) to gain a realistic behavior. The parking duration is the most important parameter regarding flexibility potential. Thus, it is parameterized with car park data from a major city in Southern Germany in the base case scenario. This specific car park is mainly used to park a car for a mix of shopping, working, and private activities yielding an average parking duration of 3.5 hours.

This scenario is compared to two other typical car park type models in terms of the parking duration parameter: Boltze et al. (1994) studied the parking behavior in Frankfurt where more than 85% of the customers use car parks for shopping and private activities. The average parking duration amounts to only 2.5 hours while approximately 20% of customers stay more than 1 hour and only 10% stay more than 5 hours in a car park. This parking behavior can be described by a Weibull distribution ($\lambda = 0.3571$ and $k = 1.5$)[17].

In contrast, a study of a car park at Ohio State University mainly used by its employees discovered three typical parking habits (Tulpule et al., 2013): Either employees park the whole work day which results in a parking range of approximately 8 hours or they leave for lunch resulting in two stays per day each lasting approximately 4 hours. Both habits are modeled as normal distributions with a standard

[17] The cumulative Weibull distribution function is $F(x) = 1 - e^{(-x/\lambda)^k}$.

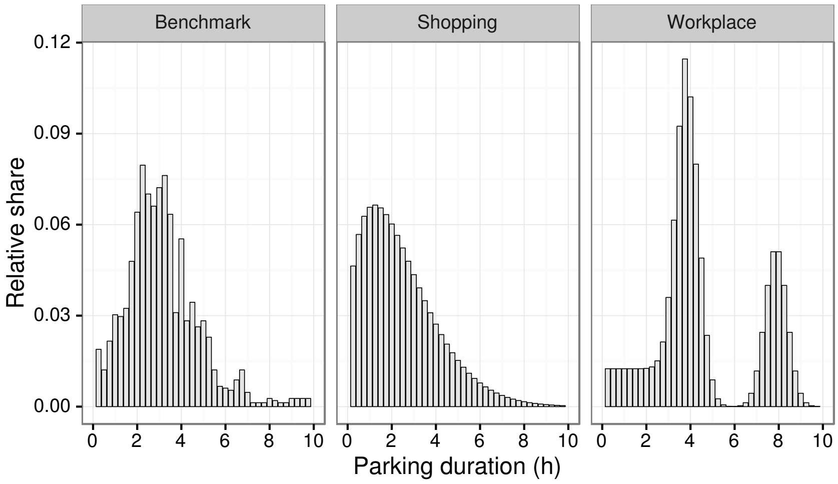

Figure 4.24: Parking duration distributions of the different car park types.

deviation of 0.5 hours. The remaining stays are uniformly distributed between 0 and 4 hours possibly being explained by stays of visitors. The parking duration distributions of the three aforementioned car park types are depicted in Fig. 4.24.

To span the potential car park type impact two artificial scenarios are added: The first one assumes that each stay lasts just as long as needed to serve the requested energy demand and the second assumes that each stay lasts until the end of the simulation day aiming for no flexibility and maximum flexibility respectively.

Since the focus of this section is on analyzing the general effects of customer diversity on deadline differentiated prices and the car park operator profit it is assumed that he has perfect knowledge of demand and his PV production. The results nevertheless allow important insights into reality as Sections 4.4.2 and 4.5 have shown that the deadline differentiated pricing concept delivers robust results with respect to the aforementioned factors under uncertainty. For reasons of statistical relevancy, each scenario is repeated 100 times with randomly drawn values.

In accordance with the last section, the number of allowed price levels is limited to four and the minimum price jump Δ_{min} is set to 0.1 ct/kWh. From the generation scenarios depicted in Figure 4.7 the “unsettled” scenario is chosen to instantiate η_t^p. The PV capacity on the car parks rooftop is assumed to have a peak power of 100 kWp which has proven to be a good balance between demand and supply in terms of provided energy over the whole year. The remaining unmentioned parameters

Table 4.3: Mean profits per day and respective 95% confidence intervals under different customer utility diversity models ($\mu = 35$ ct/kWh) and non-homogeneous scenarios ($\sigma = 5$ ct/kWh).

	Profit per day (EUR)		
Scenario	**Mean**	$\mathbf{CI}_{2.5\%}$	$\mathbf{CI}_{97.5\%}$
Homogeneous	157.38	156.72	158.05
Uniform distribution	133.56	132.38	134.73
Normal distribution	133.98	132.97	135.00

remain as presented in the base case scenario.

4.6.2 Evaluating Customer Diversity Models

Table 4.3 shows that there are substantial differences between the homogeneous and heterogeneous modeling of the outside option diversity. In the homogeneous scenario, the car park operator has an easy to solve situation: He can either set a price slightly below the valuation level inducing all customers to charge their EV in the car park and additionally offer minimum discounts for the allowance of load shifting. Or he can set prices above the homogeneous valuation and only pick flexible customers through setting the discounted prices slightly below the valuation level.

In the heterogeneous scenario setting the price to the mean (35 ct/kWh) would result in loosing approximately half of the customers. Therefore the car park operator needs to decide whether it is more profitable to meet the mass demand or to focus on the high-value customers at the expense of either margins or sales volume respectively. This implies that the — especially in macroeconomics — widely accepted homogeneous modeling of customer utilities is inaccurate for such an analysis. The significant influence shows that it is inevitable to precisely model the diversity of customer outside options in order to achieve meaningful and accurate results. Regarding the different investigated types of distribution for heterogeneous modeling, no significant differences can be identified if controlled for mean and standard deviation. This holds for other typical symmetric distribution types.

Analyzing different heterogeneous distribution parameterizations, dependencies

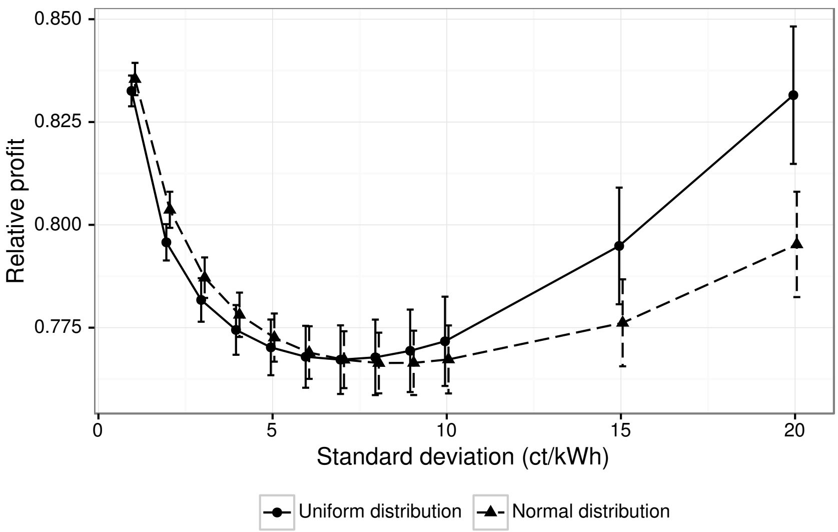

Figure 4.25: Intradistributional analysis of customer utility diversity with $\mu = 35$ ct/kWh and varying σ. Profits are normalized to the maximum profit of all runs.

between the extent of heterogeneity and the outcomes can be identified. Fig. 4.25 shows the results of the intradistributional analysis. The simulation outcomes highly depend on the distribution spread (standard deviation) in both heterogeneous utility diversity models. This implies that besides using a heterogeneous model it is crucial to accurately model the customer base in order to obtain precise results.

Interestingly, the effect of the distribution spread is non-linear. While the company benefits from a customer base with a low utility diversity spread approximating the homogeneous case because it is easier to allocate the mass, the company as well benefits from a very heterogeneous customer base. This can be explained best by recalling Fig. 4.23: The more widespread the distribution, the higher the amount of customers that have a valuation far above the cost level for the energy mix of the car park. When this ratio of customers exceeds a specific threshold of approximately 7 ct/kWh, the company benefits from heterogeneity in a polynomial function by switching the aforementioned strategies of margins and sales volume.

Additionally, in high-heterogeneous settings the investigated heterogeneous utility diversity models substantially differ in terms of the relative company profit, showing a higher outcome for the uniform distribution. A reason for that behavior is the characteristic difference between these distribution types. While the normal distri-

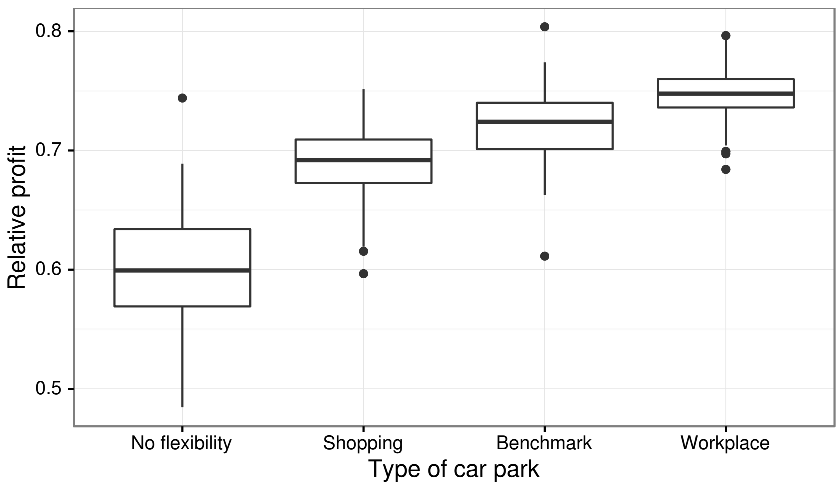

Figure 4.26: Car park type analysis regarding the parking duration. Profits are normalized to the median profit of the maximum flexibility scenario.

bution has a strong unimodal character and therefore still has big mass in the area around $\mu = 35$ ct/kWh even for high values of σ, the uniform distribution possesses a higher ratio of customers in high price regions. Therefore the car park operator is in the position to set high prices while serving more customers than in the normal distribution case.

Focusing on the other parameter variation, Fig. 4.26 highlights the effect of different car park types which highly affects the characteristic parking duration. In median, the potential of flexibility exploited by deadline differentiated prices amounts to approximately 40% in profit if comparing the two most extreme scenarios of no flexibility and full flexibility. Since longer time frames result in more freedom for the operator to allocate fluctuating PV energy to charging jobs, the amount of conventional energy acquisition and therefore respective costs for the energy mix of the car park decrease. This is the reason why profits positively correlate with higher flexibility.

Furthermore, the results show that all non-artificial car park scenarios significantly differ from the bottom line of having no flexibility respectively offering no pricing scheme that elicits flexibility. The ranking of profits earned between the car park types is in line with the parking durations depicted in Figure 4.24. Since these differences are substantial, car park operators should be aware of using suitable data when evaluating a demand side management approach for EV charging and invest considerable resources in EV customer modeling and insight.

