Market-based Allocation of Local Flexibility in Smart Grids

A Mechanism Design Approach

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List of Abbreviations

AE	Allocative Efficiency
AI	Artificial Intelligence
AMI	Advanced Metering Infrastructure
BB	Budget Balance
BDEW	German Association of Energy and Water Industries
BMWi	German Federal Ministry for Economic Affairs and Energy
BPO	Bidder-Pareto-Optimal
BRP	Balancing Responsible Party
CAP	Combinatorial Auction Problem
CBL	Compact Bidding Language
CCG	Core Constraint Generation
CHP	Combined Heat and Power
DER	Distributed Energy Resources
DLC	Direct Load Control
DR	Demand Response
DRM	Direct-revelation mechanism
DSM	Demand Side Management
DSO	Distribution System Operator
DSR	Design Science Research
DSS	Decision Support System
EBPO	Equitable Bidder-Pareto-Optimal
EC	European Commission
EEX	European Energy Exchange
EnWG	German Energy Industry Act
EPEX SPOT	European Power Exchange
ESO	European Standardization Organization
ETS	Emissions Trading Scheme
EU	European Union
EV	Electric Vehicle
FC	Flexibility Characteristics

GDP	Gross Domestic Product
GHG	Greenhouse Gas
GUI	Graphical User Interface
HVDC	High Voltage Direct Current
IC	Incentive Compatibility
ICT	Information and Communication Technology
IEM	Internal Energy Market
IR	Individual Rationality
ISO	Independent System Operator
IT	Information Technology
MC	Monte Carlo
ME	Market Engineering
MIP	Mixed Integer Problem
MU	Monetary Unit
NE	Nash Equilibrium
OO	Outside Option
OTC	Over-the-Counter
P2P	Peer-to-Peer
PAB	Pay-as-Bid
PF	Price Fairness
PV	Photovoltaic
QoS	Quality of Service
RCAP	Reverse Combinatorial Auction Problem
RES	Renewable Energy Sources
SEP	Core Constraint Separation Problem
SGCG	Smart Grid Coordination Group
SGTF	Smart Grid Task Force
SME	Small and Medium-Sized Enterprises
SPP	Set Packing Problem
TFEU	Treaty on the Functioning of the European Union
TLC	Traffic Light Concept
TOU	Time of Use
TSO	Transmission System Operator
TU	Time Unit
UML	Unified Modeling Language
US	United States
V2G	Vehicle to Grid
VCG	Vickrey-Clarke-Groves

VPN	Virtual Private Network
VPP	Virtual Power Plant
WDP	Winner Determination Problem

List of Symbols

Indices

i	Agent
j	Bid

Parameters

M	Number of bid indices
N	Number of agents
T	Number of time slots

Variables

a	Bid delivery amount
$\overline{a}$	Bid maximum delivery amount
$\underline{a}$	Bid minimum delivery amount
b	Bid price
$\mathcal{C}$	Coalition
c	Cost
d	Heterogeneity level
δ	Deviation
E	Expectation
e	Set of bids
ϵ	Payment scalar
$\mathcal{G}$	Set of products
g	Product
Γ	Set of outside option prices
γ	Outside option price
h	Transfer
$\mathcal{I}$	Set of agents

$\mathcal{J}$	Set of bid indices
$\mathcal{K}$	Set of choices
k	k-Pricing factor
κ	Choice, allocation
l	Minimum runtime
λ	Pricing function
$\mathcal{M}$	Mechanism
m	Outcome
$\mathcal{O}$	Set of outcomes
o	Outcome
ω	Equitable Bidder-Pareto-optimal core payments
p	Payment
ϕ	Bid delivery direction
Ψ	Set of outside option amounts
ψ	Outside option amount
q	Coalitional contribution
$\mathcal{R}$	Set of outside option providers
r	Outside option provider
ρ	Payment
S	Bundle
s	Strategy
σ	Bid delivery start time
$\mathcal{S}$	Set of strategies
sw	Social welfare
$\mathcal{T}$	Set of time slots
t	Time slot
τ	Iteration
Θ	Set of agent types
θ	Agent type
$\hat{\theta}$	Reported agent type
$\mathcal{U}$	Set of utility functions
u	Utility
Υ	Savings
v	Valuation

$\hat{v}$	Reported valuation
$\mathcal{W}$	Set of winners
$\mathcal{X}$	Set of allocations
x	Allocation
ξ	Runtime
z	Core constraint separation
ζ	Allocation

Part I

Introduction and Foundations

1

Introduction

The share of renewable energy sources (RES) is continuously increasing in today's electricity mix. Substantially driving factors are the ambitious goals in Europe as proposed by the European Union (EU) as part of the Energy Union strategy (EC 2015c) and by the national government in Germany (BMWi 2015a). By 2030, at least 27 % of the electricity consumption is supposed to originate from RES on a European level (EC 2015a). However, the European Commission (EC) notes that both the supply and the demand side are not sufficiently flexible to accommodate the increasing share of RES in current markets (EC 2015a). Hence, the balance of supply and demand in the midst of RES cannot be guaranteed at all times. This endangers security of supply and thus increases the probability of blackouts. In this context, demand response (DR) provides a means to resolve imbalances by fully integrating existing and new market players — including flexible demand, energy service providers, and generation from RES (Strbac 2008; EC 2015a). Moreover, to increase participation of flexible consumers in electricity markets, intermediaries such as aggregators need to assume the role of energy service providers to contribute to a successful transition of the energy system (EC 2015b).

Focusing on Germany, where distribution grid lines account for about 98 % of the power grid lines and about 90 % of RES are connected to distribution grids (BMWi 2015a), distribution system operators (DSOs) are faced with new challenges of balancing fluctuating generation from RES with an increasing consumption. However, current distribution grids were not designed with the integration of RES in mind. Instead, electricity is supposed to flow from large centralized power plants located in transmission grids to consumers located in distribution grids in a one-way and top-down manner. Nevertheless, RES can reverse the flow of electricity, which then needs to be fed from low voltage distribution grids into high voltage transmission grids, resulting in a paradigm shift towards a two-way bottom-up electricity grid (SG-CG 2014a). As a result, RES can bring capacities of current distribution grid resources, i.e., power lines and transformer stations, to their limits. Consequently, congestions in such grid resources can endanger grid stability and security of supply. In order to avoid or resolve critical grid situations in specific local areas in a short-term manner and in turn ensure security of supply, DSOs need to perform a more active, decentralized, and local grid management (BMWi 2015a). In this context, smart grids play a key role in transforming current grids to allow for the monitoring and control of low voltage distribution grid levels by means of information and communication technology (ICT) (Farhangi 2010). In smart grids, DSOs can then make use of flexibility management, i.e., the combination of demand flexibility and storage technology from consumers or prosumers, to support grid stability through market-based approaches (SG-CG 2014a; SGTF 2015). In contrast, current grid stabilization methods, such as the control reserve, represent costly emergency alternatives. The 2015 numbers for the cost of ensuring security of supply in Germany by means of redispatch and control reserve measures amounted to a record high of about one billion euro (Braune 2016). To avoid unnecessary cost of emergency measures and intelligently exploit flexibility of new, local, and so far inactive players on the demand side, the implementation of flexibility management can profoundly support this goal. As highlighted by the EC,

> [a] necessary step to achieve a successful and least-cost integration of renewables is through well-functioning short-term electricity markets, running [...] right up to the moment of consumption, which give full access to flexible technologies (EC 2015a, p. 3).

