Group Formation in Smart Grids

Designing Demand Response Portfolios

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Contents

List of Figures

List of Tables

List of Abbreviations

CHP	Combined Heat and Power
CPP	Critical Peak Pricing
DDP	Deadline Differentiated Pricing
DR	Demand Response
DSM	Demand Side Management
DSO	Distribution System Operator
EEG	Erneuerbare Energien Gesetz - Renewable Energy Act
EEX	European Energy Exchange
EnWG	Energiewirtschaftsgesetz - Energy Industry Act
EPA	Energy Policy Act
EU	European Union
EU ETS	European Union Emissions Trading System
EV	Electric Vehicle
EVP	Expected Value Program
EVPI	Expected Value of Perfect Information
HP	Heuristic Program
ICT	Information and Communication Technology
ISO	Independent System Operator
IT	Information Technology
LLP	Lower Level Problem
MILP	Mixed Integer Linear Program
NELA	National Electric Light Association
OTC	Over-The-Counter
PCR	Primary Control Reserve
PTR	Peak Time Rebates
PURPA	Public Utilities Regulatory Policies Act
PV	Photovoltaic
RES	Renewable Energy Sources
RP	Recourse Program
RTP	Real-Time Pricing

SCR	Secondary Control Reserve
SG	Smart Grid
SOC	State Of Charge
StromNZV	Stromnetzzugangsverordnung - Grid Access Law
TOU	Time-Of-Use
TR	Tertiary Reserve
TSO	Transmission System Operator
ULP	Upper Level Problem
VPP	Virtual Power Plant
VPR	Variable Peak Rate
VSS	Value of Stochastic Solution
WSP	Wait-and-See Program

List of Symbols

Indices

a Appliance
b Stationary battery
c Customer
ω Supply scenario
r Run of semi-automatically controlled appliance
s Time slot
t Time slot
v Electric vehicle

Parameters

$\mathcal{A}$ Set of household appliances
$\mathcal{A}^B$ Set of inflexible base load appliances
$\mathcal{A}^C$ Set of cooling appliances
$\mathcal{A}^H$ Set of heating appliances
$\mathcal{A}^S$ Set of semi-automatically controlled appliances
$\mathcal{B}$ Set of stationary batteries
$\mathcal{C}$ Set of (household) customers
C^F Specific costs forward power (per unit)
C^M Market power costs
C^O Specific option execution costs
C^P Option premium (per unit)
D^B Base load
D^C Curtailable load
$\overline{\gamma}^C$ Curtailing potential: Share of curtailable load that can be shed
D^S Shiftable load
$\overline{\gamma}^S$ Maximal contractible load for shifting
δ^C Discount on curtailable load if contracted

δ^S	Discount on shiftable load if contracted
E_r^R	Latest possible end time of run r
Γ	RES - generation to total demand ratio
κ	Maximum gas turbine output
N_a	Number of runs of semi-automatically controlled appliance a
Ω	Set of supply scenarios
P	Base load retail price
p	Probability of supply scenario
$\hat{\Phi}$	Charging possibility vector; charging of vehicle v possible in t $(\hat{\Phi}_{v,t} = 1)$ or not $(\hat{\Phi}_{v,t} = 0)$
$\overline{\Phi}$	Maximum charging energy per time slot
$\underline{\Phi}$	Maximum discharging energy per time slot
Φ	Energy consumption of electric vehicle (driving)
R	Generation from renewable energy sources
$\mathcal{R}_a$	Set of runs for semi-automatically controlled appliances
ρ	Demand of household appliance
$\hat{\rho}$	Share of demand from heating appliance that must be satisfied in the morning
$\overline{\rho}$	Demand of heating appliance during one run
c^ς	Shifting distance penalty function
$\overline{\psi}$	Battery capacity of electric vehicle
S_r^R	Earliest possible start time of run r
S^W	Share of wind generation in total renewable generation
$\mathcal{T}$	Set of time slots
Θ	Flexibility level (risk aversion)
$\hat{T}$	Share of the number of time slots to satisfy $\hat{\rho}$ of a heating device's demand
Θ^C	Curtailing risk aversion
Θ^S	Shifting risk aversion
u^C	Customer benefit for offering curtailable load
u^S	Customer benefit for offering shiftable load
$\mathcal{V}$	Set of electric vehicles
Ξ	Value of stored energy of electric vehicles and stationary batteries

Variables

a^C	Allocation of curtailable load
a^S	Allocation of shiftable load
a^{SR}	Load shifting matrix

c^G	Generation costs for conventionally generated power
c^M	Variable market power costs
c^T	Variable gas turbine costs
l_t	Load of all appliances in time slot t
$l^A_{a,t}$	Load of appliance a in time slot t
ϕ	Charging matrix
π^{bL}	Revenues from base load
π^{cL}	Revenues from cutrailable load
π^{sL}	Revenues from shiftable load
s^F	Allocation of power from forwards
s^M	Power procured from the market
s^O	Allocation of power from options
ψ	State of charge
s^T	Generation from gas turbine
x^A	Appliance activation vector; $x^A_{r,t} = 1$ appliance a is running in t; $x^A_{r,t} = 0$ else
x^C	Curtailing selected
x^P	Customer selected
x^R	Run activation vector; $x^R_{r,t} = 1$ run r is started in t; $x^R_{r,t} = 0$ else
x^S	Shifting selected
y^F	Supply forward
y^O	Option on supply

Part I

Foundations

1

Introduction

Scheduling of flexible demand is crucial to allow for efficiently aligning electricity generation from *renewable energy sources* (RES) with consumption (Strbac 2008). This has become increasingly challenging as fluctuating and intermittent renewable generation has seen constant growth in recent years—a trend that has been fostered by European and national objectives and incentives (European Commission 2010; BMWi and BMU 2010; BMWi 2015a). The equilibrium of supply and demand is a necessary requirement for ensuring a reliable, economically efficient, and ecologically sustainable electrical power supply. However, the quality of the scheduling result highly depends on the composition of the underlying customer portfolio since only flexibility can be used for *demand side management* (DSM) that was contracted beforehand. Therefore, this dissertation investigates the efficient formation of customer portfolios for load scheduling in *smart grid*s (SGs). Such portfolios differ in the level and in the amount of demand flexibility that an aggregator can use for DSM. This novel approach integrates the decision problems of designing and dispatching a portfolio of supply and demand assets.

End consumers differ in both the amount of flexibility that they are able to offer and in the willingness to provide *demand response* (DR) capacities. The availability of information about the endowment and characteristics of demand flexibility is vital to allow for elaborating the optimal formation of DR portfolios. Therefore, an analysis to determine both the amount of flexibility a household is able to offer to an aggregator and the value of this demand flexibility for the aggregator is conducted. Such evaluation enables the aggregator to draw conclusions about end consumer flexibility properties by using information on the appliance endowment of a household, which can be gathered by means of non-intrusive appliance monitoring (Parson et al. 2012; Liao et al. 2014). The insights from the household analysis form the basis for selecting and contracting customers through aggregators.

For customers, the provision of DR resources comes along with discomfort due to environmental or behavioral changes, e.g., temporal shifting of consumption or deviation from predefined preferences (Wang, Wang, and Yang 2012). The degree of perceived disutility depends on individual consumer characteristics such as behavioral habits and risk aversion. Therefore, remuneration payments are necessary to compensate end consumers for discomfort and to incentivize them to provide demand flexibility. To this end, an innovative approach for designing tariffs is introduced that, on the one hand, maximizes the aggregator's profit and, on the other hand, maximizes the customers' individual utility. This original method connects the insights of the end consumer flexibility evaluation and the portfolio optimization and hence enables the aggregator to design tariffs that incentivize customers to support the formation of efficient portfolios by self-selection.

1.1 Motivation

The United Nations' millennium development goals include to ensure environmental sustainability (United Nations 2015). A critical aspect to achieve this goal is the reduction of emissions from electricity generation. To this end, the *European Union* (EU) is committed to take actions against climate change. Goals to be met by 2020 include the reduction of greenhouse gas emissions by at least 20 % of 1990 levels (27 % by 2030), to generate 20 % of energy from renewable energy sources, and to reduce energy consumption by 20 % below projected levels by improving energy efficiency (European Commission 2009b). The long term goals, defined by the Energy Roadmap 2050 are even more ambitious, e.g., to reduce greenhouse gas emissions by at least 80-95 % below 1990 levels (European Commission 2010). Germany adopted these challenging objectives on a national level (BMWi and BMU 2010).

To achieve these goals policy makers have intensively promoted the extension of renewable generation capacities on both the European and the national level. Therefore, electricity generation from RES has seen enormous growth in recent years—more than one quarter of the gross electricity generation originated from RES in Germany in 2014 (BMWi 2015a). However, "todays markets are not sufficiently flexible, both on the supply and on the demand side to accommodate the increased share of renewable energy in the market" (European Commission 2015a). Due to the growing share of uncontrollable, fluctuating and intermittent renewable generation, the dogma *supply follows demand* is not contemporary anymore to secure the real-time balance of supply and demand. Instead, DSM—the operationalization of demand flexibility—represents a promising means to integrate RES and to align demand with supply (Palensky and Dietrich 2011).

DSM can be implemented through direct scheduling of loads or by DR—that is engaging consumers to adapt their energy consumption through monetary or nonmonetary incentives (Albadi and El-Saadany 2008). To this end, the communication of such incentives requires to add a suplemental communication layer to the electricity transportation layer in distribution grids. The SG provides "the utility companies with full visibility and pervasive control over their assets and services [...] and [it] empowers its stakeholders to define and realize new ways of engaging with each other and performing energy transactions across the system" (Farhangi 2010).

Three main actors are affected with respect to DSM, i.e., grid operators, aggregators, and end consumers (European Commission 2015b). Today, grid operators are responsible for maintaining grid stability and hence for dispatching generation capacities to ensure supply adequacy. However, with the implementation of DSM, formerly uncontrolled demand must be coordinated and scheduled as well. In contrast to supply dispatch, which focuses on few centrally generating power plants, this dissertation considers the direct scheduling of contracted flexible demand provided by private households. Such coordination is much more complex as a large number of end consumers is needed to gain impact. In addition, load scheduling must consider the availability of flexible demand which does not only depend on technical but also on behavioral factors and customers' preferences. Therefore, aggregators act as intermediaries that, on the one hand, manage customer relations, gather load and (distributed) generation flexibility, and schedule flexible load on the demand side (Ipakchi and Albuyeh 2009). On the other hand, aggregators merchandise flexibility in bundled products that can be processed by grid operators.

Focusing on the aggregator-customer relation, the aggregator faces a multitude of complex decisions on both the strategical and the tactical level. The aggregator's ultimate goal is to market flexibility to the grid operator optimally. To support this objective, flexible loads must be coordinated efficiently. However, the quality of the attainable scheduling result highly depends on the composition of the underlying customer portfolio, i.e., which customers are part of the portfolio as well as what type and what amount of flexibility each customer offers. To this end, a demand aggregator's problem of designing *and* dispatching a portfolio of supply (volatile RES and conventional generators) and demand assets (inflexible base, shiftable and curtailable load) is formulated and evaluated by means of a stochastic program. To determine efficient DR portfolios, information on private households' ability and willingness to provide flexibility is required. In combination with environmental conditions, long term electricity prices, and renewable generation scenarios, the household flexibility analysis hence builds the basis for the design of DR portfolios. Of course, customers are not willing to provide flexibility for free. They suffer from discomfort in case loads are shifted or curtailed to provide flexibility capacities. Therefore, the provision of DR resources must be remunerated. Tariffs need to be developed that incentivize customers to participate in demand response programs and to offer the optimal amount of flexibility by self-selection. To this end, a stochastic two-stage bi-level optimization model is presented to determine both the long term generation and customer portfolio—including flexibility provision—and the subsequent scheduling of flexible generation. Considering customer utility and preferences the model is applied to determine optimal tariffs that allow for constructing demand flexibility portfolios.

From a market engineering perspective, the aggregator faces the challenge to design tariffs and already bear technical preconditions and requirements as well as customer behavior in mind. Hence, flexibility portfolio formation through self-selection requires to consider the interaction effects between tariffs that are offered to consumers and their reaction to these offers—transaction objects and agent behavior, respectively (Weinhardt, Holtmann, and Neumann 2003). Interestingly, although tariffs are offered by the aggregator, the service that is provided—namely the provision of flexibility—is fulfilled by the end consumers.

1.2 Research Questions and Outline

The research outline follows the logical structure and interdependencies of the main contributions. Both the optimal formation of portfolios and especially the design of tariffs require information about the flexibility in private households' electricity consumption. Therefore, the initial research question refers to drivers of flexibility.

Research Question 1. *What characterizes end consumer flexibility in electricity consumption?*

Domestic electricity consumption depends on the appliance endowment of the respective home. Hence, a very fine grained view is taken that models electricity consumption and corresponding flexibility on the appliance level. In addition to technical constraints, customers' preferences are central drivers of demand flexibility which can hardly be modeled due to the lack of specific customer information. Therefore, the second research question abstracts from behavioral issues and focuses on both technical availability of flexibility and its value for aggregators to save generation costs.

Research Question 2. *What is the contribution of households' flexibility to the aggregator's system cost savings?*

To investigate the value of flexibility to an aggregator, a simulation study is executed using the appliance model which is amplified by extensive empiric data on both appliance characteristics and renewable generation. This unprecedented study allows for determining the contribution of single appliances to an aggregator's cost savings—the value of a household's flexibility can then be derived by analyzing its endowment of devices (Parson et al. 2012).

Demand flexibility can be operationalized to reduce costs from conventional generation. Hence, there is a trade-off between procuring and dispatching flexible generation and contracting and scheduling flexible load. As pointed out above, the attainable scheduling result depends on the underlying customer portfolio. Therefore, abstracting from the fine grained appliance based model and considering household consumption as a whole instead, the following research question refers to the optimal long term demand portfolio composition.

Research Question 3. *Which customers should be members of an aggregator's optimal customer portfolio and which type and quantity of flexibility should an aggregator contract?*

To answer this question, demand flexibility is characterized by two types of load mutations, i.e., load shifting and load curtailment. The optimal DR portfolio structure strongly depends on the price of demand flexibility as well as on the cost of relying on conventional generation. To investigate the interaction effects between supply and demand portfolio formation as well as their flexibility dispatch, research question 4 elaborates the optimal supply portfolio composition.

Research Question 4. *What is the optimal generation portfolio composition for an aggregator?*

The optimal design of supply and demand flexibility portfolios for an aggregator is analyzed by a simulation study. These problems are computationally hard to solve. Therefore, a heuristic is introduced and the computational feasibility of the different approaches is evaluated. Furthermore, portfolio recommendations are derived for given exogenous factors, e.g., discounts on flexible demand, generation prices, and the availability of generation from RES. These recommendations support the decision of aggregators in the process of constructing flexibility portfolios.

Operationalizing demand flexibility induces discomfort for customers due to environmental or behavior changes. The perceived disutility depends on the customers' preferences. These preferences are non-trivial to understand as a result of the large number and wide diversity of customers (Chandan et al. 2014). Therefore, the following research question elaborates on the drivers of utility.

Research Question 5. *What factors influence utility maximizing customers to offer their flexibility to the aggregator?*

Modeling utility allows for including the customer rationale into the decision process. To remunerate customers for their discomfort from load scheduling tariffs must be designed. On the one hand, these tariffs should incentivize consumers to provide flexibility. On the other hand, they must limit the aggregator's flexibility cost.

Research Question 6. *Which tariff characteristics incentivize customers to offer the optimal amount of flexibility by self-selection?*

Adding a further abstraction level by modeling customer conglomerates instead of single households, a bi-level model is presented. On the upper level the aggregator maximizes its profit by designing tariffs and on the lower level customers maximize their individual utility. Using response functions that represent the customers' reactions to tariff offers, the trade-off between tariff design including demand flexibility contracting and supply flexibility procurement is analyzed. Finally, this evaluation allows for deriving strategies and guidance for discount selection and the design of tariffs, respectively.

1.3 Thesis Structure

The outline follows the three most prominent contributions, i.e., demand flexibility valuation, customer portfolio formation, and tariff design. Supplemented by introductory foundations and a concluding finale this results in a five part structure as illustrated in figure 1.1.

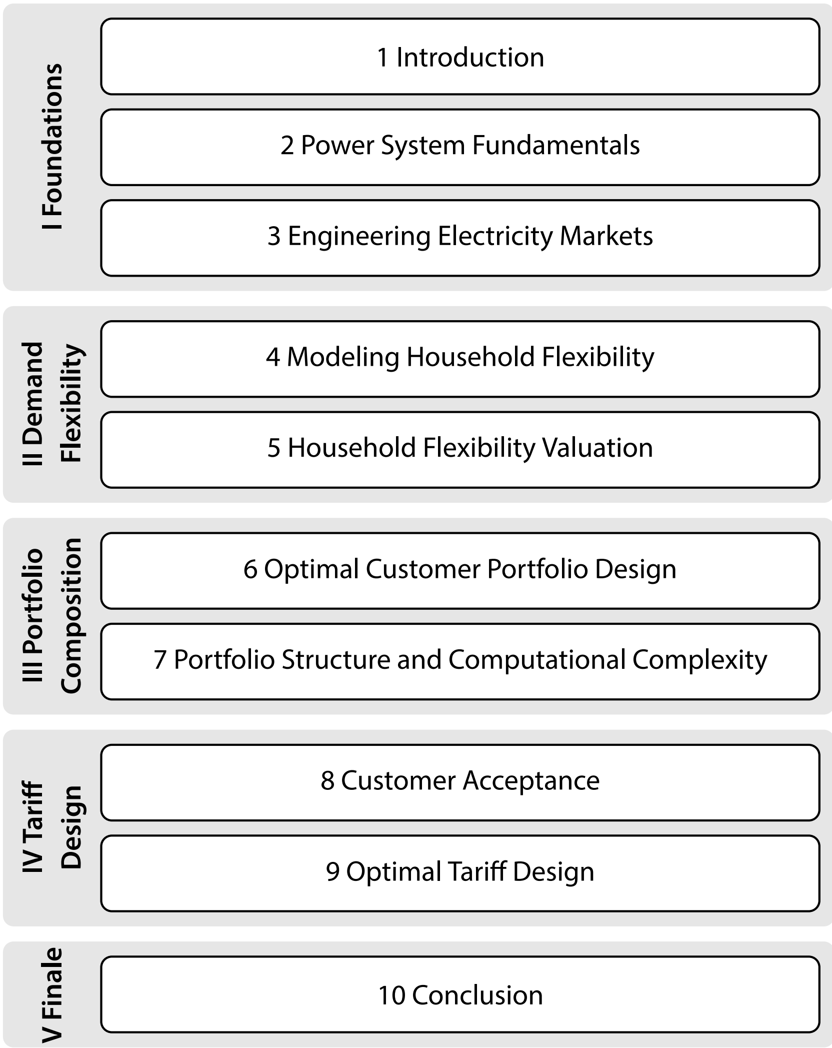

Figure 1.1: Structure

Part I provides the foundations of this work. An introduction to power systems as well as to SGs and DSM is provided in chapter 2. Chapter 3 complements this literature review by elaborating on current challenges for market engineering in the context of power systems. Part II presents both the amount of available flexibility in private households and its value to a flexibility aggregator for DSM. To this end, chapter 4 introduces a very fine grained demand scheduling model on the appliance level. Using this model, chapter 5 evaluates the amount and the value of household devices for DSM in a simulation study that builds on comprehensive empiric data. Building on the flexibility valuation, part III elaborates on the optimal DR portfolio composition for both the supply and the demand side. For this purpose, chapter 6 provides a two-stage stochastic model and a heuristic approach for designing and dispatching a portfolio of supply and demand assets. Thereby, it is abstracted from the fine grained appliance consideration and households as a whole are considered. Subsequently, chapter 7 discusses the computational complexity of the different solution methods. Then, the interaction effects between the different types of demand flexibility as well as supply flexibility are investigated by conducting a simulation study based on empiric renewable supply data and smart meter readings. Part IV combines the insights of the preceding parts to design DR tariffs that maximize the aggregators profit and simultaneously consider individually utility maximizing customers. To this end, chapter 8 adds the customer perspective and tariff design considerations to the portfolio design model. Adding an additional abstraction level to the demand side by considering customer groups, chapter 9 elaborates on the optimal choice of discounts for flexibility provision and hence provides strategies for efficient tariff design. Finally, part V concludes by summarizing the key contributions and provides an outlook on subsequent research challenges and opportunities.

2

Power System Fundamentals

The constant and reliable availability of electricity has become self-evident in western societies. The electric power system is crucial for industrial value creation, economic systems, as well as societies and private households. The electricity success story began at the beginning of the last century. Fostered by the technical and economic properties that make electric power systems natural monopolies, both electricity generation and grid operation were executed by few utilities. Although this was not very efficient for consumers, the power system demonstrated great scalability and reliability (Stoft 2002).

With the restructuring of electricity markets that took place in the last decades of the 20th century, the premises changed. The general goal was to make the market more efficient by moving away from traditional monopolies enabling and fostering competition. This had a huge influence on all segments of the electricity value chain. The shift towards a supply side with an increasing share of intermittent generation from RES supports a more sustainable provision of electricity. The energy policy objective triad of ensuring reliable, economically efficient, and ecologically sustainable electrical power supply (fig. 2.1) requires further renewal of power markets and the regulatory framework as well as the utilization of demand side flexibility (Strbac 2008).

The integration of fluctuating and uncontrollable generation from RES poses one of the main challenges of current grid operation (Ramchurn et al. 2012). A very promising approach to meeting this challenge is the activation of the formerly passive demand side to

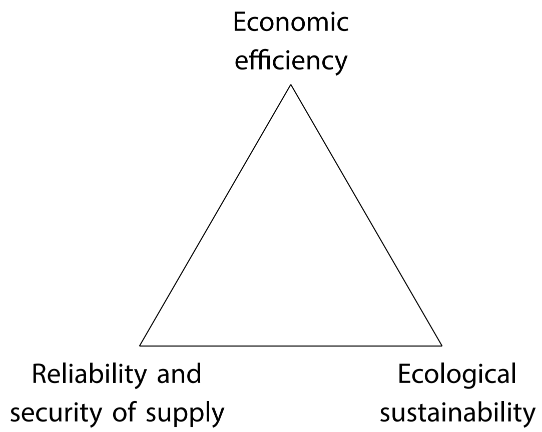

Figure 2.1: Energy policy objective triad

balance generation and consumption. The introduction of SG technologies facilitates this endeavor (Blumsack and Fernandez 2012; Sioshansi 2011). To motivate consumers to offer their flexibility, incentives and sufficiently fluctuating tariffs are inalienable (Schweppe et al. 1988).

Elaborating on both world wide power systems and especially focusing on Germany, this chapter provides an overview of power systems including a review of historic developments which induced current challenges as well as suggestions from literature to meet those challenges. First, the liberalization process and its impact on the electricity value chain is discussed, followed by flexibility in power systems that, in combination with smart grid technology, enables the utilization of demand flexibility for DSM.

2.1 Regulation

Access to electricity is essential for today's societies and economies. Key factors to establish efficiency and reliability of power supply such as supply adequacy, affordable electricity prices, and the independence of tariffs from the respective area of consumption are of public interest. The electricity sector—and especially the grid—is a natural monopoly and thus regulated (Ilg 2014). Kahn (1988) provides an extensive introduction to the principles of regulation in theory and practice. In his article "Why Regulate Utilities?", Demsetz (1968) questions "the conventional economic arguments for the existing legislation and regulation".

In the late 1800's there was intense competition in US electricity markets. In Chicago alone forty-five central power enterprises and in New York City six electric light companies competed (Behling 1938). These companies ran inefficient due to overlapping power lines and emaciating competition (Stoft 2002). In a speech, Samuel Insull, president of the *National Electric Light Association* (NELA), argued that the electricity markets were natural monopolies and outlined why they should be regulated (Insull 1898). He pointed out that "exclusive franchises should be coupled with the conditions of public control, requiring all charges for services fixed by public bodies to be based on cost plus a reasonable profit". In the following, in Europe and in the US demand for electricity was satisfied by well established, vertically integrated public, private, or mixed-economy utilities run as natural monopolies without competition.

2.1.1 Market Restructuring

Restructuring[1] of energy markets did not lead to less, but only to different regulation (Vogel 1996). Therefore, Hogan (2002) states that "restructuring is the better term, not deregulation". In the US, restructuring electricity markets started with the passage of the *Public Utilities Regulatory Policies Act* (PURPA) in the 1970s (Russo 2001). However, the market was truly opened in 1992 with the passage of the *Energy Policy Act* (EPA). In Europe, liberalization started in the 1980s when the Thatcher government proposed to restructure and privatize the power generation market (Emmons 2000). A list of selected countries with liberalized electricity markets including short descriptions of the highlights of the restructuring provides Sioshansi (2006).

Although the motivation for electricity market restructuring slightly differed in the countries (Hogan 2002), they had one goal in common, i.e., to make the market more efficient by moving away from the traditional monopolies enabling and fostering competition (Ilic, Galiana, and Fink 2013). The expectation was that more competition would lead to lower electricity prices and increase customer benefits. Sioshansi (2006) states that these productivity improvements were supposed to result from a better rationalization of resources, e.g., labor and fuel, an improved allocation of risks, and superior investment decisions.

To achieve the pursued efficiency gain, a wide set of actions was undertaken. Hunt (2002) provides a detailed list of steps that were required. A short summary of the main fields

[1] The terms restructuring and liberalization are used synonymously in literature.

affected by the changes lists the supply and demand side, the trading arrangements, the transmission business model, and the retail access. Joskow (2008) provides an extensive set of key components necessary for restructuring electricity markets[2]. The most important ones are:

- Privatization of state-owned monopolies
- Vertical separation of competitive and regulated divisions (unbundling)
- Horizontal restructuring of generators and retailers to foster competition
- Introduction of a horizontally integrated, regulated *transmission system operator* (TSO)
- Application of regulatory rules controlled by an independent regulator
- Launch of a wholesale market

The liberalization of energy markets in Europe was mainly driven by European regulation which also had a direct effect on German legislation. There are three main directives that constitute the basis for market restructuring (Langsdorf 2011). The 1996 directive, 96/92/EC, aimed at establishing a single European power market (European Commission 1996). To this end, international transmission capacities should be improved. Facilitated electricity trades would lead to more competition. Directive 2003/54/EC carried on the process by governing network access and opening national markets (European Commission 2003). In addition, electricity prices were made transparent and easily accessible. Measures were taken to protect end-users and vulnerable customers. Jamasb and Pollitt (2005) provide an overview over these directives. The latest directive, 2009/72/EC, aimed at facilitating cross-border trading and further unbundling of ownership (European Commission 2009a).

In Germany, the first EU directive was implemented into national law in 1998 via the *Energiewirtschaftsgesetz* (EnWG)[3]. In 2005, the EnWG was revised and responsibility for regulation in the energy sector (power and gas) assigned to the *Bundesnetzagentur*[4]. With the most recent revision of the EnWG in 2011 all EU directives were implemented. In summary, the main actions for restructuring the electricity market have been implemented in Germany (Ilg 2014). The main focus of energy politics and regulation recently shifted from market

[2] Ilic, Galiana, and Fink (2013) and Sioshansi and Pfaffenberger (2006) provide similar collections.
[3] Energy industry act
[4] Federal Network Agency

restructuring towards a more sustainable electricity generation and the promotion of RES to reduce global warming.

2.1.2 Energy Transition

The main goal of restructuring electricity markets was to increase market efficiency by introducing competition. However, other regulatory measures were realized to make the electricity sector ecologically more sustainable.[5] Lund (2007) quotes three major technological strategies for a sustainable development, i.e., save energy on the demand side, improve efficiency in the energy production, and replace fossil fuels by RES. These measures aim at reducing carbon dioxide emissions and greenhouse gases in general.

Investment cost for renewable generation plants is high compared to traditional power plants (Ringel 2006). Therefore, it was difficult for RES to gain significant shares in the generation mix. However, at least 164 countries defined targets for renewable energy integration, and about 145 countries established renewable energy support policies (REN21 2015). In the majority of these countries regulatory measures and support mechanisms were introduced to foster the introduction of RES (Haas et al. 2004).

Hunt (2002) cites three options for structuring subsidies that do not interfere with market mechanisms:

- *Utility based subsidies*: Prices above market prices are paid to utilities and passed through via distribution charges.
- *Government subsidies*: Government purchases (expensive) green power to resell it (at lower prices) to the market.
- *Direct consumer purchase of green power*: Consumers accept higher prices for power generated from RES.

Haas et al. (2008) provide a similar overview of promotion strategies for RES. In one dimension, strategies are classified by regulatory and voluntary measures and, in the other dimension, by direct and indirect methods. The success of supporting the introduction of RES by regulatory actions depends on political and societal parameters. Butler and Neuhoff

[5] The German Federal Government proclaimed the energy transition (*Energiewende*) which is the transition to an energy portfolio dominated by renewable energy, energy efficiency and sustainable development which leads to a substantial reduction in greenhouse gas emissions.

(2008) discuss support schemes in Germany and the UK. In contrast to Germany, that opted for a feed-in tariff scheme, the UK initially tendered for projects and then moved to a tradable green certificate scheme. Applying feed-in tariffs, cost to consumers is reduced which results in larger deployment. Similarly, Lesser and Su (2008) are in favour of feed-in tariffs. However, if not designed properly, feed-in tariffs can also be economically inefficient as they act like price floors. Therefore, a two-part tariff design is suggested that consists of both a capacity payment and a market-based energy payment. Couture and Gagnon (2010) investigate various feed-in tariff remuneration models and discuss the different ways of structuring payments which significantly influence investor risks and overall renewable energy rates. Ringel (2006) compares feed-in tariff approaches to green certificates in the EU. Both, feed-in tariffs as well as green certificates can support the introduction of RES. Finally, Ringel (2006) concludes that the result depends on in-detail regulations.

Regardless of the approach to support RES, measures have been taken all over the world. Feed-in tariffs were introduced in 108 jurisdictions, renewable portfolio standards were set in place in at least 26 countries and 60 countries had renewable energy tenders in 2015 (REN21 2015). In Germany, regulation considering the support of RES is implemented with the *Erneuerbare Energien Gesetz* (EEG)[6] since 2000. The recent revision was enacted in 2014. The EEG regulates feed-in tariffs and the preferential feed-in of electricity from RES. It has been succeeding substantially in Germany. The installed capacity of wind power plants increased by 508 % from 2000 to 2013 and installed photovoltaic capacity increased by a factor of 593 (BDEW 2015b). To respond to the massive capacity increase, the remuneration for electricity generated from photovoltaic power plants is constantly decreasing since 2004 (BDEW 2015b).

The *European Union Emissions Trading System* (EU ETS) was introduced to reduce carbon dioxide emissions (European Commission 2009b). However, Schmidt et al. (2012) note that the design of the first and second phase had flaws leading to misdirected incentives and even the third phase only had limited effects. On the other hand, the EU ETS was identified as an important long term trigger for developing low carbon technologies. This might be supported by the nuclear phase-out decisions of several European countries, e.g., Germany, Italy, Belgium, and Switzerland. In the absence of carbon dioxide free nuclear power carbon emission savings from electricity produced from RES might become more valuable as demand for carbon dioxide certificates might increase.

[6] Renewable energy act

2.2 Electricity Value Chain

The restructuring of energy markets gave rise to competition and the vertical separation of competitive and regulated divisions. The result was an unbundled electricity value chain (fig. 2.2) consisting of generation (incl. production and trading of fuels), transmission, distribution, and consumption (incl. sales and use of electricity). Whereas grid operations remain regulated monopolies, generation and consumption are active in a competitive (wholesale) market (Flath 2013).

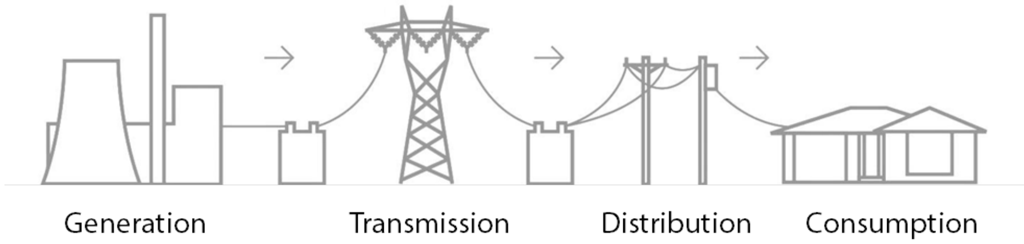

Figure 2.2: Electricity value chain after the liberalization of energy markets, adapted from EEX (2016)

2.2.1 Generation

As pointed out above, electricity was historically generated by few central large scale power plants to benefit from economy of scales (Stoft 2002). These power plants are typically fired by fossil fuels. As a consequence, fuel supply to the world electricity generation in 2013 is dominated by non-renewable resources: coal 41.3 %, natural gas 21.7 %, nuclear 10.6 %, and oil 4.4 % (IEA 2015). However, the composition of the national generation portfolio differs greatly. Norway, for example, uses its immense potential for renewable generation and satisfies more than 96 % of their electricity demand from hydroelectric plants. In contrast, France strongly relies on nuclear power which produces almost 75 % of its domestic generation (IEA 2015). Germany has a comparably diverse generation mix (fig. 2.3). The differences in the generation mix lead to different levels of emission per country. All generation technologies in the heterogeneous German market significantly differ with respect to inputs, operation and capacity costs, scalability, reliability, location, and flexibility.

The size and the long economic lifetime of generation assets required large investments in the historically developed supply mix. This led to a dominant position of the four big generation companies (RWE, E.ON, Vattenfall, EnBW) accounting for over 73 % of total electricity

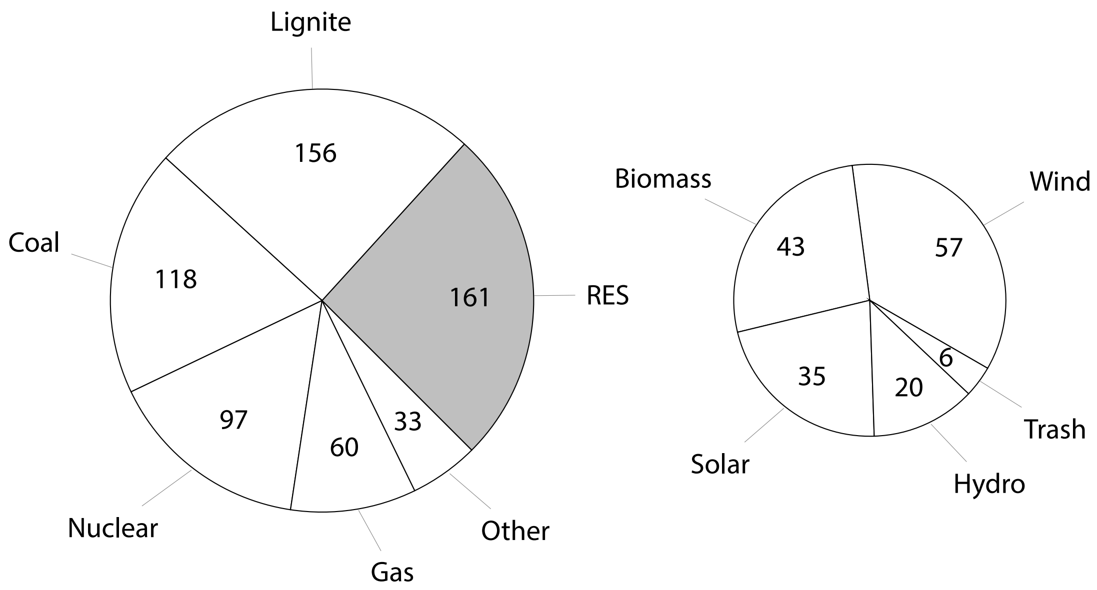

Figure 2.3: Gross electricity generation—left and right hand panel: overall energy mix and renewable energy sources—values in TWh (BMWi 2015a)

generation in Germany (Bundesnetzagentur and Bundeskartellamt 2015) as large investments favor large utilities. Encouraged by the liberalization, the unbundling of electricity markets, and the EnWG, the share of generation from RES has seen constant growth in Germany since the 1990s (BMWi 2015a). The increasing share of hardly controllable generation from RES makes flexibility a very important characteristic of conventional generation. Like the exploitation of flexibility in electricity demand, which is discussed in detail later on, the ability of adapting a power plant's output on short notice becomes more important to balance the deviation of the forecast and the actual renewable generation.

Unbundled generators offer electricity to electricity retailers that need it to satisfy their customers' demand. Although in many countries the lions share of electricity is traded *over-the-counter* (OTC) via long term bilateral transactions (Lijesen 2007; Rademaekers, Slingenberg, and Morsy 2008), short term (day-ahead and intra-day) trading is executed on spot markets. In both cases generation is scheduled in advance. On spot markets typically a merit order dispatch is executed (Schweppe et al. 1988). To this end, retailers submit bids for electricity and generators submit asks. Bids are sorted by decreasing willingness to pay and asks are sorted by increasing marginal cost. The clearing prize is determined by the highest ask that is allocated and is equal for all allocated generators (fig. 2.4). Usually, there is a separate price auction for each period. Periods are often half an hour or an hour but can be as short as 5-15 minutes (Holmberg and Newbery 2010).

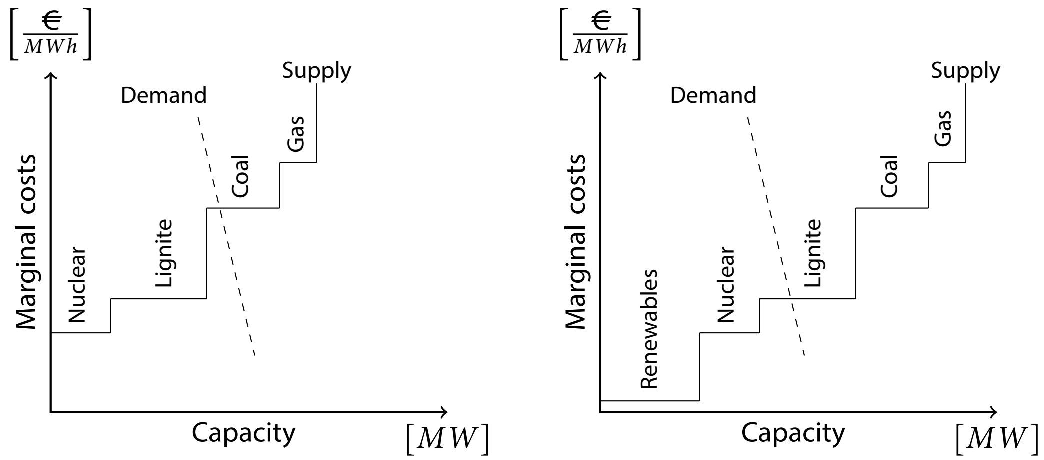

Figure 2.4: Merit order dispatch and merit order effect

Worldwide, generation from RES has seen constant growth in recent years (IEA 2015). Therefore, the power plants with the formerly lowest marginal cost is pushed to the right in the merit order as generation from RES entered the market with almost no marginal cost. This is supposed to cause an overall market price decrease which Sensfuss, Ragwitz, and Genoese (2008) named *merit order effect*. To ensure grid stability, supply has to match demand at any time. Therefore, satisfying demand during times of low generation from RES becomes increasingly challenging as not enough conventional power plants are available (Mount et al. 2010). In addition, power plants with high marginal cost are typically the most flexible ones. They are needed to smooth volatile generation from RES. Cramton and Stoft (2006) refer to this as the *missing money problem*. This trend is even fueled by renewable energy subsidies. There are several ways of addressing the *missing money problem*. One approach is to adjust electricity markets. A more integrated market design honoring both capacity provision and energy supply is the introduction of capacity markets (Cramton and Stoft 2005; Cramton and Ockenfels 2012). Another idea, which this work focuses on, is to exploit the still drowsing flexibility potentials in electricity consumption instead of investing in expensive highly flexible conventional power plants. Therefore, active DSM poses a huge opportunity to limit reserve energy cost and to support the movement towards a more sustainable electricity supply. However, this may lead to distributional effects on flexible generation, whose value may be diminished.

2.2.2 Transmission

Although the share of decentralized generation from RES has seen constant growth, electricity was, and still is, predominantly generated by few large scale centralized power plants. The power grid is used to transport electricity to the locations where it is consumed. There are typically four voltage levels, i.e., the extra high, the high, the medium, and the low voltage level. In Germany the ownership and the operation of the grid are integrated. The TSO runs the extra high voltage transmission grid and the *distribution system operator* (DSO) controls the lower voltage distribution grid (Bundesnetzagentur and Bundeskartellamt 2015). In other countries ownership and system operation are separated. Brunekreeft, Neuhoff, and Newbery (2005) introduce an *independent system operator* (ISO) that is responsible for system operation but does not own the grid. They argue that an ISO is a simple solution of expanding market areas without forcing different grids to merge into a single company. However, comparable low operation and high investment costs make electricity grids—like other network industries—a natural monopoly (Train 1991). Therefore, as noted before, they are regulated (Jamasb and Pollitt 2000).

In Germany the transmission grid is split into four control zones run by different TSOs. Figure 2.5 provides a geographic overview of the zones with the corresponding TSO: TenneT, 50Hertz, Amprion, and TransnetBW (Bundesnetzagentur and Bundeskartellamt 2015).

Figure 2.5: TSOs with corresponding control areas in Germany (Gerbaulet et al. 2013)

The TSOs manage almost 35,000 km of extra high voltage transmission lines operated at 220 and 380 kV (table 2.1). Securely managing this widespread network comes along with large investments in the grid itself and ancillary service cost to maintain grid stability. Transmission grid infrastructure and investment costs increased from 739 million euro in 2009 to 2,644 million euro in 2015 (Bundesnetzagentur and Bundeskartellamt 2015). The cost for system services, on the other hand, stayed almost constant.

2.2.3 Distribution

DSOs, in contrast to TSOs, do not operate on the extra high voltage level but the high, medium, and low voltage level. They cover the operation, maintenance and repair in a specified area. Furthermore, they are responsible for mid- and long-term planning to accommodate future supply and demand. A DSO's operating area is by far smaller than that of TSO. According to Bundesnetzagentur and Bundeskartellamt (2015), 813 DSOs are responsible for more that 1.7 million km of electricity lines and manage plus 50 million metering points (industrial and business as well as household customers) in Germany. Table 2.1 provides an overview of both TSO and DSO facts considering grid and customer characteristics.

Table 2.1: Electricity grid characteristics in Germany 2014 seperated by TSO and DSO (Bundesnetzagentur and Bundeskartellamt 2015)

	TSO	DSO	Total
System operators (number)	4	813	817
Total circuit length (km)	36,612	1,722,400	1,807,012
Extra high voltage	34,388	349	34,737
High voltage	224	96,149	96,373
Medium voltage	0	511,591	511,591
Low voltage	0	1,164,311	1,164,311
Total final customers (metering points)	565	50,087,805	50,088,370
Industrial and business customers		3,169,102	3,169,102
Household customers		46,918,703	46,918,703

Generation from RES is typically fed-in on the mid or low voltage level. Therefore, the DSOs have to deal with bidirectional power flows although the distribution grid was, historically, built for unidirectional power flows (Ströhle 2014). In addition, uncertain and fluctuating renewable generation is only partly controllable (Sharma et al. 2011). Over-provisioning of capacity and large grid investments became economically unsustainable. Albadi and El-Saadany (2008) propose to utilize demand side flexibility instead. Traditionally, little automation and information on the state of the network was available due to a lack of deployed sensors and communication capabilities (Ipakchi and Albuyeh 2009). These *information technology* (IT) driven opportunities are key improvements the implementation of a SG[7] provides. It becomes easier to exploit flexibility in electricity consumption as signals can be sent to consumers or they can even be controlled directly using SG technologies (Schuller 2013). Such DSM approaches are discussed in section 2.3. They pose enormous potential to grid operators to reducing excessive investment and system service costs.

2.2.4 Consumption

Worldwide, electricity accounted for 18 % of the total final energy consumption in 2013 (IEA 2015). In Germany, even more than 20 % of primary energy were transformed to and consumed as electricity (BMWi 2015a). The left panel of figure 2.6 shows the final electricity consumption split up by sectors. The major part of it is consumed by industry. However, private households are second in consumption. They account for almost one quarter of electricity consumption (BDEW 2015a; AGEB 2015). The right hand side of figure 2.6 depicts the household electricity consumption split up by appliance groups. These appliance groups are defined by the appliances' properties with respect to typical usage and corresponding flexibility which defines the applicability for DSM.[8] Almost half of the end consumer electricity consumption is inflexible base load.