4.7 Discussion

Electric vehicle charging is considered a prime case of load flexibility in future smart grids being a large, but also a quite flexible load. With the expected increasing market penetration of electric vehicles, car parks will constitute major future load clusters. In order to enable a sustainable individual mobility, electricity for charging of electric vehicles needs to be provided by renewable energy sources. Considering economic efficiency, the electricity should be generated locally to impede costs for grid expansions. To this end, charging requests from electric vehicles need to be coordinated according to local grid and supply conditions. Temporal charging flexibility can be leveraged to increase utilization of local generation. Price incentives are one major mechanism to achieve this goal.

This chapter examines a scenario where electric vehicles are charged in a city car park with local photovoltaic generation. A deadline differentiated pricing approach is employed to create incentives for electric vehicles customers to offer their load flexibility to the car park operator. Prices are set by the car park operator in a profit-maximizing manner considering both his free of cost electricity from photovoltaic generators and additionally purchased electricity from the grid. Simulations are conducted based on the formulation of a stochastic mixed-integer optimization problem and empirical mobility and generation data. The results of the analysis on the value of flexibility show that using a deadline differentiated pricing approach increases profits by up to 30% on average comparing it with a simple pricing approach. In most cases, the value of complexity outperforms the value of information. However, being confronted with a price menu with various options could be too time-consuming, e.g., in a setting where a car enters a car park. Reducing the number of price levels to four, still, allows exploiting most of the flexibility potential in the analyzed simulation setting.

Forecast errors regarding energy generation from photovoltaic sources are common but can be addressed by the temporal flexibility of electric vehicle charging. It is shown that deadline differentiated pricing is resilient to inaccurate forecasts for photovoltaic energy generation. Profit losses due to forecast errors are four times higher in a simple pricing approach compared to deadline differentiated prices. Additionally, deadline differentiated pricing increases the share of charging demand covered by renewable energy by up to 30%.

For an effective grid integration, it is necessary to understand how to influence the charging behavior of EV customers. The car park operator might set price menus — besides incentivizing customers to reveal their flexibility — to divide customers into low- and high-value customer segments to better skim margins using the diversity of customer flexibility. It is shown that customer segmentation plays a tangential role compared to the load flexibility potential, especially in a realistic setting with imperfect knowledge. Regarding modeling EV customers, e.g., for the reason of an ex-ante profit estimation, there are diverse ways including homogeneous and diverse heterogeneous models. Therefore, the effect of different utility diversity models and car park types on EV charging in a car park is analyzed. The results indicate that a homogeneous customer utility model overestimates the car park operator profits by more than 17% as compared to a realistic heterogeneous model. Different types of symmetric heterogeneous customer utility models do not significantly differ from each other in all but extreme parameter settings. Besides, it can be observed that the car park type, and thus the customer parking duration drives the attained profits. Therefore car park operators should be aware of using suitable data when evaluating price models and invest considerable resources in EV customer modeling and insight.

Further work should investigate sensitivity analyses and imperfect knowledge of other parameters depicted in Figure 4.8 regarding the potential profit of the car park operator. Especially increasing the EV penetration scenario with up to 100% EV shares and assessing the resulting flexibility potential would be of great interest to investigate the long-term vision of a sustainable individual mobility. Besides, the customer acceptance of the studied type of pricing regime should be explored to validate the parameterization (e.g. Dütschke and Paetz, 2013).

The presented model focuses on the operational level of EV charging. Future work could focus on the strategic level and consider the investment costs for PV generators as a decision variable in the optimization. This would implicate increasing the model complexity by adding a pre-stage for the investment decision yielding a multi-stage stochastic problem. Since this would most probably be computationally too expensive the presented simulation model could serve as a basis to understand the customer behavior and model it by parameters for a strategic simulation.

The presented model abstracts from the energy market by assuming that supply consists of local photovoltaic generation and an unlimited but costly conventional supply from the grid. This modeling has a good fit for the short-term but could be obsolete for an energy system approximating a 100% RES share. It is still an open discussion whether renewables should be integrated on a local level constituting local markets or assuming a giant copper plate one global market for an interconnected power grid (e.g., Lund and Münster, 2006). To be more precise the aggregator could purchase electricity from an explicit model representation of a market capturing the effect on market prices. A model that addresses these issues is developed and presented in Chapter 5.

Recalling the morphological box from Chapter 3 there are different ideas how to further develop the deadline differentiated pricing scheme. The presented scheme "only" addresses the temporal flexibility. Since electric vehicles have batteries they can also offer a form of quantity flexibility. One could think of a situation where a customer does not urgently need a full battery but instead a specific state of charge for the next trip. This would open up the solution space for the car park operator by adding the option of load shedding while still considering the current challenge of EV range anxiety. Other extensions could address a differentiation on the job duration (e.g., Negrete-Pincetic et al., 2016) or limited reliability for a charging request (e.g., Siddiqi and Baughman, 1993).

Chapter 5

Market Transaction Objects on Wholesale Markets

ALL over the world, motivated by environmental, political and economic reasons, large shares of RES are being integrated into energy systems. This trend is expected to continue, as many countries have set ambitious goals of 80% or more of their electricity to be produced by RES by 2050 (Notenboom et al., 2012). As extensively reported in the literature, the integration of RES poses several challenges to the operation, planning, and markets of power and energy systems (Perez-Arriaga et al., 2012; Bird et al., 2013). Many of these challenges are related to the inherent volatility and uncertainty of some RES (e.g., wind and solar energy), which require adequate levels of flexibility to handle sudden changes in power generation (Lannoye et al., 2012).[1]

Historically, this flexibility has been provided by conventional generation units, such as pumped hydro storage plants, or gas-fired power plants; however, for large shares of RES, relying only on the supply side flexibility would require a large number of backup units, which is both economically inefficient and could hinder the environmental benefits of using RES (Cochran et al., 2014). In this setting, exploiting the demand as an additional source of flexibility through DR mechanisms becomes an appealing alternative to facilitate the efficient integration of large shares of RES (IEA, 2014).

This chapter studies the impact of consumer preferences on both the portfolio and

[1]Please note that this chapter builds on a paper that is currently under review at the IEEE Transactions on Smart Grid (Salah et al., 2017).

surplus of a DR aggregator. Elements of the satisficing theory are used in order to model consumer behavior in a tractable way. Hence, consumer preferences are incorporated into electricity markets models, facilitating the design of DR programs and incentive schemes. A model to determine the incentives offered by an aggregator to consumers for joining different DR contracts is proposed. The aggregator participates in both day-ahead and real-time markets with the objective of maximizing its operational surplus.

In specific, the main contributions of this chapter include:

- Modeling of consumers in electricity markets using elements of the satisficing theory as an alternative to welfare maximizing consumers.
- Three-stage electricity market model encompassing interactions between consumers and aggregators for calculating premiums for the participation of consumers as DR providers.
- Several numerical simulations which quantify the value of flexibility and the impacts of modeling consumers' preferences on DR programs.

The remainder of this chapter is organized as follows. The next section is further evaluating existing work in the area of modeling DR aggregators and consumer preferences. Section 5.2 presents the model structure and mathematical formulation of this work. Section 5.3.1 details the scenario setup and data used. Section 5.3.2 presents and discusses several case studies with numerical results. Finally, conclusions are depicted in Section 5.4.

5.1 Related Work

This section revisits existing aggregation concepts for demand response. Furthermore, possible options to represent consumer preferences are presented with respect to their applicability and reality approximation.

5.1.1 Demand Response Schemes and Aggregators

Several works explore different dimensions of DR from the perspective of the system operator, aggregators, and consumers. Vardakas et al. (2015) and Deng et al. (2015)

present detailed surveys of DR in which different problems of DR are studied. These surveys detail how to model different DR problems, what type of mathematical problem and which approaches can be used to solve them. In the context of a DR aggregator and its interaction with wholesale markets and consumers, different characteristics have been studied in recent papers. Nguyen and Le (2015) study a microgrid DR aggregator participating in wholesale markets. The aggregator serves energy to its customers using the grid and several distributed energy resources inside the microgrid. Also, a risk management scheme is used to control uncertainty.

Parvania et al. (2013) present a scheduling scheme for DR resources, based on day-ahead prices, whereas Parvania et al. (2014) directly include DR resources in the system operator's day-ahead scheduling problem. Henriquez et al. (2017) develop a bi-level optimization problem that analyzes the interaction between the aggregator and the system operator while considering a portfolio of DR contracts to modify the aggregator's load generated by its customers. These works study distinct aspects of a DR aggregator, however, the behavior of consumers is neglected since it is assumed that the DR resources are already available (i.e. the contracts are already signed).

Gkatzikis et al. (2013) present a three-level hierarchical DR scheme, in which the aggregator interacts with the system operator and its consumers in a non-cooperative pattern. The consumer objective is to maximize his surplus, considering a compensation received by the aggregator minus its incurred dissatisfaction for modifying his load. However, in this model, a disutility is considered in an aggregated way expressed as a deviation from a reference consumption, and not on an appliance level neglecting a key parameter for dissatisfaction.

5.1.2 Consumer Preferences

In addition to several technical challenges related to the implementation of DR schemes, e.g., control, communications, grid upgrades, there is a particularly challenging key issue of DR: Bringing user preferences into consideration. In order to address this issue, modeling how consumers make decisions when it comes to electricity consumption is a requirement.

In this regard, a large part of the available literature of DR focuses on modeling consumers behavior using the *homo-economicus* perspective: welfare maximizer agents with infinite abilities to perform rational decisions. However, there is extensive evidence in behavioral economics (Henrich et al., 2001; Frank, 1987; Kluver et al., 2014), psychology (Todd and Gigerenzer, 2003; Yamagishi et al., 2014) and biology (Fehr and Fischbacher, 2003) against this canonical assumption for consumer behavior.

An alternative way of modeling user behavior is the *satisficing* theory (Simon, 1955, 1956). According to this theory, users have bounded rationality for making decisions; thus, unlike the widely used perspective, satisficing consumers just choose options that satisfy a certain aspiration level. The applications of satisficing theory have spanned several disciplines including economics (Bansal and Maglaras, 2009; Bolton and Faure-Grimaud, 2010), decision making (Nakayama and Sawaragi, 1984; Stirling, 2003; Peng, 2013), industrial organization (Spiegler, 2011) and control problems (Goodrich et al., 1998; Ren et al., 2002; Binazadeh and Shafiei, 2013). To date, there are no explicit applications of satisficing theory elements to demand response problems.

5.2 Model Formulation

This section presents an optimization model to design the optimal portfolio of contracts of a DR aggregator. Table 5.1 provides an overview of the sets, variables, and parameters used in this model. The proposed model, illustrated in Figure 5.1, considers the interactions between players in three categories: the consumers, the DR aggregator, and the wholesale energy markets represented by the ISO. These interactions occur in 3 different stages: 1) a planning stage, 2) a day-ahead stage, and 3) a real-time market stage.

The aggregator-market interactions are characterized by the bidding of energy in the day-ahead market, and subsequent bidding of up- and down-regulation in the real-time market for the sake of profit maximization, while the market is cleared by the ISO on a minimum-cost basis.[2] This interaction, depicted on the right side of Figure 5.1, is modeled using the bi-level formulation proposed by Henriquez et al.