In this spirit, the work at hand proposes a smart grid flexibility auction as such a market mechanism to address the issue of ensuring short-term grid stability within distribution grids. The flexibility auction can provide the means for the DSO to procure and in turn utilize flexibility from aggregators in a short-term setting to avoid critical grid situations. Aggregators bundle and act on behalf of consumers, producers, or prosumers as the combination of both in order to bring a critical mass of flexibility to the market. Moreover, the use of the flexibility auction allows to reduce the cost of employing emergency measures.

The main objective of this dissertation is the design, prototypical implementation, and evaluation of a market mechanism that enables the DSO to allocate electric load flexibility from aggregators in a local context in order to cope with the continuous integration of RES into the smart grid.

This work employs the market engineering (ME) approach (Weinhardt, Holtmann, and Neumann 2003), which allows to capture both the technical as well as economic requirements and objectives for the flexibility auction. Moreover, the approach provides a structured procedure to design and implement markets. Within the ME framework, this work in particular focuses on the market microstructure, which defines the market mechanism with bidding language, allocation, and pricing rules. In addition, the design of the flexibility auction artifact is conducted in accordance with the design science research (DSR) paradigm (Hevner et al. 2004). DSR targets the construction and evaluation of information technology (IT) artifacts and allows to rigorously demonstrate the utility, quality, and efficacy of a design artifact via well-executed evaluation methods (Hevner et al. 2004; Gregor and Jones 2007).

1.1 Research Outline

The central question of this dissertation is how a market mechanism for allocating flexibility in context of the smart grid can be designed. Such a market mechanism not only needs to satisfy classical economic requirements but also consider characteristics of domain-specific nature. Consequently, the first research question aims at defining the characteristics of load flexibility as well as desired economic and technical requirements and is formulated as follows:

Research Question 1 ‹ Environmental Analysis ›. *What are the characteristics of electric load flexibility, and what are resulting economic as well as technical requirements for a mechanism to integrate this flexibility into the smart grid?*

This research question is addressed by performing a literature review of domain-specific and theoretical works. Based on the literature review and identified requirements, definitions for the fundamental concepts related to the smart grid and to mechanism design are provided.

Having established the fundamentals for the design of the market mechanism, the following research questions focus on the main contribution of this work. Consequently, the second research question is concerned with the design of a market mechanism for allocating flexibility in context of the smart grid.

Research Question 2 ‹ Design of an Electric Load Flexibility Auction ›. *Which market mechanism meets the identified requirements for allocating flexible loads in the Smart Grid?*

This research question is addressed by firstly introducing auctions as a suitable mechanism implementation. Subsequently, the main contribution of this work — the design of a smart grid flexibility auction in a reverse combinatorial setting with unit prices and considering an outside option — is introduced. More specifically, a formal definition of the novel auction mechanism of this work is provided. Moreover, the flexibility auction constitutes a DSR artifact. Furthermore, the sequence of the auction process is described and illustrated.

Based on the definition of the flexibility auction model, the third research question addresses the issue of in what fashion participating aggregators can specify their flexibility as bids in the bidding language of the flexibility auction.

Research Question 3 ‹ Bidding Language ›. *Which bidding language can succinctly express electric load flexibility offers in a market environment?*

This research question is addressed by firstly reviewing existing literature. Based on the existing literature, a bidding language that can capture pooled flexibility of aggregators in a compact manner is designed. With both the auction model and the bidding language at hand, the winner determination problem (WDP) is specified as a subsequent step.

To complete the flexibility auction mechanism, a pricing rule needs to be specified. The pricing rule needs to ensure that the cost of the DSO are not unacceptably high, i.e., payments to aggregators need to be minimal. Moreover, resulting prices need to be fair for aggregators (bidders) in the sense that no losing coalition of aggregators can object the outcome of the auction and propose a mutually beneficial outcome for both the aggregators and the DSO. Accordingly, the following research question states the challenge regarding the pricing rule to be addressed in this work.

Research Question 4 ‹ Pricing Rules ›. *Which pricing rules can reduce the cost for the distribution system operator (DSO) and increase the perceived fairness of prices?*

In order to address this research question and to meet the identified requirements, several pricing rules are applied to the flexibility auction model. While the classical pricing rules such as pay-as-bid (PAB), k-pricing and Vickrey-Clarke-Groves (VCG) with the Clarke pivot rule serve as a benchmark for evaluation purposes, the contribution in context of this research question represents the application of core pricing to the reverse combinatorial auction setting with unit prices and an outside option of the flexibility auction. Core pricing in particular focuses on the perceived fairness of prices and ensures that the payments of the DSO as the auctioneer are not prohibitively large as they may be under VCG with the Clarke pivot rule (Day and Raghavan 2007).

Subsequently, the auction is implemented into a prototypical software system. The DSR approach requires the application of rigorous methods to the evaluation of software artifacts. Therefore, an experimental evaluation is performed. Simulation experiments constitute a method for an experimental evaluation in the context of DSR (Hevner et al. 2004). Hence, the following research questions deal with the evaluation of the proposed flexibility auction.

Research Question 5 ‹ Economic Evaluation ›. *What are the effects of different pricing rules on DSO payments and price fairness?*

This research question is addressed by conducting empirical simulation experiments, based on real-world data for wind and solar generation as well as balancing energy prices. Moreover, scenarios of varying complexity are defined and evaluated. The main evaluation metric describes the payments of the DSO to winning aggregators in the auction, i.e., the cost of the DSO, which are investigated with respect to different pricing rules. The goal is to show the potential for cost reduction compared to today's balancing cost by employing the flexibility auction.

As the format of the proposed auction is of combinatorial nature, the WDP is NP-hard. This also applies to several introduced pricing rules. Therefore, the empirical computational hardness of the auction needs to be assessed for realistic problem instances in addition to the economic evaluation. Therefore, the following research question deals with the computational evaluation of the flexibility auction.

Research Question 6 ‹ Computational Evaluation ›. *What is the empirical computational hardness of the proposed market design?*

This final research question is addressed by measuring the empirical computational hardness of the auction. The results of the analysis allow to reason about the real-world applicability of the auction.