Electricity tariffs were already discussed in early 1950s (Houthakker 1951). Tariff features vary in dependence with the customer type. Private households typically receive simple tariffs. Most common is a flat tariff consisting of two components, i.e., a fixed connection fee and flat rate, where the amount paid is strictly proportional to total consumption. With the widespread proliferation of nuclear power plants, *time-of-use* (TOU) tariffs in combination with storage water heaters became more popular in the 1960s (Torriti, Hassan, and Leach 2010). TOU tariffs also consist of a fix connection fee and flat rate proportional to consumption; however, the variable cost factor depends on the time the electricity is consumed. This incentivizes customers to increase electricity consumption in times at which much generation

[7] A comprehensive introduction to the SGs provides section 2.4

[8] Chapter 4 elaborates in detail on the appliance group characteristics with the corresponding scheduling ability.

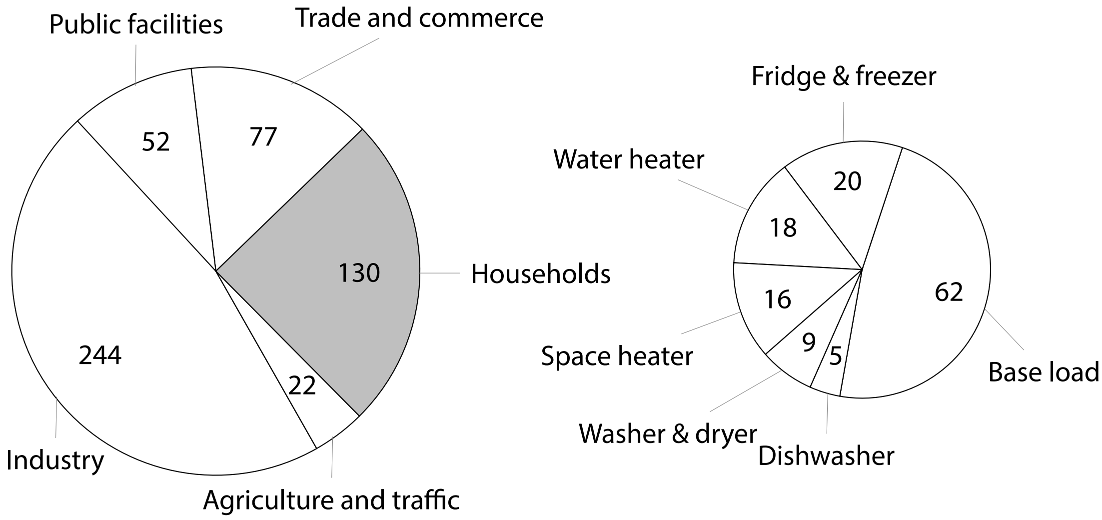

Figure 2.6: Final electricity consumption by consumer type in Germany 2014 in TWh: left panel on a national level (BDEW 2015a), right panel on household level (Gottwalt et al. 2016)

is available and vice versa (Torriti 2012). Finally, the simplest tariff is a flat rate, that provides a specified amount of energy for a fixed price. This price still must be paid in case the specified amount of energy is not consumed.

Industrial electricity customers usually receive tariffs that do not only depend on electricity consumed but also on the maximal load consumed in peak periods. This power related cost component can be combined with flat tariffs, TOU tariffs, or allowances (also referred to as flat rates). Regardless of the exact tariff design, the power related component incentivizes industrial customers to avoid excessive consumption in peak times. However, considering private households, there is no incentive for adapting consumption and give raise to inelastic, uncontrollable electricity demand.

In Germany, smart meters must be installed in refurbished or newly constructed buildings (EnWG, §21). Darby (2010) investigates to what extent smart meters improve customer engagement and Wissner and Growitsch (2010) discuss international experiences of a comprehensive smart meter roll out and their consequences for Germany.

To improve grid stability and to reduce system service cost, DSM poses a huge opportunity. Albeit (the already implemented) DSM poses an enormous technical and economical potential especially in energy-intensive industries (Roos and Lane 1998; Paulus and Borggrefe 2011), there are no proper incentives and tariffs for private customers to offer their flexibility for load scheduling. However, it is vital for a stable energy system, that power generated on the first stage of the value chain, and power consumed on the last stage are balanced at any time. To ensure this equality, flexibility on the supply or the demand side must be utilized to adapt generation or consumption to match the respective other.

2.3 Flexibility in Power Systems

Both ends of the electricity value chain, i.e., generation and consumption, must be balanced at all times to ensure safe system operation and a stable state of their intermediate, the electricity grid. Flexibility in one or both sides must be used to balance supply and demand. In addition to balancing supply and demand, the power grid constraints the transportation of electricity from the point of generation to the location of its consumption. Flexibility and rescheduling of both generation and consumption must be used to avoid bottlenecks. In conclusion, flexibility on both the supply and demand side as well as electricity storage is vital to run the power system safely and sustainably.

2.3.1 Supply Flexibility

Historically, and still today, the energy industry has applied the dogma *supply follows demand* (Liang et al. 2013). Uncertain and uncontrollable demand is forecast and supply from conventional, controllable power sources is dispatched to match consumption. The problem of optimally dispatching generation in the presence of fluctuating uncontrollable generation from RES has received much attention (Wood and Wollenberg 1984; Van Den Bosch and Lootsma 1987; Fan et al. 2013; Ma et al. 2016). To maintain system security is the responsibility of ISOs (Bhattacharya and Zhong 2001). To this end, they provide spinning reserve, energy balancing, and frequency regulation. Flexibility of conventional generation is usually traded at short notice, typically day-ahead, intraday, or, most importantly, on the ancillary service market. Oren (2001) investigates the design of ancillary service markets. Reserve types can be distinguished in terms of response time. Slower responding reserves replace faster ones.

In Germany, three types of balancing power are distinguished (Klobasa 2010), i.e., *primary control reserve* (PCR), *secondary control reserve* (SCR), and *tertiary (minute) reserve* (TR). A detailed overview provides Consentec (2014):

- *Primary control reserve* is used for very fast power line frequency stabilization. It is controlled automatically for the whole grid, regardless of grid zones. To qualify for PCR the full power must be available within thirty seconds. The minimum lot size of a bid is set to 1 MW. Considering PCR the call for tenders is symmetrical, meaning positive (additional power) and negative (less power) PCR is not called separately. Tenders are published weekly.
- *Secondary control reserve* is activated in the control area where the system imbalance occurs. In Germany, the maximum activation time of SCR is set to five minutes. Like for PCR, tenders are published weekly. In comparison to PCR, the call for SCR tenders is asymmetrical, meaning positive and negative reserve is called separately. The minimum lot size of a bid is set to 5 MW.
- *Minute reserve* provision requires a framework agreement between the supplier and connecting TSO. The tendering period for TR is one day. Compared to PCR and SCR which are controlled continuously, TR is activated in 15 minute intervals. It is used for system imbalances that last longer, e.g., forecast errors or power plant outages. Therefore, it is sufficient if it can be activated within 15 minutes.

Figure 2.7 illustrates the co-operation of the different reserve types.

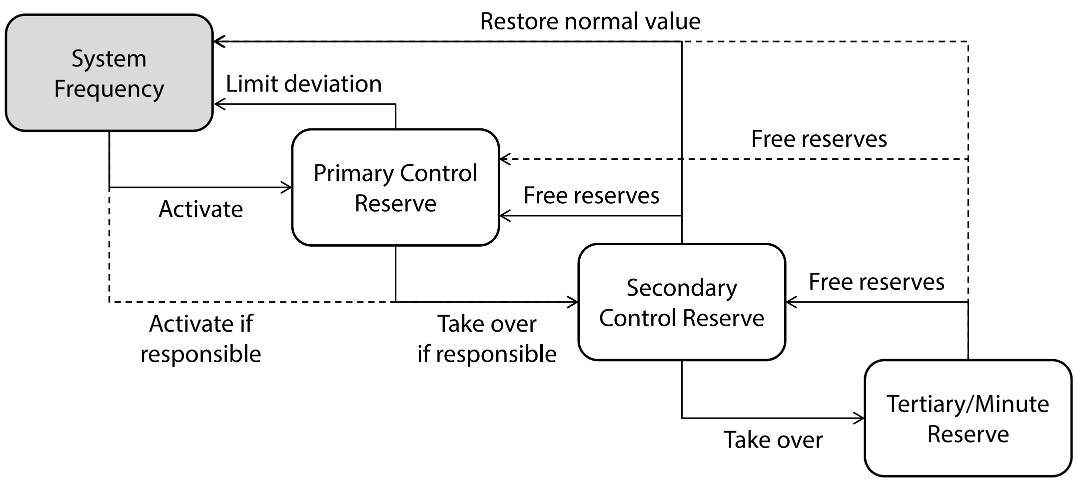

Figure 2.7: Reserve power activation, adapted from Entsoe (2004)

Each generator that wants to offer reserve energy must withstand a prequalification procedure which the connecting TSO conducts. The TSOs use the shared Internet platform `regelleistung.net` procuring all three types of reserve power. Via this platform the process of publishing tenders, processing bids, and informing bidders of acceptance or rejection of their bids is implemented. Table 2.2 provides an overview of reserve power types in Germany including their technical specification as well as action characteristics.

Table 2.2: Characteristics of reserve power types in Germany, adapted from (Consentec 2014)

	PCR	SCR	TR
Depreciation period	weekly	weekly	daily
Bid length	whole week	peek: mo-fr 8am-8pm off peak: remaining time	6 x 4 hour blocks
Product differentiation	symmetric	positive/negative	positive/negative
Minimum lot size	1 MW	5 MW	5 MW
Lot increments	1 MW	1 MW	1 MW
Winner determination	load rate merit order	load rate merit order	load rate merit order
Remuneration (pay-as-bid)	load	load and energy	load and energy

Prequalified generators can submit bids for published tenders. Bids are then sorted by load rate. This load rate merit order is used to allocate the winning bids for all three types of reserve power. Winning bids receive the load rate for provisioning of reserve power regardless of the actual usage. A SCR and TR bid contains an energy rate in addition to the load rate. Therefore, allocated bids are sorted and scheduled by ascending energy rates. The energy rate is only paid for SCR and TR which was activated (Swider 2008).

Small generators struggle with the prequalification process as comparably large plants are necessary to enable the provision of load over a long time horizon, e.g., one week for PCR. To manage this problem, generators can form *virtual power plants* by combining their capacities. Optimal bidding strategies for optimal virtual power plants (Mashhour and Moghaddas-Tafreshi 2011) as well as their operation (Papadogiannis and Hatziargyriou 2004; Lombardi, Powalko, and Rudion 2009) have recently been gaining attention.

Nevertheless, cost for reserve power is high. In 2015, cost for grid stabilization exceeded one billion euro in Germany (FAZ 2016; SPON 2016; Focus 2016). Supported by the *merit order effect*, it becomes difficult for operators of conventional power plants to run them profitably. Therefore, novel concepts like exploiting demand side flexibility or using storage and grid flexibility become essential.

2.3.2 Grid Flexibility and Electricity Storage

In comparison to generation and consumption, electricity grids themselves can only provide little flexibility. However, they provide flexibility in the intensity they are used, unless they do not get congested. In addition to volume flexibility, individual grid lines can be connected or disconnected by power switches to increase or decrease the systems transfer capacity (Ströhle 2014). Such measures change the network's topology and allow to control power flows. Kaptue Kamga, Völler, and Verstege (2009) investigate disconnecting (renewable) power plant to reduce feed-in electricity for congestion management.

Changing grid size and topology additionally adds reliability in terms of forecasting and planning security to the system. Both uncertainty in generation from RES and electricity demand flexibility can be pooled by increasing the number of generators and consumers connected to the grid. Hence, increasing the size of balancing areas or the cooperation between utilities to enhance diversity in the generation and demand patterns enables a more reliable grid operation (Denholm and Hand 2011). Compared to disconnecting individual lines or generators, which can be used as short term measures, network expansion is time-consuming and costly.

To store electricity in times when supply exceeds demand and to feed it into the grid in times of high demand and low supply requires storage technologies that can be operated in an economically sustainable fashion. Introductions to storage technologies including detailed specifications of storage characteristics, e.g., applications, capacity limitations, efficiency, number of cycles to end of life, are widely available (Van den Bossche et al. 2006; Ibrahim, Ilinca, and Perron 2008; Poullikkas 2013; Lehner et al. 2014). Table 2.3 provides an overview of battery technologies used by electricity utilities. Obviously, utilities and other users of storage technologies have to trade off cost with quality in terms of longevity or efficiency.

Barton and Infield (2004) investigate different storage technologies for their operational suitability over varying time scales in a scenario with intermittent renewable energy generation from wind power plants. Korpaas, Holen, and Hildrum (2003) investigate the optimal sizing and operation of storage capacities. The importance of proper storage sizing is shown in a case-study with fluctuating wind power generation and flow cells as well as fuel cell systems for smoothing wind feed-in. Wind power plant owners can benefit from hourly spot market prize variations applying the suggested sizing and operation method.

Table 2.3: Characteristics of battery technologies used by electricity utilities (Divya and Østergaard 2009)

Battery type	efficiency [%]	cost [€/kWh]	life span [# cycles]	energy density [Wh/kg]	self-discharge [%/month]
Metal air	50	50–200	few 100	450–650	0
Lead acid (flooded type)	72–78	50–150	1000–2000	25	2-5
Lead acid (valve regulated)	72–78	50–150	200–300	30-50	2-5
Nickel Cadmium (NiCd)	72–78	200–600	3000	45-80	5-20
Regenerative fuel cell (PSB)	75	360–1000	-	-	0
Zinc Bromine	75	360–1000	-	70	0
Vanadium redox (VRB)	85	360–1000	10000	30-50	0
Sodium Sulphur (NaS)	89	-	2500	100	0
Lithium ion	100	700–1000	3000	90-190	1

However, electricity storages are not yet disseminated widely. Storage technologies are currently very costly and suffer from degradation and limited efficiency. Further technological development could lessen these shortcomings. In combination with efficient DSM, storage operation poses a major opportunity to secure sustainable and reliable grid operations (Atzeni et al. 2013).

2.3.3 Demand Flexibility

The adaption of electricity generation to demand established the current paradigm that energy supply follows demand (Roozbehani, Dahleh, and Mitter 2010). In the absence of technologies to control end consumer appliances directly or to distribute (price) signals to customers, this approach was the most economical means to ensure system stability. Few centralized generators, typically fueled by fossil fuels, could be controlled a lot easier. However, this has become more difficult and costly as the share of fluctuating and uncontrollable generation from RES has seen constant growth in recent years. On the other hand, the technology to distribute signals and remotely control electric appliances is becoming available. Therefore, controlling electricity demand poses an attractive but still challenging opportunity to reduce system cost and to increase overall welfare.

Demand side flexibility is already being exploited in energy-intensive industries. Paulus and Borggrefe (2011) investigate to what extend such energy-intensive industries can provide system services. However, on the private household level, demand side flexibility is not yet put to use on a large scale. Electricity consumption and the corresponding flexibility hinge on multiple factors. A taxonomy for dispatching flexible loads in smart grids provide Petersen et al. (2013). McFadden, Puig, and Kirschner (1978) note that both the characteristics of appliances held by end consumers as well as current household activities impact demand for electricity. Each appliance can be related to an active or passive activity. He et al. (2013) suggest an illustrative mapping of household appliances to flexibility types. Figure 2.8 presents a modification of these flexibility types—i.e., storable, shiftable, curtailable, and base load. They differ in technical characteristics of the appliances belonging to the respective category in combination with the user behavior. Therefore, the appliances cannot be mapped uniquely to a flexibility type but the exemplary appliances sets are disjoint.

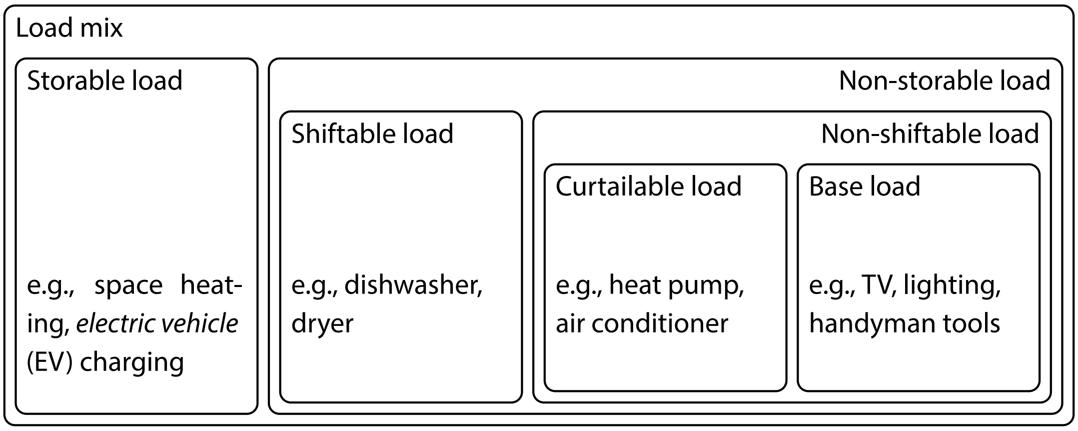

Figure 2.8: Illustrative load mix of private households split up by types of demand flexibility, adapted from He et al. (2013)

- *Storable load* consists of decoupled consumption and electricity service often containing a storage medium, e.g., electrochemical in batteries or water in heating and cooling appliances (cf. section 2.3.2). Storable loads are highly attractive for DR programs as they can respond to both static and dynamic contracts.
- *Shiftable load* can be postponed (or preempted) without affecting the service itself. Shiftable loads are usually not interruptible like a single run of a dishwasher or a washing machine.
- *Curtailable load* does not have to be fully satisfied. Therefore, the end-user service level can be reduced. However, if curtailable loads are used for DSM a certain predefined service level must be maintained at any time. Typical examples are guaranteed

temperature intervals.

- *Base load* services need instant power (they are not shiftable or interruptible) and are, consequently, not applicable for DSM.

A similar characterisation of possible demand adaptions is presented by Gellings (1985). The author states that load management was already introduced in the 1960s. The goals were to increase long term off-peak and winter demand by storage space heating and to reduce short term peaks using storage water heaters. These considerations only focused on load management that did not require customer interaction which is important from a marketing point of view. However, current research also considers such opportunities by introducing innovative electricity services that require such interaction supported through ever present mobile end devices.

There is extensive literature on modeling flexibility (especially) in household electricity consumption. Scott et al. (2013) introduce a formal definition of household electricity devices including batteries and electric vehicles. The model is applied to investigate optimal scheduling in smart homes under uncertainty of future real-time electricity prices. Alizadeh et al. (2015) provide a medium-grained stochastic hybrid model to represent a population of appliances that belong to two classes, i.e., deferrable (shiftable) or thermostatically controlled (curtailable) loads. For thermostatically controlled loads, a comfort or safety band depending on the time of the day is defined and must be met.

The level of flexibility private end consumers can provide depends on the stock of electric appliances available in the household as well as the appliance characteristics (Halvorsen and Larsen 2001). The authors investigate the long run effects of investments in new appliances using a discrete-continuous approach. Each household must trade off investment cost in "smart" devices with potential electricity bill savings from participating in DR programs. Gottwalt et al. (2016) assume that the technological requirement for exploiting demand flexibility are given. They introduce a detailed model of electricity consumption on appliance level to evaluate the system cost savings of single devices. This allows to valuate demand flexibility potentials of private households.

A central condition to successfully implement DSM is the availability of *information and communication technology* (ICT) regardless of the model which is applied to investigate demand flexibility. The SG concept represents a fully automated power delivery network that provides two-way information and power transmission. Hence, it enables the implementation of DR approaches to cost-efficiently, sustainably, and securely satisfy demand for electricity.

2.4 Smart Grids

The metamorphosis from a transmission and especially distribution grid with "blind" and manual operations towards a smart grid is crucial (Ipakchi and Albuyeh 2009). One the one hand, this transformation enables DSM which ensures cost-efficient and sustainable grid operation and, on the other hand, it facilitates to meet environmental goals. It is obvious that the implementation of SGs is relevant for all three components of the energy policy objectives triangle (cf. figure 2.1). Gellings (2009) argues, that "a smart grid is the use of sensors, communications, computational ability and control in some form [...]". This quite technical definition is well in line with U.S. Department of Energy (2003) that defines the SG as follows:

Definition 2.1 (Smart Grid). *"A fully automated power delivery network that monitors and controls every customer and node, ensureing a two-way flow of electricity and information between the power plant and the appliance, and all points in between. Its distributed intelligence, coupled with broadband communications and automated control systems, enables real-time market transactions and seamless interfaces among people, buildings, industrial plants, generation facilities, and the electric network." (U.S. Department of Energy 2003).*

The EU Commission Task Force for Smart Grids expands this technical definition by an economical perspective (EU Commission Task Force for Smart Grids 2010).

Definition 2.2 (Smart Grid). *"A smart grid is an electricity network that can cost-efficiently integrate the behavior and actions of all users connected to it [...] in order to ensure economically efficient, sustainable power system with low losses and high levels of quality and security of supply and safety." (EU Commission Task Force for Smart Grids 2010).*

In a comprehensive introduction to SGs, Sioshansi (2011) states that the SG is often, especially by engineers, seen as a "[...] grid that is self-detecting, self-healing, and more reliable and dependable than what we currently have". However, the author argues that the SG needs to be more than that. The grid of the future must be more reliable and more integrated. It must support the integration of intermittent and distributed generation (from RES), and, finally, by permitting tow-way communication, it must enable the direct interaction with devices to implement customer friendly "price-to-device" DSM (Sioshansi 2011).

The bidirectional flow of both electricity and information safeguards the grid integration of renewable generation (Ramchurn et al. 2012). This is essential to manage the reduction of greenhouse gas emissions without putting security of supply at risk. To make use of current assets is as essential as introducing new, innovative technologies in both generation, e.g., wind and solar power, and consumption, e.g., EVs and smart devices (Farhangi 2010). In conclusion, these technological enhancements enable renewable energy integration including distributed energy generation and price-responsive electricity demand (Blumsack and Fernandez 2012). The activation of demand flexibility, namely DSM, is a driver to securely operate the grid in a cost-efficient and sustainable fashion.

2.4.1 Demand Side Management

The implementation of a smart grid allows for electricity utilities and retailers to interact (constantly) with their customers in real-time. It enables flexibility aggregators to send signals to customers or to control devices directly, which is a key requirement to make DSM come true. The umbrella term DSM encapsulates a wide portfolio of activities to put demand flexibility to use for improving the energy system at the side of consumption (Palensky and Dietrich 2011).

DSM was already discussed in the 1950s (Houthakker 1951). Building on general models of electricity consumption and its drivers (Dubin and McFadden 1984; McFadden, Puig, and Kirschner 1978), the topic gained more attention in the 1980s (Delgado 1985; Limaye; Schweppe et al. 1988). Gellings (1985) defines DSM as "the planning and implementation of those electric utility activities designed to influence customer uses of electricity in ways that will produce desired changes in the utility's load shape". Five exemplary load shape objectives were identified (fig. 2.9). Following Gellings (1985), all of these demand shaping adaptions can be derived from three fundamental activities, namely demand curtailing, shifting, and enlargement.

Sioshansi (1995) splits up the evolution of DSM into three waves:

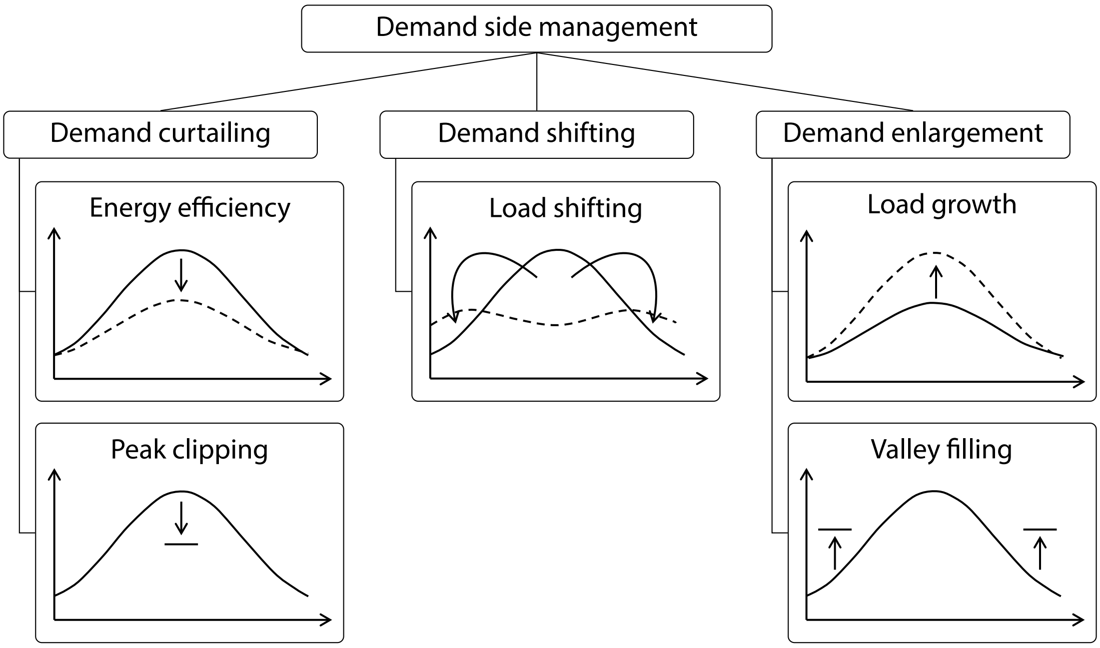

Figure 2.9: Exemplary load shape pattern objectives through DSM, adapted from Gellings (1985) and Hölker et al. (2014)

- *1973-89 - command and control but without incentives*: The first phase was a result of the 1970s oil crisis. DSM mainly aimed at energy conservation. There were plenty of opportunities to save energy and customers were easily convinced as it was considered unpatriotic not to participate.

- *1989-94 - command and control with incentives*: After the oil crisis, decreasing oil prices made the strict reduction of energy consumption dispensable. Actually, utilities lost revenues due to energy conservation measures. Therefore, utilities even would prefer not to implement DSM. This changed when the laws and regulatory measures, e.g., bonuses or financial remunerations, provided incentives for utilities to cover their DSM-related expenses in the late 1980s. This phase was put to an end by retail wheeling and mandatory transmission access.

- *Since 1994 - customer driven and customer financed*: The still ongoing third phase has been dominated by customers' decision making. Given the option to participate and (not) to pay for DSM they gained power. Therefore, utilities have been urged to design incentives that encourage customers to participate in DSM programs and, thereby, decide upon its success.

A fourth phase is currently evolving. Due to the dissemination of SGs it has become possible to even control small loads centrally and to distribute signals comprehensively in real-time. This new technology enables aggregators and utilities to launch a whole new variety of tariffs and control mechanisms to support the efficient and sustainable integration of RES.

Strbac (2008) discusses benefits and challenges of DSM. An average utilization of less than 55 % of power plant capacity utilization opens up a substantial scope for DSM, e.g., load shifting from peak to off-peak periods. Benefits of load management include the increase of transmission and distribution grid investment efficiency, cost-efficient load balancing, and support of distributed generation. On the one hand, DSM still suffers from a lack of ICT infrastructure, from an inadequate regulatory framework, and from missing competitiveness compared to traditional approaches. On the other hand, it is a key requirement to establish renewable generators and SG hardware. However, these measures alone will not realize the full potential for overall system efficiency and carbon reduction if the same operating paradigm of the grid is still used (Varaiya, Wu, and Bialek 2011).

Before DSM programs are launched for private customers they should be tested on a semi-professional level. Qureshi, Gorecki, and Jones (2014) investigate maximum profits that can be gained by an office building participating in DSM. In their model a building controller takes decisions for the whole building once a day whether or not to participate in a load management event and then schedules the electricity consumptions to maximize savings and profits, respectively. Such scheduling considerations are essential for both system operators and retailers who design and offer DSM programs and demand flexibility aggregators (like the building managers) that take part in the respective programs and administer demand flexibility.

2.4.2 Load Scheduling and Optimization

The utilities' or demand flexibility aggregators' objectives to pursue the activation of demand flexibility are manifold. However, regardless of the DSM goals, utilities must plan in which manner loads should be scheduled to achieve an optimal result from DSM. Using these schedules, DR programs that rely on tariff and incentive design can be implemented. Determining valid schedules, they must solve complex optimization problems. These can often be described as knapsack problems (Ha et al. 2008; Sianaki, Hussain, and Tabesh 2010). Knapsack problems are well investigated (Sinha and Zoltners 1979; Chu and Beasley 1998;

Lust and Teghem 2012; Setzer and Bichler 2013) but still hard to solve. Not only demand, but also supply side coordination requires efficient scheduling algorithms and optimization approaches, e.g., scheduling of reserve power (Galiana et al. 2005). The demand scheduling result hinges on characteristics of generation and vice versa. Therefore, in the process of scheduling flexible demand or supply, the behavior of the respective other must be taken into account (Ashok and Banerjee 2003).

Hobbs and Nelson (1992) analyze various economic issues that affect electric utility DSM planning using a nonlinear bi-level model. On the upper level, the electric utility tries to maximize its profits via controlling electricity rates. On the lower level, customers attempt to maximize their benefit of electricity consumption. All scheduling approaches utilities apply should consider this area of conflict. Part IV discusses a similar scenario using a two-stage optimization approach that consists of long term strategic supply and flexibility procurement and short term scheduling. A comprehensive introduction to bi-level optimization is provided by Bard (1998).

Yu and Chau (2013) model a complex-demand knapsack problem and present an approximation algorithm to solve it. In their approach they consider several agents that act selfishly, trying to maximize their own profit. Therefore, the algorithm is adapted to provide incentive compatibility which ensures that all agents report truthfully. Recently, scheduling of residential demand, even down to a very fine-grained appliance level, gained attention. Scheduling models are often formulated as mixed integer linear problems. Considering a case-study with TOU tariffs, Setlhaolo, Xia, and Zhang (2014) find that households could safe more than 25 % of their electricity bill. Gottwalt et al. (2016) show that thermal appliances provide substantial potential for DSM. Focusing on such thermal devices, Du and Lu (2011) propose a fast, robust, and flexible scheduling algorithm including physical conditions and random consumption of hot water.

The goal of mere reduction of peak consumption, cost minimization, or profit maximization can be expanded to multi-objective optimization approaches. Soares et al. (2014) manage flexible loads to minimize both the electricity bill and customer dissatisfaction. Inconvenience is affected by the time operations are realized and the risk of interruption of energy supply. In a similar vein, Baldick, Kolos, and Tompaidis (2006) investigate electricity contracts that confer the right to interrupt electricity services to the retailer in change for a financial compensation. In addition to optimal interruption strategies, Baldick, Kolos, and Tompaidis (2006) demonstrate, that "in a deregulated market, interruptible contracts can help alleviate supply problems associated with spikes of price and demand." Varaiya, Wu, and Bialek (2011) propose a "risk-limiting dispatch" operating paradigm. Thereby, generation is treated as a heterogeneous commodity of intermittent or stochastic power. It is used to design hedging techniques to manage the risk of uncertainty. This work expands former discussions on interruptible power service contracts (Tan and Varaiya 1993).

Heuristic scheduling poses attractive alternatives to computationally complex, time-intensive optimization approaches. O'Brien and Rajagopal (2015) introduce an algorithm which automatically schedules deferrable loads. The greedy algorithm attempts to curtail the error between the scheduled demand and an objective profile. A "predictive" and "agile" heuristic algorithm is presented by Petersen et al. (2013). It is used to control a virtual power plant of heterogeneous flexible loads. Logenthiran, Srinivasan, and Shun (2012) present a heuristic-based evolutionary algorithm for coordinating a large number of diverse devices on a day-ahead time horizon.

Scheduling demand and supply is often described as two-stage optimization models—on the first (stochastic) stage, supply and demand flexibility is procured and, on the second stage, procured loads must be scheduled (Gärttner, Flath, and Weinhardt 2016a). Tan et al. (2014) consider a two-stage energy storage system under uncertainty of power generation from wind power plants. Using two-stage stochastic mixed integer program, Parvania and Fotuhi-Firuzabad (2010) present both scheduling strategies for flexible loads provided by demand flexibility aggregators as well as (decentral) commitment states of generating assets.

2.4.3 Demand Response Programs

The implementation of DSM requires both technical capabilities, e.g., SG infrastructure and the ability to efficiently schedule flexible supply and demand, and proper incentive models, e.g., bonuses or discounts on electricity bills which motivate consumers and generators to provide flexibility. The goal of controlling the behavioral adaptions of customer behavior is pursued via DR programs. Albadi and El-Saadany (2008) define DR as follows:

Definition 2.3 (Demand Response). *"Demand response can be defined as the changes in electricity usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time. Further, DR can be also defined as the incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized" (Albadi and El-Saadany 2008).*

The execution of such programs is manifold. Albadi and El-Saadany (2008) classify two main categories i.e., incentive based programs and price based programs (fig. 2.10). Incentive based programs can be split up again into classical and market based programs.

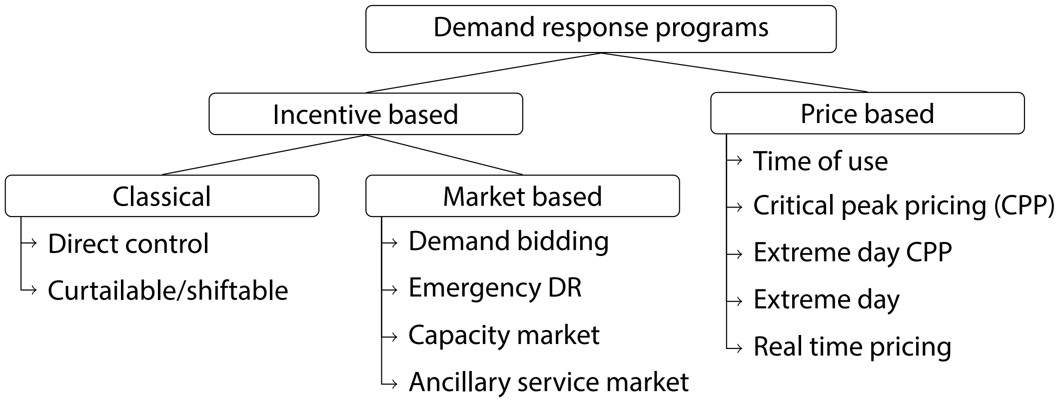

Figure 2.10: Classification of demand response programs, adapted from Albadi and El-Saadany 2008

DR incentives cause customers to change their electricity consumption behavior. Siano (2014) identifies three different ways in which customers can change their usage behavior:

- *Load curtailing* refers to a reduction in energy consumption
- *Load shifting* is the temporal preemption or deferral of consumption
- *On-site consumption* means the usage of locally generated energy to limit the dependence on the main grid

Gellings (1985) identifies similar load shaping measures (cf. figure 2.9). In the analytical main parts of this work (part II - IV) the focus lies on temporal and quantitative flexibility (fig. 2.11). To increase local on-site consumption is a goal of DSM rather than a measure as it increases consumption from (locally generated) renewable energy and relieves the grid from overloads. Consequently, DR contracts range from fully static (no flexibility) to fully flexible (both temporal and quantitative flexibility can be used), including combinations of both.

Classical incentive based DR programs typically provide more favorable contract conditions for customers, e.g., a discount on the electricity bill. Such contracts correspond to a *direct load control* setting (Haring and Andersson 2014). On the one hand, customers also relinquish control over their consumption which provides a certain degree of security to flexibility buyers. On the other hand, Borenstein, Jaske, and Rosenfeld (2002) argue that price based

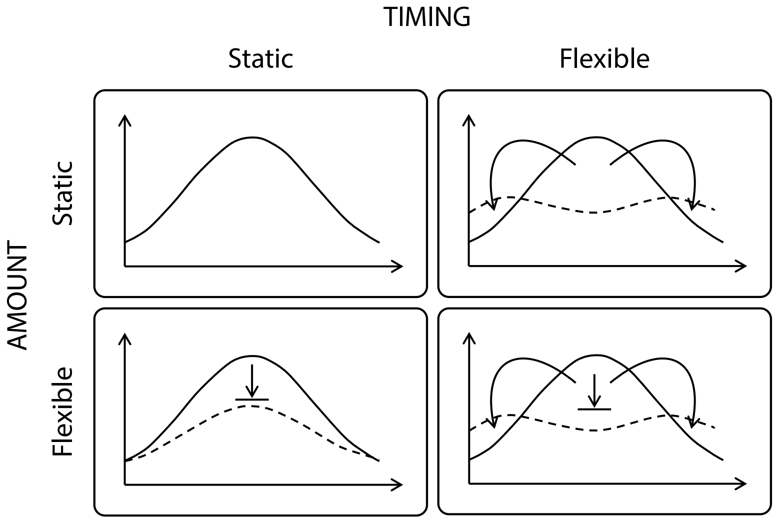

Figure 2.11: Demand response type characterization, adapted from Flath (2013)

programs try to invoke and control demand flexibility by incentive signals. Hence, decisions are taken decentralised and demand regulation is realized by *indirect load control*.

Based on existing literature and ongoing pilot projects, He et al. (2013) categorize five main contract types for DR, i.e., time-of-use pricing, dynamic pricing, fixed load capping, dynamic load capping, and direct load control.[9] Every imaginable contract type should be one of them or a hybrid of some of them. Customers who conclude DR contracts trade off comfort and security for a financial benefit. However, not only customers profit by DR but it increases the overall welfare. Albadi and El-Saadany (2008) identify four main categories of benefits from DR, i.e., participant, market-wide, reliability, and market performance benefits.[10] Similarly, Setlhaolo, Xia, and Zhang (2014) identify financial benefits, e.g., reduced electricity bills and incentive payments, and system reliability, e.g., operational security and adequacy, as the main assets of DR.

Describing electricity consumption not as a service itself but rather as a meta-service that enables customer devices and applications is another approach to DR. Nayyar et al. (2014b) define rate-constrained energy services by three components, i.e., a delivery time window that specifies the earliest possible time the service can be started and the latest possible time it must be finished, an amount of energy that must be delivered, and a maximum power rate. Given these three service specification components, a supplier should design its electricity

[9] A comprehensive overview of DR contracts is provided in appendix A, table A.1.
[10] Figure A.1 in appendix A provides on overview of benefits associated with DR.

delivery service portfolio to minimize cost for flexibility on the one hand, and to ensure security of supply on the other hand. The approach to design demand response portfolios and tariffs must deal with a similar trade-off (cf. part III and IV). Adding the condition that service contracts must be complied without interruptions, this approach can be applied for household devices, e.g., dishwashers or washing machines (Nayyar et al. 2014a).

Direct Load Control

In direct load control contracts customers grant the right to (partially) control their energy consumption to the flexibility buyer, typically referred to as "flexibility aggregator" or "load scheduler" (Haring and Andersson 2014). Obviously, the extend to load adaptions must be defined in the respective contract and contract parties must comply with it—the customer must allow load control and the aggregator must provide a certain service level. Consequently, direct load control is only reasonable for appliances that can be controlled remotely and, furthermore, have no (or very little) direct customer interaction, i.e., air conditioner, space heater, or storage water heaters. Using devices with direct customer interaction would induce unacceptable customer discomfort, e.g., switching of lights or a TV for DSM is just unrealistic.

Given a portfolio of customers with direct load control contracts, demand flexibility can be exploited to pursue various objectives. Efficient scheduling of flexible load is fundamental for DR aggregators to limit load manipulations which reduce customer comfort and hence increase contracting cost on the long run. Subramanian et al. (2013) propose an algorithm that enables an aggregator to schedule deferrable load and storage in real-time. Applying their algorithm they find that benefits of direct load control can be undertaken even with limited deferrable load participation and storage usage. To gain substantial impact on total demand, several customers can be aggregated to a *virtual power plant* (VPP). Ruiz, Cobelo, and Oyarzabal (2009) consider a large number of end consumers with thermostatically controlled appliances that are coordinated as a VPP. The model which is used to bid load reduction on the electricity market for congestion management and for aligning demand with supply is tested on a real power system in northern Spain to demonstrate applicability.

In addition to the high computational complexity to calculate schedules, the main concerns of direct load control include security and privacy concerns, incentive compatibility, and customer acceptance. On the one hand, Callaway and Hiskens (2011) identify hierarchical local control mechanisms to be the most promising ones to mitigate some of these problems. On the other hand, there is little evidence of substantial customer discomfort in scenarios with direct control of air conditioners (Kirby 2003). However, there is a time limit how long customers are willing to tolerate deviations from their preferred temperature which also limits the potential for load reduction in load control with air conditioners (Newsham and Bowker 2010).

Indirect Load Control

Instead of directly controlling electric loads, indirect load control provides incentives for customers to adapt their behavior. Decisions about load adaptions are taken by the customer (Strbac 2008). This way both discomfort and privacy issues are not as critical compared to direct load control (Schweppe et al. 1988). To implement indirect decentralized load control, it is essential to develop the ability to rapidly distribute signals and incentives, e.g., for *real-time pricing* (RTP). Therefore, the introduction of SG technologies might foster the applicability of such load control approaches and thus supports the integration of intermittent renewable energy sources and EVs (Ramchurn et al. 2011).

The challenge for flexibility aggregators is to design incentives and tariffs that, on the one hand, motivate customers to participate in DSM and, on the other hand, are cost-efficient but still functional. Already in the 1980s Schweppe et al. (1988) investigated electricity pricing for DR programs. Dutta and Mitra (2015) provide an overview of electricity rates. Their characterisation is well in line with Faruqui, Hledik, and Palmer (2012) who comprehensively elaborate on both static and time-varying rates, e.g., flat, (inclining) block, seasonal, TOU, *critical peak pricing* (CPP), *variable peak rate* (VPR), RTP, and *peak time rebates* (PTR) with the following properties:

- *Flat rates* are static tariffs. The electricity price (price per energy, e.g., €/kWh in Europe) remains constant irrespective of changes in demand or supply. Customers do not face any price uncertainty. There are no incentives to reschedule energy consumption (Dutta and Mitra 2015).
- *Inclining block rates* are semi-static tariffs to incentivize the reduction of electricity consumption. In inclining block rates the marginal energy price (price per energy like for flat rates) increases in the total amount of energy that is consumed. Pricing time windows are widespread between hourly and yearly. Like flat tariffs inclining block

rates do not require smart metering technologies (Mohsenian-Rad and Leon-Garcia 2010).

- *Seasonal rates* "[...] which vary by the time of year, but not by time of day, are another example of rates that do not require advanced metering"(Faruqui, Hledik, and Palmer 2012). Seasonal rates are used to balance both varying demand levels (winter vs. summer) and fluctuating generation (solar generation).

- *Time-of-use rates* divide the day into contiguous blocks. A certain flat rate is set for each block but prices do not vary between blocks (Strbac 2008; Newsham and Bowker 2010). TOU rates are especially eligible for decreasing demand in peak times and increasing demand in off-peak times. Hence, they are suitable to even out (typically rather constant) generation from nuclear and hard coal power palnts.

- *Critical peak pricing* is similar to TOU rates. Customers receive flate rates and in times with excessive demand or very little generation rates are increased. However, the rate variations do not occur on a regular basis but only in some "event" days of the year (Faruqui, Hledik, and Palmer 2012). Utilities commonly advertise them based on their supply and demand forecast. Compared to TOU rates the price gap between peak and off-peak periods is larger (Newsham and Bowker 2010).

- *Variable peak rates* are similar to CPP. However, the peak rates are not fixed but vary in accordance with the urgency of demand curtailment (Dutta and Mitra 2015).

- *Real-time pricing* is a very dynamic form of DSM. Prices are not known in advance and adapted by the utility according to generation (Newsham and Bowker 2010). The time span for which the prices are set can vary from hourly to real-time. This form of pricing requires a fully developed ICT as price signals must be communicated frequently (Samadi et al. 2010). An early theoretic discussion including an exemplary case study of RTP provides Baughman and Siddiqi (1991).

- *Peak time rebates* were suggested because CPP tariffs could not be rolled out due to regulatory or political constraints (Faruqui, Hledik, and Palmer 2012). Instead of increasing rates in peak times bonuses are paid for load reductions compared to a household baseline that must be established previously (Newsham and Bowker 2010).

Each pricing regime trades-off risk vs. reward. The higher bonus payments or electricity bill savings are, the more behavioral adaptions and customer attention are required. Following

Faruqui, Hledik, and Palmer (2012), figure 2.12 illustrates this relationship in a quantitative fashion.