[2]Since the model presented in this chapter refers to the US energy market, the applied market structure and used terms might slightly deviate from illustrations in Section 2.2. Notwithstanding, the main idea is transferable to the German market.

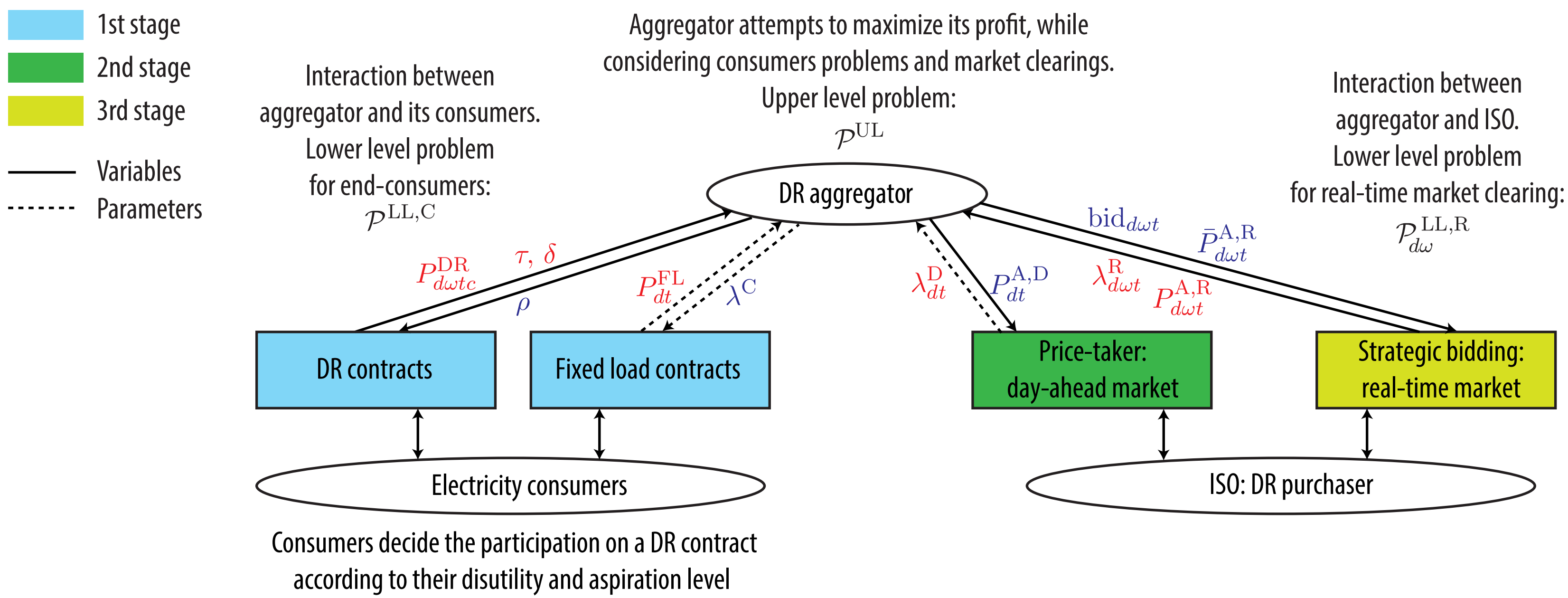

Figure 5.1: Structure of the interaction between the DR aggregator, the ISO and end-consumers.

(2017), which is described in detail in Subsection 5.2.1 and extended by modeling the aggregator-consumer interaction described next.

In the long term, the interaction between the aggregator and his consumers is characterized by the contracting of a supply option: Consumers either arbitrarily purchase energy at a fixed price per kWh, or they agree on a DR contract for a reward. The DR contract allows the aggregator to shift the consumers' loads in a limited time range. Consumers choose a supply contract based on the reward offered by the aggregator, their aspiration level, and their disutility function. The consumers' decision-making process yields an additional lower level problem, which is completely integrated into the aggregator's profit-maximization problem as a set of constraints using satisficing theory. This formulation is described in detail in Subsection 5.2.2.

In basic terms, the trade-off faced by the aggregator is as follows: The higher the premiums offered to consumers, the more consumers decide to participate in a DR scheme. At the same time, the bigger the portfolio of consumers of the DR aggregator, the more revenue it can obtain from its market participation. In this regard, the purpose of the model is to calculate the optimal premiums to be offered to consumers for their participation in different DR schemes, in order to maximize the total profits of the aggregator.

Table 5.1: Model decision variables, parameters, and sets

Decision variable		**Unit**	**Domain**
Premium for signing a DR contract	$\rho^{\mathrm{DR},\delta}$	\$/MWh	$\mathbb{R}_0^+$
Premium for permitting to dispatch by window τ	$\rho^{\mathrm{DR},\tau}$	\$/(MWh·τ)	$\mathbb{R}_0^+$
Consumer c's decision to sign an energy load contract	δ_c		binary
Permitted dispatch window of consumer c	τ_c		$\mathbb{N}_0$
Permitted dispatch window of consumer c, before original time slot	τ_c^{B}		$\mathbb{N}_0$
Permitted dispatch window of consumer c, after original time slot	τ_c^{A}		$\mathbb{N}_0$

Dispatch restriction variable for DR contracts	R_{tc}^{DR}		binary
Auxiliary dispatch variable (switch up) for non-preemption	S_{tc}^{U}		binary
Auxiliary dispatch variable (switch down) for non-preemption	S_{tc}^{D}		binary
Dispatch power variable for DR contracts	$P_{d\omega tc}^{\mathrm{DR}}$	MW	$\mathbb{R}_0^+$
Power purchased in the day-ahead market for the aggregator's resources	$P_{dt}^{\mathrm{A,D}}$	MW	$\mathbb{R}_0^+$
Up adjustment cleared in real-time market of generator g with respect to the day-ahead schedule	$P_{d\omega gt}^{\mathrm{U}}$	MW	$\mathbb{R}_0^+$
Down adjustment cleared in real-time market of generator g with respect to the day-ahead schedule	$P_{d\omega gt}^{\mathrm{D}}$	MW	$\mathbb{R}_0^+$
Real-time market price	$\lambda_{d\omega t}^{\mathrm{R}}$	\$/MW	$\mathbb{R}_0^+$
Maximum adjustment offered to the real-time auction by the aggregator	$\bar{P}_{d\omega t}^{\mathrm{A,R}}$	MW	$\mathbb{R}_0^+$
Adjustment clearance of aggregator resources at real-time stage	$P_{d\omega t}^{\mathrm{A,R}}$	MW	$\mathbb{R}_0^+$
Bid of the aggregator for offering additional production at the real-time stage (if $P_{d\omega t}^{\mathrm{A,R}}$ positive) or bid for repurchase at the real-time stage (if $P_{d\omega t}^{\mathrm{A,R}}$ negative)	$\mathrm{bid}_{d\omega t}$	\$/MW	$\mathbb{R}_0^+$

Parameter		**Unit**	**Domain**
Disutility of consumer c for permitting dispatch	$U_c^{\tau-}$	\$/(MWh$\cdot f(\tau)$)	$\mathbb{R}_0^+$
Aspiration level of consumer c including his disutility to sign an energy load contract	A_c	\$/MWh	$\mathbb{R}_0^+$
Time slot where consumer c's appliance should originally run	τ_c^{O}		$\mathbb{N}_0$

Earliest time slot where consumer c's appliance can start running	τ_c^{S}		$\mathbb{N}_0$
Latest time slot where consumer c's job should end	τ_c^{E}		$\mathbb{N}_0$
Total energy needed for the job of consumer c	TE_c	MWh	$\mathbb{R}_0^+$
End consumer price for energy	λ^{C}	\$/MWh	$\mathbb{R}_0^+$
Power demand from fixed load contracts	P_{dt}^{FL}	MWh	$\mathbb{R}_0^+$
Weight of day d	κ_d		$\mathbb{R}_0^+$
Day-ahead market price	$\lambda_{dt}^{\mathrm{D}}$	\$/MWh	$\mathbb{R}$
Available capacity for up-regulation of generator g offered at real-time stage	$\bar{P}_{dgt}^{\mathrm{U}}$	MW	$\mathbb{R}_0^+$
Available capacity for down-regulation of generator g offered at real-time stage	$\bar{P}_{dgt}^{\mathrm{D}}$	MW	$\mathbb{R}_0^+$
Price offer of generator g for up-regulation at real-time stage	c_{dgt}^{U}	\$/MW	$\mathbb{R}_0^+$
Price offer of generator g for down-regulation at real-time stage	c_{dgt}^{D}	\$/MW	$\mathbb{R}_0^+$
Weight of scenario ω in day d	$\gamma_{d\omega}$		$\mathbb{R}_0^+$
Net balance (actual net demand minus day-ahead forecasted net demand) at real-time stage	$P_{d\omega t}^{\mathrm{N}}$	MW	$\mathbb{R}_0^+$
Set			
Set of days $\{d_0, \ldots, d_j\}$	$d \in \mathcal{D}$		
Set of scenarios $\{\omega_0, \ldots, \omega_k\}$	$\omega \subseteq \mathcal{W}_d$		
Set of simulation time slots $\{t_0, ..., t_l\}$	$t \in \mathcal{T}$		
Set of consumers $\{c_0, ..., c_m\}$	$c \in \mathcal{C}$		
Set of generators $\{g_0, ..., g_n\}$	$g \in \mathcal{G}$		

5.2.1 Aggregator-Market Interaction

The DR aggregator must procure the energy needed to meet its consumers' demands (from both fixed-load contracts and DR contracts) by participating in two different energy markets: The day-ahead market and the real-time market. As discussed by Henriquez et al. (2017), DR aggregators can obtain profits from participating in these two markets by strategically bidding their consumption to buy energy during low-price hours, and sell their surplus during high-price hours. Such results rest on the assumption of the aggregator being a price taker entity in a large day-ahead market with high liquidity, and a price maker entity in the much smaller real-time market, where the aggregator is the only participant with shifting capabilities.[3]

In this work, a similar approach is used to model market interactions. Thus, the following results are subject to the same assumptions. As a price taker entity in the day-ahead market, the DR aggregator bids a desired quantity (energy) at a known market price. On the other hand, it can act strategically in the real-time market, bidding blocks of energy at different prices, where the competitors' bids are assumed to be known, and the cleared price and quantities are determined by a cost-minimizing ISO.

In order to consider the aforementioned characteristics, a bi-level optimization model is used in which the upper level (UL) represents the problem of profit maximization of the aggregator, while the lower level (LL) problem represents the real-time market clearing process performed by the ISO in a single-price auction setting. For the sake of simplicity, $\forall g$ means $\forall g \in \mathcal{G}$, $\forall t$ means $\forall t \in \mathcal{T}$, $\forall d$ means $\forall d \in \mathcal{D}$, and $\forall \omega$ means $\forall \omega \in \mathcal{W}_d$.