1.2 Structure

The outline of this dissertation is structured as illustrated in figure 1.1. The work is structured into four parts. Part I provides the foundations for this work and introduces the basics on smart grid and market design in chapters 2 and 3. An application of the market engineering approach in context of the smart grid, which connects both previous introductory chapters, is provided in chapter 4. Part II introduces the design of the smart grid flexibility auction and constitutes the main contribution of this work. Within this part, chapter 5 introduces the allocation rule and bidding language. Subsequently, chapter 6 presents the pricing rules. Within part III, the implementation of the flexibility auction into a prototypical software system as well as its evaluation are presented. Chapter 7 describes the simulation design and metrics for evaluating the proposed artifact and research questions. In turn, chapter 8 presents and analyzes results of the simulation with regard to the defined metrics and research questions. Finally, part IV with chapter 9 concludes this work by summarizing the key contributions and pointing towards further research challenges and open questions.

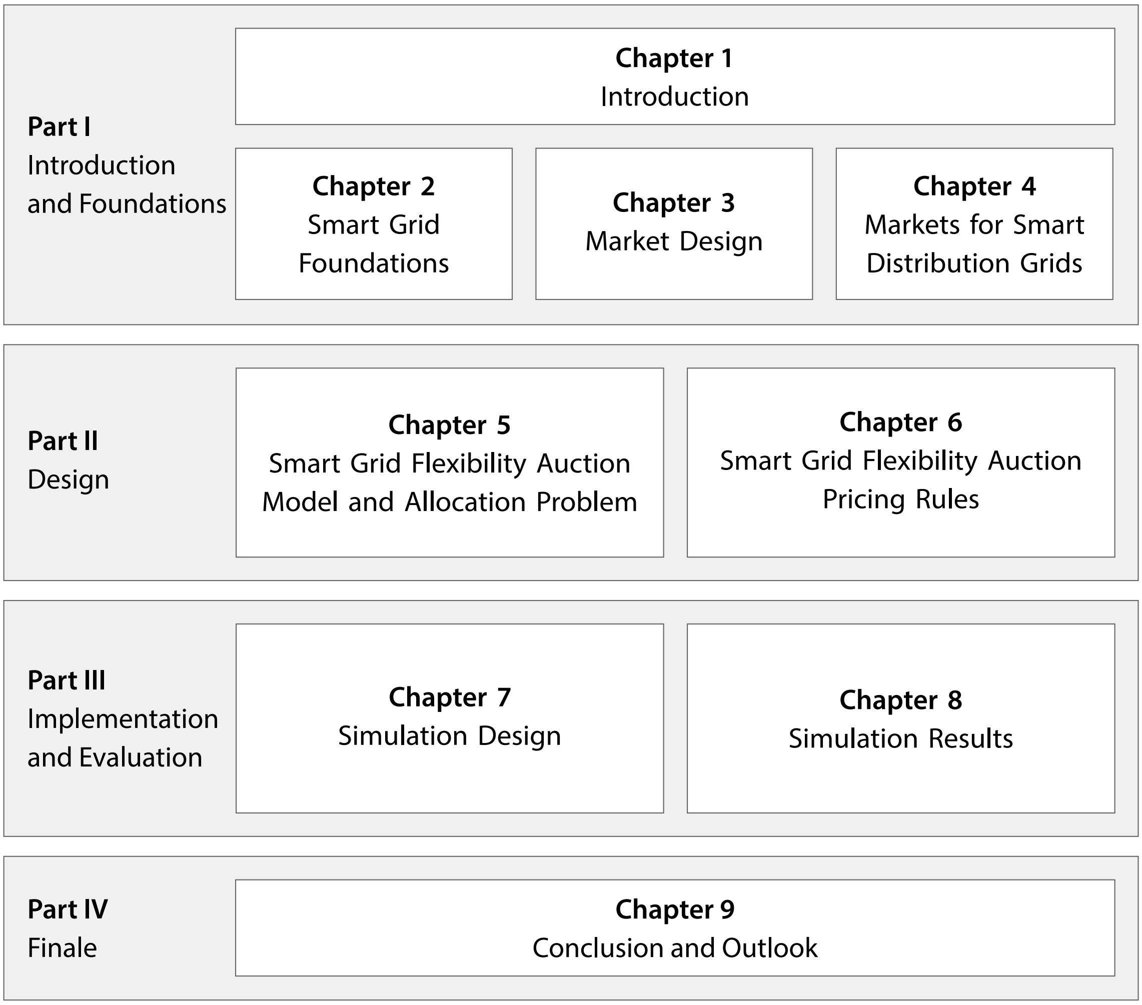


Figure 1.1: Structure of this work

2

Smart Grid Foundations

Today's electrical power system is an integral and one of the most effective parts of modern society's infrastructure and economy. In order to ensure security of supply, generation, transmission, and distribution of electricity have traditionally been organized in a highly integrated, centrally planned, unidirectional, and top-down manner. This is due to the fact that electricity is not storable and thus requires that generation and consumption of electricity be balanced at all times (Stoft 2002). However, the recent fundamental paradigm shift towards decentralized and inherently intermittent generation of renewable energy sources (RES) and distributed energy resources (DER) and the associated bi-directional flow of electricity pose new challenges to ensuring security of supply in a technical, economic, and sustainable way. This leads to the rise of the smart grid, the next-generation electric power system as a means to help balance supply and demand by intelligently integrating RES and flexible loads into power grids.

This chapter briefly introduces the current state and trends of today's electrical power system and gives insight into the nature and characteristics of the smart grid required for a subsequent classification of the market mechanism.

The structure of this chapter is as follows: Firstly, current and future policy goals from the perspectives of the European Union (EU) and Germany, respectively, are introduced. Subsequently, the current electricity market structure with focus on the EU and Germany as a prime example due to the prominent ongoing transition of the power system (*Energiewende*) is introduced. Finally, the concept of the smart grid with its key components of relevance for this work, that is flexibility, demand side management (DSM), and demand response (DR) as well as aggregators, are described.

2.1 Energy Policy

Energy policy and related legislative decisions in Germany are influenced not only by national activities, but also by EU directives affecting every EU member state. Thus, this section introduces current goals of the EU and Germany and gives an outlook on ongoing consultation processes.

2.1.1 European Policy

The basis for the EU energy policy is defined in article 194 (1) of the treaty on the functioning of the European Union (TFEU), which places EU energy policy decisions under an obligation to: "(i) ensure the functioning of the energy market; (ii) ensure security of energy supply in the Union; (iii) promote energy efficiency and energy saving and the development of new and renewable forms of energy; and (iv) promote the interconnection of energy networks " (EC 2012a). Accordingly, the European Commission (EC) began the process of provisioning three sequential *energy packages*, which are, among other EU directives, referred to in section 2.2.2.1 of this chapter. In addition, complementary agendas and legal frameworks with focus on climate change and sustainability policies as well as security of supply were established. These frameworks are subject of the following sections 2.1.1.1 and 2.1.1.2.