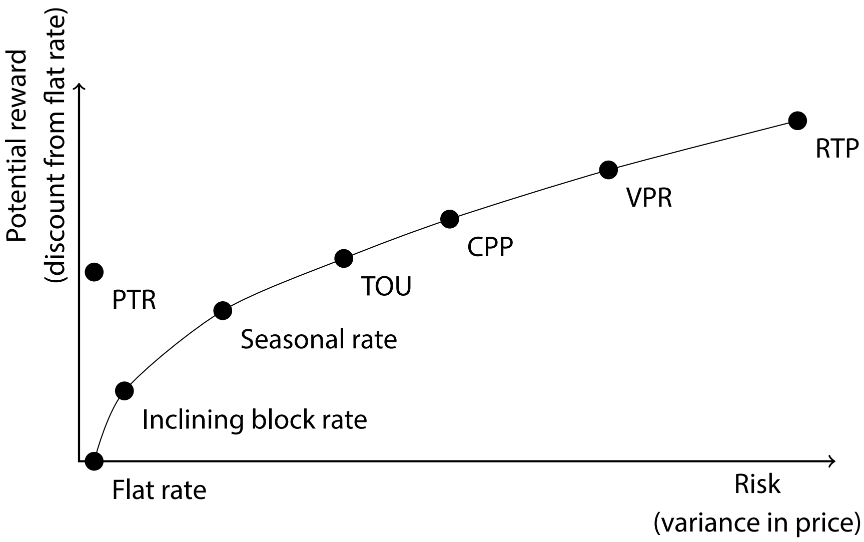

Figure 2.12: Conceptual representation of the tradeoff risk vs. reward in time-varying rates, adapted from Faruqui, Hledik, and Palmer (2012)

Obviously, an increase in risk that customers are willing to accept must be rewarded with some kind of financial incentive. Such tariffs and incentives must be designed carefully, as they directly cohere with acceptance of DSM and, consequently, with the flexibility aggregators profits. The comprehensive dissemination of DR programs critically hinge on politics and regulation. Current laws are rather designed for few centralized generators that are responsible for both generation as well as the provision of system services. The regulatory framework needs a revision to enable economic and sustainable electrical power supply. The renewal of current as well as the design and engineering of new electricity and flexibility markets in combination with further technological progress are crucial for mastering future challenges successfully.

3

Engineering Electricity Markets

Trading of goods and services can, and usually does, increase economic welfare for both trading parties (Samuelson 1939). Markets, in general, are system, institutions, procedures, and infrastructures whereby parties engage in exchange. Weinhardt and Gimpel (2007) define markets as follows:

Definition 3.1 (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).*

Markets facilitate both the matching of supply and demand and the formation of prices. They provide constraints and rules that form a framework which enables economic efficiency. Markets build the backbone of commercial activities. Therefore, electronic markets must be designed carefully. Weinhardt and Gimpel (2007) define the process of designing markets, i.e., market engineering, as follows:

Definition 3.2 (Market Engineering). *"Market engineering is the process of consciously setting up or re-structuring a market in order to make it an effective and efficient means for carrying out exchange transactions" (Weinhardt and Gimpel 2007).*

The process of engineering markets can be described as a multi-stage endeavor (Neumann 2007; Block 2010). Figure 3.1 depicts a five step process for market engineering. Each step receives input which is processed to generate an intermediary result for consecutive stages. To ensure efficiency in changing environmental conditions and needs, the process can be re-run on existing markets.

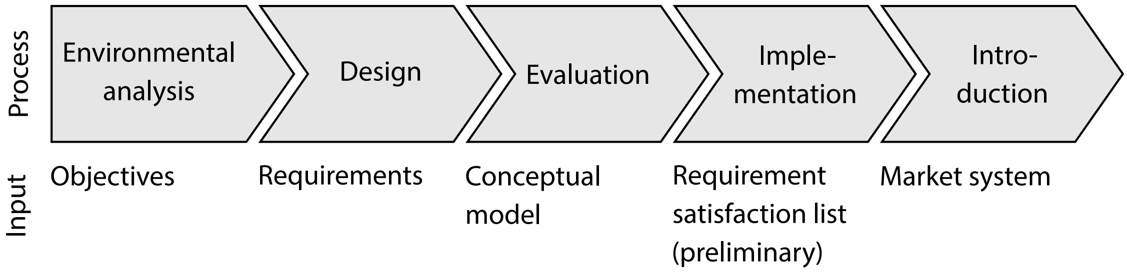

Figure 3.1: Market engineering process, adapted from Weinhardt and Gimpel (2007)

Technically oriented market engineers often ignore the strategic behavior of market participants. In the market design and evaluation process it is implicitly assumed that individuals will not necessarily report preferences, costs, availability, or service levels truthfully (Flath 2013). This threatens market efficiency as the erroneous information is used to determine payments and resource allocation. Individuals might be able to maximize their profit by strategically bidding or non-truthful reporting. However, this comes at the price of a general welfare loss and should be prevented.

Market design should ensure *incentive compatibility* (Hurwicz 1973). This means that truth-telling is a (weakly) dominant strategy. Mechanism design, which is often referred to as reverse game theory, accounts for such behavioral factors (Sonnenschein 1983). Bolton and Ockenfels (2012) discuss behavioral phenomena and behavioral economic (market) engineering. Literature on mechanism design investigates the composition of incentives that support agent behavior that results in efficient market outcomes (Dasgupta, Hammond, and Maskin 1979; Roth 2002; Dash, Jennings, and Parkes 2003).

Designing markets is important for various industries branches (Roth 2008; Bolton and Ockenfels 2012). However, in the process of designing markets domain specific characteristics must be considered—for example, electricity is hardly storable, voltage or frequency fluctuations are problematic, and disturbances are quickly transmitted and hard to isolate (Shively and Ferrare 2008). For example, McCabe, Rassenti, and Smith (1989) and McCabe, Rassenti, and Smith (1991) investigate computer-assisted bid-offer auctions on natural gas markets. Their approach considers technical aspects, e.g., delivery outlet, source, and pipelines for transportation, as well as the auction market design. Cramton (2003) discusses requirements for good (and bad) electricity market designs. Effectuated by the political goal of a cleaner and more sustainable electricity generation to reduce greenhouse gas emissions, the electric power system currently faces challenges that call for a renewal and an expansion of power markets. Consequently, market engineering plays a fundamental role to master these challenges—e.g., alignment of supply and demand, grid congestion, or regulatory reforms. The regulatory framework builds the basis but also constrains the development of innovative future markets, e.g., flexibility markets, reserve power markets for VPP, or retail tariffs. In the following, a general framework for market engineering is presented. Current research approaches and real-world development both world-wide and in Germany are then discussed along that framework. Finally, the gap in literature which this work aims to fill is discussed at the end of this chapter.

3.1 Market Engineering Framework

Market engineering is a systematic approach for designing and re-structuring markets to make them more efficient, effective and independent of market properties or domain. Hence, insights from other domains should be considered when designing electricity markets. Each market consists of several static components which a market engineer should keep in mind at all times. Weinhardt, Holtmann, and Neumann (2003) introduce a market engineering framework that incorporates these market elements (fig. 3.2). Some components can be designed directly, i.e., transaction objects and the market structure which consists of the market microstructure, the IT infrastructure, and the business structure, others depend indirectly on the market engineers decisions, i.e., the socio-economic and legal environment, the agent behavior, and as a final result, the market outcome.

The different components of the market engineering framework vary in the impact which they have on the market outcome as well as in the degree to which they can be designed:

- *Socio-economic and legal environment*: The socio-economic and legal environment surrounds the market engineering framework. It represents a fundamental base setting including both international and national (federal) laws that apply to the market. These economic and legal conditions are set externally and influence all components of the market. In the energy sector it coincidences with the regulatory framework but also incorporates political objective, e.g., reduction of greenhouse gases in generation or

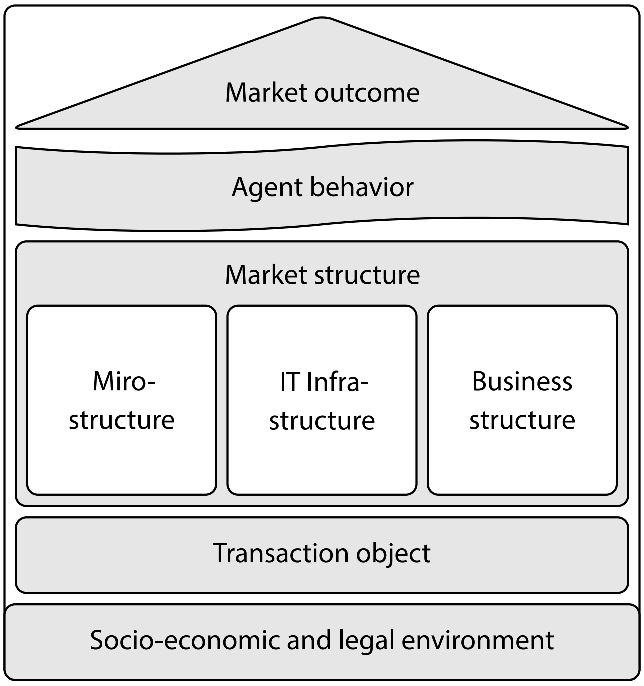

Figure 3.2: Market engineering framework, adapted from Weinhardt, Holtmann, and Neumann (2003)

reliable energy supply. When designing a market not only the status quo but also possible future adjustments should be considered by ensuring that the market is able to flexibly adapt to changing conditions if required.

- *Market outcome*: The market outcome can be considered as the ultimate objective of market design as it defines the market efficiency, applicability, and acceptance. However, it is difficult to assess the market quality as it depends not only on one metric but on several criteria (Maskin 2008). The outcome manly depends on the agent behavior which in turn is influenced by the market structure.

- *Agent behavior*: On the one hand, the agents' behavior critically hinges on the market structure but also on selfish, individually rational decisions. On the other hand, it is directly responsible for the market outcome. Therefore, it is indispensable to design incentive compatible mechanism that incentivize (rationally acting) customers to support the desired market outcome (Hurwicz 1973). Game theory which predicts and analyzes agent behavior as well as mechanism design are a central branches of research for anticipating agent decisions. Furthermore, "behavior connects motivation in the environment with the institution to yield decisions and outcomes" (Smith 2006). For energy markets historically inflexible customers might become able and ready to offer their flexibility to aggregators (if a respective market is designed).

- *Market structure*: The market structure itself can be split up into three components: the microstructure, the IT infrastructure, and the business structure (Weinhardt, Holtmann, and Neumann 2003).
  - *Microstructure*: O'hara (1995) defines the market micro structure as "the study of the process and outcomes of exchanging assets under explicit trading rules". Similarly, Madhavan (2000) states that "Market microstructure studies the process by which investors' latent demands are ultimately translated into prices and volumes." Therefore, the microstructure represents a component of spacial interest in the energy sector. Considering the distribution grid, products, i.e., flexibility services, and measures to assess their quality or fulfillment are still to be defined.
  - *IT Infrastructure*: The importance of a reliable and robust IT infrastructure has increased substantially in recent years. Digitization already found its way into markets irrespective of domains. First of all, financial markets have become unimaginable without an infrastructure that enables fast and secure trading—even in the private sector. In the energy sector, SG technologies that add ICT to sole transmission lines are currently a hot topic in research. It enables the (remote) control of devices and the distribution of incentive signals.
  - *Business structure*: The business structure encompasses the business and pricing model as well as possible trading fees in auctions (Burghardt and Weinhardt 2008). Hence, the business structure is vital for a long term success for the market itself, as it should enable the market operator to run the market economically worthwhile and thus ensure a sustainable business model. Wirtz (2013) defines business models as "a description of the value a company offers to one or several segments of customers and the architecture of the firm and its network of partners for creating, marketing and delivering this value and relationship capital, in order to generate profitable and sustainable revenue streams." It is fundamental to facilitate such profitable business models for successfully implementing future decentral and possible local energy markets.
- *Transaction object*: The good traded between parties in a market is called transaction object. In general, this can be a product or a service but also a right or certificates. Transaction objects are the actual objects that are exchanged on the market between

the seller and the buyer. It is inevitable to design new transaction objects in power markets that allow for trading goods and services that have not yet been defined—these facilitate to leverage flexibility potentials by market based control with respect to DR programs.

Each component of the market engineering framework influences its success. Therefore, they should be designed carefully. The electric power system currently experiences drastic changes that make the renewal of existing and the implementation of new markets essential. The following section discusses current research and future possibilities for electricity markets to support the evolution towards a more sustainable power system without endangering economic efficiency and reliability of supply.

3.2 Power and Energy Market Engineering

Both adapting the legal and regulatory framework and developing new types of markets are important contributions that can facilitate DSM. The market conditions currently in place are designed for large centralized generators run by monopolists. The trend towards sustainable renewable generation requires the design of new electricity products and services that allow for trading demand flexibility. Focusing on Europe and especially Germany, this section discusses the evolution and current research on these topics along the different components of the market engineering framework.

3.2.1 Economic and Legal Environment

The EU has set ambitious goals to reduce greenhouse gas emissions. Until 2020 at least 20 % of greenhouse gas emissions should be reduced compared to 1990, 20 % of energy should come from renewable generation, and energy efficiency should be improved by 20 % (European Commission 2014). The climate goals for 2050 are even more ambitious: cutting emissions by 80-90 % of 1990 levels, generating 100 % of energy from RES.

Several actions were launched to support the achievement of the climate targets:

- A carbon dioxide trading system EU ETS was introduced (European Commission 2009b). The idea is simple: a "cap" is set to overall emissions. Issuers are given allowances to emit a certain amount of greenhouse gases every year. Those that produce less than they are allowed can sell their certificates to those that emit more. This motivates investments in carbon saving technologies. By reducing the greenhouse gas cap overall emissions are lowered and the benefits of exchange are harnessed.

- Financed from EU ETS revenues, a program was set up to support the development of innovative new low-carbon technologies, e.g., for renewable energy sources or carbon capture and storage projects (European Commission 2014).
- Emission limits were set for road transports. New cars must (on average) not emit more that 130 gram carbon dioxide per kilometer. This cap is reduced to 95 gram carbon dioxide per kilometer in 2020.
- A campaign to raise awareness for climate change and greenhouse gas emissions, called "A world you like. With a climate you like", was launched in 2012 (European Commission 2014).

Partly driven by EU but mainly motivated nationally, German policy makers announced a ten point agenda that aim at the development of an advanced future electricity market: the *electricity market 2.0* (BMWi 2015b). Core measures include the integration of the EU's energy market, the improvement of market mechanisms, the support of flexibility option trading, and to prepare the regulatory framework for the digitization of smart grids.

In summary, a wide variety of measures has been implemented (or were at least proposed and discussed) recently. This evolving economic and legal environment makes the design of reliable robust markets a challenge. Flexibility in the market structure itself supports market sustainability in agile environment. The utilization of demand flexibility and the formation of an aggregator's customer portfolio require the revision of the regulatory environment as the current framework was designed for few centrally operation power plants.

3.2.2 Market Outcome

The market outcome is a result of market design rather than a design element itself. It represents the ultimate target in market engineering as a market is just the basis for enabling allocation of goods and their pricing. Market performance can be measured based on agent behavior, namely their actions and preferences that lead to a certain market outcome (Weinhardt, Holtmann, and Neumann 2003). The market outcome hence is decisive for the quality of the whole market. Sandholm (1999) identifies several criteria to assess markets and mechanisms:

- *Social welfare* represents the overall market outcome. It is calculated by the sum of all agents' payoffs (including utilities) given a certain solution. In energy markets, and especially in the design of DR programs, social welfare is a key component to engage customers. Without customer cooperation no demand flexibility can be utilized and welfare remains at a suboptimal level. However, social welfare should be maximized. Therefore, it can be used as a metric to compare market quality.
- *Pareto efficiency* is another valid evaluation criterion. If the market generates pareto efficient outcomes it will be stable as no agent can improve its payoff by deviating from its strategy. Obviously, pareto efficient solutions are a superset of social welfare maximizing strategies.
- *Stability* is similar to incentive compatibility. It means that no self-interested agent is better of by deviating from a truth-telling strategy. It ensures that the market is not manipulable. In an environment with multiple stochastic components like the energy market with substantial renewable generation, stability is a central pillar for increasing reliability.
- *Computational Efficiency* ensures limited operating expense as solutions and the market outcome in terms of pricing and allocation can be calculated efficiently. However, it should also be possible for agents to determine their strategy with limited computational effort.

The agent perspective in market design is fundamental as the agents' behavior finally defines the market outcome and its success. In a discussion of market design principles and how these should be applied to electricity markets Cramton (2003) underlines that "good market design begins with a thorough understanding of the market participants, their incentives, and the economic problem that the market is trying to solve" as markets still remain not well understood. In electricity markets, customer behavior gains importance as their active role providing and trading flexibility is one innovation of current market reforms (Chao and Huntington 2013).

3.2.3 Agent Behavior

The agent behavior strongly depends on the design of markets. In electricity markets customers may evolve from pure consumers to so-called prosumers. They consume but also sell electricity and flexibility to the market—for example, by local and often renewable generation or DSM. Tariffs must be designed that incentivize customers to offer flexibility and thereby ensure a liquid flexibility market. Hence, in the market structure design phase, models for customer utility are inalienable. These utility models should build a solid decision basis for tariff design. Xu, Li, and Low (2015) investigate the problem of an aggregators who wants to procure a certain amount of flexibility from multiple consumers and who explicitly considers individual disutility from providing flexibility. They show that their approach is stable in terms of the market outcome approximates social optimality.

However, not only extrinsic but also intrinsic motivation influences agent behavior in the acceptance and adoption of services. Especially in the energy domain, where a "green conscience" is in vogue, decisions are not always rational. Adopting services often leads an increase in individual well-being (Wunderlich et al. 2013). These factors are hard to quantify and the social component of customer emotions impedes purely rational engineering like market design approaches. To stimulate agent behavior, *gamification*, i.e., using game design elements such as rankings in not game related contexts, is one way to support the consumers' value creation (Deterding et al. 2011a; Huotari and Hamari 2012). In addition, designing the graphical user interface of a market can influence and mediate user behavior. Such *hidden market* user interfaces facilitate and motivate consumer participation (Seuken, Jain, and Parker 2010).

Assuming consumer rationality is the predominant approach to modelling agent behavior especially in stimulative tariff design research (Fischer et al. 2013; Daniels and Lobel 2014; Haring and Andersson 2014). Monetary losses from foregone consumption can be used as a measure for customer disutility (Wacker and Billinton 1989). Predictable consumer behavior is vital for reliable DSM. This can either be achieved by valid customer utility models or by contracting large sets of customers. However, in addition to short term reliability long term customer churn must also be taken into account. Multi-stage optimization and simulation approaches combine both efficient short-term DSM and long-term behavioral aspects including customer churn (Tan and Varaiya 1993; Holyhead, Ramchurn, and Rogers 2015).

This work aims to design incentives and tariffs that trigger certain customer behavior (cf. research question 5 and research question 6). Tariffs should incentivize customers to self-select themselves into contracts in a way that allows for forming optimal DR portfolios. Therefore, the development of such DR tariffs must already bear the interdependencies between agent behavior and transaction object design in mind.

3.2.4 Market Structure

The three pillars of the market structure, i.e., the microstructure, the IT infrastructure, and the business structure, are important in the design process of new energy markets. The need for a (still ongoing) renewal of market structures was induced by the liberalization of energy markets (Joskow 1997). Within the regulatory boundaries of the legal market environment, new market structures should facilitate mechanisms that support flexibility trading based on an IT infrastructure which secures privacy on profitable market platforms.

Microstructure

An early introduction to market microstructure is provided by Garman (1976) who considers a market where two goods are traded, e.g., cash and securities. Spulber (1996) describes market microstructures as an intermediary between buyers and sellers. Intermediaries “seek out suppliers, find and encourage buyers, select buy and sell prices, define the terms of transactions, manage the payments and record keeping for transactions and hold inventories to provide liquidity or availability of goods and services” (Spulber 1996). Hence, the market microstucture defines the allocation and transfer rules in the market. To capture the characteristics of electricity (and demand flexibility), e.g., non-storability, it must be designed domain specific. The microstructre must include opportunity to trade flexibility—the adaption of electriciy consumption or generation—in addition to electricity and hence facilitate the marketing of DR capacities for aggregators.

Approaches to electricity market structure and mechanism design, respectively, are manifold. Ramchurn et al. (2011) propose an agent-based mechanism for DSM. Agents are controlled decentrally and are able to react to grid prices by load deferral. Similarly, Samadi et al. (2012) consider a mechanism that uses individual utility functions to account for user preferences in order to maximize social welfare. A mechanism for a balancing market in

SGs is introduced by Höning and Poutré (2014). It performs both an ahead market and a balancing market. Finally, Lamparter, Becher, and Fischer (2010) use a highly flexible market platform to incentivize customers to report their preferences truthfully. Knowing the agents' preferences allows for determining an efficient solution for the overall market.

IT Infrastructure

A fundamental and critical component is the IT infrastructure as it is responsible for providing the market access platform for agents as well as for ensuring a reliable system operation. Market interfaces should be suitable for the market participants' requirements, e.g., professional traders but also private end consumers, and encourage participation (Seuken et al. 2012). SG technologies increase both the ability to communicate and the communication volume. If sensitive data is transferred, the latest proven security technology is required (Metke and Ekl 2010). Both firewalls and encryption mechanisms must ensure a reliable system operation (Moslehi and Kumar 2010).

Privacy is another important issue for consumers (Marmol et al. 2012). Non-intrusive load monitoring techniques allow to disaggregate private households' load curves and to identify single devices (Parson et al. 2012). Information about the presence of inhabitants, their habits as well as information about specific activities can be derived (Khurana et al. 2010). Paverd, Martin, and Brown (2014) define a set of security and privacy requirements. On the one hand, security goals can already be met, but, on the other hand, the current system architecture does not allow to meet the privacy goals. Therefore, smart meter data must be protected and anonymity must be ensured (Goel and Hong 2015; Kessler, Flath, and Böhm 2015).

Business Structure

Energy market business structures must facilitate both alluring customers by attractive market conditions, e.g., market access and trading fees, and allowing for the market maker to run the market profitably by generating sufficient revenue streams. For example, the *European Energy Exchange* (EEX) charges its traders for the connection to the exchange as well as for the trading itself. Thereby quality differentiation is realized via a categorization of the connection quality by service levels.

Aslani and Mohaghar (2013) identify and discuss key areas in the business structure for renewable energy industries. They argue that renewable energy can generate a wide field of business and economic opportunities in each of the key areas, i.e., strategy, resources, technology, feasibility analysis, customer and market, stakeholder, and value creation. However, distributed generation from RES also poses challenges to the business structure (Picciariello et al. 2015). Not only end consumer tariffs must be adapted and developed, but also network tariffs. To design robust feed-in tariffs for generation with respect to exogenous changes to keep liquidity in the market is another subject of research (Ritzenhofen, Birge, and Spinler 2014). Klein et al. (2010) investigates feed-in tariff design options in general, whereas Grünewald, McKenna, and Thomson (2014) elaborate on feed-in tariffs considering a high wind scenario.

3.2.5 Transaction Object

As stated above, the good traded between parties in a market is called transaction object. Transaction objects can be both products or services (Clearwater 1996). Schweppe et al. (1988) propose to differentiate products along temporal and spatial components. Hence, a product differentiation of electricity services would become possible, although electricity will remain a homogeneous good regarding its technical properties, i.e., voltage and frequency. In particular, temporal shifting and curtailment of demand as well as reliability requirements constitute promising opportunities to further raise efficiency (He et al. 2013).

In the electricity sector, transaction objects are predominately tariffs. The need to activate the historically passive demand side and to leverage consumer flexibility calls for tariffs and services that define such tradable flexibility products. *Deadline differentiated pricing* (DDP), i.e., a contract that defines the amount of energy delivered and the latest possible point in time the delivery must be finished, is one well investigated approach to describe flexibility contracts (Nayyar et al. 2014a). Salah and Flath (2014) apply such tariffs to a scenario in which EVs are left at a car park and drivers demand a certain driving range when they pick up their car later. *Rate constrained energy service* contracts add a further addition to DDP, i.e., the maximum rate at which this energy may be delivered (Nayyar et al. 2014b). A large number of further tariff combinations and definitions are conceivable (cf. section 2.4.3) as long as they perform efficiently for both contracting parties.

Assuming the availability of a market structure and a socio-economic and legal environment that allow for contracting and marketing of demand flexibility, this work focuses on the design of tariffs to incentivize customers to offer the optimal amount and type of flexibility by self-selection (cf. research question 6). Thereby, the interdependencies of transaction objects and agent behavior are a central issue. Nevertheless, the efficient implementation of DSM requires to consider all components of the market engineering framework.

Current challenges for electricity markets evoked by the transition towards a more sustainable and green energy sector require a renewal of both the regulatory framework and the energy markets. The market engineering framework comprises the essential components that must be considered to support the design of efficient markets which are robust and flexible enough to cope with environmental changes.

3.3 Discussion

The goal of liberalizing energy markets was to foster competition. Enforced by a whole sequence of laws, it led to unbundling, i.e, privatization of state-owned monopolies, the vertical separation of competitive and regulated divisions, and the horizontal restructuring of generators and retailers to foster competition. However, it did not lead to less regulation, especially in the grid sector.

After the liberalization, governments—first and foremost the German government—aimed at boosting sustainability in the energy sector by promoting generation from RES to lower carbon dioxide emissions. However, decentral generation from RES depends on environmental influences. Therefore, it is intermittent, mostly uncontrollable, and hard to predict. This impedes to cost-efficiently maintain the balance between electricity supply and demand which is a key requirement for a stable electricity grid. Obviously the three energy political goals, i.e., ecological sustainability, reliability of supply, and economic efficiency, conflict with each other.

Leaving behind the hitherto existing paradigm that "supply follows demand" by leveraging flexibility in electricity demand is essential to make all three energy political goals go hand in hand. There is a large body of literature that deals with questions of optimally managing and scheduling flexible demand, designing tariffs that incentivize customers to adapt their consumption, and technical requirements and implementation of the SG. However, none of these publications consider the influence of an aggregator's customer (flexibility) portfolio composition on the attainable scheduling quality from both a technical and an economical perspective.

As described in chapter 1, this work aims to fill this gap in literature. Firstly, private households potential for DSM is assessed. Secondly, assuming a scenario with generation from wind and solar power plants as well as the possibility to procure energy on the electricity market, it is calculated what customers should offer which type and which amount of flexibility to an aggregator to allow cost optimal load scheduling. The aggregator's costs thereby consist of long term contracting cost for both supply and demand flexibility as well as of short term scheduling cost. Finally, tariffs are investigated that do not only incentivize customers to adapt their consumption in a specific fashion, but also to motivate them to enter into a contract that includes the provision of flexibility.

Part II

Demand Flexibility

4

Modeling Household Flexibility

The ultimate goal of this work is to design tariffs and mechanisms that in turn allow for forming efficient demand response portfolios. On the one hand, contracts should enable electricity retailers and DR aggregators to utilize demand flexibility by defining type and amount of flexibility each customer offers. On the other hand, incentives should only motivate these customers to enter into contracts with flexibility provisions who best fit into the aggregator's DR portfolio. If this condition cannot be achieved, flexibility will be contracted that cannot be used profitably and the portfolio design will be inefficient.

In the process of designing DR contracts, it is of outstanding importance to gather and use as much relevant information about potential customers as possible. One goal could be to determine how much flexibility a household is able to offer. Another one to learn the customers' disutility induced by load adaptions which helps to forecast the households' reactions to tariff offers. For example, an aggregator could determine which electric devices are available in private households by applying non-intrusive load monitoring techniques (Parson et al. 2012; Liao et al. 2014).

The part at hand aims at determining both the amount of flexibility a household is able to offer to an aggregator and the value of this demand flexibility for the aggregator (cf. research question 1 and research question 2). Both hinge on the household's appliance endowment and the inhabitants' preferences, i.e., their risk aversion and their perceived disutility from adapting their consumption behavior. These analyses require a detailed model for demand flexibility on the private household level. Firstly, existing models for scheduling household appliances are analyzed. Secondly, household devices are split into groups with similar flexibility characteristics and, thirdly, a model to describe the appliances' scheduling properties is introduced.

The flexibility model for household appliances is used to evaluate the cost savings potential of each appliance group. In the simulated local microgrid, supply is either generated from uncontrollable RES, a gas turbine, or procured from the reserve power market. On the demand side, the flexibility of single devices and appliance groups is considered. The flexibility aggregator tries to schedule both flexible demand and controllable supply at the lowest possible cost. Figure 4.1 illustrates the local microgrid scenario.

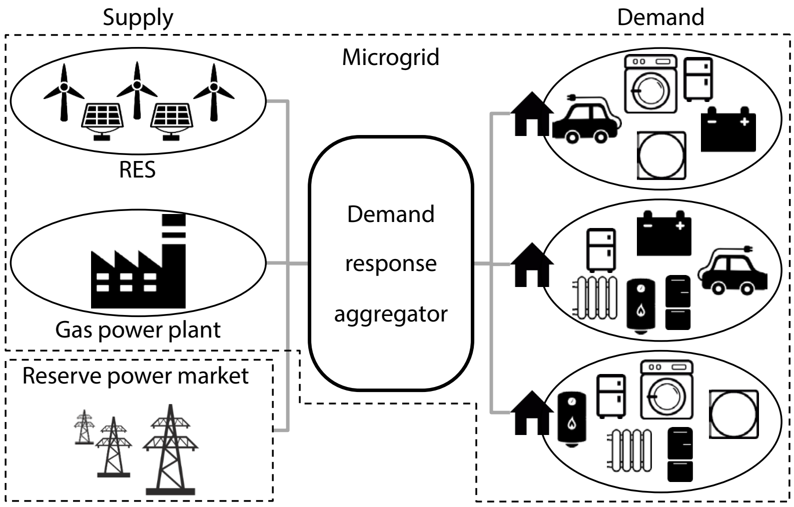

Figure 4.1: Integration of the demand response aggregator into the local microgrid scenario with supply from RES, a gas turbine, and reserve power considering single devices' flexibility

The simulation results are analyzed to determine which contribution to cost savings each appliance group can add compared to a scenario with inflexible demand. These insights, in combination with the set of appliances available in a household, build the basis for determining the value of a household's flexibility for an aggregator. Finally, the influence of the generation portfolio on overall load coverage by renewable generation is investigated.

4.1 Models for Residential Electricity Consumption

Considering the end of the electricity value chain, i.e., consumers, is central in the process of designing electricity markets. The fast development of new technologies and actors' behavior challenge market engineers and traditional planning and optimization approaches might become too complex. To overcome increasing complexity, simulation studies pose promising alternatives. Bonabeau (2002) proposes agent-based simulations as these facilitate both modeling of complex behavior patterns and building flexible simulation frameworks. The work at hand focuses on private households. Therefore, a fundamental requirement to successfully simulate electricity markets is the availability of realistic and robust customer models.

Flath (2013) proposes a four stage modeling approach to structure the process. Figure 4.2 illustrates the four stages. The first stage describes the current static customer characteristics, i.e., their typical load patterns in the absence of DSM. The second stage defines size and scope of the model, i.e., how many customers are considered, in what fashion the supply side is implemented, and what environmental conditions must be considered. Then, in the third stage, demand flexibility is introduced. This step is of outstanding importance for the model's meaningfulness. Given their appliance endowment, it defines the amount of flexibility households can provide from both a temporal and a quantitative point of view. The last (optional) stage describes the model adaptivity over time.

Figure 4.2: Four stage customer modeling process, adapted from Flath (2013)

The introduction of the load scheduling model in section 4.3 follows a slight modification of this process. On the one hand, a model which does not adapt over time is considered. On the other hand, model size and scope are not set beforehand. This allows for adapting configurations during the simulation and evaluation process. Flexibility properties in household electricity consumption, which can be derived from both static customer and demand response characteristics, are the focus of the model. Hence, these stages are described in a very detailed fashion.

4.1.1 Demand Modeling Techniques

Valid models of domestic electricity consumption are the basis for both a variety of research streams and real world decisions. Models differ in the degree of both granularity in the temporal aspect (they range from real-time models to yearly considerations) and detail (some models include single appliances, others only groups of households). In Germany, for example, DSOs use standard load profiles[1] to determine the expected power demand of their customers and procure electricity accordingly. Hence, this profile models the average household consumption pattern to forecast future demand. Moreover, models can be used to support simulative approaches to market design (Hirsch et al. 2010). Richardson et al. (2010) introduce, calibrate, and evaluate a model that maps the activity of a household's inhabitants to appliance use based on very fine grained empiric data in the UK. This model can be used to stochastically create synthetic consumption data for further analyses.

The use-case for which the model is designed influences both its characteristics and the design method by which it is built. In literature, two main categories of techniques for modeling domestic electricity consumption are applied, i.e., top-down and bottom-up approaches. A comprehensive discussion of both top-down and bottom-up models including several exemplary existing models and their applications is provided by Swan and Ugursal (2009) and Grandjean, Adnot, and Binet (2012). In the following, top-down and bottom-up models as well as their applications in modeling residential electricity consumption are briefly discussed.

Top-Down Models

At first, top-down approaches take a global perspective, e.g., statistical information on national energy use. Then, using the global information, they try to draw conclusions about electricity consumption characteristics of a stock of households or of a single household (Grandjean, Adnot, and Binet 2012). The aforementioned *H0* profiles are a classical example of a top-down approach. Historic data on consumption is gathered for the derivation of profiles that are representative for the whole household population. If augmented with additional data, e.g., weather forecasts, economic indicators, or information about special events, this approach has

[1] Standard load profiles for private households are referred to as *H0* profiles. The *Stromnetzzugangsverordnung* (StromNZV), which regulates grid access in Germany, also provides profiles for industry *G0*-*G7* and agriculture *L0*-*L2* that are divided in subprofiles to capture more detailed consumer characteristics.

allowed to successfully organize supply provisioning and has helped to support the long-term planning of grid and generation resources (Flath 2013). In combination with the increasing availability of data, the scalability and simplicity of top-down models will foster their further application.

The advantages of top-down models are manifold. However, they are not capable of including future technological influences as they typically rely on historical data (Swan and Ugursal 2009). In addition, top-down models have obvious shortcomings with respect to modeling the demand and the flexibility of single households. They are rather suitable for the analysis of a whole sector, e.g., a population of households, rather than single consumers. These limitations necessitate the development of more expressive bottom-up models.

Bottom-Up Models

In contrast to top-down models that use aggregate historic data of a whole population to draw conclusions on single households, bottom-up approaches use information from individual devices and consumption activities to calculate the aggregate load. Grandjean, Adnot, and Binet (2012) put forward that input data for bottom-up models might include individual consumption curves of domestic appliances, technical characteristics, household features, e.g., geometrical and thermal properties, environmental information, e.g., weather, electricity bills, and human behavior. Consequently, bottom-up approaches allow for developing very detailed models for residential demand. Given such a high degree of detail, demand evolutions can be quantified more exactly and future developments and technology can be included into the model (Grandjean, Adnot, and Binet 2012).

The high level of detail comes with two disadvantages. Firstly, the computational complexity drastically increases in the number of modeled appliances (Paatero and Lund 2006; Griffith et al. 2008). Secondly, bottom-up models are only able to generate high quality output if the input date is of similar quality. Therefore, they critically hinge on the availability of reliable statistical input data. However, with the large scale roll-out of smart metering infrastructure, such fine grained high quality consumption data is likely to get more readily available.

Integrated Models

Compared to top-down models, bottom-up approaches typically underestimate energy demand and overestimate efficiency. To close the gap, Koopmans and Velde (2001) propose to combine the two approaches in one model that has a top-down structure but as well employs bottom-up information. Similarly, Böhringer and Rutherford (2008) motivate "the formulation of market equilibrium as a mixed complementarity problem to bridge the gap between bottom-up and top-down analysis." Their approach allows for exploiting the advantages of both model types, i.e, economic richness of top-down models and technological accuracy of bottom-up models.

In conclusion, bottom-up approaches allow for detailed modeling of new technologies and enable their integration. Therefore, this work applies a bottom-up approach as new technologies, i.e., EVs and stationary batteries that are not yet widespread, are included. In order to evaluate the availability and potential contribution to an aggregator's demand flexibility portfolio, a high degree of detail is required. For designing tariffs and incentives the detailed models become redundant and are replaced by abstract flexibility measures that can be derived from the accurate bottom-up models.

4.1.2 Model Overview

The body of literature which develops, applies, and evaluates models for residential electricity consumption is extensive.[2] Several publications prefer bottom-up models because of the possibility to model consumption more precisely. However, if very little data in individual consumption is available, top-down models still pose an appealing alternative.

Top-Down Models

Using total load curves and appliance penetration rates for selected devices, Aigner, Sorooshian, and Kerwin (1984) present a model to decompose a household's total electricity consumption into its components. These parts are then mapped to activities or appliances. A more sophisticated model is built by Bartels et al. (1992). It also requires more input data. In addition to load curves and appliance saturation levels, the model includes weather data, socio-economical

[2] A comprehensive overview of literature on residential DR models is provided in appendix B.

and technical evolution information. Their goal was to design a simulation tool to measure the impact of environmental influences on the regional power consumption.

In an attempt to explain residential electricity demand, Haas and Schipper (1998) identify irreversible improvements in technical efficiency as one of the main drivers of domestic electricity consumption. The authors found that price-elasticity of customers differ for increasing and decreasing prices. Therefore, price reductions would not inevitably lead to a perfectly elastic rebound. Furthermore, availability of devices can lead to reduced income elasticity and, surprisingly, increasing technological efficiency can lead to an increased energy use. To determine the priorities of residential energy conservation measures Balaras et al. (2007) apply a top-down approach. These measures are necessary to accomplish the EU and Kyoto Protocol energy conservation goals (cf. section 3.2.1). They discover that "the insulation of external walls, weather proofing of openings, the installation of double-glazed windows, and the regular maintenance of central heating boilers" are the most promising approaches. Similarly, Young (2008) aims at reducing residential energy consumption. Employing a data driven top-down model, she puts forward replacement policies for household appliances that rely on household specific data.

Bottom-Up Models

An early model for residential loads is put forward by Walker and Pokoski (1985). Their model integrates psychological factors which influence residential behavior and appliance usage to create load profiles. Similarly, Capasso et al. (1994) propose a bottom-up model for synthetically establishing the load diagram of an area. The key input include the socio-economic and demographic characteristics as well as the load profiles of individual household appliances. To enclose psychological and behavioral factors probability functions were used. Fleiter, Worrell, and Eichhammer (2011) review bottom-up models for industrial energy demand. Their goal is to determine the barrier to the adoption of energy-efficient technologies. The authors argue that in state-of-the-art bottom-up models are based on existing technology rather than future options. These should be explicitly included if future barriers are investigated. The models could be improved by considering heterogeneous markets, future technologies, or hidden cost (Fleiter, Worrell, and Eichhammer 2011).

Widén and Wäckelgård (2010) present a modeling framework for stochastic generation of small-scale high-resolution consumption patterns. These patterns are then used to synthetically generate both individual household members' activity sequences and residential consumption. This data represents a valuable input for the evaluation of load scheduling approaches. The synthetic nature allows to test scheduling algorithms under full information of usage data. Building on bottom-up household appliance modeling, Du and Lu (2011) introduce a device commitment algorithm to schedule thermostatically controlled household appliances. Their method uses forecasts on both price and residential consumption as well as users' comfort settings. Similarly, Tushar et al. (2014) focus on a centralized scheduling model for EV charging coordination in addition to household appliances.

Expanding a joint work with Sebastian Gottwalt, Hartmut Schmeck and Christof Weinhardt, this work conducts a classification of household appliances and future devices.[3] The future devices are likely to gain significant saturation shares as the need for sustainable transportation and flexible devices that are applicable for DSM is fostered by both political endeavors and economical considerations provoked by the increasing share of intermittent generation from RES.

4.2 Classification of Residential Appliances

Electricity consumption in the domestic sector is usually caused by a set of appliances with a comparably small energy demand. The availability of devices varies between households and hinges on socio-economic factors, i.e., income and the inhabitants' preferences are the most important ones among others. McFadden, Puig, and Kirschner (1978) note that both the characteristics of appliances held by end consumers as well as current household activities influence electricity consumption. To use residential electricity consumption for DSM, either consumers must actively change their behavior or allow for controlling their devices automatically.

Gellings (1985) identifies three basic types of demand adaption, i.e., demand curtailment, demand shifting, and demand enlargement (cf. section 2.4.1). However, from a technical point of view, demand enlargement and demand curtailment can as well be described as load shifting, i.e., preemption or deferral, with a shifting distance that exceeds the simulation

[3] Gottwalt et al. (2016) expand the elementary approach to appliance classification and flexibility valuation from Gottwalt (2015).

horizon.[4] In this work six groups of appliances with similar flexibility characteristics are composed. This allows to describe and model the appliance specific flexibility characteristics for each group as a whole. The device sets consist of base load appliances, heating appliances, cooling appliances, devices with repeated user interaction that must run by a certain profile, EVs, and stationary batteries. Table 4.1 provides an overview of the appliance group characteristics.

Table 4.1: Appliance flexibility group characterization (high (+), medium (o), low (-)), adapted from Gottwalt (2015) with input from Schweppe et al. (1988), Stamminger et al. (2008), and Seebach, Timpe, and Bauknecht (2009)

Appliance group	Examples	Characterization				
		Control mode	Load	Operation frequency	Shifting distance	Discomfort
Base load	Lighting Television Stove and Oven Vacuum cleaner	None	- / o / +	- / o	-	+
User interaction	Dishwasher Washing machine Tumble dryer	Semi-automatic	o	-	o	o
Cooling	Fridge Freezer (Air conditioner)	Automatic	-	+	-	-
Heating	Space heater Stor. water heater (Air conditioner)	Automatic	+	o	+	-
EVs	EV	Automatic	o / +	- / o	+	- / o
Stationary batteries	Stationary battery	Automatic	-/ o / +	-/ o / +	+	-

Of course, this overview is not comprehensive, but it supports a characterization of the appliance groups. Base load appliances are of no value for DSM. This category mostly consists

[4] Although it is possible to actually enlarge or reduce consumption, only demand shifting is allowed in this part. This can be modeled more precisely without taking assumptions on consumers' preferences. In part III and IV, where the appliance based micro perspective is exchanged for a macro perspective, load curtailment is explicitly considered.

of devices which require constant direct human interaction. Therefore, using these for load shifting would cause massive discomfort and would hence require uneconomically large compensations. In contrast, the group of semi-automatically controlled appliances does not require constant but only repeated user interaction. In case of a washing machine, for example, it must be loaded and put in ready mode. Unless the clothes are not yet washed when the user wants to put them into the tumble dryer, there is little reason why the washing time should not be determined externally. Appliances that can be controlled automatically seem to have the highest value for aggregators. Comfort constraints, e.g., a temperature interval, can be set by household inhabitants. As long as the temperature stays in this predefined "comfort zone" there is no reason not to offer the flexibility to schedule heating or cooling activities.

Seemingly, the future appliances considered in this work could provide enormous load shifting potentials in both dimensions, i.e., shifting distance and shifting amount. In addition, if EV charging is not coordinated it even poses a threat to the electricity grid (Stroehle et al. 2011). Also, EVs are only used to drive very rarely. The remainder of time they idle or are being charged (Kempton and Tomić 2005; Schuller et al. 2014). Charging coordination and potentials of EVs desire to be included into the household model. Although EVs are not yet widespread, the political will to introduce them on a large scale makes their success likely. Stationary batteries can be considered EVs that are not used for driving with the ability to discharge their stored electricity back into the grid. Not surprisingly, as their main purpose is to provide flexibility, their value for DSM should be substantial. The following section builds on the classification of household appliances and introduces a formal household appliance scheduling model.

4.3 Load Scheduling Model

The model presented in this section describes the flexibility properties of household appliance groups including appliances which are currently available in households and future appliances, i.e., EVs and stationary batteries, which are likely to gain substantial saturation shares. This general approach allows for controlling appliances directly, e.g., from a flexibility aggregator, whereas the goals of DSM can be manifold, e.g., minimization of reserve power cost, maximization of consumption from locally generated electricity from RES. However, these are not set beforehand and the model can be applied for various objectives.

4.3.1 Household Appliances

The model considers a set $\mathcal{C}$ of household customers over a predefined time horizon given by a set $\mathcal{T}$ of time slots. Customers are indexed $c = 1, \ldots, |\mathcal{C}|$ and time slots are indexed $t = 1, \ldots, |\mathcal{T}|$. The set $\mathcal{A} = \{a_i | i = 1, \ldots, |\mathcal{A}|\}$ contains the household appliances owned by the overall customer population $\mathcal{C}$. The subset $\mathcal{A}_c \subseteq \mathcal{A}$ contains the devices available for customer c. To describe the shifting characteristics of the appliances, $\mathcal{A}$ is split into four subsets with similar properties: inflexible base load appliances $\mathcal{A}^B$, appliances that are controlled semi-automatically $\mathcal{A}^S$, cooling appliances $\mathcal{A}^C$, and heating appliances $\mathcal{A}^H$. Each appliance can be assigned to exactly one group and hence both $\mathcal{A}^B \cup \mathcal{A}^S \cup \mathcal{A}^C \cup \mathcal{A}^H = \mathcal{A}$ and $\mathcal{A}^B \cap \mathcal{A}^S \cap \mathcal{A}^C \cap \mathcal{A}^H = \varnothing$ holds.