The Aggregator's UL Problem $\mathcal{P}^{\mathbf{UL}}$:

$$\max \sum_{d \in \mathcal{D}} \kappa_d \left\{ \sum_{\omega \in \mathcal{W}_d} \left[\gamma_{d\omega} \sum_{t \in \mathcal{T}} \left(\lambda^{\mathrm{D}}_{dt} P^{\mathrm{A,D}}_{dt} + \lambda^{\mathrm{R}}_{d\omega t} P^{\mathrm{A,R}}_{d\omega t} \right) \right] + \mathcal{R}(\rho^{\mathrm{DR},\tau}, \rho^{\mathrm{DR},\delta}) \right\} \tag{1a}$$

[3]This is the case, e.g., in Germany as illustrated in Section 2.2.2.

subject to:

$$P_{dt}^{\mathrm{A,D}} + P_{d\omega t}^{\mathrm{A,R}} = -(P_{dt}^{\mathrm{FL}} + \sum_{c\in\mathcal{C}} P_{d\omega tc}^{\mathrm{DR}}), \qquad \forall d, \forall \omega, \forall t \qquad \text{(1b)}$$

$$\delta_c, \tau_c \in \mathcal{K}(\rho^{DR,\delta}, \rho^{DR,\tau}) \qquad \textit{(consumer constraints)} \qquad \text{(1c)}$$

$$P_{dwtc}^{DR} \in \mathcal{S}(\delta_c, \tau_c) \qquad \textit{(scheduling constraints)} \qquad \text{(1d)}$$

$$\bar{P}_{d\omega t}^{\mathrm{A,R}} \geq 0, \qquad \forall \omega, \forall t \qquad \text{(1e)}$$

$$\lambda_{d\omega t}^{\mathrm{R}}, P_{d\omega t}^{\mathrm{A,R}} \in \arg\{\mathcal{P}_{d\omega}^{\mathrm{LL,R}}\}, \qquad \forall d, \forall \omega, \forall t \qquad \text{(1f)}$$

The decision variables of the DR aggregator are $P_{dt}^{\mathrm{A,D}}$, $\bar{P}_{d\omega t}^{\mathrm{A,R}}$, $\mathrm{bid}_{d\omega t}$ and $P_{d\omega tc}^{\mathrm{DR}}$. The UL objective function (1a) includes the expected surplus of the aggregator in the day-ahead and real-time markets and revenues generated by consumer contracts ($\mathcal{R}$), detailed in Section 5.2.2. Equation (1b) ensures that the load of the aggregator's consumers is supplied by the energy purchased in both markets. Consumer constraints (1c) and contract scheduling constraints (1d) are presented in detail in the following Sections 5.2.2 and 5.2.2. Equation (1e) enforces non-negativity of $\bar{P}_{d\omega t}^{\mathrm{A,R}}$, which represents a symmetrical offer in the real-time market. Finally, real-time prices and cleared quantities are the results of solving the ISO's LL problem (real-time market clearing), as represented by equation (1f).

The ISO's LL Problem $\mathcal{P}_{d\omega}^{\mathbf{LL,R}}$, $\forall d, \omega$:

$$\min \sum_{t\in\mathcal{T}} \left\{ \sum_{g\in\mathcal{G}} \left(c_{dgt}^{\mathrm{U}} P_{dgt}^{\mathrm{U}} - c_{dgt}^{\mathrm{D}} P_{dgt}^{\mathrm{D}} \right) + \mathrm{bid}_{d\omega t} P_{d\omega t}^{\mathrm{A,R}} \right\} \qquad \text{(2a)}$$

subject to:

$$\sum_{g\in\mathcal{G}} [P_{d\omega gt}^{\mathrm{U}} - P_{d\omega gt}^{\mathrm{D}}] + P_{d\omega t}^{\mathrm{A,R}} = P_{d\omega t}^{\mathrm{N}} \ : \ \lambda_{d\omega t}^{\mathrm{R}}, \qquad \forall t \qquad \text{(2b)}$$

$$0 \leq P_{d\omega gt}^{\mathrm{U}} \leq \bar{P}_{dgt}^{\mathrm{U}}, \qquad \forall g, \forall t \qquad \text{(2c)}$$

$$0 \leq P_{d\omega gt}^{\mathrm{D}} \leq \bar{P}_{dgt}^{\mathrm{D}}, \qquad \forall g, \forall t \qquad \text{(2d)}$$

$$-\bar{P}_{d\omega t}^{\mathrm{A,R}} \leq P_{d\omega t}^{\mathrm{A,R}} \leq \bar{P}_{d\omega t}^{\mathrm{A,R}}, \qquad \forall t \qquad \text{(2e)}$$

where P_{dgt}^{U}, P_{dgt}^{D} and $P_{d\omega t}^{\mathrm{A,R}}$ are the ISO's decision variables and $\lambda_{d\omega t}^{\mathrm{R}}$ is the real-time market clearing price. The LL objective function (2a) includes the total cost to set balance in the real-time market; that is, the cost of providing up- or down-regulation from available balancing generators and the DR aggregator. The cost of up-regulation will be positive since it represents the purchase of energy not cleared in the day-ahead market, whereas the cost of down-regulation is a negative value since it represents energy that is repurchased by the producers with respect to their cleared quantities in the day-ahead market. Equation (2b) represents the demand-supply balance, and equations (2c)-(2e) limit the output generation of each participant to its offered quantities.

The complete stochastic programs are provided in Appendix B. This bi-level formulation is recast as a single level problem using the Karush-Kuhn-Tucker optimality conditions of the LL problem in a similar way as presented by Henriquez et al. (2017).

5.2.2 Aggregator-Consumer Interaction

In the long-term, the DR aggregator and the consumers negotiate the terms of the DR contracts. By entering into a DR contract, consumers allow the aggregator to shift their load within a given time window and receive a two-part reward. It is assumed that the consumers' decision strategies follow the *satisficing theory*, introduced by Herbert A. Simon in 1956 (Simon, 1956). Thus, instead of maximizing a consumer's utility function, consumer decisions are determined by a welfare threshold, known as the aspiration level, which can be different from consumer to consumer. The idea behind this approach is that consumers normally lack either sufficient information or time to make welfare maximizing decisions, and therefore they are satisfied with any solution that yields a welfare exceeding their aspiration level.

Consumer Constraints

Equation (1c) of the aggregator's UL problem represents the set of constraints relating the premiums offered by the aggregator and the consumers' decisions. For welfare maximizing consumers, this would correspond to the optimality conditions of the consumers' problems; however, in the case of *satisficing consumers*, this is reduced to a set of linear constraints. For the sake of simplicity, $\forall c$ means $\forall c \in \mathcal{C}$ in the consumers' LL problems $\mathcal{P}_{d\omega}^{\mathrm{LL,C}}$.

The consumer's welfare is defined as the premiums minus the disutility introduced by the DR contracts. For a consumer to join the contract ($\delta_c = 1$), its welfare must be greater than or equal to a non-negative aspiration level A_c, as represented by equation (1c-a). The premium consists of two terms; the first term represents a premium for joining a DR contract, regardless of its characteristics, whereas the second term represents a premium proportional to the size of the time window (integer) in which the consumer allows the aggregator to shift its load. The aggregator is assumed to offer a premium proportional to the size of the window; however, the disutility of consumers increase nonlinearly with this size[4]. Note that Equation 1c-a is not a binding inequality for all consumers since premiums are determined once for all consumers. The set $\mathcal{K}(\rho^{DR,\delta}, \rho^{DR,\tau})$ is defined as:

$$\overbrace{\rho^{\mathrm{DR},\delta} \cdot \delta_c + \rho^{\mathrm{DR},\tau} \cdot \tau_c}^{\text{premium for consumer c}} - \overbrace{f(\tau_c) \cdot U_c^{\tau-}}^{\text{disutility of c}} \geq \delta_c \cdot A_c, \qquad \forall c \qquad \text{(1c-a)}$$

$$\sum_{t=0}^{\tau_c^{\mathrm{S}}-1} R_{d\omega tc}^{\mathrm{DR}} = 0, \qquad \forall d, \forall \omega, \forall c \qquad \text{(1c-b)}$$

$$\sum_{t=\tau_c^{\mathrm{E}}+1}^{t_l} R_{d\omega tc}^{\mathrm{DR}} = 0, \qquad \forall d, \forall \omega, \forall c \qquad \text{(1c-c)}$$

$$\tau_c^{\mathrm{B}} \leq M \cdot \delta_c, \qquad \forall c \qquad \text{(1c-d)}$$

$$\tau_c^{\mathrm{A}} \leq M \cdot \delta_c, \qquad \forall c \qquad \text{(1c-e)}$$

$$\tau_c^{\mathrm{B}} \leq \tau_c^{\mathrm{O}} - \tau_c^{\mathrm{S}}, \qquad \forall c \qquad \text{(1c-f)}$$

$$\tau_c^{\mathrm{A}} \leq \tau_c^{\mathrm{E}} - \tau_c^{\mathrm{O}}, \qquad \forall c \qquad \text{(1c-g)}$$

$$\tau_c \geq \tau_c^{\mathrm{B}} + \tau_c^{\mathrm{A}}, \qquad \forall c \qquad \text{(1c-h)}$$

$$\delta_c, R_{d\omega tc}^{\mathrm{DR}} \in \{0, 1\}, \qquad \forall d, \forall \omega, \forall t, \forall c \qquad \text{(1c-j)}$$

$$\tau_c, \tau_c^{\mathrm{B}}, \tau_c^{\mathrm{A}} \in \mathbb{N}, \qquad \forall c \qquad \text{(1c-k)}$$

Equations (1c-b) and (1c-c) restrict the feasible window in which a consumer's appliance can run due to technical constraints or consumer preferences. Parameter τ_c^{B} represents the time that the load under contract c can be advanced with respect to the original time of operation τ_c^{O}. Similarly, τ_c^{A} represents the time that the load

[4]At this stage the abstract formulation $f(\cdot)$ for the non-linear disutility function is used. In Section 5.3.1 this function is specified for the presented application scenario.

can be delayed. Equations (1c-d) and (1c-e) force the dispatch window to zero if the DR contract is not taken. Equations (1c-f) and (1c-g) limit the feasible sizes of the dispatch windows. Equation (1c-h) establishes the relation between τ_c, τ_c^A, and τ_c^B.