2.1.1.1 Current Situation

The establishment and implementation of a long-term secure, renewable, sustainable, and competitive supply of electricity are the main objectives of EU energy policy. For this purpose, the EU officially communicated its ambitious 20-20-20 targets in early 2008 with the main goal of tackling important climate change and sustainability issues of carbon emissions, renewable energy, and energy efficiency (EC 2008). Not only are these targets still relevant and well-known today, they also represent a consensus among member states to further reduce greenhouse gas (GHG) emissions and increase the share of RES in the electricity consumption.

In more detail, the main targets are: (i) the reduction of GHG emissions to at least 20 % by 2020 compared to the levels of 1990, which is equivalent to a 14 % reduction compared to 2005 levels. By 2050, GHG emissions must be reduced to at least 50 %; (ii) increasing the share of RES in the EU energy mix to at least 20 % by 2020; and (iii) increasing energy efficiency by 20 %. To realize the GHG reduction target, two approaches which are supposed to work in parallel were established. Firstly, the Emissions Trading Scheme (ETS), a large-scale CO_2 emissions trading system originating from directive 2003/87/EC was set up (EPEC 2003b). A detailed description and analysis of its process, allocation rules, and results of completed trading periods can be found in Ellerman and Buchner (2007) and Zhang and Wei (2010). Secondly, emissions from industry, agriculture, buildings, and transport which are not affected by the ETS were covered by a non-ETS target to reduce emissions known as the *effort sharing decision*, i.e., decision 406/2009/EC (EPEC 2009a). The main idea of the effort sharing decision is that each EU member state contributes to the GHG reduction target according to its individual capability. In more detail, the individual extend of the contribution is measured by the gross domestic product (GDP) per capita index (Harmsen, Eichhammer, and Wesselink 2011).

Having recognized the importance of GHG reductions, the EU additionally promotes the integration and use of RES with the *renewable energy directive* 2009/28/EC (EPEC 2009b). This directive in particular tackles five main issues. Specifically, the directive establishes mandatory national targets for 2020, renewable energy actions plans, cooperation mechanisms, administrative, and regulatory reforms as well as sustainability criteria for biofuels (Howes 2010).

Within the previous directives of the climate package, primary focus was unquestionably on climate policy. At the same time, topics on security of supply and competitive electricity prices came in second line. However, the *security of supply directive* 2005/89/EC (EPEC 2005) specifies measures in its scope towards "safeguarding security of electricity supply so as to ensure the proper functioning of the internal market for electricity and to ensure: (i) an adequate level of generation capacity; (ii) an adequate balance between supply and demand; and (iii) an appropriate level of interconnection between Member States for the development of the internal market ". Moreover, it requires member states to define stable, transparent, and non-discriminatory policies compatible with an internal energy market (IEM).

For a more in-depth analysis of EU communications, decisions, directives, and their chronology regarding climate policy, the inclined reader is referred to Oberthür and Pallemaerts (2010).

2.1.1.2 Latest Developments

In 2010, the EU recognized that its "existing strategy is currently unlikely to achieve all the 2020 targets" while short and long-term challenges continue to grow (EC 2010). For this reason, a commitment towards a new *Energy 2020* strategy for competitive, sustainable, and secure energy was proposed. Building upon prior consultations, actions, and policy, five priorities for the new energy strategy have been identified (EC 2010): (i) Advancing energy efficiency in Europe to achieve the 20 % savings goal in 2020 and in addition ensuring long-term energy and climate goals. Reinforced political commitment, new policies for buildings and transport represent main concerns within this priority; (ii) building a fully integrated, interconnected, and competitive European energy market to foster pan-European trade of renewable energy. Main factors will be grid infrastructure investments and developments as well as the construction of new interconnections between EU member states; (iii) allowing consumers to benefit from a wider choice of suppliers and lower prices while ensuring the highest level of safety and security possible. Raising awareness among consumer, building "user-friendly" smart grids and smart meters as well as improving information on energy bills shall serve as main action points; (iv) developing Europe's capabilities to lead in energy technology and innovation by supporting large-scale development and demonstration projects in several domains such as smart grids, smart cities or electricity storage, between member states; and (v) improving the external partnerships of the EU energy market to allow the participation of EU neighbors in the IEM, to promote the role of the EU in energy efficiency and sustainability, and to facilitate international cooperation on nuclear-safety topics.

More recently, notable progress has been made towards the three 20-20-20 targets (EC 2014a, 2015e). Meanwhile, the EC started to collect feedback on past individual as well as global economic and environmental developments and subsequently to reflect on these and its own views in 2014. Based on identified assets and drawbacks, a 2030 climate and energy policy framework was developed (EC 2014a). The main principles of the 2030 framework cover the GHG emissions target, a reformed ETS, an EU-wide renewable energy target, measures for an improved energy efficiency, advances to further foster competition on the IEM and securing energy supply. More particularly, a 40 % reduction of GHG emissions as well as a share of at least 27 % of RES in the EU are significant objectives within the 2030 framework (EC 2014a). Additionally, based on the *energy efficiency directive* (EPEC 2012), an increased energy efficiency to at least 27 % by 2030 was set.

In accordance with the 2020 climate and energy package and the 2030 climate and energy framework, several actions were proposed recently. In 2014, the *energy security strategy* was set out to address short to long-term energy security concerns (EC 2014b). On a more global level, the *energy union package* (EC 2015c) represents the most complete policy strategy framework yet to propose the shift from many national regulatory frameworks into an unified framework. The energy union package identifies several dimensions required for greater energy security, sustainability, and competitiveness. In its appendix, a roadmap which covers all relevant actions for the coming years is specified (EC 2015d).

2.1.2 German Policy

The *energy concept* of the German federal government serves as a detailed foundation for energy policy and strategy (BMWi 2010). In the following, the key interconnected goals of the energy trilemma as well as parts of the German energy concept are introduced.

2.1.2.1 Energy Trilemma

Economic and political guidance and strategy in today's energy sector in Germany rely on the fundamental trade-off between three established key goals: competitiveness, security of supply, and sustainability. In line with the strategy of the EC (EC 2006), the German Energy Industry Act (§ 1 (1) EnWG) places the country in its preamble under an analogous obligation to align economic and policy decisions with these goals. These goals or objectives are usually illustrated as the energy policy objectives triangle, or following a more recently introduced expression by Sautter, Landis, and Dworkin (2008), as the Energy Trilemma (cp. figure 2.1).