Base Load Appliances

The demand of base load appliances $a \in \mathcal{A}^B$ cannot be influenced by the aggregator as this is technically impossible or prohibitively expensive, e.g., TV, handyman tools, stove, or oven.[5] Base load may generate revenues from an electricity retailer's point of view as it must be satisfied and customers are billed. However, base load does not contribute value for an aggregator's flexibility portfolio as it does not support the pursuit of reaching the load scheduling objectives. The demand of any inflexible appliance in time slot t is given by $l^A_{a,t}, \forall a \in \mathcal{A}^B$. Consequently, the total base load in time slot t is given by the sum of all base load appliances: $\sum_{a \in \mathcal{A}^B} l^A_{a,t}$.

Semi-automatically Controlled Appliances

Semi-automatically controlled appliances typically only run few times a week. These devices require user interaction, i.e., they must be set in a "ready mode", and have fixed consumption profiles. Therefore, semi-automatically controlled appliances cannot be interrupted once they are started, e.g., washing machine or dishwasher.

Each semi-automatically controlled appliance can run several times during the simulation horizon. The set of runs is given by $\mathcal{R}_a = \{r_{a,1}, \ldots, r_{a,N_a}\}, a \in \mathcal{A}^S$ where $N_a \in \mathbb{N}$ is the num-

[5] For the sake of readability the index is relinquished. Hence, a refers to each a_i. The description of the remaining appliance groups, including EVs and stationary batteries, proceeds accordingly.

ber of runs of appliance a.[6] A full description of one run provides the tuple $(\rho_r, S_r^R, E_r^R, x_r^R)$. Thereby, the vector $\rho_r = (\rho_{r,1}, \ldots, \rho_{r,|\rho_r|})$ with $\rho_{r,t} \in \mathbb{R}^+, \forall t \in \{1, \ldots, |\rho_r|\}$ defines the consumption profile of run r once it is started and $|\rho_r|$ is the length of the respective profile.[7] The earliest time slot the run can be started is given by $S_r^R \in \mathbb{N}$. The time slot it must be finished is provided by $E_r^R \in \mathbb{N}$. The scheduling vector $x_r^R = (x_{r,1}^R, \ldots, x_{r,|\mathcal{T}|}^R)$ defines the start of a run ($x_{r,t}^R = 1$). Hence, each start of run r must be scheduled within $\{S_r^R, \ldots, E_r^R - |\rho_r|\}$:

$$\sum_{t=S_r^R}^{E_r^R - |\rho_r|} x_{r,t}^R = 1, \quad \forall a \in \mathcal{A}^S \, \forall r \in \mathcal{R}_a. \tag{4.1}$$

The demand of a semi-automatically controlled appliance in time slot t is given by $l_{a,t}^A, \forall a \in \mathcal{A}^S$. It is calculated using the auxiliary function $\tilde{\rho}_r : s \to \mathbb{R}^+$ with $s \in \mathbb{N}^+$, which returns the value of the s-th element of ρ_r if s is smaller than the duration of the demand profile $|\rho_r|$ and zero else:

$$\tilde{\rho}_r(s) = \begin{cases} \rho_r(s), & s \in \{1, \ldots, |\rho_r|\} \\ 0, & \text{otherwise} \end{cases}, \quad \forall r \in \mathcal{R}_a. \tag{4.2}$$

Consequently, $l_{a,t}^A$ in t is given by:

$$l_{a,t}^A = \sum_{r \in \mathcal{R}_a} \sum_{s=1}^{t} x_{r,t}^R \tilde{\rho}_r(t + 1 - s), \quad \forall a \in \mathcal{A}^S \, \forall t \in \mathcal{T}. \tag{4.3}$$

Finally, the demand of the the whole set of semi-automatically controlled appliances in time slot t that are available in the household population is calculated by $\sum_{a \in \mathcal{A}^S} l_{a,t}^A$.

Cooling Appliances

Cooling appliances can be controlled automatically. They are characterized by a comparably small demand and frequent operation during the day. Their frequent but short operation, e.g., usually cooling devices are only operated for one time slot, invokes the need for constant scheduling. Typical examples of cooling appliances are refrigerators or freezers.

The number of runs $N_a \in \mathbb{N}, a \in \mathcal{A}^C$ is determined by the number of active slots of

[6] In the following, the superscript a is dropped for elements of $\mathcal{R}_a$ to improve readability.

[7] $\mathbb{R}^+ = \{x \in \mathbb{R} | x \geq 0\}$ refers to the non-negative real numbers. Similarly, $\mathbb{N}^+$ is the set of non-negative natural numbers.

appliance a. The time horizon $\mathcal{T}$ is split into consecutive intervals of equal length $\frac{|\mathcal{T}|}{N_a}$. For each run of $\mathcal{R}_a = \{r_{a,1}, \ldots, r_{a,N_a}\}, a \in \mathcal{A}^C$, the earliest possible time slot S_r^R and the latest possible time slot E_r^R build the temporal constraints for the time interval the device must be activated. Each cooling appliance must run once in each respective interval to ensure constant cooling. However, in each interval the time slot in which the cooling process is realized can be scheduled freely. A full description of one run provides the tuple $(\rho, S_r^R, E_r^R, x_a^A)$. For cooling appliances $\rho \in \mathbb{R}^+$ provides the demand in a time slot the appliance is active. S_r^R and E_r^R define the temporal scheduling constraints for the respective run. $x_a^A = (x_{a,1}^A, \ldots, x_{a,|\mathcal{T}|}^A)$ is the decision variable vector to determine when appliance a is activated ($x_{a,t}^A = 1$). For each run r, a cooling appliance must be activated once between S_r^R and E_r^R:

$$\sum_{t=S_r^R}^{E_r^R} x_{a,t}^A = 1, \quad \forall a \in \mathcal{A}^C \, \forall r \in \mathcal{R}_a. \tag{4.4}$$

The electricity consumption of a cooling appliance $l_{a,t}^A, \forall a \in \mathcal{A}^C$ in time slot t is given by:

$$l_{a,t}^A = x_{a,t}^A \rho, \quad \forall a \in \mathcal{A}^C \, \forall t \in \mathcal{T}. \tag{4.5}$$

Consequently, the consumption of the whole set of cooling appliances in time slot t is calculated by $\sum_{a \in \mathcal{A}^C} l_{a,t}^A$.

Heating Appliances

Like cooling devices, heating appliances can be controlled automatically and must run frequently. However, their runs are stretched over a lager time horizon, i.e., one day, and when they are active their loads are comparably high. Examples for heating appliances are storage water heaters or space heating devices.

Following the description of cooling devices, the time horizon $\mathcal{T}$ is split into consecutive intervals of equal length $\frac{|\mathcal{T}|}{N_a}$ and the first (S_r^R) and last (E_r^R) time slot of each interval are defined. For each appliance the set of runs is given by $\mathcal{R}_a = \{r_{a,1}, \ldots, r_{a,N_a}\}, a \in \mathcal{A}^H$. Typically, the duration of one run is one day. The total amount of electricity each appliance must consume in each run is given by $\overline{\rho}_r$. Each run of an appliance from group $\mathcal{A}^H$ is then modeled by the tuple $(\overline{\rho}_r, \rho, S_r^R, E_r^R, x_a^A)$. In each run, a heating appliance must be activated several times between S_r^R and E_r^R. Time slots in which the device is active are given by $x_{a,t}^A = 1$. The overall demand of each appliance in one run is given by $\overline{\rho}_r$. The consumption in an active time slot is given by ρ. To satisfy the customers' demand, a heating appliance must be active in $\frac{\overline{\rho}_r}{\rho}$ time slots of run r:

$$\sum_{t=S_r^R}^{E_r^R} x_{a,t}^A \rho = \overline{\rho}_r, \quad \forall a \in \mathcal{A}^H \, \forall r \in \mathcal{R}_a. \tag{4.6}$$

To ensure thermal comfort, i.e., availability of hot water and a minimum room temperature, a condition is introduced to ensure that at least $\hat{\rho}$ % of each appliance's demand is satisfied in the first $\hat{T}$ % of the time span between S_r^R and E_r^R:[8]

$$\sum_{t=S_r^R}^{\lfloor \hat{T} E_r^R \rfloor} x_{a,t}^A \rho \geq \lceil \hat{\rho} \overline{\rho}_r \rceil, \quad \forall a \in \mathcal{A}^H \, \forall r \in \mathcal{R}_a. \tag{4.7}$$

Obviously, this approach does not support intrer-day shifting and leads to an underestimation of flexibility. To allow for shifting load over longer time spans, additional information on customer behavior and preferences would be required. The electricity demand of a heating appliance $l_{a,t}^A, \forall a \in \mathcal{A}^H$ in time slot t is given by:

$$l_{a,t}^A = x_{a,t}^A \rho, \quad \forall a \in \mathcal{A}^H \, \forall t \in \mathcal{T}. \tag{4.8}$$

Therefore, the total consumption of heating appliances in time slot t is given by $\sum_{a \in \mathcal{A}^H} l_{a,t}^A$. Finally, power consumption of all currently available household appliances can be calculated by:

$$\sum_{a \in \mathcal{A}} l_{a,t}^A, \quad \forall t \in \mathcal{T}. \tag{4.9}$$

4.3.2 Electric Vehicles

EVs are likely to be established widely due to political enforcement and technological enhancements, e.g., cheaper batteries, larger driving ranges, and denser grid of charging stations. Therefore, the share of EVs' electricity demand in households' electricity consumption might increase substantially. In addition to the household appliances whose flexibility and scheduling properties are modeled above, this section focuses on EVs. The set $\mathcal{V} = \{v_i | i = 1, \ldots, |\mathcal{V}|\}$ contains the EVs available for the customer population.[9] EVs must be charged to enable

[8] This assumption is well in line with Stamminger et al. (2008). In the evaluation, $\hat{\rho}$ and $\hat{T}$ are set to 25 % to guarantee appropriate room temperatures and availability of hot water in the morning hours.

[9] Like above, indices are dropped for better readability.

them to provide an adequate driving range. Following the time discretization applied in the description of household appliances, a constant charging power within each time slot is assumed. Hence, the amount of energy charged or discharged per time slot is given (kWh) to describe the changes in a battery's *state of charge* (SOC) instead of charging power (kW).

An EV is then modeled by the tuple $(\Phi_v, \hat{\Phi}_v, \overline{\Phi}_v, \phi_v, \overline{\psi}_v, \psi_v)$. On the one hand, the vector $\Phi_v = \{\Phi_{v,1}, \ldots, \Phi_{v,|\mathcal{T}|}\}$ reflects the energy that is spent by vehicle v for driving in t. On the other hand, $\phi_v = \{\phi_{v,1}, \ldots, \phi_{v,|\mathcal{T}|}\}$ is the charging decision vector to determine the energy that is charged by vehicle v in t. However, the charging amount per time slot and vehicle is limited by $\overline{\Phi}_v$. The vector $\hat{\Phi}_v = \{\hat{\Phi}_{v,1}, \ldots, \hat{\Phi}_{v,|\mathcal{T}|}\}$ indicates if charging is possible, i.e., if the EV is connected to a charging station ($\hat{\Phi}_{v,t} = 1$). Consequently, the constraint $\phi_{v,t} \in [0, \hat{\Phi}_{v,t}\overline{\Phi}_v]$ must hold for all vehicles and time slots. The variable vector $\psi_v = \{\psi_{v,1}, \ldots, \psi_{v,|\mathcal{T}|}\}, \psi_{v,t} \in [0, 1]$ provides each vehicle's relative SOC, which is limited by $\overline{\psi}_v$. A vehicle's SOC obviously depends on the SOC in the preceding time slot and on both charging and discharging. For each vehicle the SOC in t can be calculated by:

$$\psi_{v,t}\overline{\psi}_v = \psi_{v,t-1}\overline{\psi}_v + \phi_{v,t} - \Phi_{v,t}, \quad \forall v \in \mathcal{V}\, \forall t \in \mathcal{T}. \tag{4.10}$$

Hence, the energy consumption of vehicle v in t is given by $\phi_{v,t}$ and the total energy consumption of all EVs in t can be summed up by:

$$\sum_{v \in \mathcal{V}} \phi_{v,t}, \quad \forall t \in \mathcal{T}. \tag{4.11}$$

4.3.3 Stationary Batteries

The flexibility characteristics of stationary batteries are modeled similar to those of EVs. However, instead of driving, stationary batteries can feed energy back into the grid to counterbalance supply shortages. The reasons for increasing attractiveness of stationary batteries is similar to those of EVs, i.e., decreasing cost and increasing need for storage capacity brought forth by an increasing share of fluctuating renewable generation. A set $\mathcal{B} = \{b_i | i = 1, \ldots, |\mathcal{B}|\}$ of stationary batteries is considered.[10] In contrast to EVs, stationary batteries can be charged or discharged at all times as long as they are not fully charged or empty, respectively. Like for EVs, a constant charging power within each time slot is assumed for discrete time slots.

[10] Like above, indices are dropped for better readability.

Hence, instead of charging power (kW) the amount of energy charged or discharged per time slot (kWh) is given to describe the amount of energy added or reduced in a battery's SOC.

The tuple $(\underline{\Phi}_b, \overline{\Phi}_b, \phi_b, \overline{\psi}_b, \psi_b)$ provides a full flexibility description of stationary batteries. The description of the tuple is well in line with the description of EVs. Battery charging is constrained by the maximum amount of discharging and by the maximum amount of charging energy per time slot $\phi_{b,t} \in [\underline{\Phi}_b, \overline{\Phi}_b]$, where discharging is expressed by a negative charging variable ($\underline{\Phi}_b \leq 0$). The SOC of each battery must remain below its maximum value $\psi_{b,t} \in [0, \overline{\psi}_b]$ at all times and depends on both charging and the SOC of the previous time slot. The SOC in t is calculated by:

$$\psi_{b,t}\overline{\psi}_b = \psi_{b,t-1}\overline{\psi}_b + \phi_{b,t}, \quad \forall b \in \mathcal{B}\, \forall t \in \mathcal{T}. \tag{4.12}$$

Following the description of EVs, the total energy consumption of all stationary batteries in t can be calculated by:

$$\sum_{b \in \mathcal{B}} \phi_{b,t}, \quad \forall t \in \mathcal{T}. \tag{4.13}$$

Finally, the electricity consumption of all appliances is calculated by summing up the demand of household appliances (4.9), EVs (4.11), and stationary batteries (4.13):

$$l_t = \sum_{a \in \mathcal{A}} l^A_{a,t} + \sum_{v \in \mathcal{V}} \phi_{v,t} + \sum_{b \in \mathcal{B}} \phi_{b,t}, \quad \forall t \in \mathcal{T}. \tag{4.14}$$

4.4 Discussion

The growing share of fluctuating and uncontrollable generation from RES in the supply mix has seen constant growth in recent years. Fostering renewable generation through subsidies, tax advantages, or a regulated remuneration for feeding in electricity produced by RES are approaches to support this growth. However, the increasing share of "green electricity" does not come for free. To ensure grid stability by balancing supply and demand, massive cost for reserve power could arise. Another way is to make use of demand flexibility. The model described above can be used to evaluate what contribution a household can provide for a flexibility aggregator's demand response portfolio. This approach models the flexibility of single devices that are represented by appliance groups with similar load shifting characteristics. Knowing the appliance endowment of a private household, for example from non-intrusive appliance monitoring, an aggregator can determine the saving the respective household can contribute. This information is fundamental for designing a cost efficient customer portfolio and builds the base for developing individual tariffs.

The household flexibility model presented above allows for scheduling current and future household appliances. However, one shortcoming of the approach is, that it does not allow for integrating information about households preferences, e.g., the inhabitants willingness to take risk, their ability to adapt habits, or the incentives that would be necessary to convince households to offer flexibility to the aggregator. Such "soft factors" are hard to gauge. However, these are important factors for designing DR tariffs. Hence, the customers' response to tariff offers is considered in part IV, which explicitly deals with the optimal design of DR tariffs.

Another shortcoming of this household flexibility modeling approach is the assumption that information can be readily communicated between households—and even single devices—and the demand response aggregator. To enable such communication between all agents, the SG roll-out must be expanded greatly—in particular with respect to the development of interoperable communication standards. However, this work considers a future scenario with EVs and stationary batteries commonly introduced and integrated. Therefore, the assumption of widespread ICT seems realistic.

For both stationary batteries and EVs neither losses of electricity storage nor battery degradation is considered. However, current storages achieve efficiency values up to 90 % and almost do not self-discharge (cf. table 2.3). The assumption of a 100 % efficiency is well in line with Daryanian, Tabors, and Bohn (1989). In addition, efficiency is merely a simple factor that alters the overall energy consumption and can easily be added to the model, in particular for economic considerations.

The following chapter builds on the model introduced above. It integrates base load devices and flexible appliances into a scenario with a supply model. The supply model considers generation from different energy sources, i.e, RES, a gas turbine, or the reserve market. In this scenario, both the value households for DSM and preferable renewable supply portfolios are investigated.

5

Household Flexibility Valuation

To design DR portfolios an aggregator must offer tariffs that incentivize customers to cost-efficiently provide flexibility. For that purpose, tariff design requires information about the contribution a household can add to a DR portfolio. The following assessment of household flexibility potentials is performed from the perspective of an aggregator that must balance supply and demand in a microgrid setting. In this local scenario, the demand side consists of a set of households. On the supply generation from different energy sources is considered. The main objective of this chapter is to gather information about the amount of flexibility single households can offer and the flexibility's value to the aggregator (cf. research question 1 and research question 2). In the following parts, this micro perspective is interchanged for a macro perspective with more abstract flexibility models that allow for designing customer portfolios and flexibility tariffs.

The households' electricity consumption is split up and assigned to the appliances which cause the demand. The supply side consists of three components, i.e., generation from RES, a gas turbine, and the reserve power market. Figure 5.1 illustrates the supply and demand properties of the local microgrid scenario. On the one hand, generation from RES is the cheapest form of electricity supply and, on the other hand, it is most expensive to procure electricity from the reserve power market. The flexibility aggregator thus tries to schedule both flexible demand and controllable supply at the lowest possible cost.

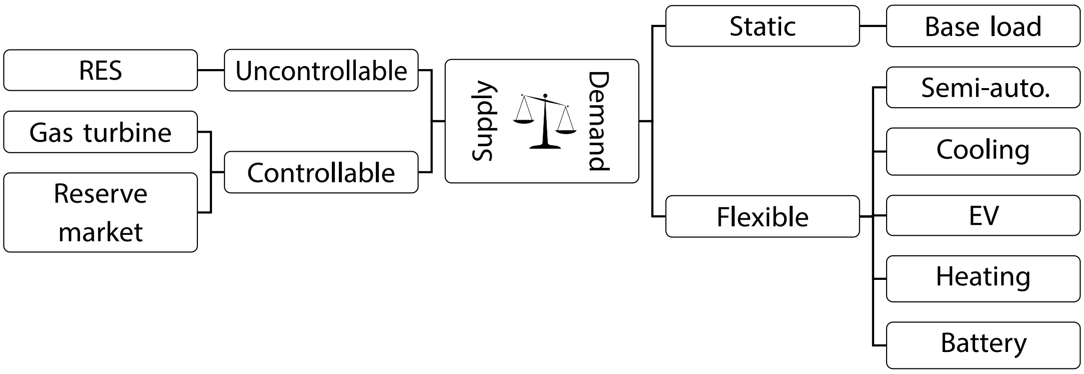

Figure 5.1: Supply and demand characterization for flexibility valuation

A simulation study is conducted to analyze which contribution to cost savings each appliance group can add compared to a scenario with inflexible demand. The insights of the evaluation, in combination with the set of appliances available in a household that can be identified by means of non-intrusive appliance monitoring (Parson et al. 2012; Liao et al. 2014), build the basis for determining the value of the household's flexibility for an aggregator. In addition, key features that drive demand flexibility are investigated. Not only the demand portfolio composition of an aggregator but also the supply portfolio structure affects reserve power cost. Therefore, the optimal composition of the renewable generation portfolio is analyzed.

5.1 Scenario and Simulation

In the simulation study the aggregator has full information on customer flexibility and can directly control the operation of flexible appliances. Similarly, perfect knowledge about future generation from RES is assumed. Hence, the evaluation rather provides an upper benchmark of household flexibility. To determine the cost savings that arise from DSM, a simulation without coordination is conducted and compared to the case with optimal load scheduling. Both uncontrolled and centrally optimized coordination assume a time resolution of 15 minute time slots.

5.1.1 Demand Side

The demand side specification represents the first simulation data input stream. It comprises all information that is necessary to initialize the household appliances that are available in the population, e.g., current device specifications and empiric data on typical usage. In addition, the load curve for the uncontrolled consumption scenario can be prepared. This demand pattern is generated synthetically from empiric data. The load curve in the uncontrolled scenario is determined by summing up the different demand components. The assignment of appliances to households is dissolved and single runs of appliances are considered—for semi-automatically operated appliances, cooling, and heating devices. Table 5.1 shows the characterization applied in the simulation including the data sources.

Table 5.1: Household appliance input data, adapted from Gottwalt et al. (2016)

Appliance	Penetration level	Consumption share	Energy per run [kWh]	Cycle duration [min]
Dishwasher	0.673[a]	0.037[b]	1.206[a]	105[a]
Washing machine	0.945[a]	0.036[b]	0.888[a]	105[a]
Tumble dryer	0.391[a]	0.024[b]	2.485[a]	105[a]
Fridge	0.997[a]	0.09[b]	0.024[d]	15[c]
Freezer	0.505[a]	0.07[b]	0.035[d]	15[c]
Space heating	0.04[d]	0.12[d]	59.0[c]	240[c]
Stor. water heater	0.06[d]	0.04[d]	6.0[d]	240[c]

Sources: [a]Destatis (2013), [b]Bürger (2009), [c]Stamminger et al. (2008), [d]Own calculations based on Bürger (2009) and Stamminger et al. (2008)

The share of flexible household appliances (excl. EVs) is responsible of about 42 % of the total residential electricity demand in Germany (Stamminger et al. 2008). Hence, 58 % of the total electricity consumption is from inflexible base load. For each household, base load is modelled using *H0* profiles (cf. section 4.1.1) that are scaled to 58 % of their original value. Figure 5.2 depicts both the *H0* profiles for a household with an annual average household electricity consumption of about $3100 kWh$ (BDEW 2013) and the corresponding base load for a winter day and different types of day, i.e, Weekday, Saturday, Sunday.

Given this information, the number of operations or runs of semi-automatically controlled

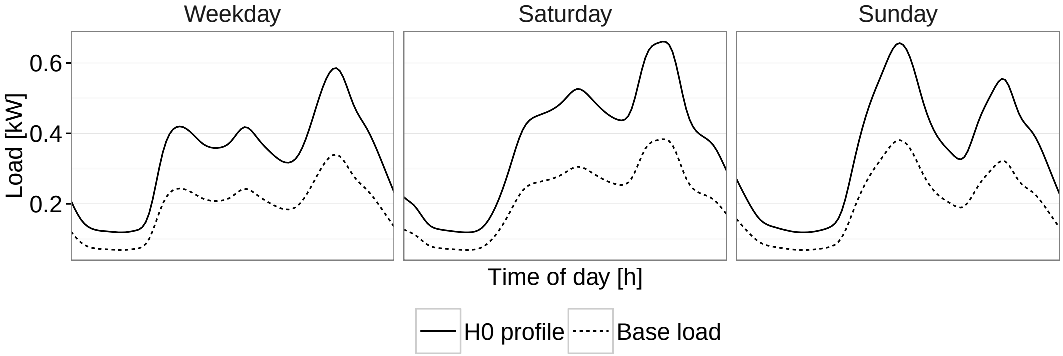

Figure 5.2: Standard H0 profile for average German households and base load for different day types in the winter time

appliances can be calculated by:

$$\frac{\text{Avg. household electricity consumption} \cdot \text{Appliance consumption share}}{\text{Energy per run} \cdot \text{Appliance penetration level}} \tag{5.1}$$

To determine the starting times for semi-automatically controlled appliances with user interaction over one day, empiric starting probability distributions are used (Stamminger et al. 2008). The probability of an appliance start is equally distributed over the days of the whole simulation horizon. Figure 5.3 depicts the density functions for appliance starts for dishwashers, washing machines, tumble dryers.

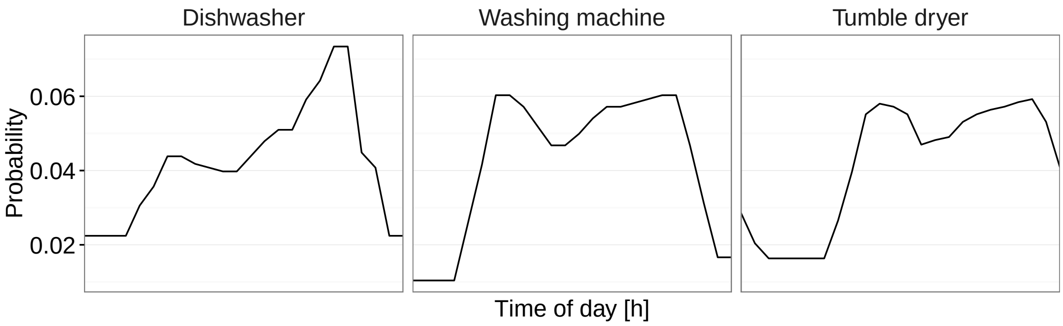

Figure 5.3: Semi-automatically appliance start density (data source: Stamminger et al. (2008))

Both heating and cooling devices work constantly—independently of customer activity (Widén and Wäckelgård 2010). Therefore, it is only necessary to calculate the number of appliances available in the population by their penetration level. If not controlled, heating appliances, i.e., storage water heaters and space heaters, usually work during off peak periods

(Stamminger et al. 2008). Formerly, these were used to balance generation from nuclear power plants that could not be shut down economically for short time periods. Therefore, in the uncontrolled scenario they are operated in a continuous stretch starting at 0 am. Fridges and freezers must operate frequently to guarantee that temperatures stay within a predefined range. In the simulation they must run in one out of three time slots. The interval length is set to 45 minutes as the length of one time slot is 15 minutes.[1] The probability of activity within the runs is equally distributed in the uncontrolled scenario.

Following Sioshansi (2012), empiric driving profiles as well as technical specifications are used for modelling the charging of EVs. Little driving profiles are available for EVs. Therefore, the simulation builds on empiric driving profiles from conventional vehicles (Flath 2013). Extracting information on trips and location of vehicles from the German Mobility Panel[2], driving profiles of full time employees are considered. It is assumed that EVs are only able to be charged at their home location. The charging process is started right after arriving at the work or home location and is finished in case the battery is full or the EV leaves again (Stroehle et al. 2011; Schuller 2013). For stationary batteries and EVs neither losses of storing electricity nor battery degradation is considered.

5.1.2 Supply Side

This work mainly focuses on the demand side of the electricity value chain. Therefore, the supply model introduced in this section is kept rather simple. In accordance with the demand flexibility model, the supply side is build for a micro perspective. It consists of generation from RES, a gas turbine, and the reserve power market.

Throughout this work a future scenario is considered. Hence, compared to the capacities that are already installed today, high availability of renewable generation from both wind and *photovoltaic* (PV) is considered. Wind feed-in from northern Germany and PV generation profiles from southern Germany are used as in these regions the availability of the respective generation capacities is high.[3] The data is provided in a 15 minute resolution. Figure 5.4 depicts the boxplots for wind and PV generation on a daily basis. Obviously, especially the generation from wind power plants varies much.

[1]The assumption of 15 minute time slots results from *H0* profiles and renewable generation data that is also provided in a 15 minute resolution.
[2]`http://daten.clearingstelle-verkehr.de/192/`
[3]Wind and PV generation data is publicly available at `http://www.eex-transparency.com`.

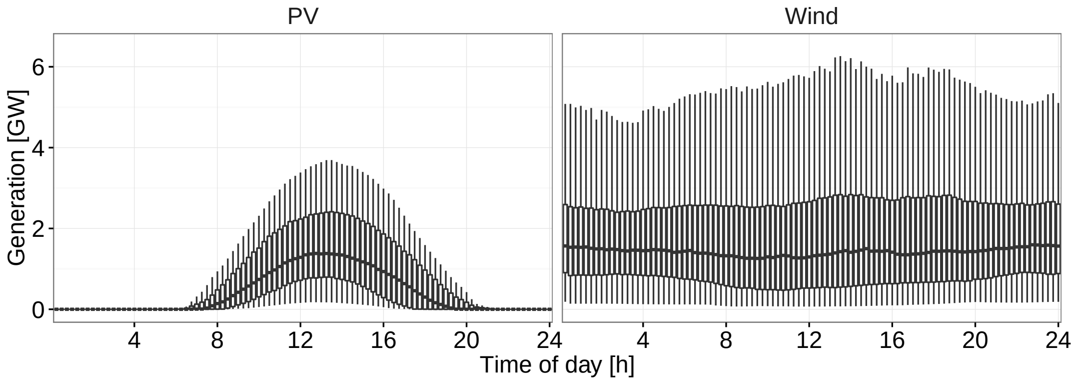

Figure 5.4: Unscaled photovoltaic generation in southern Germany and wind generation in northern Germany in 2013 (outliers are dropped for better exposition)

The total wind and PV generation is scaled over the simulation horizon. The parameter $S^W \in [0,1]$ provides the average share of wind generation in overall generation from RES. In addition, the availability of aggregated renewable generation compared to total demand is given by $\Gamma \in \mathbb{R}^+$.[4] Total renewable generation in t is given by $R_t \in \mathbb{R}^+$.

In case demand exceeds renewable generation it must be covered by conventional generation. However, from an economic perspective it is best to maximize the share of demand that is satisfied by RES as this supply type is the cheapest. Supply from the gas turbine in t is given by $s_t^T \in \mathbb{R}^+$. The parameter $\kappa \in \mathbb{R}^+$ is the turbine's maximum output ($s_t^T \leq \kappa$) and s_t^T/κ the current utilization level. To model the fact that the gas turbine must run with at least 40 % of its maximal output, semi-continuous decision variables are used:

$$0 = s_t^T \quad \vee \quad 0.4 \leq s_t^T \qquad \forall t \in \mathcal{T}$$

The variable gas turbine costs c_t^T consist of two components, i.e., variable fuel and ramping cost (Flath and Gottwalt 2016). The variable fuel cost depend on both turbine output and the gas price.[5] The turbine's efficiency directly hinges on its output. On the one hand, the turbine's minimal output cannot fall bellow 40 % ($s_t^T/\kappa = 0.4$) where efficiency is around 47 % and, on the other hand, efficiency peaks at 58.5 % for $s_t^T/\kappa = 1$ (Los, Jong, and Dijken 2009). Between the minimal and maximal efficiency a linear efficiency trajectory is assumed (Gottwalt et al. 2016). The binary auxiliary variable r_t marks turbine start ups. Following

[4]The scenario $\Gamma = 0$ represents a situation without any generation from RES and $\Gamma = 1$ constitutes a scenario in which (theoretically) all demand could be satisfied from renewable generation.
[5]Market price for gas is about 10.2€/MWh (3€/MMBtu).

Jong et al. (2010), ramping cost that equal a two hour operation at the minimum output level arises once the turbine is started. Finally, variable gas turbine costs in t are calculated by:

$$c_t^T = \underbrace{0.0147 s_t^T + 0.0028\kappa \mathbb{1}_{(s_t^T>0)}}_{\text{variable fuel cost}^6} + \underbrace{r_t 8(0.0147 \cdot 0.4\kappa + 0.0028\kappa)}_{\text{ramping cost}}, \tag{5.2}$$

where the indicator function $\mathbb{1}_{(G_G^t>0)}$ takes the value one if the gas turbine generates output.

Electricity procured from the reserve market is given by $s_t^M \in \mathbb{R}^+$. The variable cost for reserve power in t is given by $c_t^M = C^M s_t^M$, where C_t^M is the fixed market power price per kWh—in the simulation C^M=0.038€$/kWh$ is set which corresponds to the average EEX power price in 2013. The supply in t is summed up by:

$$R_t + s_t^T + s_t^M, \tag{5.3}$$

and total generation costs over the full time horizon are given by:

$$\sum_{t\in\mathcal{T}} \left(c_t^T(s_t^T) + c_t^M(s_t^M) \right). \tag{5.4}$$

5.1.3 Balancing Supply and Demand

To support grid stability, demand that exceeds supply from RES must be satisfied by conventional generation, i.e., by generation from a gas turbine or the reserve power market. Therefore, to ensure supply sufficiency, total supply (5.3) must exceed total demand (4.14) at all times:

$$R_t + s_t^T + s_t^M \geq \sum_{a\in\mathcal{A}} l_{a,t}^A + \sum_{v\in\mathcal{V}} \phi_{v,t} + \sum_{v\in\mathcal{V}} \phi_{v,t}, \quad \forall t \in \mathcal{T}. \tag{5.5}$$

To meet this condition the aggregator must schedule flexible generation and consumption capacities. Striving for profit maximization, the aggregator must realize this in a cost optimal fashion, i.e., by minimizing total generation costs:

$$\min \sum_{t\in\mathcal{T}} \left(c_t^T(s_t^T) + c_t^M(s_t^M) \right). \tag{5.6}$$

[6] From $s_t^T = \kappa \Leftrightarrow s_t^T/\kappa = 1$ follows that the variable fuel cost is given by $(0.0147 + 0.0028)\,\kappa = 0.0175\kappa = 0.0102/0.585\kappa$.

Although longer time horizons are considered, appliances are repeatedly dispatched on a daily basis to restrict computational complexity in the simulation. For household appliances this is no limitation as the flexibility model is designed for intra-day scheduling—this is rather a natural property of the household appliances than a model design issue. However, the flexibility of EVs and stationary batteries and their value for a DR portfolio, respectively, is underestimated by not allowing for inter-day scheduling. Therefore, following Scott et al. (2013), two components are added to the objective function which cause EVs and stationary batteries to charge whenever there is an excess of renewable generation. This is realized by rewarding the batteries SOC by a small $\Xi \in \mathbb{R}^{+}$. The value of Ξ must be chosen small enough to avoid both charging from conventional generation and falsification of cost savings. Test runs revealed that this approach yields results that are not significantly different from those calculated by an optimization over the full time horizon. Hence, the objective function is given by:

$$\min \sum_{t \in \mathcal{T}} \left(c_t^T(s_t^T) + c_t^M(s_t^M) \right) - \Xi \sum_{v \in \mathcal{V}} \psi_{v,|\mathcal{T}|} \overline{\Psi}_v - \Xi \sum_{b \in \mathcal{B}} \psi_{b,|\mathcal{T}|} \overline{\Psi}_b . [7] \tag{5.7}$$

The resulting optimization problem can be described as a *mixed integer linear program* (MILP). The full formulation of the MILP including comprehensive constraints for modeling supply and demand is presented in appendix C.

5.1.4 Parametrization

The simulation is run for a time horizon of twelve consecutive weeks—including weeks from winter, transition, and summer times. The following parametrization characterizes the base scenario. In the sensitivity analysis a large portion of the parameters are varied. The share of wind generation in the renewable generation mix is set to $S^W = 70\,\%$[8] and a supply-demand ratio of $\Gamma = 1$. The gas turbine capacity is set to $\kappa = 200\ kW$.

For specifying the availability and properties of household appliances the values from table 5.1 are used in combination with the starting distributions from figure 5.3. The maximal shifting intervals for semi-automatically controlled appliances are randomly set to 3, 5, or 10 hours. Following the description above, the simulation is repeatedly run for one day to cover

[7] Note that here $|\mathcal{T}|$ does not refer to the last day of the total time horizon but to the last time slot of one day of the simulation.

[8] This approximately corresponds to the current wind / solar generation ratio in 2015 (BMWi 2015a).

the time horizon of twelve weeks. Within one day, all information, i.e., appliance availability and flexibility as well as generation from RES is known.

A population of 1,000 households is considered. These households are supposed to own 160 EVs and 25 stationary batteries.[9] The EV parametrization follows Gottwalt et al. (2016). The battery capacity is set to 30 kWh and a consumption of 0.15 kWh/km is assumed. EV charging is possible at both the home and the work location. The maximum charging power is set to 11 kW which leads to $\overline{\Phi} = 2.75$ kWh per time slot. Stationary batteries have a capacity of 7 kWh and both charging and discharging power is limited to 4 kW (1 kWh per time slot). The SOC at the begin of the simulation is set to 30 % of the capacity. For the storage value of both EVs and batteries an arbitrary low value is set ($\Xi = 0.001$).

5.2 Demand Flexibility Potentials

This section firstly elaborates on the general demand side flexibility potentials and the impact of DSM and conventional generation. Secondly, the eligibility of appliance groups to contribute to reduce generation costs is evaluated. Finally, to determine the value of a household's flexibility for DSM given its appliance endowment, cost saving potentials of single appliances are investigated.

In comparison to the uncontrolled scenario, utilizing flexibility impacts both the supply and the demand side. The changes on the demand side, of course, are predominant as the generation capacities must also be dispatched in the uncontrolled approach to ensure supply sufficiency. Figure 5.5 illustrates the impact of DSM on both supply and aggregate demand curves over one exemplary week.

In the static scenario the supply curve shows the need for reserve power from the electricity market in the mornings and in the evenings caused by distinct demand peaks during these periods. In the mornings and evenings, PV generates little or no output. In addition, during these periods EVs increase these peaks as they charge right away after arriving at their work or home location. Hence, in the uncontrolled scenario conventional generation is dispatched at almost all times. In the optimized scenario, very little expensive reserve electricity and gas turbine generation is required. Flexible appliances are scheduled to match renewable generation. Especially, PV peak generation can be exploited. In the examplary week, the

[9]This corresponds to the goal of the Federal Government of Germany for 2030 (Germany 2011).

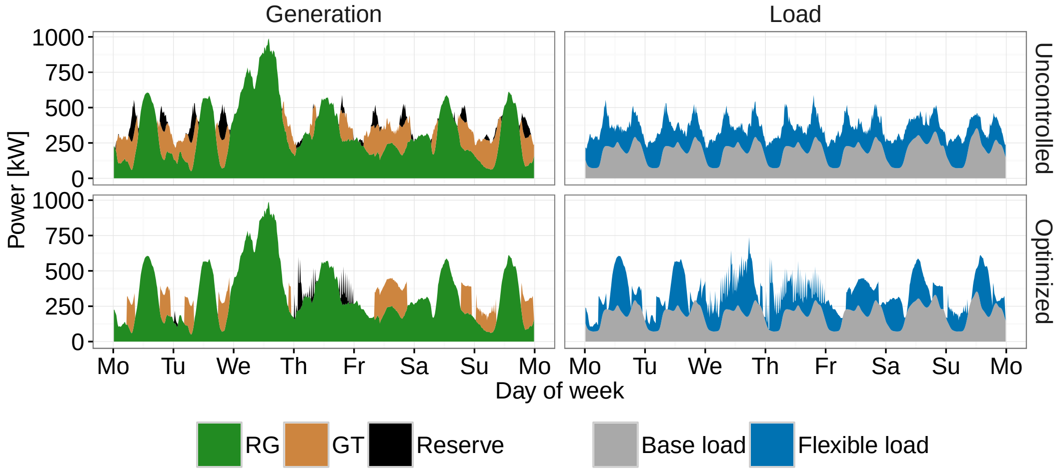

Figure 5.5: Impact of scheduling flexible demand on generation and consumption, adapted from Gottwalt et al. (2016)

share of load covered from RES is increased from 82 % to 89 %. Furthermore, if the gas turbine is started, it is used at its capacity limit—this ensures maximum efficiency.

The aggregator's goal of DSM in this microgrid scenario is to reduce generation costs to maximize its profit. Generation costs arises from reserve power procurement and the gas turbine, i.e., variable fuel cost and ramping cost. To valuate the eligibility of appliances to provide flexibility and to contribute to generation costs savings, the cost reduction potential by utilizing demand flexibility is compared to the uncontrolled scenario. To this end, figure 5.6 depicts the generation cost composition and the possible cost reduction in the base scenario by allowing for scheduling flexible load by appliance groups. The remaining demand is assumed to be static.

Cooling and semi-automatically controlled appliances pose only minor cost saving potentials, despite their high availability. In contrast, stationary batteries, heating appliances and EVs can contribute substantially to the reduction of generation costs. If demand scheduling of the latter three groups is allowed, conventional generation costs can be curtailed by more than 30 %—these three groups allow for exploiting almost the full flexibility potential.

Splitting up the cost reductions to single appliances instead of appliance groups allows for identifying promising households given their appliance endowment. The composition of the renewable generation portfolio affects the eligibility of appliances for DSM as a PV dominated portfolio calls for intra-day shifting whilst a wind dominated portfolio requires the ability to

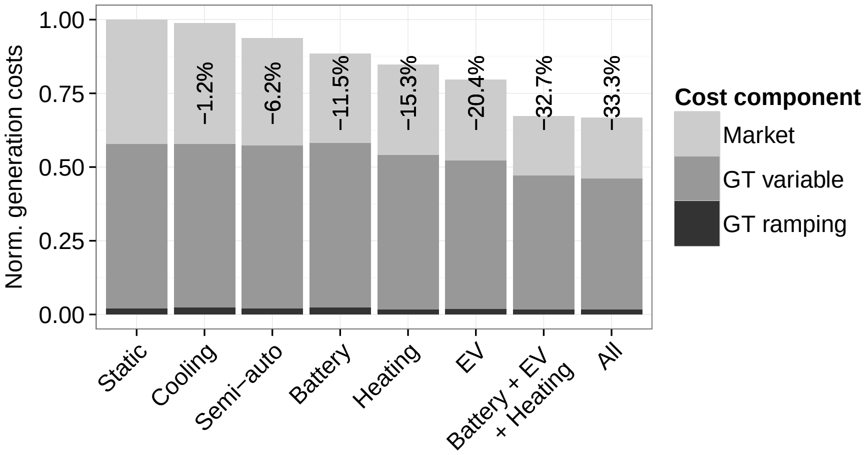

Figure 5.6: Flexibility potential per appliance group split up to cost components, adapted from Gottwalt et al. (2016)

shift loads over longer time horizons. Figure 5.7 shows the cost reduction potentials of single appliances for varying renewable generation portfolio compositions.

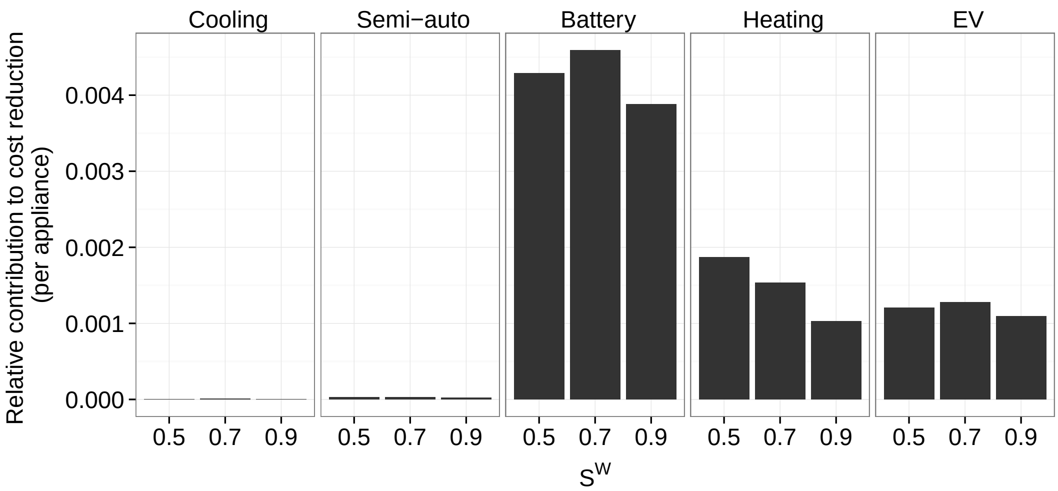

Figure 5.7: Flexibility potential per individual appliance

Obviously, given their little overall impact and high availability, cooling and semi-automatically controlled appliances are of little value for DSM. In addition to their very limited contribution to cost savings, utilizing semi-automatically controlled appliances' flexibility requires user interaction and hence generates discomfort. In contrast, EVs pose larger potentials. Although scheduling EV charging requires user interaction as well, their comparably high demand

and large shifting distance makes them attractive candidates for DSM. Similarly, heating incorporates large demand with the ability of daily scheduling which makes them outstanding aspirants for balancing PV generation peaks. Therefore, their value to the aggregator increases in the availability of PV. Not surprisingly, stationary batteries pose the largest value for an aggregator's flexibility portfolio. Batteries are fully flexible and only used for DSM. They perform best given a wind dominated portfolio with a PV share around 30 %. This best fits the batteries' ability of storing large loads over more than one day.

A demand flexibility aggregator should try to contract households that own large appliances, i.e., an EV, electric space or storage water heating, or a stationary battery. Tariffs must be designed to explicitly incentivize the respective customers to enter a supply contract and to allow for scheduling their flexible loads. Obviously, the composition of the renewable generation portfolio is an important driver for eligibility and potentials of different appliances for DSM. Consequently, the following section investigates favorable combinations of wind and solar generation to best make use of demand flexibility in domestic electricity consumption.