Scheduling Constraints $\mathcal{S}(\delta_c, \tau_c)$

The set $\mathcal{S}(\delta_c, \tau_c)$ is defined as follows:

$$R^{\mathrm{DR}}_{d\omega\tau_c^{\mathrm{O}}c} = 1 \qquad \forall d, \forall \omega, \forall c \tag{1d-a}$$

$$\sum_{t=0}^{\tau_c^{\mathrm{O}}-1} R^{\mathrm{DR}}_{d\omega tc} \leq \tau_c^{\mathrm{B}} \qquad \forall d, \forall \omega, \forall c \tag{1d-b}$$

$$\sum_{t=\tau_c^{\mathrm{O}}+1}^{t_l} R^{\mathrm{DR}}_{d\omega tc} \leq \tau_c^{\mathrm{A}} \qquad \forall d, \forall \omega, \forall c \tag{1d-c}$$

$$M \cdot R^{\mathrm{DR}}_{d\omega tc} \geq P^{\mathrm{DR}}_{d\omega tc} \qquad \forall d, \forall \omega, \forall t, \forall c \tag{1d-d}$$

$$\sum_{t\in\mathcal{T}} P^{\mathrm{DR}}_{d\omega tc} = \delta_c \cdot \mathrm{TE}_c \qquad \forall d, \forall \omega, \forall c \tag{1d-e}$$

$$R^{\mathrm{DR}}_{d\omega tc} - R^{\mathrm{DR}}_{d\omega,t+1,c} \leq S^{\mathrm{D}}_{tc} \qquad \forall d, \forall \omega, \forall c, \forall t \in \mathcal{T} \setminus t_l \tag{1d-f}$$

$$R^{\mathrm{DR}}_{d\omega,t+1,c} - R^{\mathrm{DR}}_{d\omega tc} \leq S^{\mathrm{U}}_{tc} \qquad \forall d, \forall \omega, \forall c, \forall t \in \mathcal{T} \setminus t_l \tag{1d-g}$$

$$\sum_{t\in\mathcal{T}} S^{\mathrm{D}}_{tc} \leq 1 \qquad \forall c \tag{1d-h}$$

$$\sum_{t\in\mathcal{T}} S^{\mathrm{U}}_{tc} \leq 1 \qquad \forall c \tag{1d-i}$$

$$S^{\mathrm{D}}_{tc}, S^{\mathrm{U}}_{tc}, R^{\mathrm{DR}}_{d\omega tc} \in \{0,1\} \qquad \forall d, \forall \omega, \forall t, \forall c \tag{1d-j}$$

Equation (1d-a) ensures that the load can be served at the original time of operation, irrespective of τ_c. Equations (1d-b) and (1d-c) constrain the time window in which the consumer's load can be dispatch ($R^{\mathrm{DR}}_{d\omega tc}$) according to the contract agreement. $P^{\mathrm{DR}}_{d\omega tc}$ stands for the actual power being delivered to the consumer at each time, which can only be positive within the dispatchable time window, as indicated in Equation (1d-d). Equation (1d-e) ensures that the total demand of each consumer is met. The rest of the equations are needed to guarantee a non-preemptive, continuous time window around the original time step τ_c^{O} in which the consumer's load can be served.

The revenues and costs associated with realized contracts, included in the objective function of the aggregator's profit maximization problem, can be expressed as:

$$\mathcal{R}(\rho^{\mathrm{DR},\tau}, \rho^{\mathrm{DR},\delta}) = \lambda^{\mathrm{C}} \cdot P_{dt}^{\mathrm{FL}} + \sum_{c \in \mathcal{C}} \mathrm{TE}_c \cdot \left[(\lambda^{\mathrm{C}} - \rho^{\mathrm{DR},\delta}) \cdot \delta_c - \rho^{\mathrm{DR},\tau} \cdot \tau_c \right],$$

adding $\rho^{\mathrm{DR},\delta}$ and $\rho^{\mathrm{DR},\tau}$ as decision variables for the aggregator. The first term corresponds to the revenues from fixed-load contracts at a standard price, whereas the second term corresponds to the revenues from DR contracts at discounted prices.

Linearization of Non-Linear Terms

Several of the previously presented equations contain non-linear terms and therefore need to be linearized in order to take advantage of robust and efficient mixed-integer programming solvers.

The central term $\rho^{\mathrm{DR},\delta} \cdot \delta_c$, representing the premium for entering a DR contract, is a multiplication of a continuous and a binary variable. Since $\rho^{\mathrm{DR},\delta}$ is bounded by zero and an arbitrarily chosen upper bound M the term can be replaced by the variable $U_c^{\delta+}$ following some simple rules (Bisschop, 2012):

$$\begin{aligned} &U_c^{\delta+} \leq M \cdot \delta_c, && U_c^{\delta+} \leq \rho^{\mathrm{DR},\delta} \\ &U_c^{\delta+} \geq \rho^{\mathrm{DR},\delta} - M \cdot (1 - \delta_c), && U_c^{\delta+} \geq 0 \end{aligned}$$

The term for calculating the consumer's premium is based on the size of the dispatchable time window. This contains the bilinear term $\rho^{\mathrm{DR},\tau} \cdot \tau_c$, which is a multiplication of two continuous variables. The only viable option to linearize this term is to approximate it using a piece-wise linear function. Therefore, two additional, continuous variables are defined:

$$U_{c,1}^{\tau+} = \frac{1}{2}(\rho^{\mathrm{DR},\tau} + \tau_c) \qquad U_{c,2}^{\tau+} = \frac{1}{2}(\rho^{\mathrm{DR},\tau} - \tau_c)$$

Now the above-mentioned term can be replaced by the separable function

$$(U_{c,1}^{\tau+})^2 - (U_{c,2}^{\tau+})^2$$

which can be approximated by replacing the quadratic terms by piece-wise linear

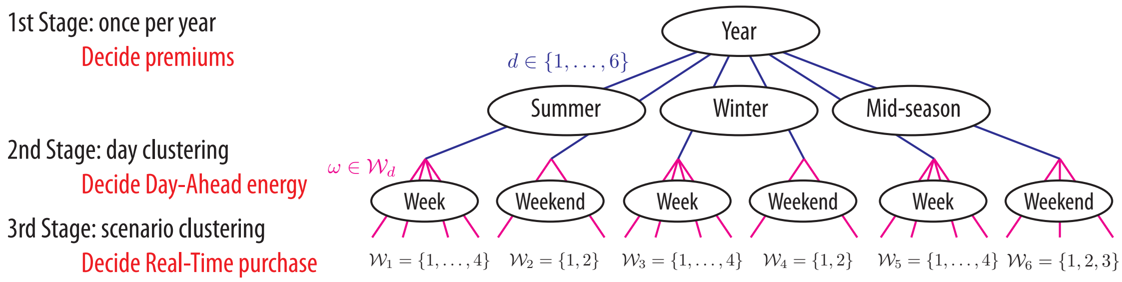

Figure 5.2: Stage structure of the complete and integrated optimization problem from the viewpoint of the DR aggregator.

functions.

Lastly, the term $f(\tau_c)$ in Equation (1c-a) is a non-linear function. However, due to the discrete nature of τ_c, it can be linearly implemented using a lookup table.

5.3 Simulations

In this section extensive simulations highlighting the key impact of consumer behavior are reported. The simulations follow the stage structure of the overall model depicted in Figure 5.2. On a yearly basis, the DR aggregator defines premiums that apply for all of his consumers. These premiums come into consideration, whenever a consumer chooses to enter a DR contract. Before each day of the year, the DR aggregator decides on how much energy to purchase at the day-ahead market. The overall simulation length will be one year to cover seasonal effects. Representative days are chosen and projected to represent a whole year based on a cluster analysis. On the last stage, the DR aggregator decides on energy purchase from the real-time market within each day. Here, different scenarios for each representative day to account for information uncertainty at the day-ahead stage, e.g., intermittency of renewables, are considered.

5.3.1 Data and Scenario Setup

Data inputs and the scenario composition that will be used to run the simulations are specified in the following.

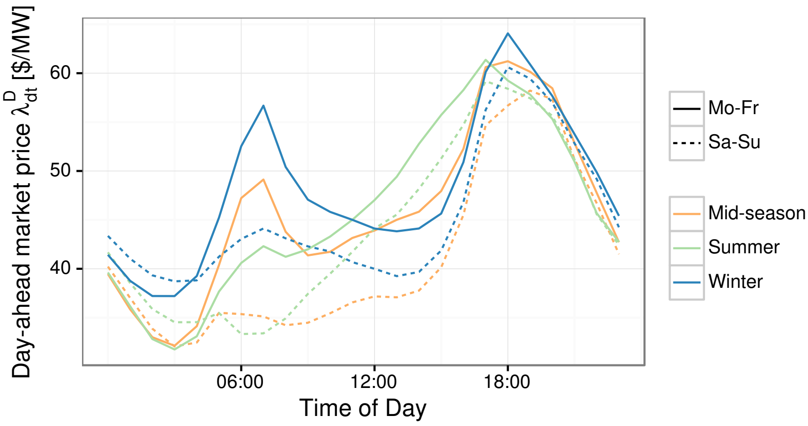

Figure 5.3: Representative day-ahead market prices generated from local marginal prices of the node *MIDWAY_5_B1* in California from the year 2014 (OASIS).

Construction of Energy Market Data

For day-ahead market prices publicly available historical data on local marginal prices in the CAISO region from the year 2014 are employed. [5] From this data, one node is chosen (*MIDWAY_5_B1*) and six typical scenarios based on seasonal (summer, winter, mid-season) and behavioral (weekend, during week) effects are defined. For each manually defined cluster, the average prices per hour are calculated, as depicted in Figure 5.3. The corresponding weight, κ_d, of the day-ahead market price $\lambda^{\mathrm{D}}_{dt}$ equals the number of days that each representative day stands for. Thus, the sum of weights results in 365 days.

Similarly, net balance data is produced from the difference of day-ahead forecast data and actual data on energy demand minus wind and solar energy generation of the same data source as above (OASIS). For this, data of the year 2014 is separated analogously into the 6 above-defined day-clusters. For each representative day, another clustering approach is implemented to define net balance scenarios. The DTW algorithm (Berndt and Clifford, 1994; Liao, 2005) is applied to define appropriate clusters and calculate their means. Figure 5.4 exemplarily shows the net balance scenarios for the representative day during a mid-season week. The number of net balance scenarios depends on the heterogeneity of the net balance accuracy for each day-cluster. Obviously, weekend clusters need fewer scenarios as they represent fewer

[5] Data is available at `http://oasis.caiso.com` (California ISO Open Access Same-time Information System (OASIS))

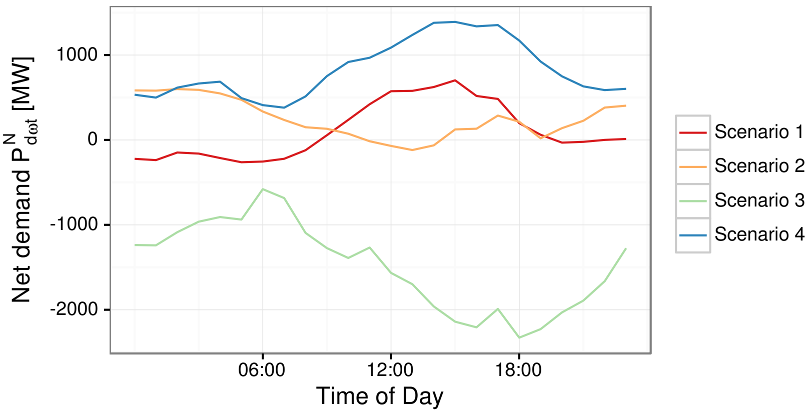

Figure 5.4: Representative net balance scenarios (here for the representative day during a mid-season week) generated from day-ahead forecasted and actual data on demand and renewable energy generation in California in 2014 (OASIS).

days of a year. For each scenario, the corresponding weight $\gamma_{d\omega}$ is calculated equivalently to the day-ahead price except that they sum up to 1 for each day-cluster.