Ideally, all objectives should be considered for economic and policy assessments. However, these policy objectives are often correlated to a certain degree. To some extend, there exists a clear conflict of objectives for different players in the energy sector. For this reason, careful balancing of these objectives is required to avoid counter-productive or negative effects of the objectives on each other. For example, (i) increasing the share of sustainable generation may implicate a decrease in security of supply as such generation is usually intermittent and

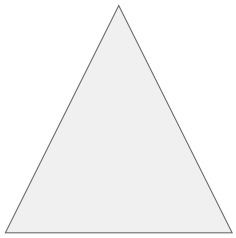


Figure 2.1: Energy Trilemma

thus not entirely reliable; (ii) a higher environmental sustainability or increase in security of supply may result in higher prices for consumers; and (iii) a sole focus on competitiveness may entail less devotion and effort towards the goals of security of supply and particularly sustainability.

2.1.2.2 Energy Concept

Against the background of the energy trilemma and EU regulation, the German energy concept aims towards a long-term secure, competitive, and sustainable energy supply (BMWi 2010). The following nine key fields of action for Germany are identified: (i) Cost-efficient expansion and integration of RES by providing economically viable options for generation and consumption sides. Among others, the most important challenges include on- and off-shore wind generation, sustainability for biogas, and combining RES with heating and cooling technologies; (ii) improving energy efficiency in private and industry domains through appropriate economic incentives, information campaigns, and empowering self-awareness of consumers; (iii) creating a more flexible energy mix without nuclear generation that still includes a sufficient amount of balancing power; (iv) a faster grid expansion where necessary to expedite the integration of RES into the grid. In particular, the generation of offshore wind power and its transport from northern to southern Germany as well as the integration of the national grid into the EU's network are of utmost importance; (v) energy-saving modernizing measures for buildings and energy-efficient building construction to further reduce CO_2 emissions. (vi) promoting electric mobility, with one million electric vehicles on the road by 2030 and the long-term goal of using electric vehicles as storage devices; (vii) research into RES, energy efficiency, storage technology, and synergies between energy technologies; (viii) integrating and harmonizing energy supply within a European

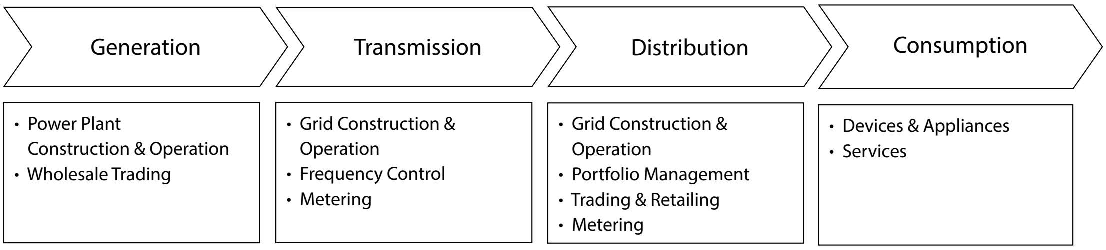


Figure 2.2: Electricity value chain with selected fields of competence (based on Hoitsch, Goes, and Burkhard (2001) and Valocchi et al. (2008))

and international context. Required actions include the promotion of EU grid expansion and the IEM as well as improving the ETS and energy efficiency; and (ix) ensuring transparency and consumer acceptance when improving and extending the grid infrastructure by means of detailed supply of information and participation processes.

2.2 Electricity Markets

Electricity markets have traditionally been managed with a high degree of technical and economic integration. However, they have been confronted with several issues recently. On the one hand, they are subject to significant governmental deregulation efforts, while on the other hand, they are faced with new technical, economic, and environmental challenges. In the following, this section provides an overview of the status quo and challenges concerning electricity market participants, design, and regulation with focus on Europe and particularly Germany.

2.2.1 Electricity Value Chain

The traditional market structure can best be described along the electricity value chain as shown in figure 2.2. The electricity value chain itself focuses on power flow, i.e., delivering electricity to the consumer (Valocchi et al. 2008). Electricity generation is performed by generators, while electricity transmission is handled by the transmission and distribution system. Ultimately, consumer devices and appliances utilize electricity (Stoft 2002).

2.2.1.1 Generation

Electricity supply is typically ensured by a heterogeneous portfolio of different generators with varying characteristics. These characteristics include available input resources, operational cost, locality, scalability, and flexibility (Stoft 2002). Manifestations of these characteristics differ significantly per country, in particular due to availability of input resources, technological advancements, and policy decisions. For example, while the the electricity generated from renewable sources in Norway already represented 105.5 % of the gross electricity consumption in 2013 (Eurostat 2015a), for countries such as France, this share only accounted for 16.9 % (Eurostat 2015a) RES, as the country focuses more on nuclear power generation. Specifically, nuclear energy is at a level with a 34.6 % share of gross inland consumption compared to the available energy for final consumption (Eurostat 2015b, 2015c) and has a share of 48 % of the total EU-28 nuclear power generation (Eurostat 2015c). However, the generation portfolio is generally more diverse. In 2015, for example, Germany generated its electricity from coal (42.2 %), RES (30.0 %), nuclear (14.1 %) and natural gas (8.8 %). This particular diversification is illustrated in figure 2.3. The average electricity generation portfolio of OECD countries in 2012 was composed of 32.1 % coal, 25.3 % gas, 18.1 % RES, 18 % nuclear, 3.6 % oil, 2.2 % biofuels and 0.7 % waste as well as 0.1 % other sources (International Energy Agency 2015). In most cases, capacities of these generators have been designed to take advantage synergies of economies of scale and therefore reduce generation cost (Stoft 2002). As a result, four major generation companies – EnBW, E.ON, RWE, and Vattenfall – have emerged in Germany. These companies owned 80 % (80.7 GW) of the available capacity and 82 % (390.4 TWh) of the total electricity feed-in in 2009 (Bundeskartellamt 2011). In addition, large generators are often located near areas of high population density to take advantage of the physical laws of power flow as electrical power always flows to the nearest point where it can be consumed and cannot be directed to a specified location (Stoft 2002; Schweppe et al. 1988).