5.3 Forming Supply Portfolios

The flexibility characteristics of household appliances determine if the appliances are better suitable for shifting loads over shorter or over longer distances. The need for short distances is predominant in PV dominated portfolios as demand must be shifted from times with little generation, i.e., nights, to times with much generation, i.e., day time. In contrast, in wind dominated portfolios the ability to shift demand over longer periods of time, i.e., from a day with little generation from wind turbines to a stormy day, is of great value.

Availability of generation from wind and solar power plants greatly differ on a regional level. Like pointed out above, a different generation portfolio composition affects both the eligibility of different appliances for RES and the demand that can be satisfied from RES. Figure 5.8 shows the share of demand that must be covered by conventional generation, i.e., a gas turbine and the reserve power market, for different renewable generation portfolios, which are described by the share of wind generation in the portfolio S^W for both the uncontrolled and the optimized scenario. The more load must be covered by conventional generation, the lower is the share that can be covered from RES. Section 5.2 proves that EVs, heating appliances, and stationary batteries allow for yielding almost all the flexibility potential. Therefore, this analysis considers the appliance groups pointed out above to be flexible.

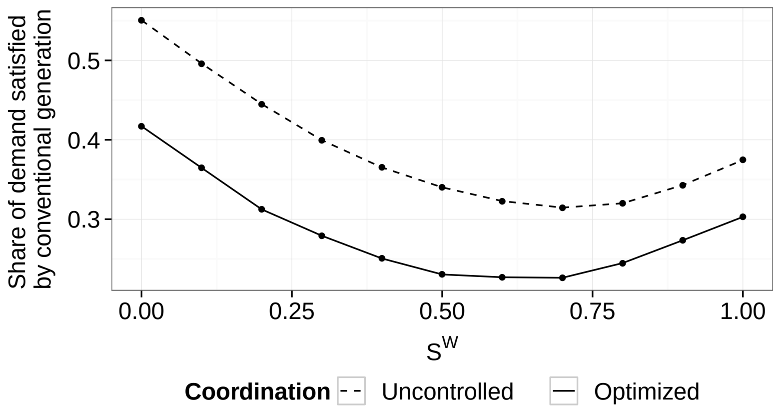

Figure 5.8: Demand satisfied by conventional generation for varying renewable generation portfolios

In terms of load coverage from RES which is cost-efficient, the optimized scenario performs better regardless of the portfolio composition. This is not surprising as the uncontrolled solutions are a subset of possible solutions from the optimized approach. Generation from wind is spread more equally over each day. Hence, for both the optimized and the uncontrolled scenario, the PV-only portfolio requires more conventional generation than a wind-only portfolio. Furthermore, the two sources complement each other. Heating devices allow to balance intra-day PV generation and both stationary batteries and EVs inter-day wind supply. On the one hand, a slightly wind dominated portfolio ($S^W = 70\,\%$) allows for maximal demand coverage from RES as in this case renewable generation fits the natural demand pattern. On the other hand, utilizing flexibility in the optimized case allows for better balancing PV output. This slightly shifts the optimal renewable portfolio composition towards an equally balanced renewable generation portfolio ($S^W \in [50\,\%, 70\,\%]$).

There is a strong interdependency between the availability and the value of flexible loads on the demand side and the optimal portfolio structure of RES on the supply side. Hence, in the process of designing demand flexibility portfolio and investing in generation capacities these interdependency must be taken into account.

5.4 Demand and Supply Interdependency

The composition of the renewable portfolio composition as well as the availability of demand flexibility affects the extent of demand that can be covered from RES. The flexibility of cooling appliances and semi-automatically controlled devices is negligible in comparison to stationary batteries, heating devices or EVs. Therefore, this section focuses on these appliances. To assess the interaction between portfolio structure and device flexibility, figure 5.9 depicts the share of demand that can be covered by RES for varying combinations of these two factors for both the uncontrolled and the optimized scenario. The saturation of the "large" appliances in the population is separately increased while keeping the remaining appliance saturation at a constant level.

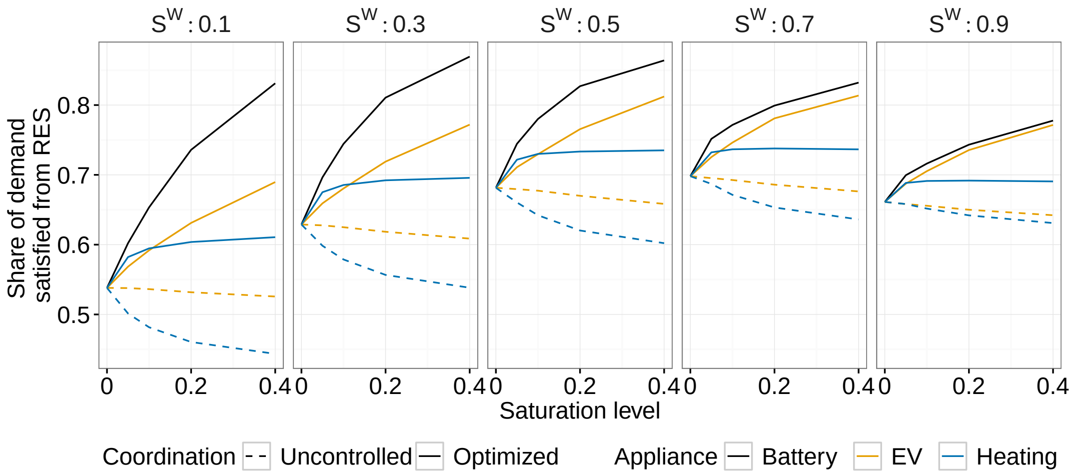

Figure 5.9: Interdependency of generation portfolio with large appliance flexibility and saturation, adapted from Gottwalt et al. (2016)

Assuming a saturation of zero corresponds to a scenario where only base load, cooling devices, and semi-automatically controlled appliances are included and all of these demand components are inflexible. In the uncontrolled mode, increasing the share of EVs that are available in the population only slightly decreases the share of demand covered from RES. In contrast, predominately for PV dominated renewable generation portfolios, increasing the share of heating devices has a substantial effect on load coverage from RES. This is due to the acyclic PV generation during day hours and consumption of heating appliances during night hours—in contrast, EVs at least partly charge during day hours and can make use of PV generation.

Especially for PV dominated portfolios, even a small saturation of flexible devices allows for substantially increasing load coverage from RES in the optimized scenario. The daily shifting of charging and heating activities from night to day hours facilitates this effect. For heating devices this trend rapidly flattens as excess PV capacities are exhausted by the large demand of heating appliances. Stationary batteries outperform the load coverage gains that can be achieved by EV although in the simulation the storage capacity of EVs is larger than the storage capacity of stationary batteries. Two main reasons for this can be identified. Firstly, EVs must enable customers to realize their driving profiles and, secondly, EVs are not able to feed electricity back into the grid. Surprisingly, the highest level of load coverage from RES is realized in a PV dominated scenario ($S^W = 30\,\%$) and a large share of stationary batteries. Batteries are used to store electricity at daily peak generations times and feed-back electricity in times of high demand. The performance difference of stationary batteries and EVs almost fully vanishes given wind dominated scenarios. This results from the fact that in these cases electricity cannot be fed back regularly but must be stored over longer time horizons.

5.5 Discussion

Applying the household flexibility model presented in chapter 4, this chapter evaluates the flexibility of domestic electricity consumption as well as the impact of the renewable generation portfolio composition on attainable shares of load coverage from RES. The evaluation is realized by a simulation study that considers a local microgrid in which a flexibility aggregator can schedule both conventional generation and flexible demand. In the base scenario a set of 1000 households is considered. The households' appliance endowment is determined by empiric data. Similarly, empiric renewable supply data for both wind and PV generation is used.

The results indicate that EVs, stationary batteries, and heating appliances are the most promising devices for DSM. They incorporate the major share of demand flexibility. Controlling these appliance groups allows to exploit almost the full cost reduction potential. In addition, the number of appliances that are required to gain substantial impact is comparably small—both the appliances' demand and their flexibility properties in favor of balancing generation from RES are large. Hence, the investment cost for rolling out hardware that facilitates direct (remote) load control are limited.

Elaborating on research question 1, these insights can be used to derive a general (illustrative) classification of the appliance groups' flexibility and their potential contribution to conventional generation cost reductions. Figure 5.10 proposes such a characterization.

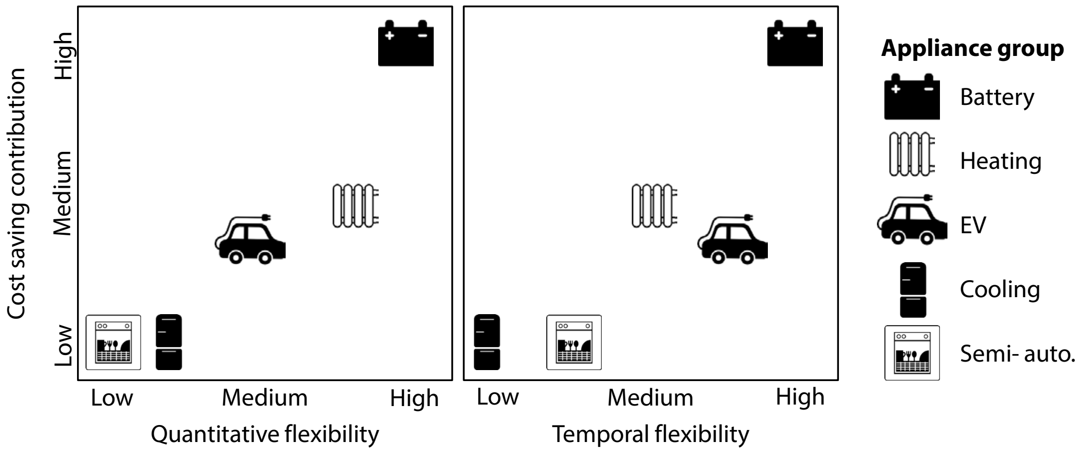

Figure 5.10: Illustrative characterization of individual appliance flexibility (quantitative and temporal) and flexibility value (cost saving potential) characterization

Flexibility is split up into two components, i.e.,quantitative and temporal flexibility. Quantitative flexibility refers to how much load can be shifted. Temporal flexibility indicates how far load can be shifted. On the one hand, stationary batteries are the predominant flexible device in both the temporal and quantitative perspective. On the other hand, cooling devices and semi-automatically controlled appliances are of minor (or even no) interest. Whilst heating appliances offer some more quantitative flexibility in the considered scenario, EVs provide further shifting distances.

Section 5.2 provides fundamental insights to answer research question 2 and research question 3. In accordance with figure 5.10, a household's potential contribution to an aggregator's flexibility portfolio hinges on its appliance endowment. Households that own an EV or an electric heating device are of major attractiveness. Stationary batteries are not yet prevalently rolled out but could pose significant potentials in case battery aging and investment costs can be decreased. An aggregator should always consider both a household's appliance endowment and the renewable generation portfolio whose output needs to be matched when designing (individual) DR tariffs.

Although this approach models flexibility properties in a very detailed fashion it completely abstracts from individual preferences and it does not consider investment cost in hardware and software. Furthermore, the long term effects of load scheduling on customer satisfaction and discomfort are not included in the model. Such consideration could be considered in further studies. In addition, full information about future renewable generation is assumed. Similarly, appliances can be controlled centrally and directly. Both stochastic optimization approaches under uncertainty of future generation and appliance usage as well as indirect load control and incentivization pose interesting future fields of research. The scenario focuses on a microgrid in which renewable supply and total demand are balanced. This could be extended by a simulation study applying varying parametrization as well as a deeper consideration of seasonal effects and influences. Finally, the study focus on German household data. It would be interesting to investigate the appliances' flexibility potentials in other countries.

Nevertheless, the insights from this part allow for investigating optimal demand portfolio structures as well as efficient tariff design on a more global perspective. To this end, the following parts take one step back and focus on a macro perspective. The portfolio optimization abstracts from a single device view and households as a whole are considered instead. Furthermore, in addition to shifting loads a second type of flexibility is considered, i.e., load curtailment (cf. section 2.3.3 and section 2.4.1). Similarly, the supply side also abstracts from the micro prospective of modeling one single gas turbine. Instead, long term supply contracts (forwards), options on generation capacities, and a short term market procurement is considered. The knowledge of ideal demand response portfolio structures builds the indispensable basis for designing tariffs that target at contracting customers including their flexibility in the best possible fashion.

Part III

Portfolio Composition

6

Optimal Customer Portfolio Design

The success and the possibilities of scheduling loads are strongly affected by the composition of an aggregator's customer portfolio and by the corresponding customers' flexibility provision. However, flexibility does not come for free. Domestic customers that offer flexibility must be compensated for their discomfort from DSM. Discomfort results from changes in daily environmental and behavioral preconditions, e.g., room temperature, starting times of semi-automatically controlled appliances, or available EV driving ranges. Therefore, the portfolios must be designed carefully. This is realized via the design of tariffs that incentivize customers to offer flexibility. To enable the aggregator to properly design incentives, knowledge about both customer flexibility—which was investigated in part II—and about the optimal composition of its customer portfolio is needed (cf. research question 3).[1]

On the one hand, considering the aggregator's decision dilemma, cost for scheduling flexible supply from conventional power plants or the spot market must be limited. On the other hand, demand flexibility contracting and dispatching costs must be restrained. The part at hand investigates the optimal structure of customer flexibility portfolios in combination with efficient supply procurement strategies (cf. research question 4)—both must be realized over long time horizons—as well as the efficient dispatch of both supply and flexible demand.

[1]Note that this part as well as the subsequent part builds upon a paper that is currently under review at the Journal of Operational Research (Gärttner, Flath, and Weinhardt 2016b).

To this end, the underlying two-stage optimization program is described as a special case of a knapsack problem which is hard to solve. Therefore, in order to reduce computational complexity, this part also presents and evaluates a method for supporting both long term supply and demand flexibility procurement as well as their efficient dispatch.

Assuming that aggregators apply non-intrusive load monitoring techniques (Parson et al. 2012; Liao et al. 2014) and build on the insights about household flexibility and contribution to a DR portfolio from part II, this part considers both the supply and the demand side on a more abstract level. Figure 6.1 illustrates the abstraction level of both supply and demand side. With respect to generation, aggregators manage supply from RES that is generated within their local microgrid. Generation from RES is uncertain, so only generation scenarios are known at the time the customer portfolio is designed. In addition, forwards and options can be procured OTC or on electricity markets. Finally, if necessary, electricity can be procured on the spot market. Instead of describing the flexibility properties of single household devices (cf. part II) this part abstracts from this very fine grained view and considers a households' flexibility by three load types, i.e., base, shiftable, and curtailable load (Gellings 1985; He et al. 2013).

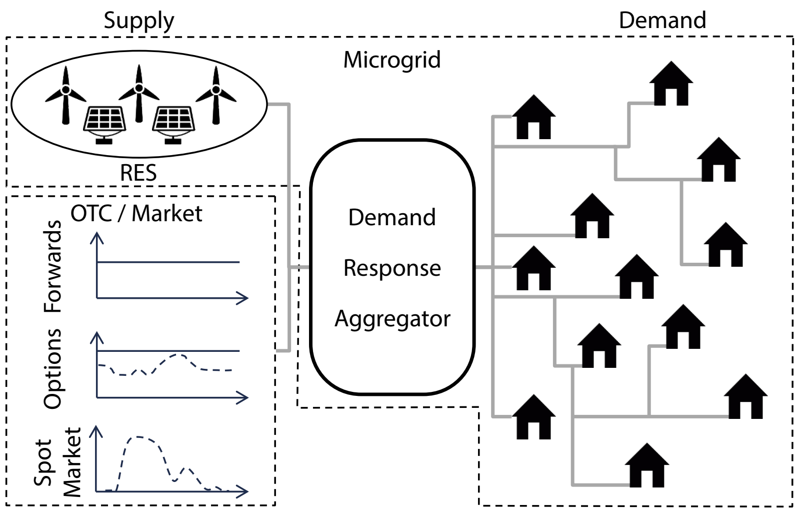

Figure 6.1: Illustration of supply and demand abstraction level in a local microgrid scenario with supply from RES, forwards, options and the spot market considering single households which consume base, shiftable, and curtailable load on the demand side

To determine optimal customer portfolio compositions and to design an efficient approach to calculate these, the scenario and sequence of decisions is firstly introduced. In this scenario, both the supply and the demand side are formally described and a comprehensive mixed integer linear optimization model is presented to support long term contracting and short term dispatching decisions. Long term decisions are taken under uncertainty of future generation from RES, which additionally increases complexity. To reduce computational complexity an alternative non optimal heuristic is developed. This allows for solving the problem for large customer sets, long time horizons, and variable future supply scenarios.

The model is evaluated using empiric renewable generation data and empiric domestic electricity consumption data. In addition to demand and supply contracting, this part evaluates the potentials of reducing computational complexity by applying heuristic approaches. The insights can be used for designing tariffs that incentivize customers to form optimal DR portfolios by self-selection.

6.1 Designing Demand Response Portfolios

To maximize the benefits obtained from contracted flexible loads, operators need to optimize the utilization of these assets. To this end, scheduling approaches for flexible loads have attracted significant research activity. Parvania and Fotuhi-Firuzabad (2010) schedule load shifting and curtailment as well as decentral generation assets to minimize wholesale electricity cost. Using a mixed-integer programming model, Sou et al. (2011) determine cost-minimizing power profiles which satisfy complex constraints such as non-interruptible and sequential operations. Gottwalt et al. (2013) show that optimal dispatch of electric vehicle fleet charging activity can integrate much higher levels of intermittent generation. Using different scheduling routines, Subramanian et al. (2012) show that efficient demand side coordination can already be achieved with modest load flexibility endowments. Scott et al. (2013) present a powerful framework that handles scheduling problems for various types of flexible loads in the presence of multiple sources of uncertainty. Papavasiliou and Oren (2014) explore computational approaches for solving very large stochastic unit commitment problems with flexible loads.

Besides this scheduling-oriented literature, demand response assets have also been evaluated with respect to portfolio design concerns. Abstracting from individual load dispatching, this stream of literature analyzes generic demand entities to identify efficient portfolio composition rules.

6.1.1 Portfolio Theory and Applications in Other Domains

The origin of modern portfolio theory was established in the finance sector. The general challenge is to structure a portfolio of assets that optimally trades off risk (variance in returns) and discounted expected returns. Markowitz (1952, 1959) investigates construction and design of such risk efficient portfolios. For his work on theory of portfolio choice, Markowitz won the Nobel Prize in 1990. The considerations in conjunction with this work are summarized in Markowitz (1991). They build the basis for modern portfolio theory and finance. Today, simplified versions of the mean-variance portfolio theory approach are still being discussed (Mangram 2013). Cochrane (2014), for example, splits up returns into risk-free payoffs and a long-run mean-variance payoff. Starting from micro-theory considerations of individual portfolios, Adler and Dumas (1983) expand domestic financial theory and risk-return considerations to an international scale. The authors put forward that both cases are similar and that an economic setting of nationhood is needed "to distinguish between the domestic and international settings".

In addition to the finance sector, portfolio theory is applied in supply-chain management, production industries, and marketing to hedge risks. Turnbull (1990) states that although the Markowitz portfolio concept "was an instrument for the management of equity investments", it has viable applicability in other fields. The author presents a comprehensive overview of portfolio planning models for industrial marketing and purchasing management. One possible application is the fashion industry. In order to satisfy different—and in the fashion industry rapidly changing—demand patterns, Brun and Castelli (2008) develop and empirically test a supply-chain strategy which allows for handling domain specific challenges. Also focusing on supply-chain risk, Chopra and Sodhi (2004) argue that the supply chain "managers' role here is akin to that of a stock portfolio manager: Attain the highest achievable profits (reward) for varying levels of supply-chain risk and do so efficiently". In the construction industry, managing subcontractors involves risk. Projects might be endangered by insufficient attention to the subcontractor selection. Applying portfolio management to construction industry, Abbasianjahromi et al. (2016) put forward a model for reaching the optimal contractor and subcontractor portfolio including task selection and task assignment.

Portfolio models are also applied to manage customer relations (Olsen and Ellram 1997; Armstrong and Brodie 1994). For strategic planning, such models have received much attention (Porter 1980). Johnson and Selnes (2004) analyze customer portfolio management from a marketing perspective. To this end, three types of customers are identified and characterized, i.e., acquaintances, friends, and partners. Guidelines for customer relation management are derived by applying a stimulative approach. In the simulation, (external) effects on customer (portfolio) lifetime value, e.g., decreasing economies of scale, increasing customer churn probability, or external shocks, are investigated. Even though close customer relations usually create the highest customer (portfolio) lifetime value, such close relationships often backfire (Johnson and Selnes 2005). Hence, the customer portfolio should be diversified.

6.1.2 Demand Response Portfolio Design

There already exists portfolio related literature for both the demand and the supply side. On the supply side, optimal design and dispatch of generation portfolios is investigated (Stoughton, Chen, and Lee 1980). This has been an important task for grid operators and electricity retailers. However, DSM is a comparably new branch of research. Here, the scheduling and coordination of flexibility resources and portfolios has predominantly been investigated. However, the optimal design of customer flexibility portfolios and its effects on scheduling quality is not yet comprehensively explored. This section provides an overview of portfolio literature for the supply and the demand side which builds the basis for the subsequent construction and analysis of optimal generation and DR portfolios.

Supply portfolio management and hedging approaches to limit risk for electricity retailers are well studied (Xu et al. 2006; Oum and Oren 2008; Arnesano, Carlucci, and Laforgia 2012). Similarly, Doege, Schiltknecht, and Lüthi (2006) discuss how a generation portfolio can be hedged through its own production assets, i.e., how to hedge a hydro pump storage plant. Similarly to the valuation of household demand flexibility presented in part II, they "quantify the value of [...] operational flexibility in the framework of coherent risk measures." Applying the conditional value at risk theory, which is well studied in finance literature, Huang, Yan, and Hou (2008) propose an electricity procurement portfolio model for electricity retailers and evaluate the model in a simulation study. In order to enable (small) distributed renewable electricity generators to participate in electricity markets, they form VPPs, which can be considered as generation portfolios. This increases both predictability and robustness of generation. Robu et al. (2012) design payment mechanisms to incentivize renewable generators to enter into a VPP.

Literature considering the design of consumer and demand portfolios is rather sparse. Baldick, Kolos, and Tompaidis (2006) determine the value and optimal execution of demand interruption programs using option pricing techniques. Deng and Xu (2009) also consider interruptible load contracts and propose a mean-risk analysis to guide the portfolio design decision. Valero et al. (2007) use data mining techniques to test customer demand and response options in different price scenarios. Parvania and Fotuhi-Firuzabad (2010) put forward a stochastic model to schedule reserves provided by DR. Aggregators supply and manage flexibility and customers portfolios. Kota et al. (2012) suggest the formation of DSM cooperatives—which are customer portfolios—and enable these to participate in electricity markets. They present a mechanism for "estimating suitable reduction amounts, placing bids in the market, and redistributing the obtained revenue amongst the member agents."

The composition of an energy retailers' customer portfolio is a crucial input for defining an optimized load dispatch schedule. Literature on load scheduling is already extensive whilst there is a gap in literature on optimal demand response portfolio design. This part connects these branches of literature by accounting for load scheduling and the prior portfolio design problem.

6.2 A Two Stage Supply and Demand Model

To match demand with supply, energy retailers face a complex multi-stage decision problem. Upfront, they need to procure DR capacities from heterogeneous retail customers as well as long term conventional generation. Subsequently, procured capacities need to be dispatched in response to fluctuating renewable power generation and stochastic demand (Zugno and Conejo 2015). The attainable scheduling quality (with respect to a given objective) critically hinges on the structural composition and capacities of the portfolio. Consequently, the management and optimization of both long term supply option procurement and the customer portfolio is of great importance. In line with Tan et al. (2014), the interdependency between supply and demand portfolio design and optimal scheduling is reflected as a two-stage MILP.

6.2.1 Sequence of Events

In the first stage, the electricity retailer determines the composition of the customer portfolio. Customers whose flexible demand is contracted for DSM receive more favorable electricity rates. These are implemented by discounts on the base load electricity price. In this part, a scenario with exogenously given discount levels is investigated. This represents a situation where the supplier is a price-taker with respect to procuring flexible demand (competition between aggregators). On the supply side, the energy retailer has to decide on buying forwards and options on conventionally generated power. The first stage problem needs to cope with the uncertainty of possible future realization of scenarios with respect to renewable generation as the portfolio design decisions have to be taken in advance, i.e. without recourse.

In the second stage, supply and flexible demand are scheduled. These recourse scheduling decisions are determined for a shorter optimization horizon—typically day ahead or potentially even in real-time. Figure 6.2 illustrates the chronological order of decisions. Customer flexibility endowments in the load scheduling problem hence depend on the decisions in the first-stage portfolio composition problem.

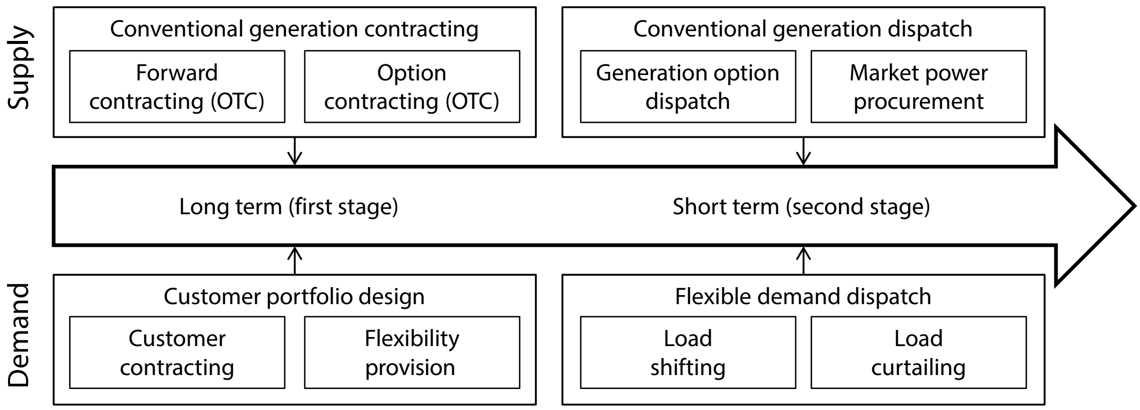

Figure 6.2: Timeline of portfolio design decisions

6.2.2 Demand Model

The time horizon is given by a set $\mathcal{T}$ of time slots. Time slots are indexed $t = 1, \ldots, |\mathcal{T}|$. The demand side is constituted by a set $\mathcal{C}$ of customers that are labeled by $c = 1, \ldots, |\mathcal{C}|$. Following He et al. (2013), each customer's demand consists of three distinct load components, i.e., base load ($D^B_{c,t} \in \mathbb{R}^+$), shiftable load ($D^S_{c,t} \in \mathbb{R}^+$), and curtailable load ($D^C_{c,t} \in \mathbb{R}^+$).

- *Base load* cannot be controlled by the electricity retailer and contracted load must be served unconditionally at any time. Customer contracting is described by the variable $x^P_c \in \{0, 1\}$. Base load is remunerated at the standard retail price $P \in \mathbb{R}^+$.

- Contracted *shiftable load* can be shifted freely over time. The first stage contracting variable $x_c^S \in \{0,1\}$ reflects the decision if the retailer contracts shiftable demand as flexible load. Yet, a customer's total shiftable demand has to be fully covered over the optimization horizon (6.1). The variable $a_{\omega,c,t}^S \in \mathbb{R}^+$ provides the amount of shiftable load served at t after load shifting (Ω describes the set of supply scenarios $\omega = 1, \ldots, |\Omega|$):

$$\sum_{t \in \mathcal{T}} a_{\omega,c,t}^S = \sum_{t \in \mathcal{T}} x_c^S D_{c,t}^S, \quad \forall \omega \in \Omega \; \forall c \in \mathcal{C}. \tag{6.1}$$

For each scenario ω, the recourse shifting dispatch variable $a_{\omega,c,t,s}^{SR} \in \mathbb{R}^+$ indicates how much load of customer c is shifted from time slot t to time slot s. Clearly, only demand can be shifted away from time slot t that is contracted as flexible load and was requested at the very same time slot in the first place:

$$\sum_{s \in \mathcal{T}} a_{\omega,c,t,s}^{SR} = x_c^S D_{c,t}^S, \quad \forall \omega \in \Omega \; \forall c \in \mathcal{C} \; \forall t \in \mathcal{T}. \tag{6.2}$$

The shiftable load actually served in a specific time slot is given by the total load that is shifted to it:

$$a_{\omega,c,t}^S = \sum_{s \in \mathcal{T}} a_{\omega,c,s,t}^{SR}, \quad \forall \omega \in \Omega \; \forall c \in \mathcal{C} \; \forall t \in \mathcal{T}. \tag{6.3}$$

Shiftable load is sold at a discounted price $(1 - \delta_c^S)P$, where $\delta_c^S \in [0,1]$ is the discount on the base price for customer c. In addition, to penalize extensive load shifting distances, a penalty function $c^{\varsigma} : \mathbb{N} \times \mathbb{N} \to \mathbb{R}; (t,s) \to c^{\varsigma}(t,s)$ is introduced. This function generates cost c_ω^{ς} which depends on the shifting distance. The distance penalty function c^{ς} typically grows monotonically in the shifting distance as shifting load farther usually generates more discomfort.

- *Curtailable load* can be shed at any point in time. Like for shiftable load, $x_c^C \in \{0,1\}$ reflects the decision if the retailer contracts curtailable demand as flexible load. The recourse curtailing variable $a_{\omega,c,t}^C \in \mathbb{R}^+$ specifies how much curtailable load is served. Unlike base and shiftable load, curtailable load does not have to be fully satisfied but is only bounded from above by the original level:

$$a_{\omega,c,t}^C \leq x_c^C D_{c,t}^C, \quad \forall \omega \in \Omega \; \forall c \in \mathcal{C} \; \forall t \in \mathcal{T}. \tag{6.4}$$

The total curtailable amount per customer is constrained to at most $\overline{\gamma}^C \in [0,1]$ of the gross shedding potential. At least a share of $(1 - \overline{\gamma}_c^C)$ of each customer's contracted curtailable demand has to be satisfied:

$$\sum_{t \in \mathcal{T}} a^C_{\omega,c,t} \geq \sum_{t \in \mathcal{T}} x^C_c (1 - \overline{\gamma}^C_c) D^C_{c,t}, \quad \forall \omega \in \Omega \, \forall c \in \mathcal{C}. \tag{6.5}$$

Again, customers are granted a discount $\delta^C_c \in [0, 1]$ on the base price P.

Naturally, only customer loads contracted with shifting or curtailing provisions can be controlled in this fashion. To contract customer flexibility, the respective customer must be included in the portfolio:

$$x^S_c \leq x^P_c, \quad \forall c \in \mathcal{C} \quad \text{and} \quad x^C_c \leq x^P_c, \quad \forall c \in \mathcal{C}. \tag{6.6}$$

Figure 6.3 illustrates the relation between contracting customers and demand flexibility types. Customers that provide both shiftable and curtailable flexibility are referred to as flexible customers. Both shiftable and curtailable load components are treated as base load if the flexibility is not contracted although the customer is part of the portfolio.

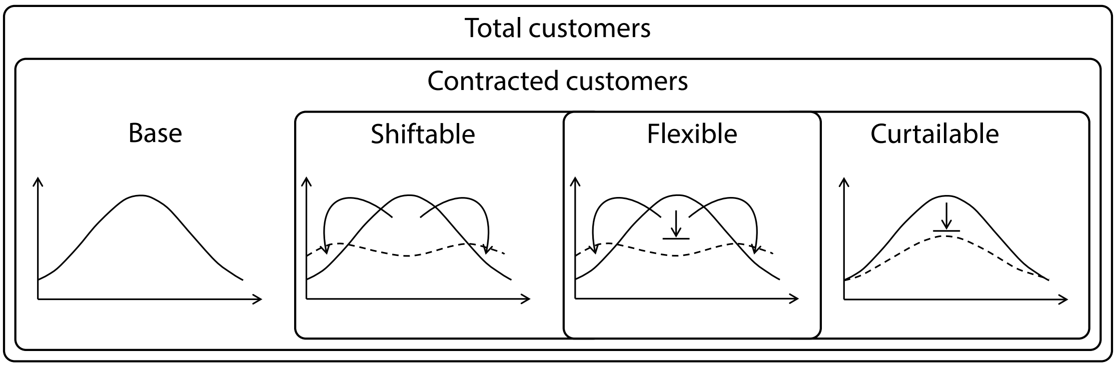

Figure 6.3: Opportunities and conditions of contracting customers and flexible demand. Base load of contracted customers must be satisfied. Flexible customers offer both shiftable and curtailable flexibility

6.2.3 Supply Model

Supply uncertainty is characterized by the set of future supply scenarios Ω. The individual scenario $\omega = 1, \ldots, |\Omega|$ occurs with a probability $p_\omega \in [0, 1]$. Supply scenario realizations are given by $R_{\omega,t} \in \mathbb{R}^+$. Empirical wind and solar generation data is used to create supply scenarios for the analysis. Following the previous part, a RES portfolio composition with a wind generation S^W of 70 % is assumed. Supply data is scaled by overall demand. The factor Γ represents the share of overall demand that could be satisfied by RES.

If demand exceeds renewable energy supply, the supplier can call upon conventional generation capacities (besides demand response capabilities). With respect to conventional generation, inflexible forward contracts, options on supply capacity, and reserve market transactions are considered. The different supply options are modelled as follows:

- Binding *forward agreements* on conventional generation capacity can be entered in the first stage. The contracted capacity $y^F \in \mathbb{R}^+$ is subsequently dispatched (6.7) in each time slot of the second stage at price $C^F \in \mathbb{R}^+$. Dispatch amounts are denoted $s^F_{\omega,t} \in \mathbb{R}^+$:
$$s^F_{\omega,t} = y^F, \quad \forall \omega \in \Omega \, \forall t \in \mathcal{T}. \tag{6.7}$$

- *Option contracts* on conventional generation capacity can be procured in the first stage for an option premium $C^P \in \mathbb{R}^+$. In the second stage, options can be executed for a cost of $C^O \in \mathbb{R}^+$. The capacity of options bought is given by $y^O \in \mathbb{R}^+$ and dispatch by $s^O_{\omega,t} \in \mathbb{R}^+$:
$$s^O_{\omega,t} \leq y^O, \quad \forall \omega \in \Omega \, \forall t \in \mathcal{T}. \tag{6.8}$$

- *Spot market transactions* are the most flexible supply choice. Reserve requests $s^M_{\omega,t} \in \mathbb{R}^+$ can be procured as a last resort for a unit cost of $C^M \in \mathbb{R}^+$.

In-line with Varaiya, Wu, and Bialek (2011) generation costs are assumed to be increasing in dispatch flexibility, that is $C^F \leq C^P + C^O \leq C^M$. Total cost of supply is denoted by $c^G_\omega \in \mathbb{R}^+$.

6.3 Portfolio Design

In this part, a scenario where discount levels are exogenous is investigated. As pointed out above, this represents a situation where the supplier is a price-taker with respect to procuring flexible demand (competition between aggregators). The optimization model $PD(\delta^S, \delta^C)$ maximizes the expected profit for the case of exogenously given discounts on flexible load. The decision variables include both the *non-recourse* variables to describe the portfolio composition for demand response (x^P_c, x^S_c, x^C_c) and supply (y^F, y^O) as well as the *recourse* scheduling variables for shiftable and curtailable load $(a^{SR}_{\omega,c,t,s}, a^C_{\omega,c,t})$ and conventional generation ($s^F_{\omega,t}, s^O_{\omega,t}, s^M_{\omega,t}$). The problem solution yields the optimal first stage customer portfolio composition and long term conventional generation procurement strategy as well as the subsequent scenario-specific load and generation schedules. To ensure supply sufficiency, the gap between scheduled load and renewable generation must be served by means of conventional generation:

$$\begin{aligned} & s^F_{\omega,t} + s^O_{\omega,t} + s^M_{\omega,t} + R_{\omega,t} \geq \\ & \quad \sum_{c \in \mathcal{C}} \left(x^P_c D^B_{c,t} + (x^P_c - x^S_c) D^S_{c,t} + (x^P_c - x^C_c) D^C_{c,t} + a^S_{\omega,c,t} + a^C_{\omega,c,t} \right), \forall \omega \in \Omega \; \forall t \in \mathcal{T}. \end{aligned} \tag{6.9}$$

The objective function (6.10) is a weighted sum of the profits for each scenario. The four profit components are revenues from served base load (π^{bL}), shiftable load (π^{sL}), curtailable load (π^{cL}), and costs for conventional power generation (c^G_ω):

$$PD: \max_{\underbrace{x^P,x^S,x^C,y^F,y^O}_{\text{non-recourse variables}},\underbrace{a^{SR},a^C,s^F,s^O,s^M}_{\text{recourse variables}}} \sum_{\omega \in \Omega} p_\omega \left(\pi^{bL}_\omega + \pi^{sL}_\omega + \pi^{cL}_\omega - c^G_\omega \right). \tag{6.10}$$

The four components of the objective function are calculated as follows:

- Base load revenues (6.11) reflect both contracted base load as well as inflexibly contracted shiftable or curtailable load which is cast into base load. In each scenario the sum over customers and time slots of these three components represents the amount of electricity that is sold at the base load retail price P:

$$\pi^{bL}_\omega = P \sum_{c \in \mathcal{C}} \sum_{t \in \mathcal{T}} \left(\underbrace{x^P_c D^B_{c,t}}_{\substack{\text{served} \\ \text{base load}}} + \underbrace{(x^P_c - x^S_c) D^S_{c,t}}_{\substack{\text{shiftable load} \\ \text{cast to base load}}} + \underbrace{(x^P_c - x^C_c) D^C_{c,t}}_{\substack{\text{curtailable load} \\ \text{cast to base load}}} \right), \forall \omega \in \Omega. \tag{6.11}$$

- The discount δ^S_c compensates a customer for offering shifting flexibility to the energy retailer. Furthermore, a distance penalty compensates for extensive load shifting distances:

$$\pi^{sL}_\omega = \underbrace{\sum_{c \in \mathcal{C}} \left((1 - \delta^S_c) P \sum_{t \in \mathcal{T}} a^S_{\omega,c,t} \right)}_{\substack{\text{revenues from con-} \\ \text{tracted shiftable load}}} - \underbrace{c^\varsigma_\omega}_{\substack{\text{shifting dis-} \\ \text{tance cost}}}, \quad \forall \omega \in \Omega. \tag{6.12}$$

Shifting distance cost is calculated using the load shifting matrices:[2]

$$c_{\omega}^{\varsigma} = \sum_{c\in\mathcal{C}} \sum_{t\in\mathcal{T}} \sum_{s\in\mathcal{T}} c^{\varsigma}(t,s) a_{\omega,c,s,t}^{SR}, \quad \forall \omega \in \Omega. \tag{6.13}$$

- Contracted curtailable load is marketed at a discounted retail price $(1-\delta_c^C)P$:

$$\pi_{\omega}^{cL} = \sum_{c\in\mathcal{C}} \underbrace{\left((1-\delta_c^C) P \sum_{t\in\mathcal{T}} a_{\omega,c,t}^{C} \right)}_{\text{revenues from contracted curtailable load}}, \quad \forall \omega \in \Omega. \tag{6.14}$$

- The final component of the objective function reflects the costs of conventional generation. Conventional generation costs obtain as the total of the three conventional generation components:

$$c_{\omega}^{G} = \underbrace{|T| C^F y^F}_{\text{forward cost}} + \underbrace{|T| C^P y^O}_{\text{option premium cost}} + \sum_{t\in\mathcal{T}} \left(\underbrace{C^O s_{\omega,t}^{O}}_{\text{option strike cost}} + \underbrace{C^M s_{\omega,t}^{M}}_{\text{reserve market power cost}} \right), \quad \forall \omega \in \Omega \tag{6.15}$$

A full formulation of the MILP including comprehensive constraints for modeling supply and demand is presented in appendix D. The model at hand can be solved by means of commercial optimization software, e.g., the IBM ILOG CPLEX Optimizer or the Gurobi Optimizer. However, in case a large number of customers, a long time horizon, or numerous renewable generation scenarios are considered, determining the optimal solution becomes computationally very complex and hence time intensive. This calls for alternative solution approaches, e.g., the application of a heuristic.

6.4 Alternative Solution Approaches

Given the combinatorial nature of the previously introduced model, computational complexity is growing exponentially in the number of customers and scenarios. To mitigate this problem, a heuristic approach to solve the customer portfolio design problem is presented in

[2]Note that this approach permits arbitrary functional forms of the distance penalty.

the following. The heuristic approach consists of two steps: Firstly, the optimal portfolio is determined for each future supply scenario. Secondly, the comprehensive portfolio is built based on each solution for the different scenarios. Algorithm 1 summarizes the heuristic portfolio design approach.

Algorithm 1: Heuristic portfolio composition

Input: R, D^B, D^S, D^I
Output: Generation and customer portfolio composition $(y^F, y^O, x^P, x^S, x^C)$
for $\omega \in \Omega$ **do**
  Solve portfolio problem for supply scenario ω
  Save scenario based demand $(x^P_\omega, x^S_\omega, x^C_\omega)$ and supply (y^F_ω, y^O_ω) portfolio
for $i \in \{P, S, C\}$ **do**
  Calculate $\overline{x}^i = \left\lfloor \left(\sum_{\omega \in \Omega} \sum_{c \in C} p_\omega x^i_{\omega,c} \right) + 0.5 \right\rfloor$
for $i \in \{P, S, C\}$ **do**
  for $c \in \mathcal{C}$ **do**
    Calculate the average contracting decision $p^i_c = \sum_{\omega \in \Omega} p_\omega x^i_{\omega,c}$
for $i \in \{P, S, C\}$ **do**
  Sort customers descending by p^i_c to list l^i
  for $j \in \{0, \ldots, |\mathcal{C}|\}$ **do**
    if $l^i_j > \overline{x}^i$ **then**
      set $x^i_c = 1$, where c is the customer in the $j-th$ position of l^i
    else
      $x^i_c = 0$, where c is the customer in the $j-th$ position of l^i
Calculate $y^F = \sum_{\omega \in \Omega} p_\omega y^F_\omega$ and $y^O = \sum_{\omega \in \Omega} p_\omega y^O_\omega$
return x^P, x^S, x^C, y^F, y^O

Firstly, the optimization problem introduced in the previous section is solved for each supply scenario $\omega \in \Omega$. In each iteration the selected scenario ω is assumed to occur for sure without uncertainty. Effectively, the probability of occurrence of ω is set to one, i.e., $p(\omega) = 1$. As the customer portfolio is optimized for each scenario, the decision variable x^P_c turns into $x^P_{\omega,c}$ to reflect the fact that there are $|\Omega|$ resulting portfolios. The solution of the optimization problem then consists of two components: the customer portfolio and the load schedule. However, only the $|\Omega|$ customer portfolios that are designed optimally for the considered supply scenario are used to calculate the final portfolio composition.

Initially, the total number of customers to be included in the portfolio is determined. To this end, the weighted mean number of customers included is calculated by:

$$\overline{x}^P = \left\lfloor \left(\sum_{\omega \in \Omega} \sum_{c \in C} p_\omega x^P_{\omega,c} \right) + 0.5 \right\rfloor. \tag{6.16}$$

For each customer p_c^P expresses the individual weighted probability of being included in the portfolio:

$$p_c^P = \sum_{\omega \in \Omega} p_\omega x_{\omega,c}^P, \quad \forall c \in \mathcal{C}. \tag{6.17}$$

Subsequently, the contracting decision is taken for each customer based on these values by sorting all customers by p_c^P in descending order. The first $\overline{x}^P$ customers in this sorted list are contracted.

The assignment of customer flexibility is realized in a similar way. To calculate the mean share of shiftable and interruptible customers all customers that were considered in the optimization are included:

$$\overline{x}^S = \left\lfloor \left(\sum_{\omega \in \Omega} \sum_{c \in \mathcal{C}} p_\omega x_{\omega,c}^S \right) + 0.5 \right\rfloor \quad \text{and} \quad \overline{x}^C = \left\lfloor \left(\sum_{\omega \in \Omega} \sum_{c \in \mathcal{C}} p_\omega x_{\omega,c}^C \right) + 0.5 \right\rfloor. \tag{6.18}$$

Then the weighted probability p_c^S (p_c^I) that a customer's shiftable (curtailable) load is contracted to be flexible is calculated:

$$p_c^S = \sum_{\omega \in \Omega} p_\omega x^S{}_{\omega,c}, \quad \forall c \in \mathcal{C}, \quad \text{and} \qquad p_c^I = \sum_{\omega \in \Omega} p_\omega x_{\omega,c}^C, \quad \forall c \in \mathcal{C}. \tag{6.19}$$

Obviously only flexibility of contracted customers ($x_c^P = 1$) can be considered for contracting. This condition is already included in the optimization problem by the constraints:

$$x_c^S \leq x_c^P, \quad \forall c \in \mathcal{C} \quad \text{and} \quad x_c^C \leq x_c^P, \quad \forall c \in \mathcal{C}. \tag{6.20}$$

Hence, the condition $x_c^P = 1$ for assigning flexibility to customers is dropped.