Table 5.2 represents the defined generator data following the *high cost competitor* scenario from Henriquez et al. (2017). These generators reflect the ability of different balancing generators to adjust their power level in real time. For example, g_1 can adjust the power level at low costs (spread to day-ahead market price equals 1) while g_6 is acting as the last option.

Table 5.2: Generator capacity and cost data

	$\bar{P}^{\mathrm{U}}_{dgt}$ MW	$\bar{P}^{\mathrm{D}}_{dgt}$ MW	c^{U}_{dgt} $\$/MW$	c^{D}_{dgt} $\$/MW$
g_1	350	350	$\lambda^D_{dt}+1$	$\lambda^D_{dt}-1$
g_2	350	350	$\lambda^D_{dt}+5$	$\lambda^D_{dt}-5$
g_3	350	350	$\lambda^D_{dt}+8$	$\lambda^D_{dt}-8$
g_4	350	350	$\lambda^D_{dt}+11$	$\lambda^D_{dt}-11$
g_5	350	350	$\lambda^D_{dt}+15$	$\lambda^D_{dt}-15$
g_6	∞	∞	300	1

Remark: Values for $\bar{P}^{\mathrm{U}}_{dgt}$ and $\bar{P}^{\mathrm{D}}_{dgt}$ apply $\forall d, t$.

Consumer and Contract Data

For simulation purposes, consumers are aggregated into four representative consumer types, each of which is represented by an appliance and some parameters. Thus, consumers of the same type are assumed to respond in the same way to incentives for participating in DR programs.

Suitable appliances for load shifting in Germany have been identified by Gottwalt et al. (2016). The consumption share data from a subset of these appliances are employed to represent consumer types: storage water heaters (4%), washing machines (3.6%) and dishwashers (3.7%). Pool pumps are additionally considered as they hold a large share of residential electricity consumption in California (3%). Data for pool pumps is calculated from the number of households with swimming pools (The Association of Pool & Spa Professionals, 2013), average pool pump electricity consumption (Rivera et al., 2008) and overall residential electricity consumption in California (California Energy Commission, 2013). These ratios are applied to the total daily energy employed by Henriquez et al. (2017), $\sum_{t \in \mathcal{T}} P^{\text{FL}}_{dt} = 4307$ MWh and $P^{\text{FL}}_{dt} \in [132, 239.2]$ Megawatt (MW). The daily energy of each appliance (except the pool pump) is allocated in two time slots, according to the *probabilities of start time* and *general pattern* plots from Stamminger et al. (2008). The pool pump's energy is concentrated in one time slot, at noon. The parameterization of the base case following the aforementioned considerations is given in Table 5.3.

Table 5.3: Base case for consumer data

Consumer Type	TE_c *MWh*	τ_c^{O} *hh:mm*	τ_c^{S} - τ_c^{E} *hh:mm*	$U_c^{\tau-}$ $\frac{\$}{MWh \cdot f(\tau)}$	A_c $\frac{\$}{MWh}$
SWH[a] 1	85	02:00	01:00 - 04:00	0.1	1.01
SWH[a] 2	85	22:00	21:00 - 24:00	0.1	1.01
WM[b] 1	78	08:00	07:00 - 11:00	0.3	1.53
WM[b] 2	78	20:00	17:00 - 21:00	0.3	1.53
DW[c] 1	60	13:00	13:00 - 15:00	0.2	1.32
DW[c] 2	100	19:00	18:00 - 22:00	0.2	1.32
PP[d]	130	12:00	01:00 - 24:00	0.0	1.00

Abbreviations: [a]Storage Water Heater, [b]Washing Machine, [c]Dishwasher, [d]Pool Pump

The relative magnitudes of the disutility and aspiration level of consumers are determined using the consumer acceptance questions presented from Stamminger et al. (2008). Their absolute magnitude is subject to a sensitivity analysis around values that accomplish the inclusion of DR contracts because they affect the premiums for each consumer. This sensitivity analysis is instantiated by scaling the base case parameterization.

In the presented application scenario, $f(\cdot)$ in equation 1c-a is chosen as the square-root function, and implemented with a look-up table due to the discrete nature of its argument τ. This particular function is chosen because it is assumed that once a consumer agrees to participate in a DR scheme, for each extra τ the disutility impact is smaller than the previous one, for which an increasing-concave function as the square-root is suitable.

5.3.2 Results

This section incorporates the analysis of numerical results of the model for the base case presented previously along with several new scenarios. Simulations show that the disutility parameter only slightly affects results. Therefore, the remainder rather concentrates on analyzing the effect of the aspiration level.

The contractual participation in scenarios with altering aspiration factor (α) are shown in Table 5.4. Since premiums are paid equally to appliances participating in a DR contract, some devices like WM2 and DW2 are never contracted due to higher

Table 5.4: Contractual participation of consumers

	Aspiration factor (α)								
	1	2	4	6	8	10	12	14	16
SWH 1	•	•	•	•	•	•	○	○	○
SWH 2	•	•	○	○	○	○	○	○	○
WM 1	•	•	○	○	○	○	○	○	○
WM 2	○	○	○	○	○	○	○	○	○
DW 1	•	•	○	○	○	○	○	○	○
DW 2	○	○	○	○	○	○	○	○	○
PP	•	•	•	•	•	•	•	•	○

• = contracted, ○ = not contracted

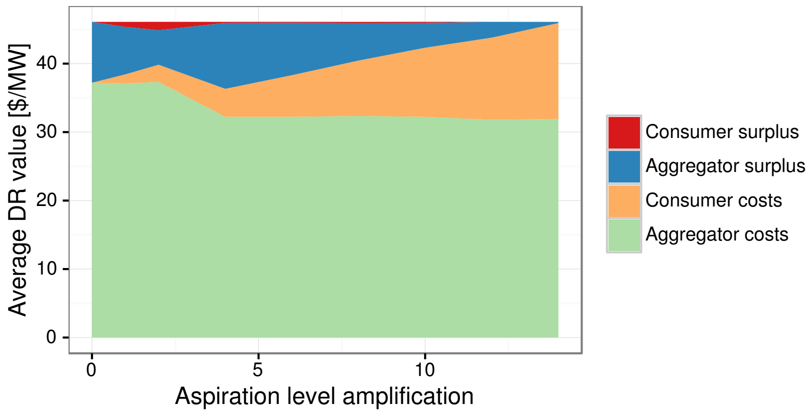

Figure 5.5: Average value breakdown with demand response under aspiration levels amplified from the base case given in Table 5.3.

aspiration and disutility levels that make them not attractive for the aggregator. On the other hand, other types of appliances, like PP or SWH1, participate most of the times since they provide cheaper flexibility (see Table 5.3).

Higher aspiration implies that consumers demand a higher premium to participate (see Equation 1c-a). When increasing α, either the total premium the aggregator is paying for each appliance grows or the highest premium demanding appliance falls out. The aggregator increases premium as long as it does not exceed the added value that results from flexibility. This is depicted in Figure 5.5 and Table 5.4.

Figure 5.5 shows the average value breakdown of energy contracted within a DR contract. It is assumed that the average value of energy, that consists of costs and surplus, is equal to the market price consumers would pay for a supply contract that is not subject to any type of demand side management. From the input data, this market price is calculated at 46.10 $/MW, matching the aggregator's average cost to supply inflexible load. In case of DR contracts, the aggregator has reduced costs since he benefits from flexibility, while the consumer costs increase for offering that flexibility ($U_c^{\tau-}$ and A_c). The arising surplus is apportioned among both the aggregator and the consumer. Obviously, the consumer cost increases with an increasing aspiration level since it is part of the consumer cost.[6] Simultaneously, the aggregator surplus shrinks until costs of both parties would outstrip the average value of energy

[6]One could argue that at least a part of the aspiration level should be assigned to the consumer surplus since it can be understood as the minimum surplus needed for a consumer to become active considering taking part in a DR contract.

(46.10 \$/MW) leading to no contracted DR resources.

The aggregator's average costs per MW decrease with an increase of the aspiration level. In case of low aspiration levels, the aggregator can offer low premiums and therefore contracting DR resources with a low or unsuitable flexibility potential is profitable. By increasing the aspiration level, the aggregator has to pay higher premiums and the first DR resources become unprofitable ending up in no contraction (compare Table 5.4). The remaining DR resources have a higher flexibility potential. Hence, the aggregator's average cost to supply these remaining DR contracts decrease.

As mentioned earlier, the part of the model that describes the DR aggregator-market interaction is based on the work of Henriquez et al. (2017). However, while Henriquez et al. (2017) assumes that the DR resources are always available for the aggregator not considering any costs, the work at hand explicitly models the aggregator-consumer contract interaction. Therefore, the value of DR resources obtained in the aforementioned related work serves as an upper bound for the numerical results presented in this section. This can be confirmed since the difference between the average aggregator costs (≥30 \$/MW) and the average energy value (46.10 \$/MW) in Figure 5.5 is subjacent to the calculated value of flexibility from Henriquez et al. (2017) (18.83 \$/MWh), which underlines the validity of the presented model.

The value and surplus breakdown in absolute numbers normalized to the "zero cost" scenario ($\alpha = 0$) is depicted in Figure 5.6. Both graphs show that the aspiration level highly impacts the volume of DR contracts and especially the surplus. The aspiration level can be understood as a barrier to consumers (expressed in consumer value) subscribing to a DR contract. For practitioners[7] this implies that barriers to take part in DR scenarios are critical and should be lowered to increase market acceptance (e.g., simpler contracts, reliable and non-invasive technology).

Apparently, with increasing premium requirements, the surplus decreases. This is driven by two factors: First by higher costs to activate demand resources and second by less sold energy through consumers' dropping out. In the case of increasing the aspiration factor α, consumers demand a higher premium to participate which

[7]Practitioners could be companies offering DR products, traditionally utilities, or even policy makers.

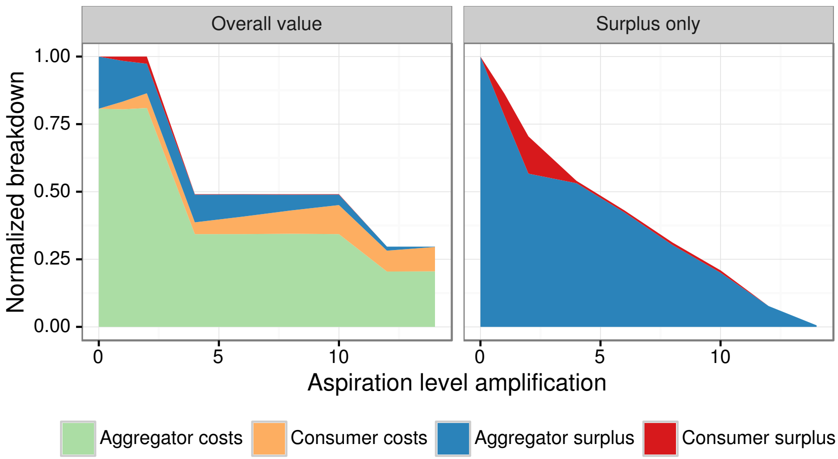

Figure 5.6: Normalized absolute value and surplus breakdown of the demand response aggregator-consumer interaction.

reduces the margin the DR aggregator can get as observed on the left side of Figure 5.6, until no DR contracts participate.