In light of the EU 20-20-20 targets and the promotion of the most recent 2030 framework, which sets the target of the share of RES in the EU to at least 27 % (EC 2014a), electricity generation portfolios are changing significantly. For example, the development of installed electricity generation capacity and actual gross generation in Germany since 1991 is depicted in figure 2.4. While the generation capacity in 1991 amounted to 126.1 GW, it increased by 50.2 % to 189.4 GW by the end of 2013. At the same time, actual electricity generation only grew by 17.2 % from 540.2 TWh in 1991 to 633.2 TWh in 2013. Investments into solar and wind generation as well as the discontinuation of all nuclear generation in Germany were promoted

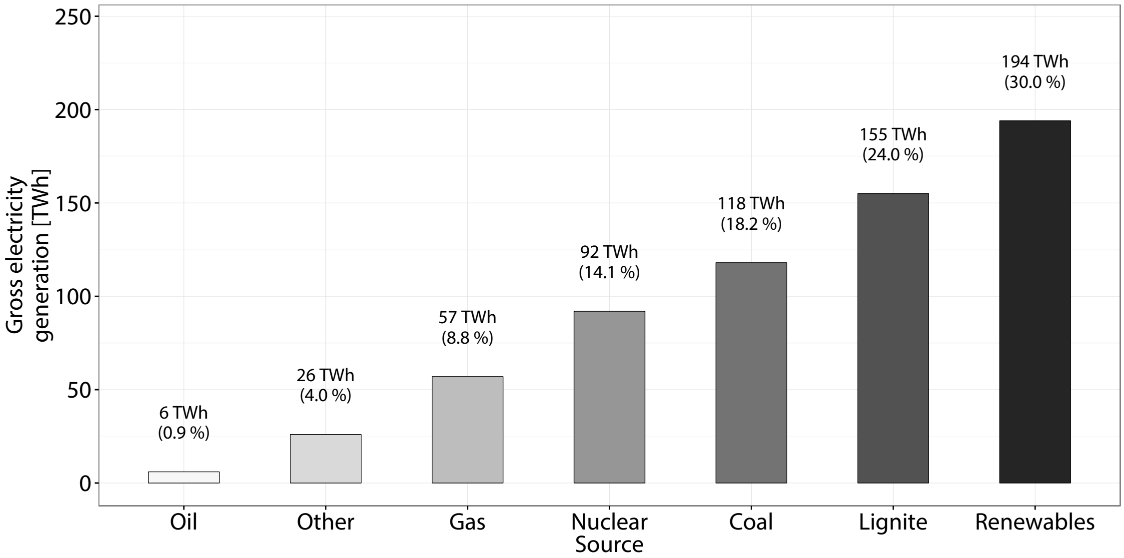


Figure 2.3: Gross electricity generation in Germany 2015 (*Source*: Data from BMWi (2016))

by major political decisions in recent years (Henning and Palzer 2014). These changes can already be observed in the development of installed generation capacity since 2005 and have peaked since 2011 to an all-time high today. The difference between installed capacity and actual generation of wind and photovoltaic (PV) illustrates the stochastic nature of these RES. Simultaneously, this also emphasizes the indispensable requirement to operate with an advanced generation portfolio of base and peak load plants to ensure a continuous balance of supply and demand. The base load is usually covered by nuclear and coal generation plants, as they have greater ramping constraints that do not allow for short-term start up or shut down phases. Additionally, base load plants are characterized by their low variable generation cost (Stoft 2002). At the same time, peak loads which cannot be covered by RES such as wind or PV are supported by gas or hydro generation plants with low ramping constraints but high variable generation cost.

2.2.1.2 Transmission and Distribution

Transmission and distribution grids represent the backbone of electricity delivery to consumers. Transmission lines transport electricity from large generators to transformer stations in close proximity to areas of high population density or areas with large industry (Stoft 2002). Initially, electricity output from generators is either transported directly to transformers or first transformed through converter stations from 380-500 kV to 220-380 kV

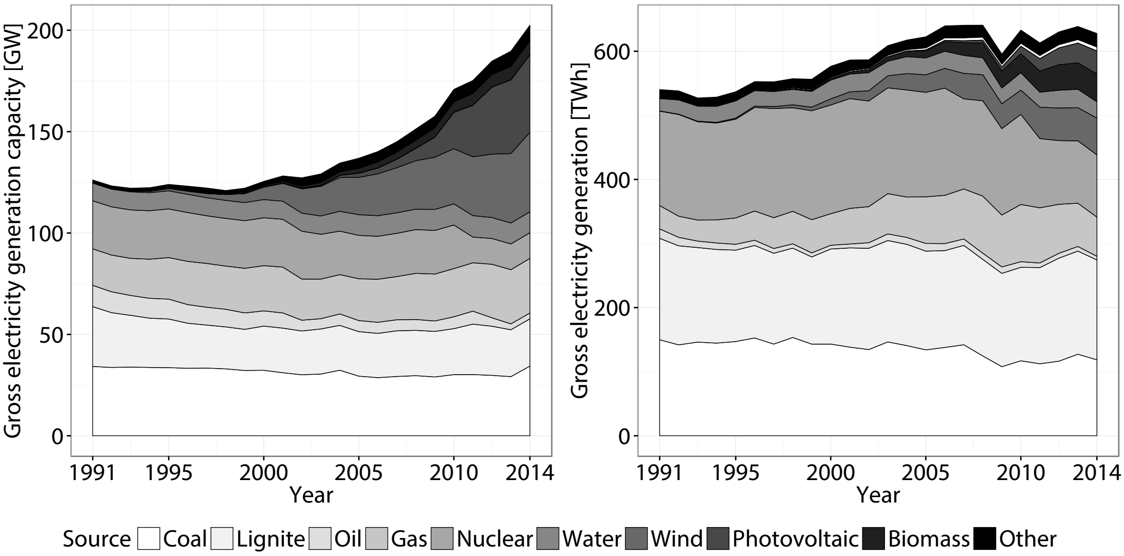


Figure 2.4: Installed generation capacity and gross electricity generation since 1991 (*Source*: Data from BMWi (2016))

in case of the usage of high voltage direct current (HVDC) transmission (Bahrman and Johnson 2007). Electricity transport is carried out by means of extra-high voltage overhead, undersea or underground cable or line systems (Stoft 2002; El-Hawary 2008). Voltage levels in transmission grids range from 220 to 380kV. Subsequently, electricity is transformed to lower voltage levels and fed into the distribution grid. Starting from this point in the grid, electricity is distributed to consumers, i.e., transported either directly to large consumers or to transformer stations which in turn convert incoming electricity to lower voltage levels and thus allow electricity delivery to medium and smaller consumers, each with individual requirements on different voltage levels (Stoft 2002). Distribution system voltage levels in Germany encompass high (60-110 kV), medium (6-30 kV), and low voltage (230-440 V) (Schwab 2009). The high-level transmission and distribution architecture and voltage levels are illustrated in figure 2.5.