Analogously as before, customers are sorted by p_c^S (p_c^I) in descending order. The first $\overline{x}^S$ ($\overline{x}^C$) customers in the sorted list are then contracted to allow for load shifting (curtailing). For supply contracting, weighted means for both forwards and options are taken:

$$y^F = \sum_{\omega \in \Omega} p_\omega y_\omega^F \quad \text{and} \quad y^O = \sum_{\omega \in \Omega} p_\omega y_\omega^O. \tag{6.21}$$

Finally, the algorithm returns the customer portfolio consisting of selected (x^P), shiftable (x^S) and curtailable (x^C) customers as well as the supply portfolio of forwards (y^F) and options (y^O).

6.5 Discussion

This chapter presents a model that enables a DR aggregator to determine the optimal composition of both a generation portfolio and a demand flexibility portfolio for DSM. The question of how to design such flexibility portfolios has gained importance as electricity generation from RES, which is (partially) uncontrollable, has seen enormous growth in recent years. Prior research has mainly focused on determining dispatch schedules for exogenously given portfolios of flexible electricity demand. However, the attainable scheduling quality (with respect to a given objective) critically hinges on the composition of the underlying customer portfolio. The customer portfolio design decision needs to determine which loads to contract as well as the corresponding contracting terms—the latter is investigated in the subsequent part IV.

The model presented in this chapter abstracts from modeling flexibility on the appliance level and allows for determining the optimal composition of supply and demand response portfolios for investigating both research question 3 and research question 4. To this end, a two-stage approach is chosen. On the first stage, the aggregator needs to contract flexible supply, i.e., forwards and options on generation, and to design its demand response portfolio, i.e., contracting customers and flexibility in terms of shiftable and curtailable load, in a setting with high availability of stochastic renewable generation. On the second stage, conventional generation and flexible demand are dispatched. Obviously, the portfolio design must already consider future renewable generation scenarios as well as the dispatch of flexible loads.

The portfolio design model can be considered as a variation of a knapsack problem. Consequently, due to its structure, it is computationally hard to solve. In order to reduce complexity, a heuristic approach is presented, which also allows for calculating flexibility portfolios. The heuristic firstly solves the problem for each future renewable supply scenario. Then, using this information, the supply and demand contracting decisions are taken.

The model at hand comes along with two main shortcomings. Firstly, the abstraction from appliance based flexibility and only using flexibility measures that build on the household load curve is not as exact as the approach chosen in the previous part. However, it is necessary to keep computational complexity on a level that allows for solving the problem efficiently. In addition, the assumptions on each household's flexibility is build upon current literature as well as the insight from part II. Secondly, the model completely abstracts from the customers' utility and preferences. It is assumed that the aggregator can decide upon contracting and customers as well as their flexibility. This assumption seems unrealistic. However, it allows for determining the optimal portfolio structure as a precondition to the optimal design of tariffs—which explicitly considers customer reactions to tariff offers and hence models their preferences. Tariff design is investigated in part IV.

The following chapter uses the model and the heuristic which are introduced above. The computational feasibility of both the optimal and the heuristic approach is investigated by conducting a simulation study that uses empiric data for both the supply and the demand side. Finally, a comprehensive elaboration on the optimal portfolio composition and flexibility interdependencies is conducted.

7

Portfolio Structure and Computational Complexity

The design of demand response portfolios constitutes the foundation for designing efficient electricity tariffs that allow for optimally contracting and dispatching supply and demand. Building upon the model that was introduced chapter 6, this chapter aims at analyzing the optimal composition of a DR aggregator's customer portfolio, i.e., which customers should be contracted with which flexibility provisions. Furthermore, it reveals the main drivers of computational complexity to determine flexibility portfolios and it investigates the potential of further heuristic approaches to reduce this complexity.

In the evaluation, a stimulative approach is chosen that uses empiric data for both supply and demand. The supply side is modeled by uncontrollable generation from RES and controllable conventional generation. Thereby conventional generation must be contracted OTC from generators or bought on the electricity market. Forwards and options must be procured far in advance of the time of contract fulfillment, i.e., the delivery of electricity. Subsequently, on the second stage, these loads are dispatched. Abstracting from the fine grained appliance based model that was applied in part II, customers' consumption is split into static and flexible load on the demand side. Flexible demand can either be shiftable load or curtailable load. Similarly to the process of procuring supply, customers and flexibility must be contracted in advance, i.e., on the first optimization stage. Contracted load can then be dispatched on the second optimization stage. Figure 7.1 illustrates the composition of both supply and demand.

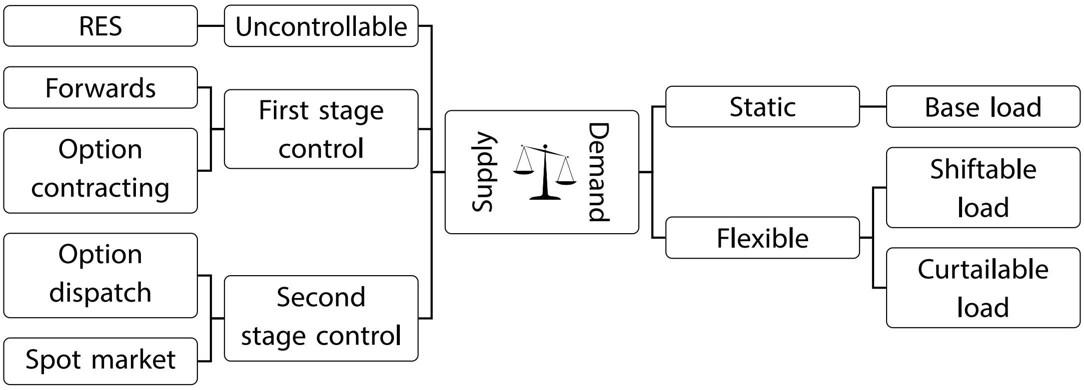

Figure 7.1: Supply and demand characterization for portfolio design

In the following, four methods for calculating supply and demand portfolios are considered, i.e., the *recourse problem* (RP), the *wait-and-see program* (WSP), the *expected value program* (EVP), and the *heuristic program* (HP). The RP corresponds to the stochastic optimization approach described preceding chapter. In contrast, the WSP represents the RP under the assumption of perfect information, i.e., future generation from RES is known on the first optimization stage. Similarly, determining the solution to the EVP, only the expected value of future renewable generation is known, i.e., the weighted mean of the renewable generation scenarios. Finally, following its introduction in section 6.4, the HP builds on the scenario based WSP solutions.

7.1 Simulation Scenario and Data

In the simulation, the aggregator has full information on customers' flexibility potential. In contrast to part IV where customers' reactions to contract offers are included into the investigation, customers and flexibility can be discretionarily contracted. However, considering RES, on the first optimization stage only supply scenarios are known. Due to the structure of the demand data used in this part, a time resolution of 30 minute time slots is chosen. In the following, customers flexibility endowment as well as the generation of renewable supply scenarios from empiric data is described more detailed.

7.1.1 Demand Side

In the numerical study, the demand side is modeled using data from the Irish Social Science Data Archive.[1] This data set provides smart meter readings from over 5,000 Irish homes and small businesses in 30 minute intervals. The collection of data was realized over one and a half years in 2012 and 2013. In the simulation study of this work, data from 2013 is exclusively used. As this is aggregate load, there is no detailed information about the underlying load flexibility. To extract additional information from aggregate load data collections, Carpaneto and Chicco (2008) suggest interpreting residential load curve collections as probability distributions. Building upon this assessment, the underlying flexibility level using the likelihood of a certain demand level is approximated. This way, the demand components of a given customer are derived by splitting up the collection of half-hourly aggregate smart meter readings.

For the analysis, a customer's base load level is fixed at the 30 % quantile of the collection of smart meter readings for that given 30 minute interval. Similarly, shiftable load is determined as the intersection of the members of the 60 % and 30 % quantiles and, to smooth outliers, curtailable load is determined by the 85 % and 60 % quantiles. By applying these quantile levels as well as the shedding limitations, it is obtained that in the base scenario on average 64 % of the original load needs to be served as required, 25 % can be shifted, and up to 11 % can be curtailed ($\overline{\gamma}_c^C = 0.25$). These values are well in line with the investigation presented in part II as well as with previous studies (Stamminger et al. 2008; He et al. 2013). Figure 7.2 shows exemplary daily load curves of three customers.

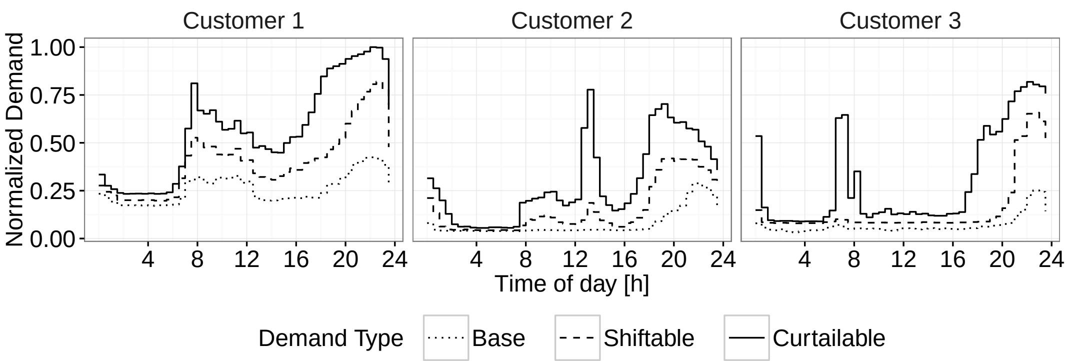

Figure 7.2: Exemplary customer demand profiles split up into base load, shiftable load, and curtailable load

[1] The data set of smart meter readings is not publicly available but can be requested at `www.ucd.ie/issda/data/commissionforenergyregulationcer/`.

7.1.2 Supply Side

In line with deriving flexibility properties from smart meter data, the creation of renewable supply scenarios builds upon empiric wind and PV generation data. Algorithm 2 describes the process of deriving and scaling such generation scenarios.

Algorithm 2: Generation of renewable supply scenarios

Input: Renewable supply: W^{gen}, S^{gen}; Shares: S^W, Γ ; Demand: D^B, D^S, D^C
Output: Supply time series R

for $\omega \in \Omega$ **do**
  $r = randInt(0, \frac{365}{|\Omega|})$
  for $i \in \{W, S\}$ **do**
    for $t \in \mathcal{T}$ **do**
      $R^i_{\omega,t} = i^{gen}_{\omega \cdot \frac{365}{|\Omega|} + r + t}$
for $\omega \in \Omega$ **do**
  for $i \in \{W, S\}$ **do**
    for $t \in \mathcal{T}$ **do**
      $R^W_{\omega,t} = R^W_{\omega,t} \frac{S^W}{\sum_{\omega \in \Omega} \sum_{t \in \mathcal{T}} R^W_{\omega,t}}$ and $R^S_{\omega,t} = R^S_{\omega,t} \frac{1 - S^W}{\sum_{\omega \in \Omega} \sum_{t \in \mathcal{T}} R^S_{\omega,t}}$
for $\omega \in \Omega$ **do**
  for $t \in \mathcal{T}$ **do**
    $R_{\omega,t} = \left(R^W_{\omega,t} + R^S_{\omega,t}\right) \left(\sum_{c \in \mathcal{C}} \sum_{t \in \mathcal{T}} D^B_{c,t} + D^S_{c,t} + D^C_{c,t}\right) |\Omega| \Gamma$
return R

Firstly, the year is split up into $|\Omega|$ intervals of equal length and from each interval a day is randomly selected. The generation time series from wind (W^{gen}) and PV (S^{gen}) of these days is saved. These build the basic renewable generation scenarios. Subsequently, the time series are scaled by overall renewable generation from the respective energy source and the corresponding wind share (S^W). Figure 7.3 illustrates boxplots of exemplary renewable generation scenarios for one day that are scaled by S^W (but not yet by total generation). In the base scenario a wind share of $S^W = 0.7$ is assumed which approximately corresponds to the relation of the two energy sources in Germany. Wind feed-in from the western Germany Amprion control area[2] and local solar generation of a single PV power plant is used to capture the volatile characteristics of local feed-in to low voltage grid.

The resulting time series are then scaled to match total demand in accordance with the externally given supply-demand ratio Γ. In the base scenario this value is set to one. Figure

[2] The data can be retrieved from `http://www.eex-transparency.com`.

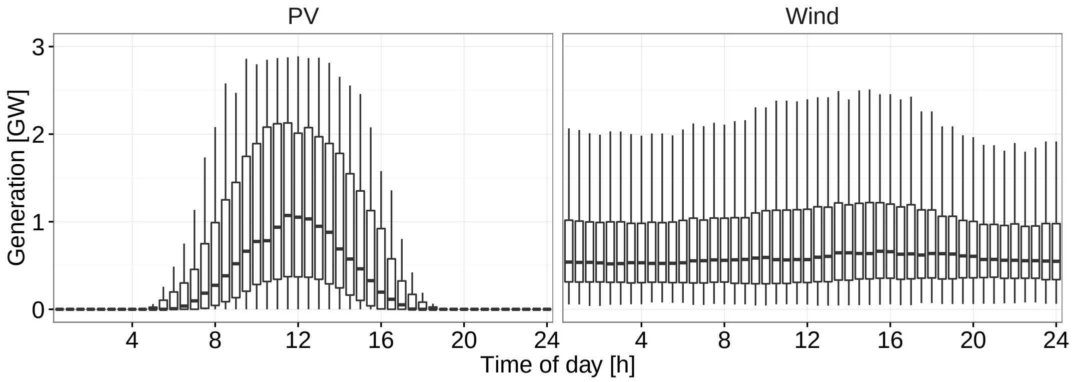

Figure 7.3: Photovoltaic generation in southern Germany and wind generation in western Germany in 2013. PV generation is scaled to 70 % of wind generation (outliers are dropped for better exposition)

7.4 depicts exemplary renewable supply scenarios. Consequently, the mean of the total generation of the resulting renewable supply scenarios over the whole time horizon equals overall demand. Furthermore, the share of wind generation, and hence PV generation, is also externally set. Midday peaks are caused by substantial feed in from solar power. The absolute difference in the time series is caused by seasonal effects as the scenarios are equally distributed over the year. Intuitively, the impact of PV during the summer time is larger compared to the winter season.

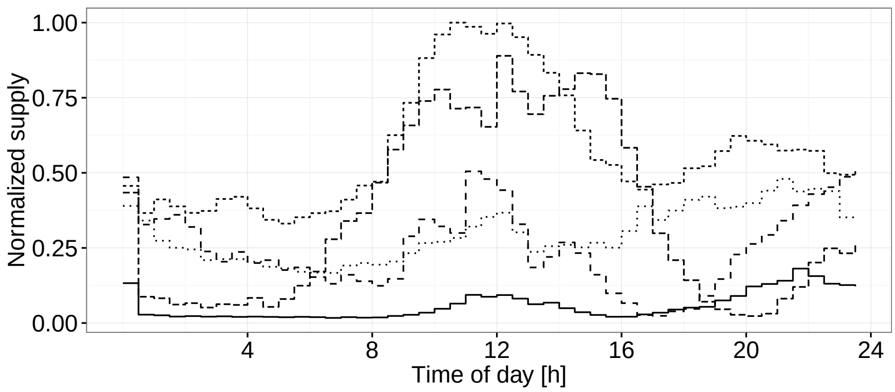

Figure 7.4: Illustration of exemplary renewable supply scenarios

7.1.3 Parametrization

This section defines a base scenario. However, quite a few of the parameters that are described vary in the sensitivity analysis. A time horizon of one year is considered on the first optimization stage. The scheduling is conducted in a day-ahead fashion. Each day is split up into 48 time slots of equal length and a population of 100 customers is considered.

The aggregator takes binary decisions, e.g., whether to contract the entire shifting potential of a customer or not, and the aggregator is able to exclude customers from the portfolio. Discounts on flexible load vary between zero and one in the sensitivity analysis. Customers do not receive individual but uniform discounts, i.e., each customer receives the same compensation for offering flexibility. The base load retail price, which corresponds to the end consumer electricity price if no flexibility is contracted, is set to $P = 0.3$. Cost and prices are given in €/kWh.

Following Grünewald, McKenna, and Thomson (2014), the cost for conventionally generated electricity procured OTC or from the market is set to $C^F = 0.15$, $C^O = 0.225$, and $C^M = 0.6$ in the simulation study. For C^O a sensitivity analysis is executed. Option premium cost vary but do not exceed 0.1. In the base scenario five different RES generation scenarios are considered. The ratio of demand and generation from RES Γ varies between zero and one in the sensitivity study but is set to one in the base scenario. Finally, a quadratic shifting distance penalty function is assumed to penalize load shifting and to avoid extensively large shifting distances.

7.2 Quality vs. Complexity

The applicability of the different portfolio design methods depend on two main factors. The quality of the solution that is achieved applying an optimization approach is traded off for the time that is required to determine the solution. Investigating these measures, this section assesses the four approaches described above, i.e., RP, HP, WSP, EVP.

7.2.1 Scheduling Results

Making use of demand flexibility affects both an aggregator's generation dispatch and the scheduling of flexible load. Figure 7.5 depicts exemplary supply and demand schedules for two scenarios. Firstly, a fully flexible portfolio is considered (upper panel). This typically occurs in case discounts for flexible load are low. Secondly, a completely inflexible customer portfolio is assumed (bottom panel). This results from a scenario where high remuneration payments for demand flexibility are required. Regardless of the discounts, the given renewable generation scenario is equal for both cases.

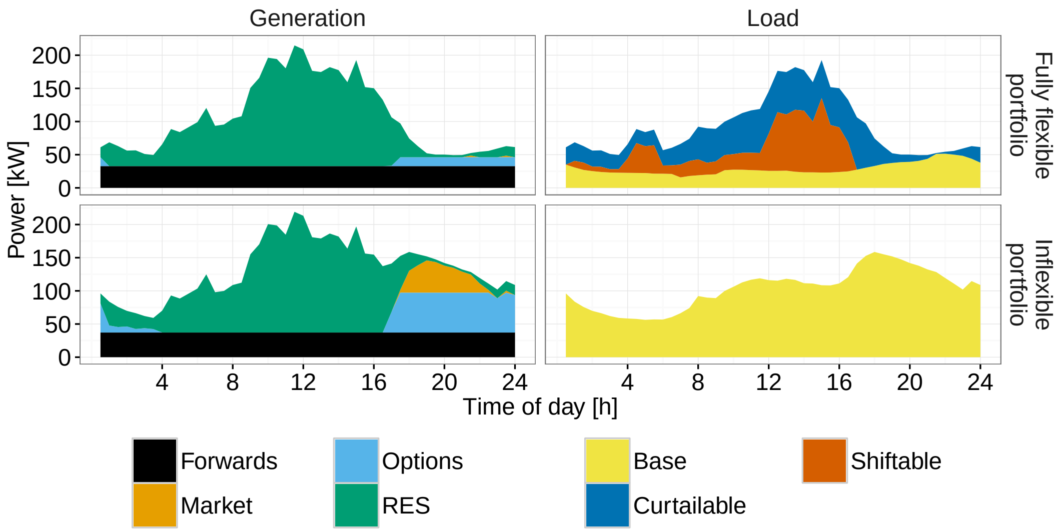

Figure 7.5: Exemplary illustration of effects of demand flexibility on supply and demand schedules given a fully flexible and an inflexible customer portfolio

Considering the demand side, no flexibility is contracted on the first optimization stage in the inflexible scenario and hence all demand is cast into base load. Similarly to *H0* curves, the base load follows the typical pattern with little demand at night and in the early morning and a peak at midday and in the evening. However, the supply side incorporates both wind and PV generation. However, in the exemplary scenario wind generation is rather low and PV feed-in high, which causes a peak during the afternoon and a renewable generation valley during the night. The corresponding supply and demand valleys in the early hours of the day almost perfectly complement one another. Therefore, despite of the absence of demand flexibility only little supply from options is needed and demand is almost fully satisfied from forwards and RES. In contrast, little RES is available but demand is high in the late afternoon and evening. The difference must be balanced by means of options and even costly generation from the reserve market is needed.

The upper panel makes use of demand flexibility. By shifting load from the evening to midday and massive load curtailment, demand is substantially reduced at night. Therefore, only little supply from options is required to satisfy demand at that time. In addition, the generation peak in the afternoon caused by PV generation can be used to satisfy the shifted load. Obviously, demand flexibility is used to converge renewable supply and demand and, consequently, reduces the dispatch of costly conventional generation, i.e., options and reserve market power.

The decision which alternative is preferable, i.e., using supply or demand flexibility, depends on both conventional generation costs and demand flexibility costs. This decision of contracting either supply flexibility or demand flexibility (or both) must be taken in advance, when only renewable supply scenarios are known. This leads to slightly over-contracting of flexibility and increases the importance of valid generation forecasts.

7.2.2 Objective Values

The quality of the first stage portfolio design is measured by the scheduling results that can be achieved on the second optimization stage by applying supply and demand contracting decisions. Therefore, the first stage contracting decision variables turn into second stage portfolio parameters for dispatching flexibility. To quantify the impact on the solution quality gap arising from the method that is applied to calculate the DR and supply portfolio the scheduling objective values are compared. The methods WSP and EVP serve as upper and lower bounds for the RP and the HP, respectively. Figure 7.6 presents the normalized mean objective values attained by applying the different portfolio design approaches for a varying number of customers that can be contracted (left panel) and a varying number of future renewable supply scenarios (right panel). To ensure statistical reliability, the experiment was repeated fifteen times with various combinations of discounts on flexibility—this results in more than 5000 stand-alone portfolio design problems. The values are normalized so that the maximum objective value that can be obtained (with 225 customers and the WSP portfolio design) equals one and the worst result (25 customers and EVP) equals zero.

The impact of the number of supply scenarios considered for designing the flexibility portfolios does not follow a trend. In contrast, the more customers are considered the higher

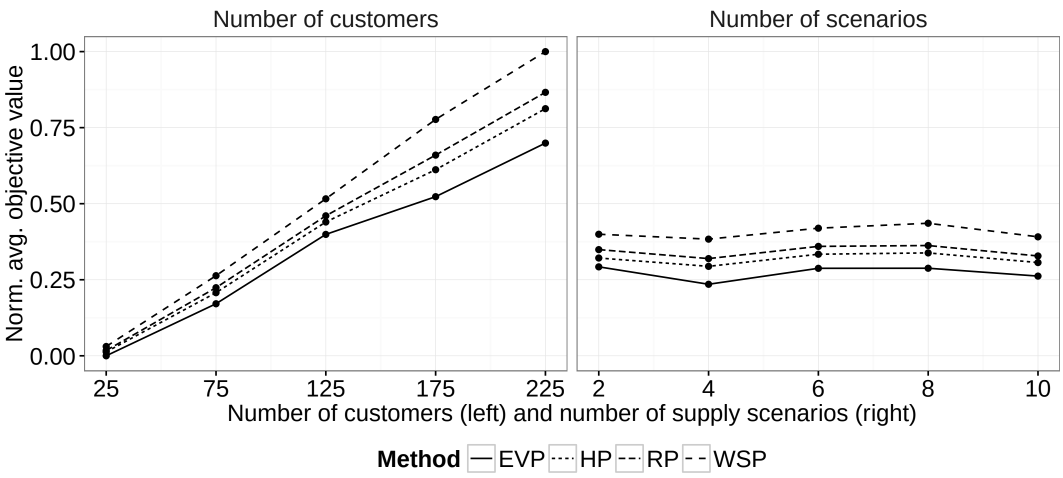

Figure 7.6: Comparison of objective values applying different solution methods

are the profits that can be gained. On the one hand, this is an early indication that it is not reasonable to exclude potential customers from the DR portfolio—especially in case a lot of renewable energy capacities are available. On the other hand, such conclusions must be interpreted carefully as these effects are sensitive with respect to electricity generation costs, retail prices, and flexibility discounts.

Obviously, the WSP that assumes perfect information on future generation from RES achieves the best results. The EVP, which only builds upon the mean of future supply scenarios, performs worst. As expected, the RP outperforms the HP. Following Birge and Louveaux (2011), two quality measures are introduced for investigating the value of information in the portfolio design process, i.e. the *expected value of perfect information* (EVPI) and the *value of stochastic solution* (VSS).

Definition 7.1 **(Expected value of perfect information).** *"The expected value of perfect information measures the maximum amount a decision maker would be ready to pay in return for complete (and accurate) information about the future" (Birge and Louveaux 2011).*

Consequently, the EVPI is calculated by the difference of the objective values of the WSP and the RP. Similarly, the VSS allows to obtain the quality of the RP compared to EVP.

Definition 7.2 **(Value of stochastic solution).** *"The value of stochastic solution [...] is the difference between the result of using an expected value solution (EVP) and the recourse problem solution (RP)" (Birge 1982).*

Hence, a low additional profit of perfect information generates a small EVPI and a good approximation of the RP by the EVP induces a small VSS (Escudero et al. 2007). Table 7.1 presents both the normalized EVPI and the normalized VSS for a varying number of customers and supply scenarios.

Table 7.1: EVPI and VSS for a varying number of potential customers and future supply scenarios

			$\lvert\mathcal{C}\rvert$					$\lvert\Omega\rvert$			avg
	25	75	125	175	225	2	4	6	8	10	
EVPI	0.11	0.11	0.09	0.14	0.12	0.10	0.14	0.12	0.14	0.13	0.121
VSS	0.16	0.17	0.17	0.11	0.18	0.18	0.13	0.21	0.16	0.17	0.164

In contrast, table 7.2 assumes a constant number of customers and supply scenarios and reports both the EVPI and the VSS for varying discounts on shiftable and curtailable demand.

Table 7.2: EVPI and VSS for varying discounts on shiftable and curtailable demand

δ^S		0.05			0.2			0.35		avg
δ^C	0.05	0.2	0.35	0.05	0.2	0.35	0.05	0.2	0.35	
EVPI	0.120	0.119	0.114	0.126	0.126	0.121	0.122	0.125	0.119	0.121
VSS	0.212	0.148	0.125	0.223	0.156	0.131	0.211	0.150	0.122	0.164

Both the EVPI and the VSS are rather stable for increasing discounts on shiftable load. However, the VSS substantially decreases in increasing discounts on curtailable load. Similarly, no clear trend can be observed for variations in the number of customers or the number of supply scenarios. However, the findings indicate that efficiency of DSM can be increased considerably by applying stochastic optimization compared to the expected value approach—the average VSS is 16 %. Although the RP performes quite well, improving forecast quality still appears to be worthwhile—the average EVPI is 12 %. However, the gains in objective values and the corresponding improvements in solution quality does not come for free. It must be traded-off for computational complexity. To elaborate which method should be used, the runtime required to calculate a flexibility portfolio must be investigated.

7.2.3 Computational Complexity

Computational complexity, which is responsible for the runtime that is needed to solve a problem, determines whether a method is applicable for large scale portfolio design. Figure 7.7 shows the boxplots of runtimes needed to determine flexibility portfolios for a varying number of customers (left panel) and a varying number of renewable supply scenarios (right panel). Like before, the experiment was repeated fifteen times with various combinations of discounts on flexibility.

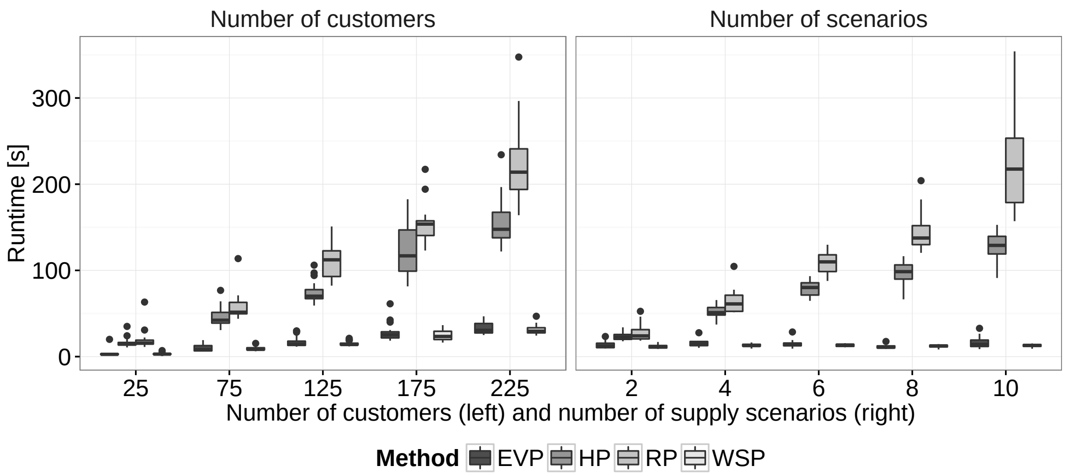

Figure 7.7: Comparison of runtime to calculate optimal portfolio with varying methods

It is not surprising that there is no effect of a varying number of supply scenarios on the runtime for the EVP and the WSP. Both methods only consider one supply scenario, i.e., the EVP assumes the means of scenarios and the WSP takes the scenario that eventually occurs. In contrast, the complexity of both approaches increases in an increasing number of customers. The runtime to solve the HP is the sum of runtimes of WSP. Hence, an increase in both the number of customers and the number of supply scenarios results in an growing complexity of the HP. Similarly, the RP's complexity increases in both factors. Note that the runtime differences are due to the combinatorial nature of the RP—the HP only needs to solve $|\Omega|$ portfolio design problems while RP solves one single problem with much more variable interdependencies. The runtime differences may become relevant in two contexts, i.e., solving the problem for much larger customer populations and supply scenarios than considered in the numerical study or solving the problem more frequently in an alternative scenario context, e.g., online re-optimization of the customer portfolio. Consequently, the decision which method should be used depends on the trade-off between complexity and quality together with various factors. Such environmental and strategical considerations of the flexibility aggregator must be taken into account.

7.3 Optimal Portfolio Structure

How much and which type of flexible load an aggregator should contract depends on various exogenous influences, e.g., the availability of renewable generation, the discounts that must be granted to incentivize customers to offer flexibility, or costs for conventionally generated power. On the one hand, some of these can be adapted over longer time horizons, e.g., the ratio of supply and demand. On the other hand, others cannot be influenced, e.g., prices on electricity markets. To allow for optimally forming DR portfolios and contracting supply flexibility, the impact of these factors on the first stage contracting decisions is investigated in this section. All of the following elaborations build upon calculations applying the RP.

7.3.1 Exclusive Contracting of Shiftable and Curtailable Load

The main factors that influence the contracting decision of flexible demand are the availability of renewable generation, the discounts on flexible demand, and the electricity prices. The subsequent analysis focuses on the impact of these three essential drivers. To eliminate interdependencies between shiftable and curtailable demand both flexibility types are investigated separately.

Figure 7.8 reports the optimal contracting of shiftable load for an exogenously given discount δ^S. The facets differ in the availability of RES and line types represent supply flexibility cost which is given by option premiums C^P. Similarly, figure 7.9 depicts the dependencies of an exogenously given discount on curtailable load δ^C on the contracting of curtailable demand for a varying Γ and C^P.

For low flexibility discounts, almost all shifting and curtailing capabilities are contracted even if little generation from RES is available. In these cases, the demand flexibility is used to create a level load profile to match supply which is dominated by (flat) forward commitments (especially in the case of costly options). Contracted amounts for high flexibility discounts are small. The effect of varying the availability of RES is rather low. Nevertheless, slightly

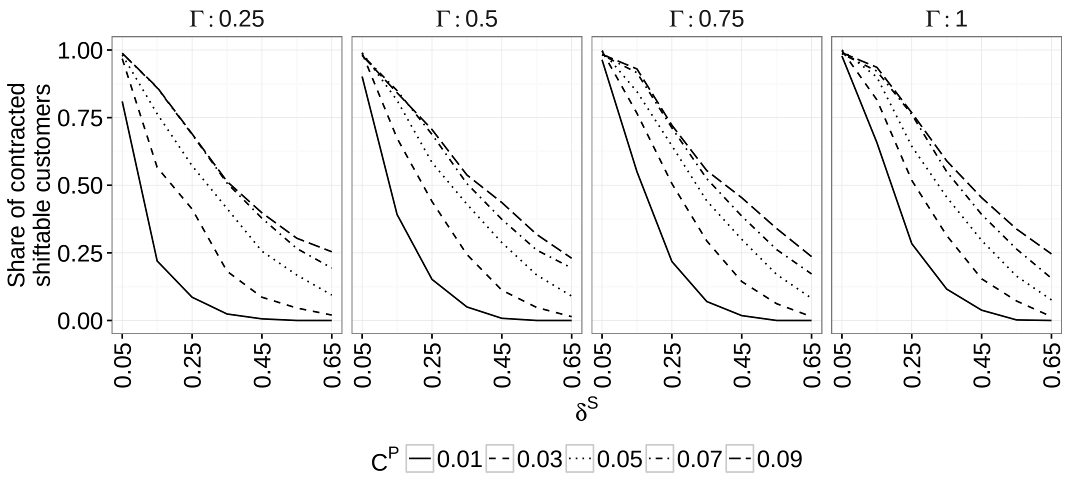

Figure 7.8: Optimal contracting of shiftable load for varying Γ and C^P and given δ^S

more shiftable load is contracted for increasing Γ—especially for low C^P. This finding is well in line with the general assumption that more RES require greater demand flexibility (Denholm and Hand 2011). However, this relation does not hold for curtailable load.

Surprisingly, in the case of curtailable load, the direction of the interaction between the amount of procured flexibility with Γ depends on the discount level. For low discounts contracted demand flexibility is marginally increasing in the RES availability, whereas for high discounts it is declining. This effect especially holds for high C^P. The reason behind this unexpected effects are due to different flavors of using curtailable capacities. In the less stochastic low RES setting, the generation mix is dominated by forward commitments (especially in the case of costly options). Due to the non-rampability of this base supply, energy provision will typically be excessive. However, curtailable demand provisions can be used to optimize the supply-demand match and to avoid oversupply. For increasing RES levels, this aspect of employing curtailable load is superseded by available costless renewable generation.

The impact of option premiums is quite strong. For increasing C^P, substantially more customers should offer flexible load. This observation holds for both shiftable and curtailable demand. It underlines the trade-off between supply and demand flexibility—both types of flexibility can substitute one another. Hence, the optimal contracting of flexibility hinges on the relation of the cost of flexibility.

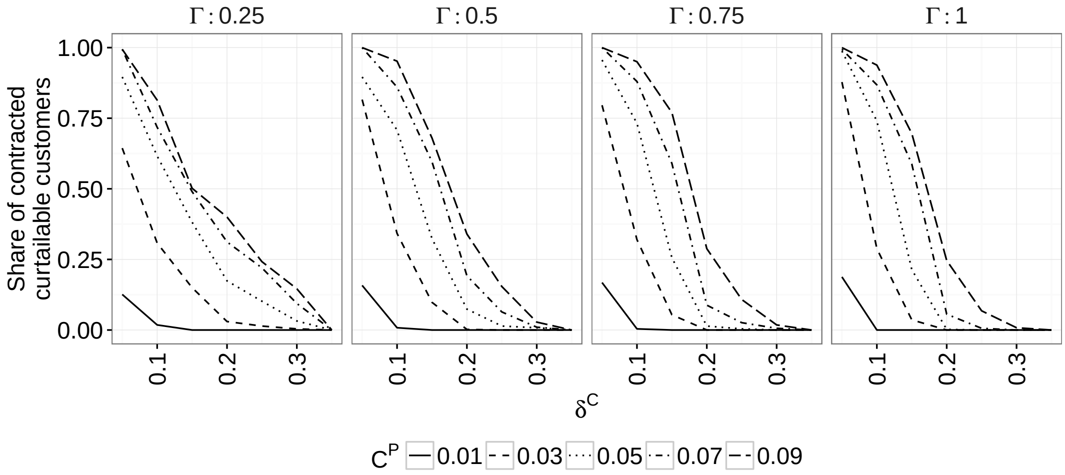

Figure 7.9: Optimal contracting of curtailable load for varying Γ and C^P and given given δ^C

7.3.2 Demand Flexibility Interaction

To explore the relative values of shifting and curtailing capabilities as well as their interdependencies, the corresponding contracting discounts δ^S and δ^C are varied, while holding all other parameters constant. Figure 7.10 presents the results of this experiment. On the one hand, base customers do not provide any flexibility. Both shiftable and curtailable demand are merged into inflexible and sold at the not discounted retail price P. On the other hand, flexible customers provide both shiftable and curtailable demand for load scheduling. Shiftable customers allow for load shifting whilst their curtailable demand is cast into base load. The definition of curtailable customers follows the characterization of shiftable customers.

Not surprisingly, the aggregator does not make use of its right to exclude customers from the portfolio. As shown in section 7.2.2 the objective value—and profit, respectively—increases in the number of customers that are contracted. Naturally, for increasing discounts, the corresponding load flexibility type is contracted less often, irrespective of the chosen availability of generation from RES. Conversely, at the lowest discount levels a large share of the load is contracted with both shifting and curtailing provisions.

The flexibility types do not fully substitute one another. For constant δ^C and increasing δ^S some customers that were formerly shiftable customers are contracted as base customers, others as flexible customers. The same holds for increasing δ^C and constant δ^S. However, it is remarkable that demand shifting remains attractive given larger discounts than demand

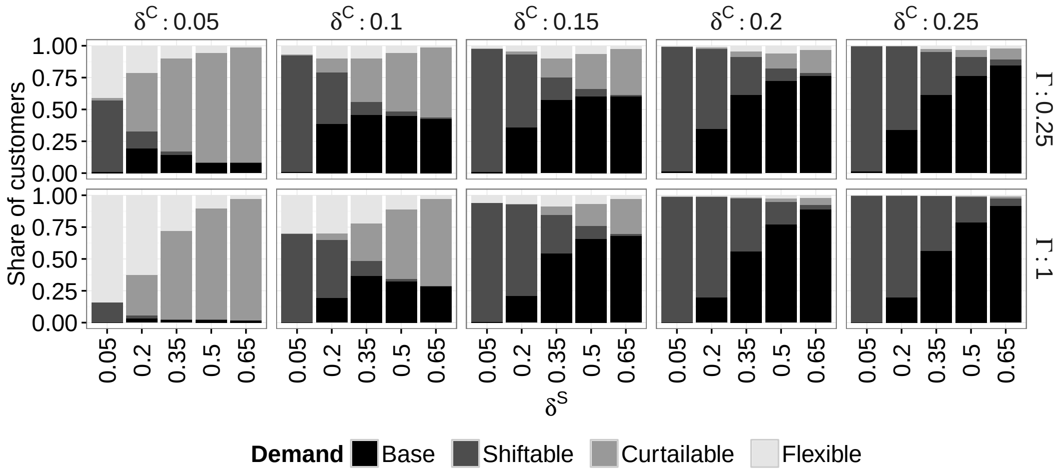

Figure 7.10: Interaction effects between contracting shiftable and curtailable load for varying discounts on flexibility and supply-demand ratio Γ and $C^P = 0.05$

curtailing. This might arise from the flexibility properties. Regardless of the utilization of flexibility, contracting both flexibility types generates costs. Contracted flexible load is sold at a discounted retail price. In case load is shifted, only a limited additional shifting distance penalty accrue. In contrast, whenever load is curtailed, the aggregator foregoes any revenues from this load type.

7.3.3 Supply Composition

For demand aggregators it is not only important to design their customer portfolio in an optimal fashion but also to decide what type of generation should be procured and dispatched in addition to renewable generation. Figure 7.11 reports the optimal generation portfolio composition for a fully flexible and an inflexible DR portfolio that result from very low and high discounts, respectively. Contracting of forwards and options directly results in the optimal supply dispatch which is calculated for varying option premiums that reflect the price for supply flexibility.

The left and right panel illustrate how increasing levels of renewable generation capacity can only displace base generation in the presence of sufficient system flexibility—either on the supply side or on the demand side. For the case of high discounts (inflexible demand side) and option premiums, generation from forwards serves almost the total demand for Γ

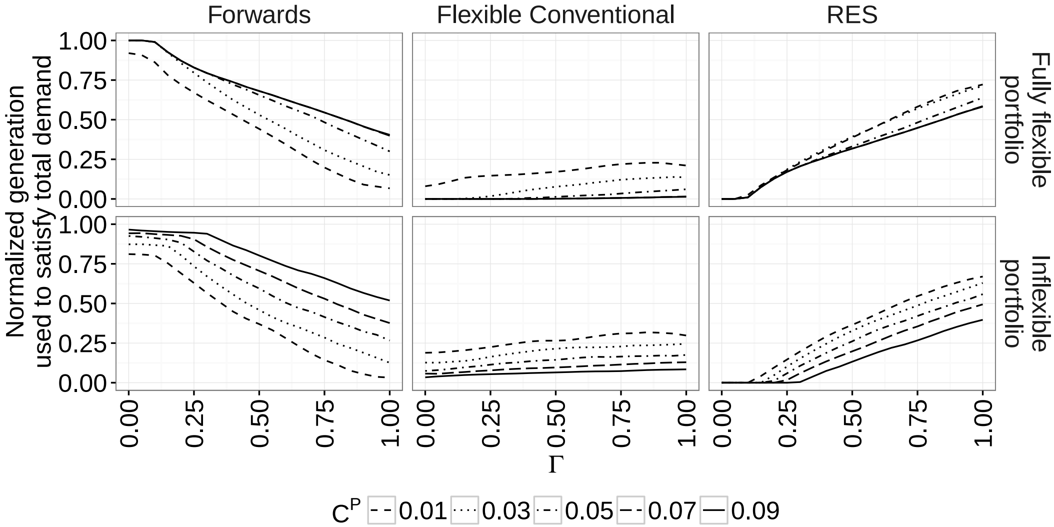

Figure 7.11: Optimal supply portfolio composition

values below 0.25. Conversely, generation from RES can serve up to 75% of total demand in the case of low discounts (flexible demand side) and low option premiums. Finally, it is noteworthy that low cost of flexible conventional generation (options and reserve market) not only increases the output of flexible generation but also increase RES usage.

The results are robust for different renewable generation scenario sets. On the one hand, for growing cost of supply side flexibility (given by the option premium), the share of contracted generation flexibility decreases. On the other hand, increasing discounts on flexible demand force the aggregator to accept higher option premiums. Consequently, the aggregator faces a trade-off between supply and demand flexibility contracting which is driven by supply flexibility cost C^P as well as demand flexibility costs δ^C and δ^S. Costly short term market transactions only play a minor role in case the costs of both options and flexible demand are high.

7.4 Discussion

The efficiency of scheduling flexible loads critically hinges on the underlying DR portfolio. Therefore, the process of forming such portfolios is a key component for DSM and must be realized carefully. Applying the model presented in chapter 6, this chapter investigates the optimal composition of both supply and demand flexibility portfolios. Furthermore, the value of information and computational complexity is evaluated. The findings indicate that there is a trade-off between solution quality and computational complexity. Hence, a profit maximizing DR aggregator should steadily reconsider and re-decide which approach to apply—a decision which depends on situational aspects and needs.

Firstly, elaborating on research question 3, the optimal demand response portfolio composition is analyzed. Secondly, the interaction of contracting supply and demand flexibility is investigated to answer research question 4. The simulation analysis builds on empiric data from wind and PV generation. On the demand side, smart meter readings from Ireland are split up into the three flexibility components, i.e., base load, shiftable load, and curtailable load. The results indicate that the optimal portfolio composition is driven by exogenous factors, e.g., prices for supply flexibility (modeled via option premiums), the availability of renewable generation, and cost of demand flexibility (given by discounts on flexible demand). The decision of contracting demand or supply flexibility is strongly influenced by these exogenous drivers. Similarly, shiftable and curtailable load can be considered as substitutes.