5.4 Discussion

This chapter proposes a model for analyzing the impacts of consumer preferences on DR portfolio design for a DR aggregator. It presents a three-stage electricity market model which considers the interaction of the aggregator with both consumers and wholesale electricity markets. Consumer behavior is modeled using elements of satisficing theory assuming bounded rationality. The DR aggregator determines incentives offered to consumers for joining different DR programs based on their aspiration levels and disutilities.

Several numerical experiments are presented to investigate the impacts of consumer characteristics on the value of the DR resources. Data from actual flexible loads are used. Results show that premiums for participating in DR programs increase with the aspiration level of consumers and therefore reduce the surplus of the aggregator imposing a limit for the cost of contracting DR: The point in which the potential profit for exploiting load flexibility equals the contract costs. Additionally, these results provide insights for designing DR programs. In particular, the use of satisficing theory for modeling consumers might facilitate the implementation of surveys and polls to investigate threshold levels of different types of consumers.

Future work should include the consideration of DR contracts with other features such as rate-constrained services, load curtailment, and storage. The parameters chosen for the disutility and aspiration level of each consumer type constitute a shortcoming of this work. Even though their relative magnitude is based on a consumer acceptance survey and their absolute values are subject to a sensitivity analysis, they should be validated by means of an updated consumer survey. Finally, alternative ways to model consumer behavior are to be explored and validated.

Part III

Finale

Chapter 6

Conclusion

The constantly growing share of renewable energy generation in the electricity generation mix is a consequence of actions to achieve climate goals. The integration of this uncontrollable generation poses several challenges for the power system that was originally designed to control centralized generators to follow demand. Relying solely on generation-side flexibility would be economically inefficient and even undermine the environmental benefits RES generation. Instead, the so far mainly passive demand side must be activated to become an additional source of flexibility. Due to the distributed nature of the demand side, directly managing its flexibility with established, mostly centralized approaches is probably too intricate. On this account, intermediation will become a pivotal task in future energy markets constituting the overarching topic of this dissertation.

The first main contribution of this work addresses the product development process for energy services. The presented morphological approach proposes a systematic and standardized way to guide the structured design of energy services. It facilitates developing new and innovative combinations of service design options that can support the activation of the demand side flexibility potential. A prototypical decision support system is implemented by means of formally describing the morphological approach that simplifies the product development process. Hereby, the basis for the other main contributions of this work is formed. Firstly, an energy service eliciting the demand side flexibility from EV charging is presented focusing on the downstream activity of an intermediary. Car parks will constitute major future load clusters pooling the flexibility from an increasing mass of electric vehicles. RES generation in proximity to these future load clusters, e.g., rooftop PV panels, further increases the value of flexibility since grid limitations can be neglected. Deadline differentiated pricing sets incentives for EV customers to offer their load flexibility to the car park operator who can then schedule the aggregate load to follow PV generation. Analyzing this setting with real-world data, profit increases by up to 30% can be reached compared to a simple pricing approach. The results show that deadline differentiated pricing is resilient to the inaccuracy of forecasts for PV generation, that commonly occur in reality. In addition, the analysis of the intermediation function is expanded by addressing the upstream activity in a comprehensive three-stage bi-level model formulation. In this model, a DR aggregator offers incentives to household consumers to join a DR program. The DR aggregator utilizes the flexibility from household appliances to reduce costs for procuring electricity from a day-ahead and a real-time market. The results show that depending on the appliance type the DR aggregator can reduce his procurement costs by up to one third. Besides, this model formulation lays the foundation to further study the strategic bidding behavior of DR aggregators. The following subsection is organized in accordance with the research questions and the structure of this work presented in Chapter 1.

6.1 Summary and Implications

The structure of the power system and the energy market is introduced in Chapter 2. The power system was historically designed to transmit electricity from few, large power plants to a multitude of small power consumers. Its top-down architecture is not predestined for the integration of distributed generators that play an important role to reduce the carbon footprint of electricity generation. The missing money problem and the exploding costs for redispatch and ancillary services are only two of many examples that illustrate the need for a redesigned market structure. Guided by the market engineering framework this chapter closes with an overview how to structure the economic transformation and finally argues setting the focus of this dissertation on transaction objects from an intermediary point of view.

A system with a high share of generators with nearly no marginal costs requires new services that facilitate transmitting the right economic signals to the system stakeholders. To this end, the notion of energy services — the central transaction object in future energy markets — is refined in Chapter 3. While this answers the first part of Research Question 1, its second part is addressed by proposing a framework to systematically design quality differentiated energy services for consumers. This approach facilitates a value-based economic assessment of energy services that deviates from the marginal-cost-paradigm. Besides, pricing options, infrastructural needs, and additional use case-specific product properties for these new energy service products are outlined. To illustrate the practical applicability of this framework a prototypical decision support system is implemented. To this end, the morphological approach is formalized using a mathematical programming formulation. It is complemented by a complexity measure that facilitates assessing potential adoption obstacles for end consumers.

Having established the fundamentals for the understanding and design of energy services, Chapter 4 provides a deep dive into the application of a promising energy service. EV charging is considered a prime provider of load flexibility in future energy markets. It forms the basis for the following case study. A scenario where EVs are charged in a car park with local PV generation is examined. The car park operator applies a deadline differentiated pricing scheme to incentivize the provision of flexible loads. With respect to Research Question 2 a stochastic mixed-integer optimization problem is formulated that solves the price menu determination problem of the car park operator based on empirical mobility and generation data. It is shown that the learning process of the implemented stochastic optimization is consistent and therefore yields a better solution the more training data is available. Depending on the level of available information about customers, the value of flexibility ranges between 20 and 30% of the company profit in a realistic scenario setting. Addressing Research Question 3, the reduction of product complexity is implemented by limiting the number of price levels the consumer can choose from. The simulation results indicate that reducing the product complexity can account for a profit loss of more than 10%. Even though, limiting the price menu with a maximum of four price levels seems to be a practical solution since such a price menu setting elicits most of the flexibility potential while substantially reducing the product complexity for customers. With respect to Research Question 4 the analyses address the main obstacle of RES electricity generation: inaccurate forecasts. The results show that the temporal flexibility elicited by deadline differentiated pricing can reduce the vulnerability of the car park operator profits to forecast errors. Profit losses due to forecast errors are four times higher in a simple pricing approach compared to deadline differentiated prices. In addition, deadline differentiated pricing increases the share of charging demand covered by renewable energy by up to 30%. All results are based on a realistic representation of customer diversity with respect to their outside option and parking duration. Still, the assumed outside option might differ in other markets or car park types might have a deviating typical parking duration eventually affecting the findings. On this account, based on Research Question 5 the defined model is examined with regards to different utility diversity models and car park types. The results show that different types of symmetric heterogeneous customer utility models do not significantly differ from each other in all but extreme parameter settings. However, further results show that the — especially in macroeconomics — widely accepted homogeneous modeling of customer utilities overestimates profits by more than 17% compared to a realistic heterogeneous model. Besides, it can be observed that the car park type, and thus the customer parking duration, affects the attained profits.

Finally, Chapter 5 puts a stronger focus on the upstream activity of intermediaries. A scenario is examined in which a DR aggregator offers incentives to household consumers to elicit the flexibility of their household appliances. The aggregated flexibility is utilized to reduce the intermediary's costs to procure the demanded electricity from wholesale markets, namely a day-ahead and a real-time market. Consumer behavior is modeled using elements of satisficing theory assuming bounded rationality. The scenario is analyzed by means of a three-stage bi-level model formulation that solves the DR contract problem and determines the procurement strategy. The results illustrate the potential of flexibility with regards to wholesale procurement. The costs of the DR aggregator can be reduced by up to one third compared to a scenario with only fixed-load consumers. Furthermore, the formulated model serves as a basis for further research, e.g., examining the strategic bidding behavior of an aggregator in different market types.

6.2 Outlook and Further Research Opportunities

Even though this dissertation addresses several research gaps in literature on innovative energy services, research is never complete. Therefore, the following paragraphs identify drawbacks of the proposed approaches and provide an overview of prospective research opportunities.

In the foundations of this work, it is elaborated that product differentiation is important to retain the economic feasibility of power systems that are dominated by renewable energy sources. The proposed framework focuses on the conceptual side to innovate energy services. To effectively realize this approach the economic implications have to be evaluated and designed. Therefore, future work should refine the design options with respect to costs and benefits. Subsequently, the service design optimization suggested in Section 3.4 could be realized.

Section 3.4.4 illustrates the morphological approach as a prototypical interactive decision support system. The main idea of such a tool is to free product designers from any formal limitations or implicit interdependencies and to put their focus on creative aspects. This prototype needs to be further developed and transferred to a specific use case to increase the probability that this idea is applied by practitioners. As a next step, the design of an individualized morphological box should be simplified by defining a higher level description language.

For decades until today, the good electricity has been seen as a homogeneous good by both providers and consumers. It remains an open question when and to what extent consumers can be faced with differentiated energy services. Assessing the consumer acceptance of such product ideas by means of surveys or experimental approaches is crucial to pick the right moment for product releases. Besides, the concept of risk aversion is important when dealing with energy services that pass uncertainties to the demand side. Surveying the risk preferences of specific customer groups and integrating it into the framework would facilitate formulating promising business cases.

Turning the gaze towards the proposed deadline differentiated pricing scheme a bunch of parameters depicted in Figure 4.8 are addressed by this work. Still, there remain critical parameters that need to be further assessed by means of sensitivity analyses. Investigating the long-term vision of a sustainable individual mobility system, scenarios with up to 100% EV shares should be examined. Furthermore, the assumed customer acceptance of this pricing regime should be scrutinized.

The presented analyses are limited to the operational level of EV charging in a car park. The model could be expanded in terms of the strategic level to be able to map investment costs for PV generators while probably reducing the detail level on the consumer side of the model. Parameter values for a reduced consumer model could be defined by using the model formulation presented in this dissertation.

Even though solution quality improves with information about customers, the quantity of information to be utilized by the optimization can not arbitrarily be increased due to computational limitations as noted in Chapter 4. Heuristic approaches could tackle the computational complexity while still benefiting from an increased exploitable quantity of information. First implementations of hybrid approaches that primitively combine solutions from optimizations of subsets of the available information show promising results. The progressive hedging algorithm proposed by Rockafellar and Wets (1991) is a comparable approach that could perfectly match the presented model: According to Watson and Woodruff (2011) it is an appropriate heuristic for very large or difficult mixed integer stochastic problems, while effective techniques exist for solving the individual scenarios.

In the style of the morphological approach from Chapter 3, the deadline differentiated pricing scheme could be rethought in many directions: This work focuses on the temporal flexibility, even though in case of electric vehicles an energetic flexibility is usually present. This would dramatically expand the solution space of viable load curves of the car park yielding additional improvements. However, the energetic flexibility should not be exploited to the limits, since range anxiety is currently one of the major concerns of potential EV owners. Duration differentiation or limited reliability of charging requests are further possible and already touched research topics (e.g., Negrete-Pincetic et al., 2016; Siddiqi and Baughman, 1993).