In Germany, transmission system operators (TSOs) and distribution system operators (DSOs) are responsible for grid operation, maintenance, stability, and reliability. In particular, TSOs provide ancillary services to ensure security of supply through measures such as frequency and voltage control. In addition, the N-1 criterion requires transmission lines to be deployed in parallel as well as at the same time to be operated at only half their nominal capacity to improve failure resistance (Schwab 2009). Moreover, DSO have to ensure adequate grid development. Specifically, they manage the connection of new consumer or

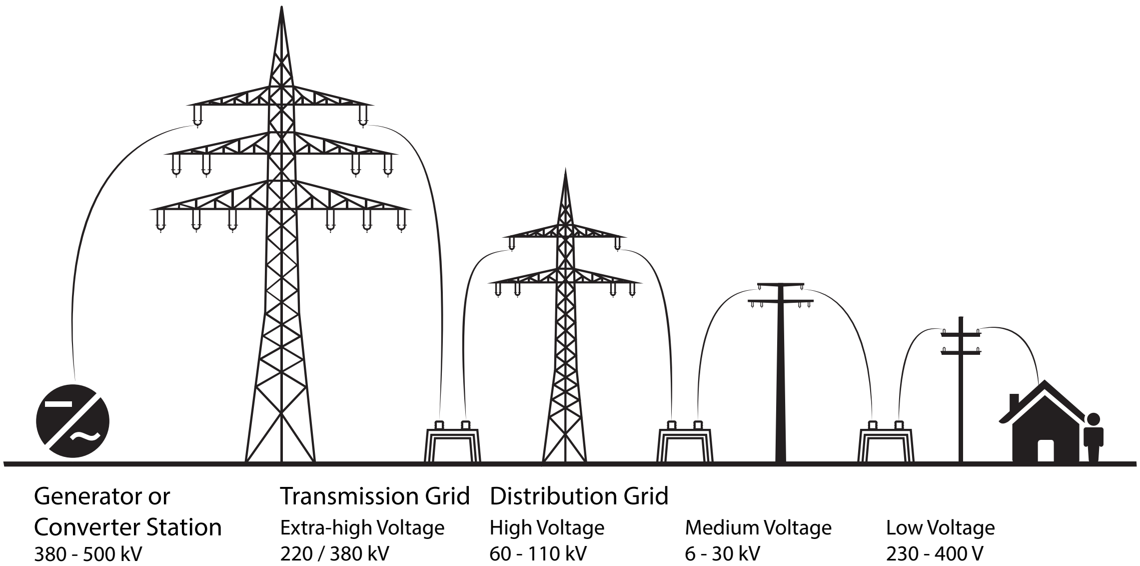


Figure 2.5: Grid structure and voltage levels (based on EnBW AG (2015))

industry loads or, more recently, RES generation. Expected grid expansion investments into German distribution grids amount to EUR 27.5 billion (dena 2012). Incurred grid expansion and maintenance cost are usually allocated to consumers via additional grid charges (Bundesnetzagentur and Bundeskartellamt 2014).

Both TSOs and DSOs are considered natural monopolies (Bundesnetzagentur and Bundeskartellamt 2014) as high investments in grid infrastructure are necessary. Consequently, they remain under regulatory supervision from the German Network Agency. Namely, there are four TSOs in Germany – Tennet TSO, 50Hertz Transmission, Amprion, and Transnet BW – who each are responsible for a control zone. While the number of TSOs has remained constant at four since 2006, the total number of DSOs increased from 876 to 884 in 2014 (Bundesnetzagentur and Bundeskartellamt 2014). As of the of 2013, the total length of underground and overhead lines amounted to 34,885 km for TSOs and 1,763,083 km for DSOs. An overview of key grid figures for Germany is presented in table 2.1.

Table 2.1: Key figures of the electricity grid in Germany for 2013

Grid figures 2013	TSO	DSO	Total
Number of operators	4	804	808
Total circuit length [km]	34 855	1 763 083	1 797 938
Extra-high voltage	34 631	348	34 979
High voltage	224	96 084	96 308
Medium voltage	0	509 866	509 866
Low voltage	0	1 156 785	1 156 785
Number of total final consumers	664	49 934 777	49 935 441
Industrial and business	0	3 829 740	3 829 740
Households	0	46 105 037	46 105 037
Consumption [TWh]	41	469.6	510.6
Industrial and business	30.7	342.2	372.9
Households	0	126.1	126.1
Pumped storage	10.3	1.3	11.6

Source: Data from Bundesnetzagentur and Bundeskartellamt (2014)

As shown above, DSOs are responsible for over 95 % of the grid lines. Additionally, about 90 % of RES generation is connected at distribution grid levels. This emphasizes the importance of distribution grids for an efficient integration of RES. With this purpose in mind, DSOs need to take a more active role in managing their grids than today, not only because this task is becoming more and more complex but also as their responsibility in ensuring security of supply is growing continuously (BMWi 2015b). In particular, this also entails a more active role within market environments. A more detailed review focusing on today's and future electricity markets and related DSO activities is given at a later point in this chapter.

2.2.1.3 Consumption

As illustrated in figure 2.6, within the ranking of final energy consumption by energy source type in Germany of 2014, electricity consumption is ranked third with 509.51 TWh (21.2 %) out of 2404.11 TWh, following only fuel with 711.79 TWh (29.6 %) and gas with 584.56 TWh

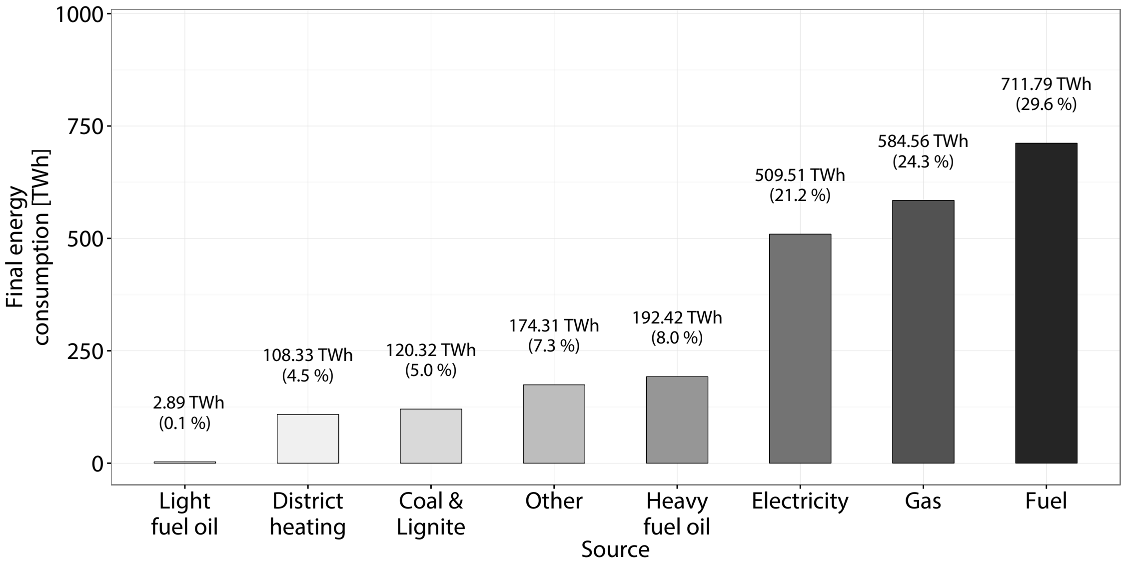


Figure 2.6: Final energy consumption by energy source type Germany 2014 (*Source*: Data from BMWi (2016))

(24.3 %) consumption (BMWi 2016). This again highlights the heterogeneous energy mix in Germany, in this case for the consumption side, i.e., demand side.