Figure 7.12 considers general portfolio compositions by dropping the contracted customer shares. Hence, the composition of optimal DR portfolios can be categorized by considering if they include demand flexibility (left panel curtailable, right panel shiftable) and/or supply flexibility (option contracts). Clearly, regimes without demand side flexibility are more

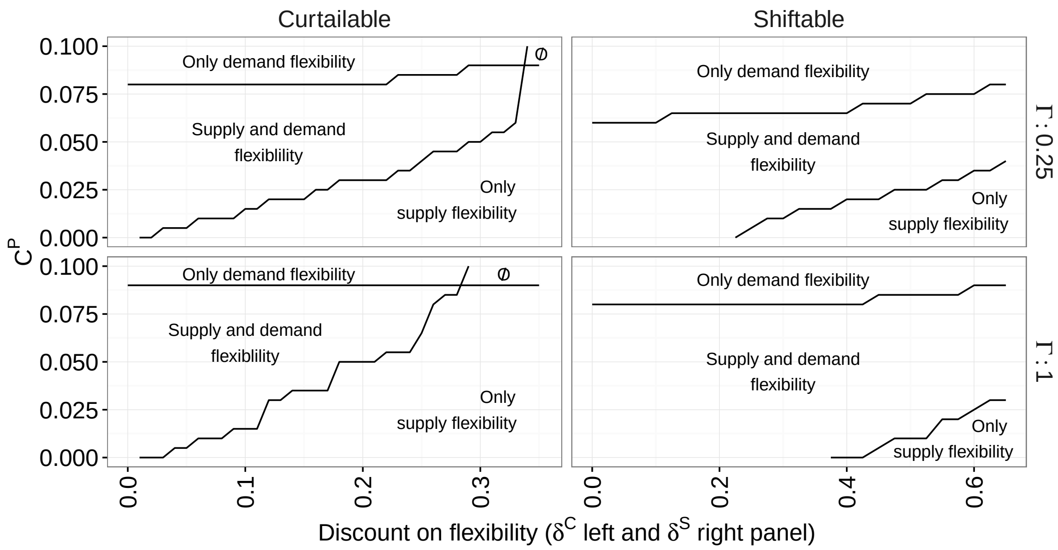

Figure 7.12: Optimal flexibility portfolio structure depending on discounts on flexible demand, option premiums, and the availability of renewable generation

likely for higher flexibility discounts. Conversely, supply options are not procured in case of excessive option premiums. In the case of curtailable load, all possible configurations of demand and supply side flexibility occur (including no flexibility). Interestingly, the no flexibility region is largest in the case of high renewable generation capacity—this is an interesting finding as it contrasts with the standard assumption of complementarity between volatile generation and flexibility. Nevertheless, for shiftable load the parameter region does not give rise to portfolios without any flexibility provisions.

The assumptions on customer flexibility builds upon the findings of part II that allow for predicting the amount of flexibility a private household could offer. Still, the abstraction from modeling single appliances and using a quantile based approximation of demand flexibility is comparably raw. However, it allows for keeping the computational complexity within reasonable boundaries and is well in line with literature. Furthermore, the simulation analysis includes an extensive sensitivity study for flexibility prices. However, it is hard to realistically assume the levels of these values. Long term supply flexibility is modeled via option premiums. Forwards and options are usually not traded on energy markets but OTC instead. Therefore, the terms of contract which describe these commitments are not available publicly. Hence, the presented results must be taken carefully. They should rather be used to consider and interpret the interaction effects between the different types of flexibility than to evaluate absolute contracting recommendations.

The model presented in this part fully abstracts from customer preferences and utility. It is assumed that an aggregator can centrally decide which customer to contract. Customer must—and will—accept these contract offers exactly as provided by the aggregator. In addition, the terms of contract, i.e., the provision of demand flexibility, is analyzed without including customers' utility from offering it—an approach that might seem unrealistic. However, it allows for determining the portfolio structure that would be optimal and hence an aggregator should strive for.

The scenario at hand can be improved by modeling customers' reactions to tariffs given their individual utility. This leads to a bi-level decision problem in which, on the upper level, the aggregator must design tariffs to incentivize customers to offer the exact amount of demand flexibility that should be contracted. On the lower level, each customer decides whether to accept this tariff and to offer flexibility or to reject it. The following part includes such utility considerations and investigates tariffs that enable an aggregator to optimally form DR portfolios under consideration of end consumer behavior.

Part IV

Tariff Design

8

Customer Acceptance

Scheduling of flexible loads both on large scale (industrial level) and on small scale (private household level) is a central opportunity to face the challenges induced by the constant growth of renewable generation capacities. To balance this intermittent, fluctuating, and hardly predictable generation, demand flexibility allows for avoiding inefficient investment in reserve power capacities. Private households account for about one quarter of the electricity consumption in Germany and are hence crucial for DSM (BMWi 2015a). Indeed, household flexibility poses a chance to support the energy policy goals of reliably providing ecologically sustainable electricity in an economically efficient fashion.

For the activation of the still passive demand side, mechanisms should be designed to incentivize the flexibility provision by household customers. This may be accomplished through offering tariffs that delineate the contractual conditions for scheduling flexibility as well as its remuneration. The designing of appropriate transaction objects must already consider agent behavior, i.e., the acceptance of contract offers (cf. chapter 3), to achieve an aspired market outcome. The development of DR tariffs builds upon knowledge about household characteristics, i.e., the availability of flexibility and the consumers' willingness to provide this flexibility. The former is investigated in part II, where both flexibility potentials are analyzed for given appliance endowments and where recommendations for contracting are derived. The willingness to provide DR capacities is discussed in the following (cf. research question 5). Consequently, the design of tariffs for harnessing demand flexibility enriches the findings from both the demand flexibility valuation (cf. part II) and the customer portfolio design (cf. part III). In contrast to the scenario in the previous part where the aggregator was a price-taker with respect to procuring flexible demand, this part corresponds to a situation where the supplier has market power—potentially due to exclusive customer relationships or regulatory privileges. Still, these tariff offers need to account for utility-maximizing customer behavior. Otherwise, customers will opt for contracts that avoid flexibility provision.

Similar to the previous part, the four types of generation on the supply side remain, i.e., generation from RES, forwards, options, and the reserve market. Forwards and options must be procured on the first decision stage. In contrast to less flexible forwards that are dispatched as procured, options provide the right but not the obligation to be scheduled up to the full capacity. Consequently, both dispatching options and market power procurement is part of the second optimization stage. On the demand side, an additional abstraction level is added to the simulation scenario, i.e., the single household model is replaced by a more coarse scenario. The decision of contracting flexibility now turns from a binary decision, i.e., contract all flexibility a customer can offer or none, into a continuous decision. Figure 8.1 shows the supply and demand scenario including the adapted, more coarse demand side.

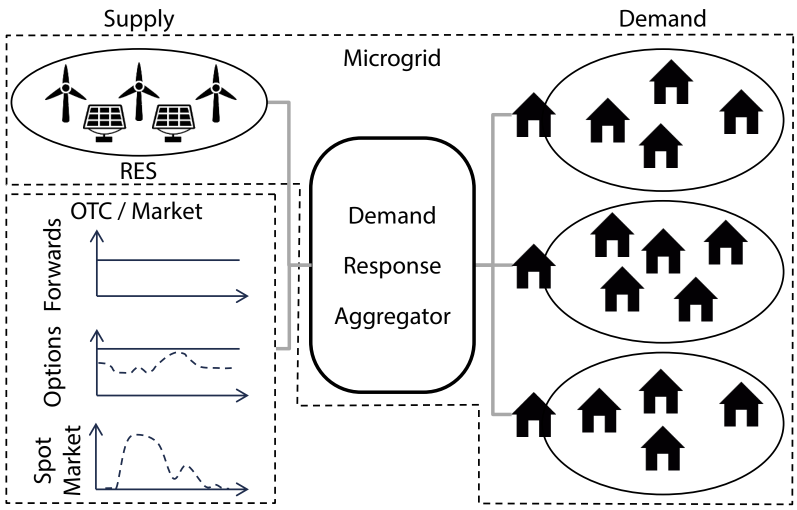

Figure 8.1: Integration of a flexibility aggregator into a microgrid with supply from RES, forwards, options and the spot market and demand consisting of household cooperatives which consume base, shiftable, and curtailable load on the demand side

This adaption allows for modelling two scenarios. Firstly, a scenario can be described where households are very well informed and ready to actively participate in DR. Single appliances are separately considered and valuated which enables customers to not only decide to (not) accept a contract offer, but also to decide which share of flexible demand to provide for DSM. Secondly, households form electricity cooperatives that are managed by a representative household or a professional aggregator. This work follows the second scenario as it seems to be the more realistic case. Comfort is increased for single consumers as these do not have to take care of continuously managing electricity contracts. Instead, flexibility is pooled and managed by a representative. Such approaches are already being implemented for large industrial consumers or small generators. Energy service providers like *Enernoc*[1] offer energy management solutions and leverage flexibility from both industry and business customers. *Next Kraftwerke*[2] pools distributed renewable generation and flexible demand in a VPP to trade aggregate power on markets.

To design successful and accepted tariffs, the household customers' disutility from offering flexibility and respective load scheduling must be investigated. To this end, this chapter expands the introductory elaborations on tariff design in electricity markets in section 2.4.3 and, subsequently, discusses drivers of discomfort from load scheduling. Expanding the model for designing demand response portfolios, a bi-level optimization model is introduced to calculate optimal tariffs on the upper level (aggregator's perspective) and the optimal response of households on the lower level (customers' perspective). Finally, the model is reformulated as a parametric program and applied in the evaluation.

8.1 Designing Demand Response Tariffs

Customers differ in their electricity consumption and their ability to provide flexibility. Both are mainly driven by the customers' endowment of appliances. In addition to technical aspects, the provision of flexibility critically hinges on customer behavior and preferences, e.g., risk aversion and price elasticity. To encounter this customer heterogeneity, tariffs can be adapted for different customer types (Wilson 1993). The DR aggregator's objective is to design a customer portfolio that efficiently trades off the cost associated with supply and demand flexibility. The contracting of customers is realized by offering DR tariffs, which support the provision of flexibility. Such tariffs can be a two-sided trade—on the one hand, the aggregator sells electricity for a (possibly discounted) retail price, on the other hand, the customer sells flexibility. Consequently, both parties try to optimize their individual

[1] `http://www.enernoc.de/`
[2] `https://www.next-kraftwerke.com/`

goals—the aggregator tries to maximize its profits and each customer tries to maximize its utility from electricity consumption.

8.1.1 Tariff Design

Tariffs are often used to implement nonlinear service pricing structures. In addition to electricity, typical domains where tariff composition plays an important role include telecommunications, information technology, healthcare, and insurances (Danaher 2002; Rao 2009). Köhler (2013) identifies four basic components tariffs can be composed of, i.e., a fixed fee, a variable price, an allowance, and a cost cap:

- A *fixed fee* is a regularly charged payment independent of the actual consumption. This license, or lump sum fee grants the right to access the service (Murphy 1977). In household energy consumption this fee is often implemented as a meter rental charge (Houthakker 1951).
- The *variable price* is often referred to as a (constant) flat rate. In contrast to the fixed fee which accrues independently of consumption, the variable price maps consumption to the amount that must be paid—the mapping is strictly proportional to total consumption.
- An *allowance* is often combined with a fixed fee and a variable price that applies if the allowance is depleted (Köhler 2013). An allowance allows for consuming a predefined amount (of electricity) at a variable price of zero. If consumption exceeds the allowance a variable price larger than zero applies. To date, allowances are not wide spread in private household electricity contracts as the marginal cost of generation is usually larger than zero. However, an allowance strongly influences customers' tariff choice, especially in case of uncertain future consumption (Lambrecht, Seim, and Skiera 2007).
- Finally, the *cost cap* can be found in telecommunication tariffs. In the electricity sector, cost caps are not yet widely available. Cost caps represent an upper bound for the total bill. Again, tariffs that include such a component are interesting in telecommunication markets rather than electricity markets as telecommunication sector marginal cost can be considered zero (Krämer and Wiewiorra 2012).

Tariffs can be composed by combining these components. For electricity end consumers, the dominant tariff that is currently available is a combination of a fixed fee (referred to as meter rent) plus a variable price that must be paid per consumed unit. A more detailed overview of electricity tariffs and pricing provide section 2.4.3 and appendix A.

As already pointed out above, this part considers two-sided tariffs. An aggregator sells electricity to customers whilst a customer can sell flexibility to the aggregator. The tariff design investigated in the following focuses on the latter, i.e., contracts that specify the remuneration for providing flexibility. These tariffs include both a fixed fee which is implemented by discounts that are paid if flexibility is contracted and a variable price represented by a remuneration for shifting (including the shifting distance) and the abolition payments for curtailed load. In case of limited shifting distance penalties that do exceed base load revenues, a cost cap de facto applies as well. The aggregator can forgo any revenues from selling electricity. In case all flexibility is contracted and used, no revenues are accumulated. Hence, the cost cap is given by potential turnovers.

8.1.2 Sequence of Events

The sequence of events in tariff design is inspired by the temporal procedure of portfolio design. Two main decision stages are considered. On the first stage, both supply and demand contracting is realized. Subsequently, on the second stage, flexible supply and demand is dispatched. The design of tariffs determines the amount of demand flexibility that will be available and should be contracted. Therefore, the demand side of the first decision stage is examined in more a more detailed fashion.

Figure 8.2 illustrates the temporal sequence of events, activities, and decisions for both aggregator and customers. It describes the first stage of the customer portfolio design process—the whole two stage approach which is presented in figure 6.2 includes supply and demand contracting as well as load scheduling.

To properly design tariffs, the aggregator gathers and analyzes as much information about its customers as possible (cf. part II). This allows for estimating the customers' flexibility potentials. Based on this information, the aggregator calculates the optimal portfolio composition (cf. part III). Flexibility on the supply and the demand side are traded off to ensure supply adequacy and hence to satisfy the customers at all times. Tariffs are then offered to the customers. This step is critical for the aggregator's future profit. On the one hand, in case discounts are too high, customers offer more flexibility than the aggregator wants to contract. On the other hand, the flexibility that is offered by customers does not suffice and

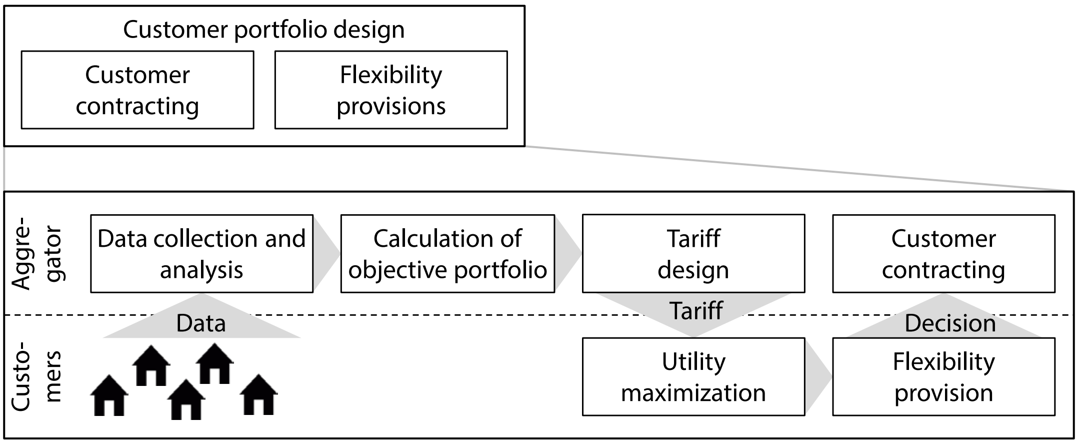

Figure 8.2: Temporal sequence of tariff design events

costly options must be contracted if discounts are chosen too low. Given the tariff offer, each customer individually decides how much flexibility should be offered to maximize its utility. Finally, based on this decision, the aggregator can contract up to the level customers agreed to.

The main drivers for choosing discount levels are the availability of flexibility and the customers' willingness to provide it. Yang et al. (2013) investigate the proper design of TOU tariffs under the consideration of consumer behavior. The problem is described as a bi-level problem. On the upper level, a producer defines a TOU tariff. On the lower level, customers react to the tariff by adapting their electricity consumption. The work at hand pursues a similar approach. However, to properly describe customer behavior it is essential to investigate the main drivers of (dis-) utility in electricity consumption and flexibility usage.

8.2 Customer Utility Models

The customers' decision to offer demand flexibility depends on the trade-off between the compensations that customers receive for offering flexibility and the expected disutility they experience from load adaptions by the aggregator. The individual disutility is influenced by various factors and it is perceived differently. Customer portfolio design and its development needs to consider these factors. However, due to the large-scale and variability of consumers it is non-trivial to understand such preferences (Chandan et al. 2014).

Conejo, Morales, and Baringo (2010) introduce a DSM optimization model to schedule demand of a given consumer in response to hourly electricity prices. Applying a general customer utility function their model aims to maximize customer utility. Similarly, Gkatzikis, Koutsopoulos, and Salonidis (2013) assume a convex utility function to capture the dissatisfaction caused by the deviation from a reference consumption through DSM. Their model considers three entity levels, i.e., an operation cost minimizing grid operator, profit maximizing DR aggregators, and end consumers that face a trade-off between remuneration payments and discomfort from consumption modifications. Correspondingly, Fakhrazari, Vakilzadian, and Choobineh (2014) derive a preference function that focuses on the interplay between utility and reward. Hence, two competing objectives are considered, i.e., the end user's electricity cost on the one hand, and preferred comfort levels on the other hand.

Using general utility functions to capture customers' discomfort from DSM and to model their decisions offers many advantages. Due to their synthetic nature, such general utility models can easily be parametrized. They allow for conducting sensitivity analyses as the number of factors that influence the form of the functions can be exogenously set. However, abstracting from the drivers of discomfort impedes the investigation of the drivers of the customers' reactions to tariff offers. In their approach to coordinate and minimize power consumption in smart and energy efficient buildings, Wang, Wang, and Yang (2012) explicitly model three main comfort factors. The inhabitants' utility of electricity consumption depends on environmental temperature, illumination level, and indoor air quality which is given by the carbon dioxide concentration. In contrast, Li, Chen, and Low (2011) do not consider factors that influence comfort but rather the utility provided by the operation of devices. In accordance with part II, households are considered that operate current domestic devices as well as EVs and stationary batteries. Again, the households' goal is to maximize their individual benefit by optimally scheduling loads.

Following the literature, customers are assumed to react to tariff offers in an utility maximizing manner. Their gross utility is governed by base utility as well as disutility terms arising from the provision of greater load flexibility levels. Consequently, customers face a trade-off between discounts (and corresponding electricity cost savings) and the discomfort arising from entering flexible contracts. A generic utility function for the shiftable load component is given by $u_c^S : \left(\overline{\gamma}_c^S, \delta_c^S, \Theta_c^S\right) \rightarrow u_c^S\left(\overline{\gamma}_c^S, \delta_c^S, \Theta_c^S\right)$, where $\overline{\gamma}^S$ is the share of shiftable load the customer provides and Θ_c^S is a measure for the customer's individual shifting ability, i.e. how much discomfort arises from larger shifting intensity (distance and volume). Analogously, the utility function for offering curtailable load can be characterized as $u_c^C : \left(\overline{\gamma}_c^C, \delta_c^C, \Theta_c^C\right) \rightarrow u_c^C\left(\overline{\gamma}_c^C, \delta_c^C, \Theta_c^C\right)$, with Θ_c^C being a parameter for the customer's individual curtailing ability, i.e., how much discomfort arises from larger curtailing intensity (volume).

Both parameters Θ_c^S and Θ_c^C measure individually perceived discomfort from offering flexible load. However, these measures rather represent the expected (maximum) disutility as flexible load is contracted on the first decision stage, i.e., long before the actual scheduling. Therefore, each customer's decision to offer flexibility is rather a worst case consideration under uncertainty. It is influenced by its risk aversion (reflected by Θ_c^S and Θ_c^C) as well as potential cost savings (given by δ_c^S and δ_c^C).

To capture the perspective of both the aggregator and the customers, Fadlullah et al. (2014) differ between these actors. One way to implement both views are bi-level models (Yang et al. 2013) or multi-level models (Gkatzikis, Koutsopoulos, and Salonidis 2013). The following section describes a bi-level model that considers both the perspective of a profit maximizing aggregator on the upper level and utility maximizing customers on the lower level.

8.3 Bi-level Tariff Design Model

Bi-level models allow for capturing both the aggregator's and the customers' perspectives and their objectives. Before DSM has gained more attention by the growing share of generation, Hobbs and Nelson (1992) proposed a nonlinear bi-level model which considers both views. On the upper level, an electric utility tries to maximize its profits via controlling electricity rates. On the lower level, customers attempt to maximize their benefit of electricity consumption. The analysis of DR portfolio design in part III assumes exogenous discount levels to analyze the the optimal composition of both the generation and the demand portfolio. Now, discounts on shiftable and curtailable load are not exogenously given anymore but turn into first stage decision variables—which corresponds to designing DR tariffs. Hence, a situation is assumed where the supplier has market power, potentially due to exclusive customer relationships or to regulatory privileges. Therefore, customers cannot be excluded from the portfolio anymore. However, tariff design needs to account for utility-maximizing customer behavior as customers can opt for non-flexible contracts.

The *upper level problem* (ULP) reflects the DR aggregator's objective to maximize its profit:

$$ULP: \max_{\delta^S, \delta^C, \mathbf{x}, \mathbf{y}, \mathbf{a}, \mathbf{s}} \sum_{\omega \in \Omega} p_\omega \left(\pi_\omega^{bL} + \pi_\omega^{sL} + \pi_\omega^{cL} - c_\omega^G \right). \tag{8.1}$$

Hence, the ULP—the aggregator's profit maximization—is equivalent to the portfolio design objective function (6.10) except for the additional inclusion of the discounts (δ^S, δ^C) as decision variables. In the *lower level problem* (LLP), customers individually try to maximize utility. Each customer's utility is given by the sum of its utility from offering shiftable and curtailable demand flexibility. Thereby, the main drivers are discounts for flexible load (δ_c^S and δ_c^C) and risk aversion (Θ_c^S and Θ_c^C):

$$LLP: \forall c \in \mathcal{C} \quad \max_{\overline{\gamma}_c^C, \overline{\gamma}_c^S} u_c^S \left(\overline{\gamma}_c^S, \delta_c^S, \Theta_c^S \right) + u_c^C \left(\overline{\gamma}_c^C, \delta_c^C, \Theta_c^C \right). \tag{8.2}$$

Consequently, the customers decide upon the amount of flexibility they are ready to provide given discounts—which are determined by the aggregator on the ULP—and personal risk aversion. Hence, the share of shiftable load that a customer is ready to provide—and the aggregator can contract, respectively—is limited by $\overline{\gamma}_c^S$:

$$x_c^S \leq \overline{\gamma}_c^S, \quad \forall \omega \in \Omega \, \forall c \in \mathcal{C}. \tag{8.3}$$

Similarly, for customers that allow load curtailment, at most $\overline{\gamma}_c^C$ of their original demand can be shed:

$$\sum_{t \in \mathcal{T}} a_{\omega,c,t}^C \geq \sum_{t \in \mathcal{T}} x_c^C (1 - \overline{\gamma}_c^C) D_{c,t}^C, \quad \forall \omega \in \Omega \, \forall c \in \mathcal{C}. \tag{8.4}$$

Note again, that contracting flexibility now becomes a continuous decision instead of the formerly binary contracting. The remainder of the constraints that define the supply and demand side as well as the objective function components follow the description of the portfolio optimization scenario and hence remain unchanged.

Each customer's utility maximization problem—which is the ULP—can be simplified by introducing *flexibility response functions*. For a given discount a customer will always offer the same amount of flexibility as its risk aversion is supposed to remain unchanged and exogenously given. Therefore, these correspondences posit a direct and monotone mapping from the quoted flexibility discount to the flexibility amount offered by the customer, that is $\delta_c^S \mapsto \overline{\gamma}_c^S$ and $\delta_c^C \mapsto \overline{\gamma}_c^C$. By the introduction of such flexibility response functions, each customer's reaction to a tariff offer, which represents its willingness to provide flexibility given a certain discount, can be predefined. This allows for capturing the LLP by the response functions.

The demand reformulation facilitates an efficient representation of LLP as ULP constraints. Still, the problem exhibits non-linearity. Each of the terms in the ULP's objective function (8.1) is bounded via constraints. The revenues from curtailable load, for example, are given by the amount of served curtailable load that is sold at the discounted retail price:

$$\pi_{\omega}^{cL} = \sum_{c \in \mathcal{C}} \left(\left(1 - \delta_c^C\right) P \sum_{t \in \mathcal{T}} a_{\omega,c,t}^C \right), \quad \forall \omega \in \Omega. \tag{8.5}$$

Revenues from shiftable load are calculated in an analogue fashion. Discounts as well as load scheduling amounts are modeled as continuous variables. This gives rise to $2\omega|\mathcal{C}|$ products of continuous decision variables—these impede efficient solution techniques for large problem instances. Hence, this necessitates a reformulation of the optimization problem.

8.4 Reformulation and Parametric Approach

The large number of products of continuous decision variables makes the problem infeasible for currently available commercial solvers. Therefore, an alternative approach is chosen. To improve problem tractability, the model is solved iteratively with discounts as exogenous parameters instead of decision variables. This dissolves the variable products and substantially increases computational efficiency. In each iteration discounts are adapted and the approximation converges towards the optimal solution. The reformulated problem approximates the optimal discount to any level of precision for sufficient iterations.

The *objective value function* $f : [0,1]^{|\mathcal{C}|} \times [0,1]^{|\mathcal{C}|} \to \mathbb{R}; (\delta^S, \delta^C) \to f(\delta^S, \delta^C)$ ceteris paribus maps from discount combinations of δ^S and δ^C to the objective value $f(\delta^S, \delta^C)$—for the purpose of designing tariffs, the contracting and scheduling variables are considered internal variables. Since generation and demand contracting as well as discounts are continuous variables it can be shown that f is continuously differentiable ($f \in C^1$). To demonstrate a globally profit-maximizing discount combination it is necessary to show that f is a quasi-concave function.[3]

[3] A function $f : M \to \mathbb{R}$ defined on a convex subset M of a real vector space is quasi-concave if for all $m_1, m_2 \in M$ and $\lambda \in [0,1]$ the condition $f(\lambda m_1 + (1-\lambda)m_2) \geq \min\{f(m_1), f(m_2)\}$ holds.

To show the quasi-concavity of the aggregator's objective value function, the marginal utility of each flexibility unit is considered. In case there is not yet any flexibility available (corresponding to zero discounts), new demand side flexibility offers are most useful to the aggregator as they will allow to displace the so-far most expensive conventional generation dispatch activities. The marginal benefit of demand side flexibility is decreasing as it will displace less expensive marginal generators. Consequently, the aggregator will only continue to contract more flexibility as long as the savings from it exceed the costs of conventional generation (up to this point its profit increases as costs are avoided by contracting demand flexibility). In case discounts are too high and procuring conventional generation is cheaper than contracting flexibility, the aggregator will prefer conventional generation even though more flexible demand would be available. The flexibility contracted comes along with higher discounts and, consequently, the objective value decreases. Hence, the objective value function f increases in case the discount on flexible load δ_c^S or δ_c^C is increased. In case a critical value is exceeded, increasing discounts lead to profit losses as conventional generation becomes cheaper than demand side flexibility. Consequently, f is quasiconcave in each coordinate direction. Furthermore, from the aggregator's ability to contract any amount of generation it follows that the objective value function is Lipschitz-continuous and unimodal by the definition used in Morozova (2008). In case a local maximum is reached, increasing discounts lead to a decreasing objective value. Hence, further discount increases cannot generate higher objective values (as increasing discounts only cause increasing flexibility costs but not the contracting of more demand flexibility). Therefore, a local maximum is always a global maximum.

In the subsequent chapter, flexibility discounts are assumed to be homogeneous across customers, that is $\forall c \in \mathcal{C} : \delta_c^C = \delta^C$ and $\forall c \in \mathcal{C} : \delta_c^S = \delta^S$. This corresponds to a transparent market with well-informed customers. The objective value function is quasi-concave in both δ^S and δ^C. To determine the optimal choice of discounts the multidimensional bisection method (Wood 1992; Morozova 2008) can be applied. By iteratively solving the parametric optimization problem the feasible set from which possible discounts are chosen is given by simplices that are adjusted in each iteration. The multidimensional bisection method finally pinpoints the optimal discount combination to any level of precision. So far, discounts were assumed to be continuous variables. However, discrete discounts may be a more plausible assumption in real markets. This would simplify the iterative approach as it drastically reduces the number of feasible tariffs.

8.5 Discussion

This chapter relaxes the portfolio design model in a sense that formerly discrete decision—contracting of households and demand flexibility—becomes continuous. Hence, single, well informed, and responsive households are assumed or groups of households, represented trough one entity, are considered. These do not accept tariff offers as a whole but rather decide upon the amount of flexibility they are ready to offer for given discounts. This gives rise to a complex bi-level decision making problem. On the upper level, an aggregator designs tariffs to incentivize customers to offer flexibility. On the lower level, utility maximizing customers trade off risk aversion and remuneration payments they receive in form of discounts on the electricity base price.

The model of the demand side abstracts from uncertainty in demand. Already in the contracting phase, both the future consumption and the corresponding availability of flexibility through possible load adaption are assumed to be known. On the one hand, including uncertainty in the model for electricity consumption and flexibility provision poses an opportunity for expanding this work. On the other hand, by considering sets of households or electricity cooperatives instead of single households, both the security of future consumption and its predictability is increased.

Customer utility is driven by two main factors, i.e., the discounts offered by the aggregator and an individual parameter that represents the customers' soft impacts like perceived discomfort and risk aversion. This rather raw utility model could be improved by building upon empiric information on customer contracting decision. As this information is not yet available, this work follows current literature to best define utility and the corresponding customer response functions. In addition, no long term effects of load scheduling is included in the model. Customers might get tired from excessive load adaption and reject tariff offers or demand for higher remuneration payments (Holyhead, Ramchurn, and Rogers 2015).

The following chapter demonstratively elaborates the approach to determine the optimal choice of discounts and the design of tariffs, respectively. In accordance with part III, the evaluation uses empiric data for both the supply and the demand side. To allow for better investigating effects, contracting of shiftable and curtailable demand is investigated separately. In addition, the impact of the customers' risk aversion on the optimal discount choice and the aggregator's profit is discussed.

9

Optimal Tariff Design

Customers require incentives for offering flexibility. These can be of monetary or non-monetary nature. The increasing awareness of environmental challenges, e.g., climate warming, motivates customers to contribute to programs and actions that aim at protecting nature. The current trend towards a "green conscience" might be one driver for increasing flexibility provision from private households. Gamification is one opportunity to reward customers (Deterding et al. 2011b). For example, providing information that allow for comparing carbon dioxide reductions accomplished by behavioral adaption could incentivize individual ambition in peer groups. The advantage of nonmonetary incentives is that flexibility remuneration costs can be avoided. However, these approaches do not allow for confidently predicting customer behavior and directly scheduling flexible loads. In addition, it is hard to analyze and assess nonmonetary incentives in simulation studies. Therefore, this work focuses on monetary incentives.

Following the supply side model presented in part III, the aggregator's generation portfolio includes renewable generation capacities. To balance fluctuating generation from RES with demand, conventional generation, demand flexibility, or both must be used. Forwards and options must be contracted on the first optimization stage. Contracted options and spot market electricity are then dispatched on the second stage. Similarly, contracting flexible demand must be realized on the first optimization stage. Contracted flexible demand, i.e., shiftable and curtailable loads, can then be scheduled on the second stage. Base load cannot be used for DSM and must be served unconditionally. Figure 9.1 illustrates the supply and demand characterization.

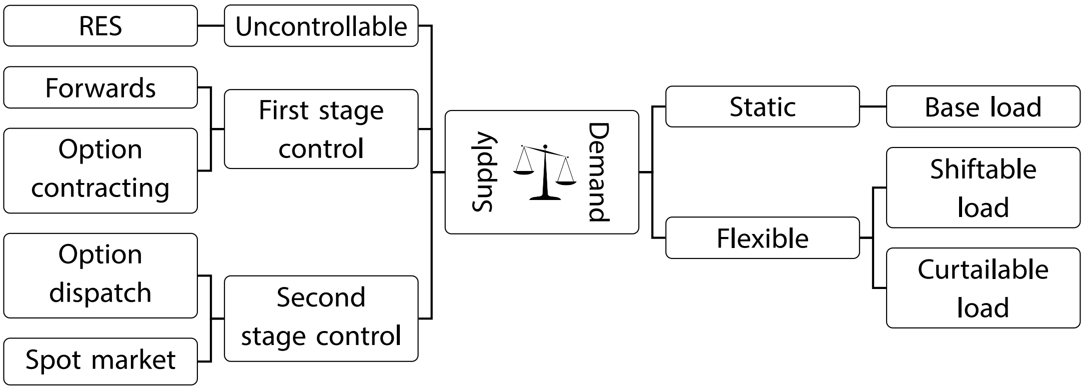

Figure 9.1: Supply and demand characterization for tariff design

In contrast to the supply side, the demand side differs from the model applied to analyze optimal DR portfolio structures in part III. Still, flexibility must be contracted in advance. However, the previous contracting of single households (binary decision) is replaced by a more pronounced model that allows for considering partial flexibility contracting or groups of households (continuous contracting decisions). Most importantly, customers' preferences and utility are included in the model. Tariffs are designed that incentivize customers to participate in DSM. These tariffs consist of two components (Köhler 2013). Firstly, a fixed discount on contracted flexibility is granted—this corresponds to a fixed remuneration fee. Secondly, load shifting is compensated depending on the shifting distance and for curtailed load no turnovers are earned—this represents the variable flexibility price.

Firstly, the following simulation study investigates the changes to the ideal DR portfolio composition caused by the contracting problem relaxation. The results are interpreted and compared to the findings in part III—which requires to assume indifferent customers and strong customer responsiveness. Secondly, the optimal choice of discounts is discussed using various flexibility response functions (cf. research question 6). Finally, this chapter elaborates on the interdependencies between the customers' risk aversion (and corresponding responsiveness), the optimal choice of discounts, and the attainable profits.

9.1 Parametrization of Simulation Scenario

Although the aggregator has full information about the availability of demand flexibility, tariff design must be realized under uncertainty of future generation from RES. However, customers cannot be contracted discretionarily anymore. Instead, they respond to tariff offers which are given by discounts on flexible loads. Their reaction depends on the height of the discounts but also on soft factors, e.g., risk aversion and price elasticity, which are expressed via one parameter. Customers do not receive individual but uniform discounts. However, in contrast to part III the discounts are not exogenously given but set by the aggregator. Hence, in such a scenario the supplier has market power. However, in case flexibility tariffs are not attractive for utility-maximizing customers, they will opt for a non-flexible contract.

In the simulation, a time horizon of one year is considered on the first optimization stage. The dispatch of flexible supply and demand is conducted in a day-ahead fashion. Supply and demand side time series are given in a 30 minute resolution. A population of 100 customers is considered. Both the brief description of empiric input data for the demand side and the supply side follows the comprehensive introduction in section 7.1. The base load retail price, which corresponds to the end consumer electricity price if no flexibility is contracted, is set to $P = 0.3$. Like before, cost and prices are given in €/kWh. In the simulation study the costs for conventionally generated electricity procured OTC or from the market is set to $C^F = 0.15$, $C^O = 0.225$, and $C^M = 0.6$ (Grünewald, McKenna, and Thomson 2014). Like before, a sensitivity analysis is executed for C^O. Option premium cost varies but does not exceed 0.1. In the base scenario, five RES generation scenarios are considered. The ratio of demand and generation from RES Γ varies between zero and one in sensitivity study but is set to one in the base scenario. Finally, a quadratic shifting distance penalty function is assumed to penalize load shifting which reduces the attractiveness of extensively large shifting distances.

9.1.1 Demand Side

To ensure variability in load data and to realistically reflect consumption patterns, empiric smart meter profiles serve as input data to the demand side. In addition to smart meter readings from over 5,000 Irish homes and small businesses the data set from the Irish Social

Science Data Archive[1] provides a comprehensive pre-trial and post-trial survey about the participating households, e.g., living conditions, technical household specifications (appliance endowment, insulation, heating), their electricity consumption, and their willingness to save electricity.

Again, load curve collections are interpreted as probability distributions (Carpaneto and Chicco 2008). Information on flexible demand is extracted by approximation flexibility levels using the likelihood of a certain demand level. To obtain flexibility levels that are in line with part II as well as with previous studies by Stamminger et al. (2008) and He et al. (2013), a customer's base load level is fixed at the 30 % quantile of the collection of smart meter readings for that given 30 minute interval. With this assumption it is obtained that on average 64 % of the original load needs to be served as required. Following literature an average scenario where 25 % of the original demand can be shifted and up to 11 % can be curtailed should be achieved. To this end, shiftable load is determined as the intersection of the members of the 60 % and 30 % quantiles and, to smooth outliers, curtailable load is determined by the 85 % and 60 % quantiles (cf. figure 7.2).

9.1.2 Supply Side

To derive generation scenarios, empiric wind and PV generation data is used. The wind generation data is taken from the Ampiron control area[2] and solar generation is taken from a single PV power plant in southern Germany. Firstly, $|\Omega|$ single days equally distributed over the whole year are randomly selected. Subsequently, the time series are scaled by overall renewable generation from the respective energy source and the corresponding wind share (S^W). In the base scenario a wind share of $S^W = 0.7$ is assumed which approximately corresponds to the relation of the two energy sources in Germany in 2014 (BMWi 2015a). Then, the resulting renewable generation scenarios are scaled again so that an average supply-demand ratio of Γ is achieved. In the base scenario the supply-demand ratio is set to one ($\Gamma = 1$). Consequently, the mean of the total renewable generation in the resulting supply scenarios over the whole time horizon equals overall demand. This approach ensures that seasonal effects are considered in the simulation as well as the intra-day characteristics of supply from RES, e.g., midday peaks from PV generation.

[1] `www.ucd.ie/issda/data/commissionforenergyregulationcer/`
[2] The data can be retrieved from `http://www.eex-transparency.com`.

9.2 Demand Portfolio Structure

There are two main adaptions for the tariff design part at hand and the previous portfolio design analysis. Firstly, customers try to maximize their individual utility instead of accepting any tariff offer—the aggregator becomes a price maker instead of a price taker and must design its portfolio with respect not only to flexibility prices but also to customers' reactions to tariff offers. Secondly, the problem is relaxed—formerly binary flexibility contracting decision variables turn into continuous variables. To check for feasibility of these assumptions, this section abstracts from customer utility. Hence, the response function takes the value one for shiftable load and 0.25 for curtailable load regardless of the discount the aggregator offers. This corresponds to the portfolio design scenario in which customers accept any tariff and hence ensures the comparability of the binary approach and the relaxed model.

Figure 9.2 illustrates the substitution effects between curtailable and shiftable load for varying option premiums. In combination with the lower panel of figure 7.10 (Γ = 1) it allows for discussing the feasibility of the problem relaxation. Horizontal lines represent constant discount on shiftable load δ^S. The discount level is given at the left end of each line. The vertical dotted lines show constant discounts on curtailable load δ^C. The discount levels are given at the bottom end of each line.

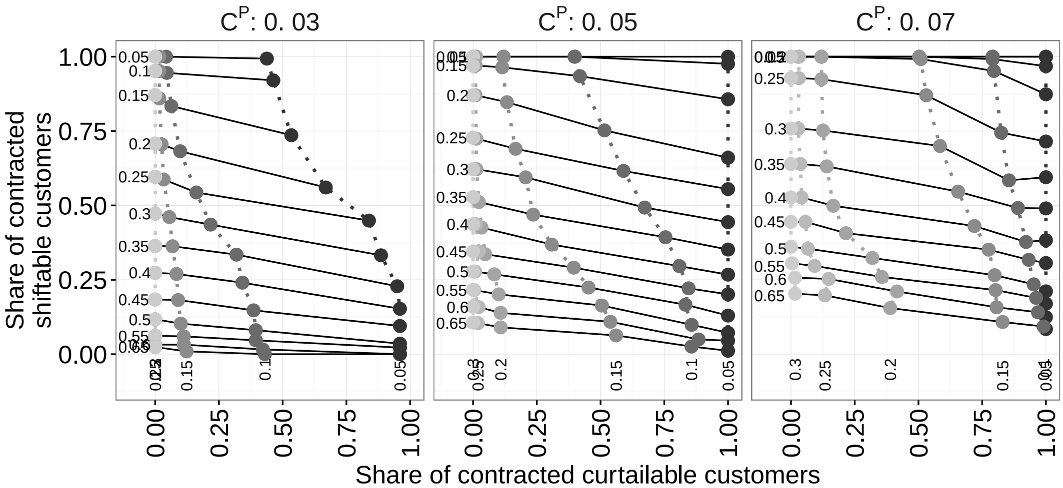

Figure 9.2: Optimal demand response portfolio composition for varying discount tuples (δ^C, δ^S) and option premiums C^P

In contrast to the previous part that focused on the share of contracted customers, figure 9.2

reports contracted load. Each point represents one optimal DR portfolio for a given discount tuple (δ^C, δ^S). Besides flexibility discounts conventional generation costs also influence the DR portfolio structure (the previous part demonstrated the trade-off between demand and supply flexibility which is mainly driven by flexibility costs). To signify the interdependency with supply side flexibility, the optimal composition for different cost levels for supply side flexibility is evaluated.

The analysis supports the feasibility of the problem relaxation as the substitution effects between both the two types of demand flexibility and demand and supply flexibility remain observable. For increasing discounts the share of the corresponding flexibility in the DR portfolio decreases independently of the type of flexibility. At the same time the other flexibility type will be more readily procured—this interdependency illustrates the cross price elasticity of both shiftable and curtailable load. This substitution effect is a natural consequence of the need for demand side flexibility in face of generation uncertainty. However, the substitution is not 1:1 as the two flexibility types cannot fully replace each other. Furthermore, the influence of δ^S on the share of contracted curtailable customers is more pronounced than the influence of δ^C on the share of contracted shiftable customers. In case supply options are cheap (left panel: $C^P = 0.03$), it is very unattractive to contract demand flexibility customers even at very low discounts—efficient portfolios conglomerate in the lower left corner of the flexibility space. For increasing option cost demand flexibility becomes more attractive. Naturally, the substitution effect between generation option premiums and contracted flexibility is stronger for curtailable load as both can be used to reduce consumption or to increase generation, respectively.

9.3 Flexibility Response Functions

To account for customer utility and the lower level problem, respectively, the customer reaction to tariffs is modeled via flexibility response functions. These reflect the maximum amount of flexibility a utility maximizing customer is ready to offer given a tariff offer provided by the aggregator. Hence, by adapting discounts, the aggregator can control the availability of demand flexibility. Of course higher discounts increase flexibility provision. However, the trade-off between optimally choosing discounts to allow for efficient portfolio design and the contracting of forwards and options under uncertainty adds an decision layer to the portfolio design problem and hence even increases the complexity.

Literature that takes assumptions about the shape of customers' utility functions for electricity consumption, its main drivers, and the factors that define the provision of flexibility is manifold but has not been substantiated by empiric evidence (Conejo, Morales, and Baringo 2010; Gkatzikis, Koutsopoulos, and Salonidis 2013; Fakhrazari, Vakilzadian, and Choobineh 2014). However, flexibility response functions can be derived directly from such utility functions as the utility maximization returns the same decisions for given exogenous parameters—in the model at hand these are customer specific, e.g., individual risk aversion. Concerning the shape of flexibility response functions, concave functions are—besides monotonicity—natural candidates as they capture a natural "quick wins first" rationale (Downward, Young, and Zakeri 2015). However, retail markets often exhibit customer inertia which may only be overcome by offering a minimum compensation early on. To account for both aspects of consumer behavior, censored square root functions are adopted to model supply of shiftable load:

$$\overline{\gamma}_c^S : (\Theta_c^S, \delta_c^S) \rightarrow \max\left\{0, \min\left\{1, \sqrt{\Theta_c^S \delta_c^S}\right\}\right\} \tag{9.1}$$

as well as curtailable load:

$$\overline{\gamma}_c^C : (\Theta_c^C, \delta_c^C) \rightarrow \max\left\{0, \min\left\{1, \sqrt{\Theta_c^C \delta_c^C}\right\}\right\}. \tag{9.2}$$

For ease of exposition the superscripts are dropped and Θ refers to Θ^S as well as Θ^C (both types of flexibility are investigated separately and a representative value is assumed for all customers). This parameter refers to the *"customer flexibility level"*. Figure 9.3 depicts exemplary flexibility response functions with varying customer flexibility level Θ.

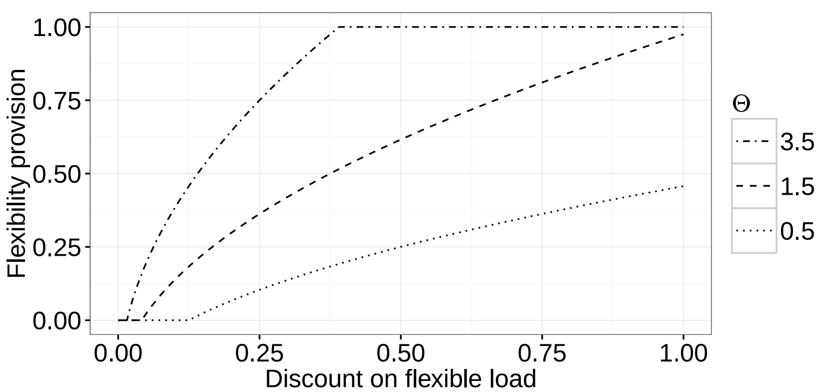

Figure 9.3: Exemplary flexibility response functions with varying customer flexibility level Θ

The response functions increase monotonically and independently of the customers' flexibility level. Obviously the functions must be bounded between zero and one as flexibility provision can only vary between 0 % and 100 %. That no flexibility is provided for positive but low discounts is a result of the assumption the customers might take fright at the initial investment in "smart appliances" that allow for automatically controlling load. In general, a customer's utility and its corresponding response to contract offers is unknown to both the aggregator as well as the customers themselves. Gathering this information will be instrumental to create meaningful and efficient tariff offer sets. Going forward, this will necessitate further research in the field of load data analytics.