Finally, the complex model formulation presented in Chapter 5 leaves space for a multitude of additional analyses. The features in the applied DR contracts could be extended or replaced, e.g., by a constraint on the maximum rate, by load curtailment or by adding the operation of stationary batteries. One major drawback is the parameterization of the consumer utility function that is based on resources of a consumer acceptance survey. However, the absolute magnitude is chosen arbitrarily and is therefore subject to a sensitivity analysis. Further research should critically question this or validate it by means of an updated consumer survey. Furthermore, the market liquidity for short-term electricity products is low (compare Section 2.2) and therefore exercising market power can constitute an issue. This issue could even become more severe with both supply volatility and demand side flexibility expected to increase in the future. Regulators could simulate potential future scenarios based on the formulated simulation model.

Appendix A

Deadline Differentiated Pricing Model

$$\max_{p,\delta,\eta,\Delta,j,u,\sigma} \mathcal{P}^{\mathrm{UL}} = \sum_{s\in S} w_s \cdot \left(\sum_{c\in C} \left(p_{\bar{f}_{s,c}} \cdot \delta_{s,c} \cdot e_{s,c} \right) - \sum_{t\in T} \left(\eta^{g}_{s,t} \cdot c_{s,t} \right) \right)$$

subject to

$$
\begin{aligned}
p_f &= p_{f-1} - \Delta_{f-1}, && \forall f \in F_{>0} \\
\Delta_{f-1} &\le j_{f-1} \cdot \xi, && \forall f \in F_{>0} \\
\Delta_{f-1} &\ge j_{f-1} \cdot \Delta^{min}, && \forall f \in F_{>0} \\
\sum_{f=0}^{n-1} j_f &\le J^{max} - 1 && \\
j_{f-1} &= 0, && \forall f \in F_{>0} \cap f \bmod \rho > 0 \\
u^{max}_{s,c} &\ge U_{s,c}\left(e_{s,c}\right) - p_{\bar{f}_{s,c}} \cdot e_{s,c}, && \forall s \in S, \forall c \in C \\
u^{max}_{s,c} &\le \delta_{s,c} \cdot \left(U_{s,c}\left(e_{s,c}\right) - p_{\bar{f}_{s,c}} \cdot e_{s,c} \right), && \forall s \in S, \forall c \in C \\
\sum_{t\in T} \sigma_{s,a,f,t} &= 1\,, && \forall s \in S, \forall a \in A, \forall f \in F \\
\sum_{t\in T\setminus\{a,\ldots,a+f\}} \sigma_{s,a,f,t} &= 0\,, && \forall s \in S, \forall a \in A, \forall f \in F \\
\sum_{t=a_{s,c}}^{a_{s,c}+d_{s,c}+1} \lambda_{s,c,t} &= \delta_{s,c} \cdot e_{s,c}\,, && \forall s \in S, \forall c \in C \\
\sigma_{s,a,f,a+t} &\le j_{t-1}\,, && \forall s \in S, \forall a \in A, \\
& && \forall f \in F_{>0}, \forall t \in \{1,\ldots,f\}
\end{aligned}
$$

$$\sum_{\tau=a_{s,c}}^{t+t^{\bar{\lambda}}_{s,c}} \lambda_{s,c,\tau} \geq \sigma_{s,a,f,t} \cdot \delta_{s,c} \cdot e_{s,c}\,, \qquad \forall s \in S, \forall a \in A, \forall f \in F,$$

$$\forall c \in C_{a,f}, \forall t \in T$$

$$\sum_{c \in C} \lambda_{s,c,t} \leq \eta^{p}_{s,t} + \eta^{g}_{s,t}\,, \qquad \forall s \in S, \forall t \in T$$

Appendix B

Demand Response Aggregator Model

The Aggregator's UL Problem $\mathcal{P}^{\mathbf{UL}}$:

$$\max_{P_{dt}^{\mathrm{A,D}}, \bar{P}_{d\omega t}^{\mathrm{A,R}}, \mathrm{bid}_{d\omega t}, P_{d\omega tc}^{DR}} \sum_{d \in \mathcal{D}} \kappa_d \Bigg\{ \sum_{\omega \in \mathcal{W}_d} \left[\gamma_{d\omega} \sum_{t \in \mathcal{T}} \left(\lambda_{dt}^{\mathrm{D}} P_{dt}^{\mathrm{A,D}} + \lambda_{d\omega t}^{\mathrm{R}} P_{d\omega t}^{\mathrm{A,R}} \right) \right]$$
$$+ \lambda^{\mathrm{C}} \cdot P_{dt}^{\mathrm{FL}} + \sum_{c \in \mathcal{C}} \mathrm{TE}_c \cdot \left[(\lambda^{\mathrm{C}} - \rho^{\mathrm{DR},\delta}) \cdot \delta_c - \rho^{\mathrm{DR},\tau} \cdot \tau_c \right] \Bigg\}$$

subject to

$$P_{dt}^{\mathrm{A,D}} + P_{d\omega t}^{\mathrm{A,R}} = -(P_{dt}^{\mathrm{FL}} + \sum_{c \in \mathcal{C}} P_{d\omega tc}^{\mathrm{DR}}), \qquad \forall d, \forall \omega, \forall t$$

$$\rho^{\mathrm{DR},\delta} \cdot \delta_c + \rho^{\mathrm{DR},\tau} \cdot \tau_c - f(\tau_c) \cdot U_c^{\tau -} \geq \delta_c \cdot A_c, \qquad \forall c$$

$$\sum_{t=0}^{\tau_c^{\mathrm{S}}-1} R_{d\omega tc}^{\mathrm{DR}} = 0, \qquad \forall d, \forall \omega, \forall c$$

$$\sum_{t=\tau_c^{\mathrm{E}}+1}^{t_l} R_{d\omega tc}^{\mathrm{DR}} = 0, \qquad \forall d, \forall \omega, \forall c$$

$$\tau_c^{\mathrm{B}} \leq M \cdot \delta_c, \qquad \forall c$$

$$\tau_c^{\mathrm{A}} \leq M \cdot \delta_c, \qquad \forall c$$

$$\tau_c^{\mathrm{B}} \leq \tau_c^{\mathrm{O}} - \tau_c^{\mathrm{S}}, \qquad \forall c$$

$$\tau_c^{\mathrm{A}} \leq \tau_c^{\mathrm{E}} - \tau_c^{\mathrm{O}}, \qquad \forall c$$

$$\tau_c \geq \tau_c^{\mathrm{B}} + \tau_c^{\mathrm{A}}, \qquad \forall c$$

$$\delta_c, R^{\mathrm{DR}}_{d\omega tc} \in \{0,1\}, \qquad \forall d, \forall \omega, \forall t, \forall c$$

$$\tau_c, \tau_c^{\mathrm{B}}, \tau_c^{\mathrm{A}} \in \mathbb{N}, \qquad \forall c$$

$$R^{\mathrm{DR}}_{d\omega\tau_c^{\mathrm{O}}c} = 1 \qquad \forall d, \forall \omega, \forall c$$

$$\sum_{t=0}^{\tau_c^{\mathrm{O}}-1} R^{\mathrm{DR}}_{d\omega tc} \leq \tau_c^{\mathrm{B}} \qquad \forall d, \forall \omega, \forall c$$

$$\sum_{t=\tau_c^{\mathrm{O}}+1}^{t_l} R^{\mathrm{DR}}_{d\omega tc} \leq \tau_c^{\mathrm{A}} \qquad \forall d, \forall \omega, \forall c$$

$$M \cdot R^{\mathrm{DR}}_{d\omega tc} \geq P^{\mathrm{DR}}_{d\omega tc} \qquad \forall d, \forall \omega, \forall t, \forall c$$

$$\sum_{t \in \mathcal{T}} P^{\mathrm{DR}}_{d\omega tc} = \delta_c \cdot \mathrm{TE}_c \qquad \forall d, \forall \omega, \forall c$$

$$R^{\mathrm{DR}}_{d\omega tc} - R^{\mathrm{DR}}_{d\omega,t+1,c} \leq S^{\mathrm{D}}_{tc} \qquad \forall d, \forall \omega, \forall c, \forall t \in \mathcal{T} \setminus t_l$$

$$R^{\mathrm{DR}}_{d\omega,t+1,c} - R^{\mathrm{DR}}_{d\omega tc} \leq S^{\mathrm{U}}_{tc} \qquad \forall d, \forall \omega, \forall c, \forall t \in \mathcal{T} \setminus t_l$$

$$\sum_{t \in \mathcal{T}} S^{\mathrm{D}}_{tc} \leq 1 \qquad \forall c$$

$$\sum_{t \in \mathcal{T}} S^{\mathrm{U}}_{tc} \leq 1 \qquad \forall c$$

$$S^{\mathrm{D}}_{tc}, S^{\mathrm{U}}_{tc}, R^{\mathrm{DR}}_{d\omega tc} \in \{0,1\} \qquad \forall d, \forall \omega, \forall t, \forall c$$

$$\bar{P}^{\mathrm{A,R}}_{d\omega t} \geq 0, \qquad \forall \omega, \forall t$$

$$\lambda^{\mathrm{R}}_{d\omega t}, P^{\mathrm{A,R}}_{d\omega t} \in \arg\{\mathcal{P}^{\mathrm{LL,R}}_{d\omega}\}, \qquad \forall d, \forall \omega, \forall t$$

The ISO's LL Problem $\mathcal{P}^{\mathbf{LL,R}}_{d\omega}$, $\forall d, \omega$:

$$\min_{P^{\mathrm{U}}_{dgt}, P^{\mathrm{D}}_{dgt}, P^{\mathrm{A,R}}_{d\omega t}} \sum_{t \in \mathcal{T}} \left\{ \sum_{g \in \mathcal{G}} \left(c^{\mathrm{U}}_{dgt} P^{\mathrm{U}}_{dgt} - c^{\mathrm{D}}_{dgt} P^{\mathrm{D}}_{dgt} \right) + \mathrm{bid}_{d\omega t} P^{\mathrm{A,R}}_{d\omega t} \right\}$$

subject to:

$$\sum_{g \in \mathcal{G}} [P^{\mathrm{U}}_{d\omega gt} - P^{\mathrm{D}}_{d\omega gt}] + P^{\mathrm{A,R}}_{d\omega t} = P^{\mathrm{N}}_{d\omega t} \;:\; \lambda^{\mathrm{R}}_{d\omega t}, \qquad \forall t$$

$$0 \leq P^{\mathrm{U}}_{d\omega gt} \leq \bar{P}^{\mathrm{U}}_{dgt}, \qquad \forall g, \forall t$$

$$0 \leq P^{\mathrm{D}}_{d\omega gt} \leq \bar{P}^{\mathrm{D}}_{dgt}, \qquad \forall g, \forall t$$

$$-\bar{P}^{\mathrm{A,R}}_{d\omega t} \leq P^{\mathrm{A,R}}_{d\omega t} \leq \bar{P}^{\mathrm{A,R}}_{d\omega t}, \qquad \forall t$$

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