9.4 Designing Tariffs

The reformulated tariff design model is a parametric problem that is repeatedly solved. This reduces the computational complexity as it is reasonable to assume that only discrete discounts are realistic. However, the granularity can be freely set. The optimal discount choice is calculated iteratively. In each iteration discounts are varied to approximate the optimal tariff. For better illustration, in the following only one type of flexibility is considered at the same time. Figure 9.4 shows an exemplary iterative approximation of the discount on shiftable load. In the example a supply-demand ratio of $\Gamma = 0.25$ and an option premium of $C^P = 0.05$ is assumed. Customers are in favor of the aggregator and willing to provide flexibility ($\Theta = 3.5$).

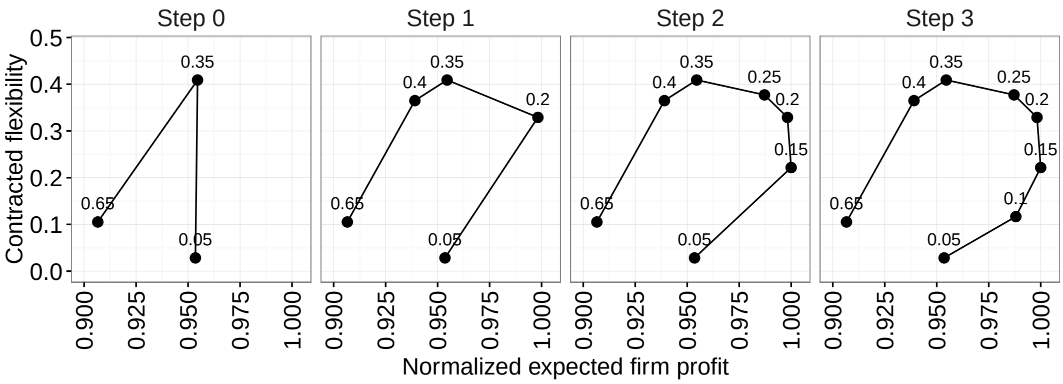

Figure 9.4: Normalized objective values and corresponding reserved shiftable load for varying discounts on shiftable load to illustrate iterative approximation of the optimal tariff

In the first iteration, three discount levels are randomly selected. In case the aggregator has already gained experience in tariff design, "good" start values can be set. The choice of discounts to investigate subsequent iterations uses the characteristics of the objective value function, i.e., they are unimodal and quasi-concave (cf. section 8.4). Hence, in case one of the border discounts generates the highest profit, the search space is expanded in the respective direction. Otherwise, two new discounts are selected that are above and below the discount that generates the maximum profit—in the example the values $\delta^S = 0.4$ and $\delta^S = 0.2$ are chosen as $\delta^S = 0.35$ achieves the largest expected profit. This procedure is repeated until the approximation reaches the predefined granularity. In the example the value was set to 0.05 and hence after four iterations the (expected) optimal discount is determined ($\delta^S = 0.15$). This approach can be applied for both shiftable and curtailable load. Figure 9.5 illustrates the optimal discount choice and the corresponding share of contracted flexibility for varying demand and supply flexibility cost and $\Theta = 3.5$.

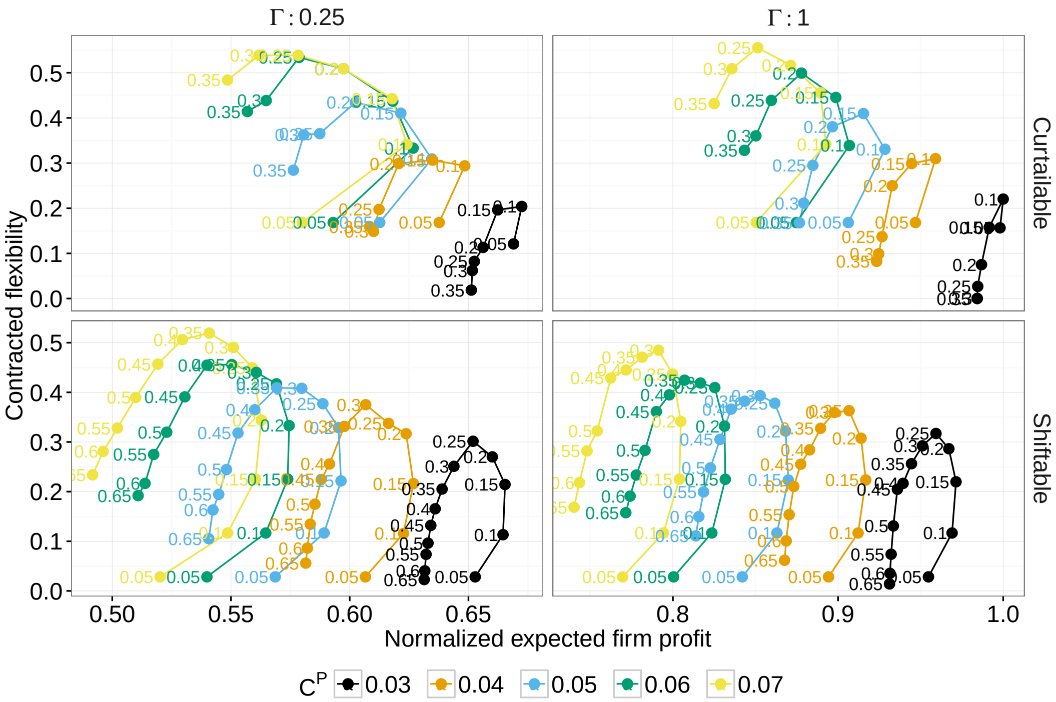

Figure 9.5: Normalized objective values and corresponding reserved curtailable load for varying discounts for flexible load and generation flexibility reservation cost

The objective value function can be split into three sections. For low discounts both profit and contracted flexibility increase in increasing discounts—more flexibility becomes available which is contracted and contributes to generation cost savings. Then, after the maximum profit is reached, it is still optimal to further contract more flexibility, which becomes available because of high discounts. However, high remuneration payments decrease the expected profit. In the third section, discounts are very high. A lot of (or all) flexibility is provided but both the amount of contracted flexibility and the aggregator's profit decrease anyway. In this case, it is cheaper to contract supply flexibility than demand flexibility. The objective function characteristics support the preliminary considerations in section 8.4 and allow for applying iterative tariff design approaches.

Finally, this representation nicely illustrates the aggregator's profit maximization problem for varying discounts for flexible load and option premiums. The optimal discount is given by the point which is the furthest to the right. A less coarse approximation scheme will result in better resolution with respect to the optimal discounts. Naturally, profit values will depend on the cost and flexibility parametrization of a given scenario. Therefore, rather the structural behavior of optimal solutions should be explored. Suppliers will in general be interested in standard guidelines for determining optimal discount choices based on a given market scenario.

9.5 Optimal Discount Choice

DR aggregators require standard procedures and strategies for designing tariffs. In line with the customers' flexibility response functions, such procedures should provide the ideal choice of discount levels for given environmental circumstances, e.g., availability of supply from RES, or supply flexibility prices (given by C^P). Such decision support tools can be designed by calculating optimal tariffs for a comprehensive set of parameter combinations. Figure 9.6 provides an overview of such a decision logic for varying supply-demand ratio, option premiums, and customer response functions.

Optimal flexibility discounts increase in the option premium C^P. Demand flexibility can be made more readily available by raising discount levels as the customers face a trade-offf between remuneration payments and risk aversion. Hence, the trade-off between demand and supply flexibility—which was already identified in part III—causes this discount increase as it allows for replacing supply flexibility by demand flexibility. On the one hand, in the case of shiftable load, the effect of the customer flexibility level is monotone—a less flexible customer population is enticed with higher discounts. Notably, even if options can be contracted for

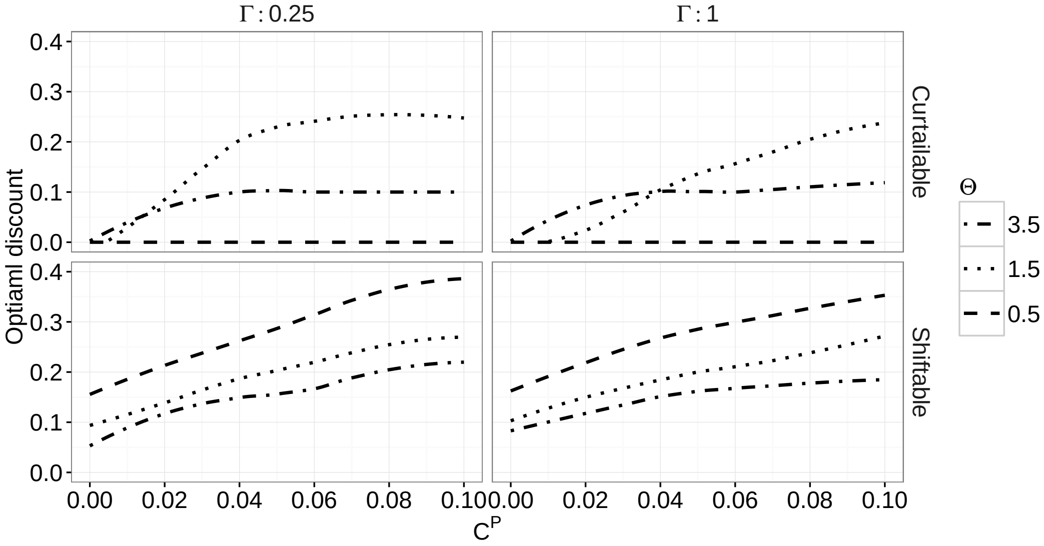

Figure 9.6: Optimal choice of discounts for given option premiums and availability of renewable supply Γ under the assumption of varying flexibility levels Θ

free ($C^P = 0$), the discount for shiftable load is set to a positive value—in this case, shiftable load can be used for smoothing demand to better match generation from forwards. On the other hand, for curtailable load contracting, a very different pattern emerges—the least flexible population is offered no discount at all and any demand flexibility is foregone for any value of C^P. However, for the intermediate and high flexibility level, the ordering is not constant. For low option premiums the high flexibility population is offered a larger discount, for higher values this relationship is switched. The option premium level at which this regime switch occurs is increasing in the renewable generation capacity Γ. This effect might be induced by the saturation of curtailable load. For flexible customers ($\Theta = 3.5$), the flexible load offered by the customers already suffices for low discount levels and the aggregator cannot profit from further increasing them. For more risk averse customers ($\Theta = 1.5$), higher discounts are needed to reach the saturating level. Similar to customer preferences, the effect of Γ on optimal discount choice is also non-monotone and depends on the flexibility type, on the populations' flexibility level Θ as well as on an the cost of supply side flexibility C^P.

Besides optimal discount offerings, the aggregator is also interested in profitability results and the sensitivity of profit for tariff adaptions. Figure 9.7 reports normalized expected objective values for varying customer flexibility levels, supply flexibility cost and renewable generation capacities.

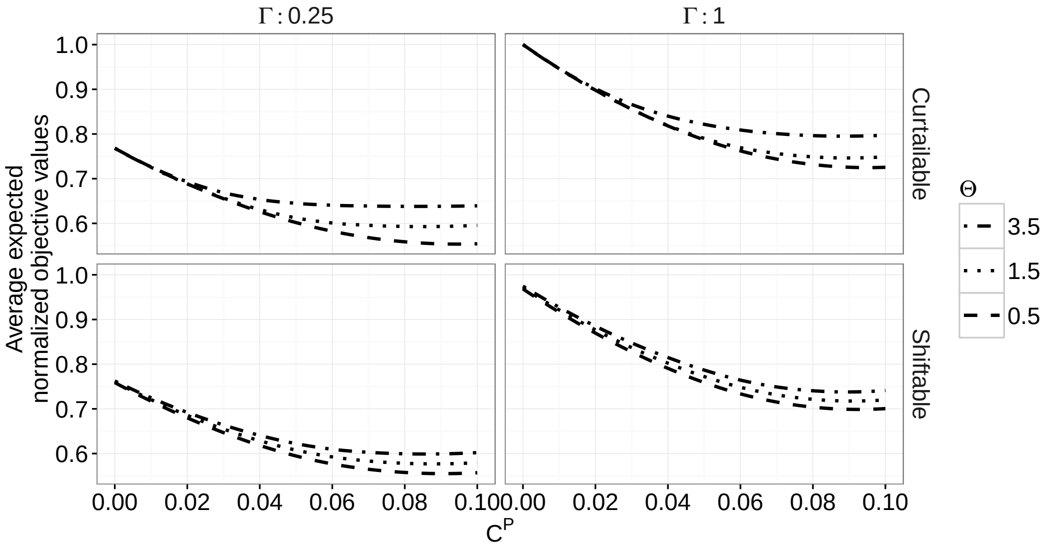

Figure 9.7: Average normalized expected objective values for varying option premiums and availability of renewable supply Γ under the assumption of varying flexibility levels Θ

Naturally, attainable profits are higher for a generation portfolio that contains more renewable generation as the variable cost for RES are assumed to be zero. In the case of curtailable load, the objective values coincide for the case of zero option premium. Here, the optimal discount choice is $\delta^C = 0$, regardless of the flexibility level Θ. Consequently, no curtailable load is contracted. This observation supports the finding that options and curtailable load are natural substitutes. Both incorporate the ability to reduce demand or increase supply up to a predefined limit without catching up on it later on. For shiftable load the objective values are very similar at $C^P = 0$. However, there is some minimal benefit from a more flexible population (higher Θ). Even in case options can be contracted at an option premium of $C^P = 0$, shiftable load can be used to balance generation from forwards and RES which results in even less generation costs.

Of course, the objective value is decreasing in supply flexibility cost (C^P). However, the decrease is less pronounced in the case of greater flexibility level Θ. Generally, the objective value flattens out for higher C^P values as supply side flexibility is replaced by flexible demand. This plateau is reached sooner in the case of higher flexibility levels as less options are contracted and hence the option premiums' impact becomes negligible. Finally, in the case of curtailable load the aggregator generally achieves higher profits than for shiftable load—more shiftable load is used and hence discounts must be set at a higher level to incentivize customers to offer it.

9.6 Discussion

By scheduling flexible demand, an aggregator can avoid costs for conventionally generated electricity which is used to balance uncontrollable and intermittent generation from RES and (formerly) stochastic demand. However, the underlying DR portfolio is decisive for the attainable scheduling result and the corresponding profit. Therefore, such portfolios must be designed carefully. Yet, customers will not offer their flexibility for free. Behavioral and environmental restrictions as a result of DSM must be compensated. Hence, the aggregator needs to design tariffs which contractually regulate the aggregator's customer relationship including the provision of flexible loads and their remuneration. The trade-off between high discounts which ensure the availability of plenty but expensive demand flexibility and contracting supply flexibility is a complex decision making problem that the aggregator must tackle under the uncertainty of future renewable generation. Interestingly, although flexibility tariffs are designed by the aggregator, the commodity traded—which is flexibility in electricity consumption—is sold by the customers.

The part at hand elaborates on both research question 5 and research question 6. The main factors that influence the flexibility provision by customers are discussed in chapter 8. Individual utility maximizing customers are considered. Although concrete drivers of customer utility are identified, e.g., environmental temperature, illumination level, and indoor air quality, current literature mostly applies general utility functions. The utility maximizing customers' reactions to tariff offers are approximated by flexibility response functions. These provide the flexibility a customer is ready to offer given a discount for flexible load—as remuneration for possible future discomfort—and the customers' individual flexibility level—which reflects the customers risk aversion and further nonmonetary factors.

Using the flexibility response functions the complex bi-level tariff design problem is reformulated as a parametric model. This is solved iteratively to elaborate on research question 6, i.e., which tariff characteristics incentivize customers to offer the optimal amount of flexibility by self-selection. The trade-off between contracting flexible demand and options on generation is—in combination with the customers' flexibility level and the availability of generation from RES—the main driver of the optimal discount choice. Section 9.5 provides general insights and strategies in what tariffs maximize the aggregators profit.

To preclude interaction effects, the evaluation focuses on either contracting shiftable or curtailable load. Allowing for simultaneously contracting both flexibility types would substantially impede tariff design. However, the two-dimensional bisection approach facilitates joint optimization of discounts for curtailable and shiftable load. The corresponding two-dimensional objective value levels are illustrated in figure 9.8.

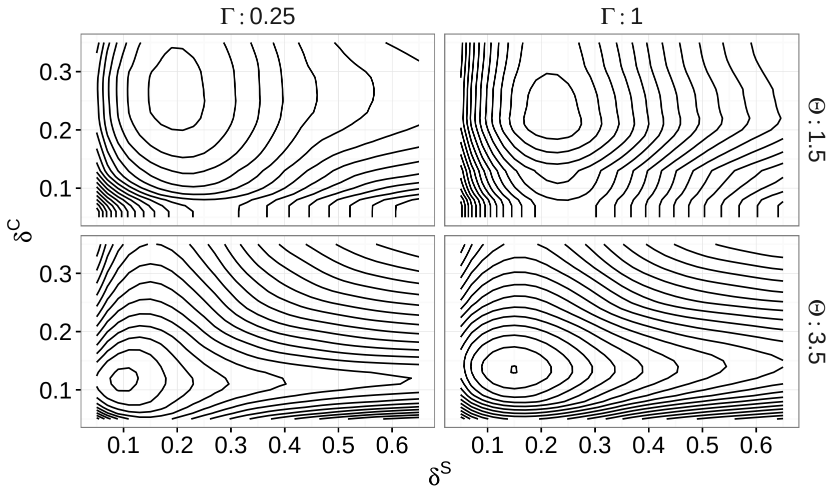

Figure 9.8: Average normalized expected objective values for varying option premiums and availability of renewable supply Γ under the assumption of varying flexibility levels Θ

While these level curves are less tractable than the simple projections described above, some structural aspects of the optimal solutions can be explored. For larger Θ values—flexibility is more readily provided—both optimal curtailing and shifting discounts are reduced. Higher renewable generation capacity Γ leads to slightly increased shifting discounts. For discount on curtailable load no pronounced effect can be observed. This reconfirms the observation that contracting of demand side flexibility is not monotonously increasing in RES availability.

The approach presented in this part can be further extended. In addition to simultaneously optimize discounts on shiftable and curtailable loads, individual and customer specific discounts pose further potentials for profit acceleration. By analyzing individual smart meter readings this would allow for picking raisins out of the customer portfolio and lead to less but more efficient customer contracting. Thereby, the average discount can be further reduced by designing individual contracts instead of considering uniform prices. The consideration of individual customer utility and corresponding flexibility response functions hence facilitates the selection of less but more promising customers for flexibility contracting. This adaption would improve both the aggregator's profit and the overall comfort.

Part V

Finale

10

Conclusion

This dissertation supports the design of flexibility portfolios for DR aggregators. Formerly, electricity generation has been adapted to match uncontrolled and stochastic demand at any time. However, with the constantly growing share of generation from uncontrollable RES the paradigm *supply follows demand* becomes economically infeasible. Instead, supply and demand must complement one another—this requires scheduling of flexible consumption by DSM. However, the attainable scheduling result and the corresponding economic efficiency strongly depend on the underlying customer and generation portfolio. On this account, these portfolios must be designed optimally.

The three pivotal contributions of this work enable aggregators to design such flexibility portfolios. Firstly, properties of end consumer demand flexibility are analyzed. This facilitates the valuation of households' flexibility to an aggregator customer portfolio in terms of avoidable costs of conventionally generated electricity. The evaluation shows that stationary batteries can contribute best to a flexibility portfolio, followed by EVs and electric heating devices. Therefore, an aggregator should try to contract households for DSM that own such appliances. In addition, utilizing devices that require user interaction should be avoided to reduce customer discomfort. Secondly, building on these findings, the optimal composition of both the demand and the supply portfolio is investigated. The results show that aggregators face a trade-off between contracting the different types of demand flexibility, i.e., shiftable and curtailable load. In addition, there is a strong interdependence between contracting DR capacities and conventional generation. Finally, load adaptions come along with environmental and behavioral changes. Hence, customers suffer from discomfort in case they provide flexibility for DSM. The analyses indicate that the optimal choice of discounts that define the flexibility tariffs, strongly depend on environmental conditions that cannot be influenced by the aggregator, e.g., generation flexibility cost or customers' preferences. Therefore, the efficient design of tariffs to incentivize customers to participate in DSM programs is elaborated and strategies for choosing discount levels are derived for varying environmental conditions. The following summary is guided by both the research questions and the thesis structure introduced in chapter 1.

10.1 Summary and Implications

The current design of electricity markets hinders the large scale implementation of DSM. It dates back to times when few but large central power plants fueled by non-renewable resources were responsible for (nearly) the entire electricity generation (Stoft 2002). The ongoing energy transition towards a more sustainable and decentralized generation requires a profound remodeling of electricity markets and regulation. Following a comprehensive discussion of the power system's evolution and literature concerned with past and present challenges in chapter 2, chapter 3 puts forward the need for the redesign of electricity markets along the market engineering framework proposed by Weinhardt, Holtmann, and Neumann (2003). Thereby, this work focuses on the interaction between the design of transaction objects and the agent behavior to allow for achieving an efficient market outcome.

The formation of DR portfolios requires information about the flexibility private households can offer. The availability of DR capacities is mainly driven by technical factors, e.g., the appliance endowment of households, and by customers' preferences, e.g., their risk aversion. To this end, chapter 4 introduces an appliance based model for temporal shifting of demand. With respect to research question 1 this model focuses on technical drivers of flexibility, i.e., load shifting. However, the elicitation of customers' preferences opens up a great future research opportunity. Using empiric data for both supply and demand, the flexibility model is applied in chapter 5 to evaluate the potential contribution of appliances to an aggregator's flexibility portfolio. Knowing a household's appliance endowment, this information is used for answering research question 2 by assessing the value of each customer's flexibility to reduce generation costs. The novel findings of the simulation study show that especially households that own electric heating devices, stationary batteries, or EVs are attractive for DSM. Appliances that require a high amount of user interaction, e.g., dishwashers or washing machines, can hardly contribute to system cost savings. In addition, using such appliances for DSM induces substantial discomfort for the customers and hence this flexibility should not be operationalized in the fist step without the support of automation technology. These findings are of great virtue for aggregators as they strengthen the decision-making basis for contracting by adding information on the value of individual customers to the flexibility portfolio.

Adding one abstraction level by considering customers as a whole instead of on appliance level, chapter 6 presents a model for designing flexibility portfolios. This model fills a gap in literature by incorporating the decisions for both contracting and dispatching of flexibility. To elaborate research questions 3 and 4 the model considers both the supply and the demand side. In this approach a stochastic two-stage program is modeled and implemented. On the first stage, the aggregator must design both the supply portfolio (by procuring forwards and options on future generation) and the demand portfolio (by contracting customers including their flexibility provision). These decisions must be taken under uncertainty of future generation from RES—only generation scenarios are supposed to be known. On the second stage, contracted flexible generation capacities and demand must be scheduled to ensure supply adequacy. The subsequent simulation study in chapter 7 uses empiric data for renewable generation and demand. The results indicate that there is a trade-off between contracting supply and demand flexibility. Hence, both portfolios are driven by exogenous factors, e.g., prices for supply flexibility, the availability of renewable generation, and the cost of demand flexibility. Consequently, contracting options, shiftable load, and curtailable load can be considered to be substitutes. In combination with information on the customers' flexibility, these insights enable aggregators to determine the optimal composition of both the supply and the demand portfolio.

End consumers will potentially suffer discomfort from offering demand flexibility. Therefore, tariffs must be designed that incentivize customers to provide flexibility and remunerate its usage. Elaborating on research question 5, chapter 8 discusses tariff design principles as well as customer utility models from literature. Building on this analysis, the portfolio design model is expanded by the customer perspective. This results in a bi-level optimization approach which on the upper level considers the aggregator's profit maximization (by designing tariffs) and on the lower level each customer's individual utility optimization.

Customers face a trade-off between remuneration payments given by discounts on flexible demand and their perceived discomfort. The latter includes possible load adaptions which induces environmental and behavioral changes as well as risk aversion. Chapter 9 investigates research question 6—namely, the profit maximizing design of tariffs. To this end, an iterative parametric approach is chosen which facilitates the efficient determination of discounts for given exogenous parameters. The evaluation discusses strategies and provides guidance for aggregators to design tariffs. Interestingly, the optimal setting of discounts is strongly driven by environmental conditions, e.g., customers' preferences and generation prices. Hence, such strategies must take the current external preconditions into account and allow for flexible reactions to environmental changes. Furthermore, this innovative approach empowers aggregators to design tariffs in a way that customers provide the optimal amount of DR capacities by self-selection.

10.2 Outlook

The outstanding contribution of this dissertation is an innovative expansion of comprehensively discussed scheduling literature. While the literature on optimal usage of flexibility endowments is ample, there remains a research gap concerning the preceding demand response portfolio design problem. In this work, three novel components are investigated that together allow for designing optimal DR portfolios, i.e., the analysis and valuation of end consumer flexibility, the formation of optimal flexibility portfolios, and the design of tariffs that incentivize customers to provide flexibility for DSM. Nevertheless, there remain various future research opportunities to complement and expand the work at hand.

This work focuses on economic aspects and hence does not consider technical aspects such as ICT and power grid constraints in detail. Further research should allow for incorporating such considerations—especially with respect to distribution grids on which aggregators will operate. Flexibility is investigated with respect to amount (load curtailment) and time (load shifting). From a technical perspective this approach permits additional investigations and improvements. For example, further parameters could be included in the model, e.g., ramping ability and rate of change, response time and responsiveness of customers.

The model of the demand side abstracts from uncertainty in demand. Already in the contracting phase, future consumption and availability of flexibility is assumed to be known.

On the one hand, including uncertainty to the model for electricity consumption and flexibility provision poses a major opportunity for expanding this work. On the other hand, by considering sets of households or electricity cooperatives both security of future consumption and its predictability is increased.

Another possibility to expand this dissertation is to include behavioral aspects and the customers' willingness to provide DR capacities as it is abstracted from these facets. Hence, rather theoretical assumptions on technically available flexibility are taken. This necessitates an empiric study to elaborate the actual availability of flexible demand for DSM and the remuneration payments that would incentivize end consumers to provide it. Possible incentives could obviously include monetary but also nonmonetary components and gamification approaches (Deterding et al. 2011b; Huotari and Hamari 2012). Such an empiric analysis would support the learning of customers' preferences and hence build the foundation for describing a sustainable customer electricity consumption and flexibility utility model.

A further promising opportunity to expand the work at hand is to include long term customer churn management considerations. Contracted flexibility is exploited regardless of the discomfort this implies for customers. This could give raise to an increase in customers' risk aversion and hence reduce the willingness to provide flexibility or even cause customer churn. Therefore, considering long term effects of exploiting flexibility on customer contracting poses an interesting new branch of research (Holyhead, Ramchurn, and Rogers 2015). Furthermore, decision support tools could be developed that promote customer management with respect to various facets, e.g., customer contracting (including flexibility provision), inclusion of customer properties into scheduling decision, design of interfaces to facilitate aggregator-customer interactions, or learning of customer utility functions and preferences.

The flexibility analysis showed that stationary batteries are most suitable for DSM. The trend towards electrified transportation through EVs caused a great push to research aiming at increasing battery efficiency and reducing battery production cost. Therefore, it is likely that in addition to EVs, stationary batteries will also benefit from declining prices and increasing efficiency. This prospect opens the door for developing business models for stationary batteries. Exemplary approaches might include the formation of cooperatives that aggregate battery capacities to conjointly providing reserve power and using arbitrage opportunities by buying electricity when market prices are low and reselling the stored electricity when prices are high. The latter poses a great opportunity as electricity is traded day-ahead and prices are set for the whole consecutive day. Another business model could be to enhance the consumption of (cheaper) locally generated electricity from RES instead of purchasing (rather expensive) electricity sold by utilities.

Current market design and regulation does not support an easy implementation of DSM. There are no transaction objects designed or market platforms available to trade demand flexibility. In addition, each provider of reserve energy—which today typically is a controllable power plant but could prospectively as well be a DR aggregator—must withstand a prequalification procedure conducted by the connecting TSO. Aggregators suffer from both the prequalification procedure which is virtually impossible due to the distributed nature of demand flexibility sources, e.g., private households, and the current minimum reserve energy bid size requirements. Therefore, the market design and the regulatory framework could be revised based on the findings of this work.

Finally, DSM allows for local matching supply and demand. Hence, splitting up national markets into local or regional markets could pose an attractive alternative to cost-intensive investments in transmission grids. The engineering of such local markets evokes a whole set of new research challenges. Not only the local markets themselves must be designed but also mechanisms for interactions between local markets as well as the coupling to superordinate markets. On local markets prices would better reflect the scarcity of resources. This allows for designing innovative marketing strategies and tariffs. In analogy to telecommunication markets, investigating allowances or flat rates in combination with cost caps poses a huge opportunity as on (local) markets with a high penetration of RES marginal costs of generation would fall to zero. Similarly to roaming fees, local markets could also allow for allocating grid usage charges to the actual initiator instead of apportioning them to end consumers.

Appendix

A

Demand Response Benefits and Contracts

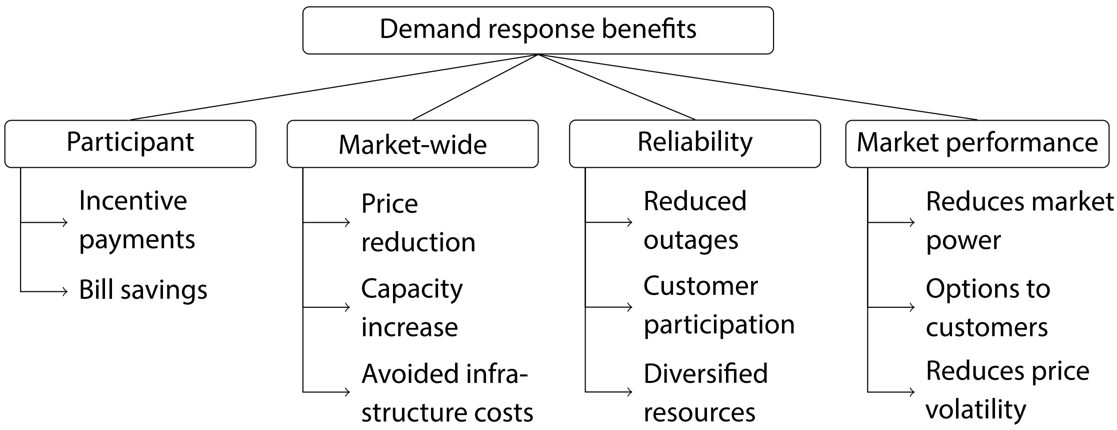

Figure A.1: Benefits of demand response, adapted from Albadi and El-Saadany (2008)

Table A.1: Technical and financial characterization of demand response contracts, adapted from He et al. (2013)

Contract type	Technical features		Financial features				
	Signal form	Signal volatility	Price risk	Volume risk	Com-plexity	Privacy loss	Financial compensation
Time of Use pricing	Price-based	Static	Low	None	Low	None	Limited
Dynamic pricing	Price-based	Dynamic	High	None	High	None	High potential
Fixed load capping	Volume-based	Static	None	Low	High	Limited	Limited
Dynamic load capping	Volume-based	Dynamic	None	High	High	Limited	High potential
Direct load control	Control-based	Predefined	None	None	None	High	Limited/High

B

Overview of Residential Demand Response Models

Table B.1 provides a brief overview of bottom-up residential demand response models presented in literature. This overview is not extensive. A more comprehensive collection of bottom-up domestic demand response models provides Gottwalt (2015), which also served as the main source for the overview at hand. In addition to the appliances presented in part II this overview includes *combined heat and power* (CHP) plants. The collection is split into subgroups with respect to the size of the modeled population , i.e., single households, local populations, and federal populations. For theses groups information about the scenario, the devices that were modeled, the input data, and the coordination approach as well as its objective presented.

Similarly, table B.2 presents a summary of bottom-up load curve reconstitution models that is very comprehensively presented by Grandjean, Adnot, and Binet (2012). Three general types of models are included in the overview, i.e., statistical random models, time of use based models, and probabilistic empirical models. For each source the model input and output is provided. In addition, a brief description of the models objective is presented as well as some information about in what fashion it was validated. For a more comprehensive overview the reader is referred to Grandjean, Adnot, and Binet (2012).

Table B.1: Overview of bottom-up residential demand response models, adapted from Gottwalt (2015)

Type	Reference	Scenario		DR devices		Input Data			Coordination and objective
		Household population	Simulation horizon	Flexible appliances	Future technologies	Consumption statistics	Appliance propperties	Thermal needs	
Single Household	Scott et al. (2013)	1	1 mo.	6	BAT EV	yes	yes	yes	Residential load control by dynamic pricing. Uncertainty in prices, weather and occupant behavior. Use of online stochastic algorithms to assess electricity bill savings
	Allerding (2013)	1	1 yr.	7	CHP	yes	yes	yes	Home energy management for appliances and local generators via evolutionary algorithm to raise self-consumption or reduce electricity bill
Local population	Shinwari, Youssef, and Hamouda (2012)	1,000	1 day	3	EV	yes	yes	no	Decentralized control of dryer, washing machine and EVs via starting time probabilities for peak shaving and valley filling
	Tushar et al. (2014)	200	1 day	2	—	no	yes	no	Direct control of washing machine, dishwasher, dryer, battery and EVs and decentralized control of EV charging to use local generation from RES
Federal population	Guo et al. (2008)	1 Mio.	3 days	1	—	no	yes	yes	Self-adaptive approach for load control of air-conditioning to reduce energy consumption while retaining a stable comfort level.
	Van Den Briel, Scott, and Thiébaux (2013)	2.5 Mio.	1 day	3	EV	no	yes	no	Distributed approach for scheduling of washing machine, dishwasher and dryer operation based on probabilities for start times to achieve a given ideal load

Table B.2: Overview of bottom-up load curve reconstitution models, adapted from Grandjean, Adnot, and Binet (2012)

Type	Reference	Input	Output	Goal	Validation
Statistical random model	Yao and Steemers (2005)	Occupation scenarii	Daily multi end-uses load curves returned at a 1, 5, 15, or 30 min time step corresponding to, from a single household, to an entire community	Support for the design of energy systems including RES. Prediction of the load curve for a selected community	On total load curves
Time of use based model	Walker and Pokoski (1985)	Occupation, activities and end-use scenarii	Daily load curves returned at a 15 min time step for a household (or a sample of households) that is specified with taking into account of the psychological and behavioral influences	Prediction of the load curve as support for the planning of new power generation capacities	On total load curves
Time of use based model	Armstrong et al. (2009)	Occupation and activities scenarii, measured and constructed unitary load cycles, mean annual consumption available at the household and appliances level	Daily load curve for electricity specific appliances returned at a 5 min step for typical households	To get electricity consumption profiles for the modeling of micro-cogeneration devices	On reconstructed load curves for specific electricity appliances
Time of use based model	Widén and Wäckelgård (2010)	Occupation and activities scenarii, measured daily load curves per appliance, and constructed unitary load cycles	Daily load curves returned at a 1–60 min time step for a household and possible aggregation to get results at a larger scale	Support for studies on electricity production at the household level	On total load curves
Probabilistic empirical model	Paatero and Lund (2006)	Daily load curves measured at the household level, constructed unitary load cycles, daily consumptions measured at the household level	Daily load curve at a 60 min time step for a household and possible aggregation at a larger scale	To get accurate domestic electricity consumption data to identify the impact of DSM measures	On total load curve and household's consumption

C

Flexibility Valuation Model

The objective function consists of four components, i.e., gas turbine generation costs, costs from procuring reserve power from the electricity market, an end-of-day EV storage reward, and an end-of-day stationary battery storage reward (the latter ones to bridge intra-day flexibility):

$$\min_{x^R, x^A, \phi, s^T, s^M} \sum_{t \in \mathcal{T}} \left(c_t^T(s_t^T) + c_t^M(s_t^M) \right) - \Xi \sum_{v \in \mathcal{V}} \psi_{v,|\mathcal{T}|} \overline{\Psi}_v - \Xi \sum_{b \in \mathcal{B}} \psi_{b,|\mathcal{T}|} \overline{\Psi}_b.$$

The supply sufficiency constraint ensures that total supply exceeds total demand at all times:

$$0 \geq \sum_{a \in \mathcal{A}} l_{a,t}^A + \sum_{v \in \mathcal{V}} \phi_{v,t} + \sum_{b \in \mathcal{B}} \phi_{b,t} - R_t - s_t^T - s_t^M \qquad \forall t \in \mathcal{T}.$$

The constraints for modeling the supply side mainly limit the gas turbines output and provide the formula to calculate the variable generation costs:

$$\begin{aligned} 0 &\geq s_t^T - \kappa && \forall t \in \mathcal{T} \\ 0 &= c_t^T - 0.0147 s_t^T + 0.0028 \kappa \mathbb{1}_{(s_t^T > 0)} - 0.06944 r_t \kappa && \forall t \in \mathcal{T}. \end{aligned}$$

To model the fact that the gas turbine must run with at least 40 % of its maximal output, semi-continuous decision variables are used:

$$0 = s_t^T \quad \vee \quad 0.4 \leq s_t^T \qquad \forall t \in \mathcal{T}.$$

Finally, to describe the demand side flexibility characteristics, the household appliance model is applied:

s.t.

$$
\begin{aligned}
&1 = \sum_{t=S_r^R}^{E_r^R - |\rho_r|} x_{r,t}^R && \forall r \in \mathcal{R}_a \; \forall a \in \mathcal{A}^S \\
&0 = l_{a,t}^A - \sum_{s=1}^{t} x_{r,t}^R \tilde{\rho}_r(t+1-s) && \forall t \in \mathcal{T} \; \forall a \in \mathcal{A}^S \\
&1 = \sum_{t=S_r^R}^{E_r^R} x_{a,t}^A && \forall r \in \mathcal{R}_a \; \forall a \in \mathcal{A}^C \\
&0 = l_{a,t}^A - x_{a,t}^A \rho && \forall t \in \mathcal{T} \; \forall a \in \mathcal{A}^C \\
&0 = \overline{\rho}_r - \sum_{t=S_r^R}^{E_r^R} x_{a,t}^A \rho && \forall r \in \mathcal{R}_a \; \forall a \in \mathcal{A}^H \\
&0 \geq \lceil \hat{\rho} \overline{\rho}_r \rceil - \sum_{t=S_r^R}^{\lfloor \hat{T} E_r^R \rfloor} x_{a,t}^A \rho && \forall r \in \mathcal{R}_a \; \forall a \in \mathcal{A}^H \\
&0 = l_{a,t}^A - x_{a,t}^A \rho && \forall t \in \mathcal{T} \; \forall a \in \mathcal{A}^H \\
&0 \leq \phi_{v,t} && \forall t \in \mathcal{T} \; \forall v \in \mathcal{V} \\
&0 \leq \hat{\Phi}_{v,t} \overline{\Phi}_v - \phi_{v,t} && \forall t \in \mathcal{T} \; \forall v \in \mathcal{V} \\
&0 = \psi_{v,t} \overline{\Psi}_v - \psi_{v,t-1} \overline{\Psi}_v - \phi_{v,t} + \Phi_{v,t} && \forall t \in \mathcal{T} \; \forall v \in \mathcal{V} \\
&0 \leq \phi_{b,t} - \underline{\Phi}_b && \forall t \in \mathcal{T} \; \forall b \in \mathcal{B} \\
&0 \leq \overline{\Phi}_b - \phi_{b,t} && \forall t \in \mathcal{T} \; \forall b \in \mathcal{B} \\
&0 = \psi_{b,t} \overline{\Psi}_b - \psi_{b,t-1} \overline{\Psi}_b - \phi_{b,t} && \forall t \in \mathcal{T} \; \forall v \in \mathcal{B}.
\end{aligned}
$$

D

Portfolio and Tariff Design Model

The goal of designing DR portfolios is to allow for efficiently scheduling of flexible demand. The attainable scheduling result critically hinges on the underlying customer portfolio—including flexibility provisions—that an aggregator should manage actively. A profit maximizing aggregator that, firstly, builds its customer portfolio and then, secondly, dispatches flexible supply and demand is considered. Hence, the objective function consists of four profit components: revenues from served base load, shiftable load, curtailable load, and costs for conventional power generation:

$$\max_{x^P,x^S,x^C,y^F,y^O,a^{SR},a^C,s^F,s^O,s^M} \sum_{\omega\in\Omega} p_\omega \left(\pi^{bL}_\omega + \pi^{sL}_\omega + \pi^{cL}_\omega - c^G_\omega\right).$$

Maximizing its profit, the aggregator must ensure supply adequacy at any time:

$$\begin{aligned} &s^F_{\omega,t} + s^O_{\omega,t} + s^M_{\omega,t} + R_{\omega,t} \\ &\quad \geq \sum_{c\in C} \left(x^P_c D^B_{c,t} + (x^P_c - x^S_c) D^S_{c,t} + (x^P_c - x^C_c) D^C_{c,t} + a^S_{\omega,c,t} + a^C_{\omega,c,t}\right), \forall \omega \in \Omega\ \forall t \in \mathcal{T}. \end{aligned}$$

The profit and cost components are calculated by:

$$\pi_\omega^{bL} = P \sum_{c\in\mathcal{C}} \sum_{t\in\mathcal{T}} \left(x_c^P D_{c,t}^B + (x_c^P - x^S{}_c) D_{c,t}^S + (x_c^P - x_c^C) D_{c,t}^C \right) \qquad \forall \omega \in \Omega$$

$$\pi_\omega^{sL} = \sum_{c\in\mathcal{C}} \left((1-\delta_c^S) P \sum_{t\in\mathcal{T}} a_{\omega,c,t}^S \right) - c_\omega^\varsigma \qquad \forall \omega \in \Omega$$

$$c_\omega^\varsigma = \sum_{c\in\mathcal{C}} \sum_{t\in\mathcal{T}} \sum_{s\in\mathcal{T}} c^\varsigma(t,s) a_{\omega,c,s,t}^{SR} \qquad \forall \omega \in \Omega$$

$$\pi_\omega^{cL} = \sum_{c\in\mathcal{C}} \left((1-\delta_c^C) P \sum_{t\in\mathcal{T}} a_{\omega,c,t}^C \right) \qquad \forall \omega \in \Omega$$

$$c_\omega^G = |T| C^F y^F + |T| C^P y^O + \sum_{t\in\mathcal{T}} \left(C^O s_{\omega,t}^O + C^M s_{\omega,t}^M \right) \qquad \forall \omega \in \Omega.$$

The supply model considers all controllable types of generation that are constrained by first optimization stage decisions, i.e., forwards and options. On the second stage, forwards are delivered exactly as contracted on the first optimization stage. Options can be called up to the amount that was primarily contracted:

$$s_{\omega,t}^F = y^F \qquad \forall \omega \in \Omega \, \forall t \in \mathcal{T}$$

$$s_{\omega,t}^O \leq y^O \qquad \forall \omega \in \Omega \, \forall t \in \mathcal{T}.$$

Finally, the two-stage demand side flexibility model is given by the constraints for shiftable and curtailable load:

$$0 = \sum_{t\in\mathcal{T}} a_{\omega,c,t}^S - \sum_{t\in\mathcal{T}} x_c^S D_{c,t}^S \qquad \forall \omega \in \Omega \, \forall c \in \mathcal{C}$$

$$0 = \sum_{s\in\mathcal{T}} a_{\omega,c,t,s}^{SR} - x_c^S D_{c,t}^S \qquad \forall \omega \in \Omega \, \forall c \in \mathcal{C} \, \forall t \in \mathcal{T}$$

$$0 = a_{\omega,c,t}^S - \sum_{s\in\mathcal{T}} a_{\omega,c,s,t}^{SR} \qquad \forall \omega \in \Omega \, \forall c \in \mathcal{C} \, \forall t \in \mathcal{T}$$

$$0 \geq a_{\omega,c,t}^C - x_c^C D_{c,t}^C \qquad \forall \omega \in \Omega \, \forall c \in \mathcal{C} \, \forall t \in \mathcal{T}$$

$$0 \leq \sum_{t\in\mathcal{T}} a_{\omega,c,t}^C - \sum_{t\in\mathcal{T}} x_c^C (1-\overline{\gamma}_c^C) D_{c,t}^C \qquad \forall \omega \in \Omega \, \forall c \in \mathcal{C}.$$

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