In more detail, households and industry sectors account for the largest subset of consumers in the electricity consumption since 1991. The development of these shares is depicted in figure 2.7. While a growth in total consumption can be noted starting from 1993 until 2007, consumption has been monotonically decreasing since 2010.

Typical usage of electricity at consumer level, i.e., net energy, encompasses appliances and various other applications. Specifically, heating (space heating, water heating), work (cooling, motion, information, and communication), light (lighting, laser) or other purposes represent consumer utility to gain from electricity (Erdmann and Zweifel 2008).

Historically, electricity consumption, in particular by households, has been assumed to be inelastic. In accordance with current law (§ 12 StromNZV), generation plants in Germany are still scheduled based on synthetic load profiles for different consumer types. A load profile represents simplified consumption values, which are used to forecast and balance electricity. For industry, there exist profile types G0-G7, for households, profile type H0. The fundamental assumption of load profiles is that a profile will be consumed on average. Therefore, individual deviations are accounted for as their consumption will be flattened in the actual consumption. The profile is communicated from DSOs to utilities, which have to

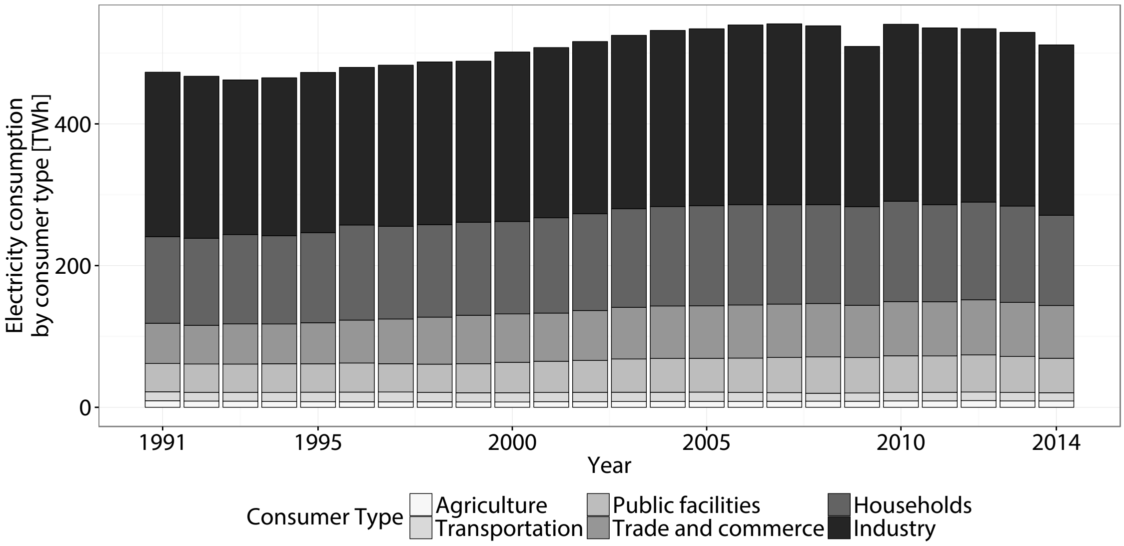


Figure 2.7: Timeline of final electricity consumption per consumer type in Germany since 1991 (*Source*: Data from BMWi (2016))

procure generation capacities accordingly. Yet, larger industrial consumers equipped with advanced metering infrastructure (AMI), i.e., smart meters, can detach themselves from this standardized process and switch from synthetic load profiles to individually optimized profiles and appear in a more autonomous role.

Since the late 1980s, research on creating incentives for consumers, which would encourage them to become more active and adapt their demand to the current supply situation, have appeared (Schweppe et al. 1988). More recently, DSM and DR approaches have gathered pace in the research community. Especially in presence of RES, both DSM and DR present the prospect of large benefits to balancing supply and demand (Strbac 2008). In addition, measures from DSM can support improving energy efficiency, time of use (TOU) tariffs, DR or spinning reserves (Palensky and Dietrich 2011). However, major challenges such as coordination and inventive issues are still to be resolved (Strbac 2008; Ipakchi and Albuyeh 2009). In general, DSM and DR aim at the consumer's flexibility. Engaging consumers in DR and additionally exploring and exploiting their flexibility remain critical issues as well (Petersen, Hansen, and Mølbak 2012; He et al. 2013). A detailed review of DSM, DR and flexibility follows in a subsequent section.

2.2.2 Market Structure

2.2.2.1 Liberalization

Global developments specific to energy market reforms can be referred to by several terms. The most commonly used terms encompass *deregulation*, *restructuring* or *liberalization* (F. P. Sioshansi 2006). While *deregulation* is considered a misnomer because complete deregulation in the sector is regarded as not possible (Sioshansi and Pfaffenberger 2006), *restructuring* is considered as a more suitable term (Hogan 2002). In context of the EU (EC 2012b) and the remainder of this work, the synonymous term *liberalization* is used.

Liberalization efforts towards state-owned enterprise structures or regulated monopolies in order to create open markets started in the 1980s (F. P. Sioshansi 2006). Before these efforts, all functions of the electricity value chain, i.e., generation, transmission, distribution, and retailing, were carried out by a single vertically integrated entity. Such an entity was then unbundled, i.e., separated by function, in the interest of creating competition to achieve positive effects for end consumers. Note that transmission and distribution grids are excluded from unbundling as duplicating grid structure is considered economically inefficient (Stoft 2002). On the retail level, effects of unbundling include lower electricity prices as well as better service levels given the freedom to choose any provider among a large set of alternatives (EC 2012b).

In more detail, liberalization efforts for the electricity sector encompass, among others, the following components (Joskow 2008): (i) Privatization of state-owned companies; (ii) vertical separation, i.e., unbundling within the electricity value chain where economically more efficient; (iii) horizontal restructuring, i.e., fostering competition, of the generation segment; (iv) designation of an independent system operator (ISO) and independent regulator; (v) introduction of a wholesale spot and an operating reserve market; and (vi) utilization of DSM approaches. For an exhaustive list and a detailed explanation see Joskow (2008).

In Germany as well as in other EU member states, liberalization activities are based on several successive legally binding directives, i.e., legislation, originating from the EC. Liberalization efforts were constituted in 1996 in accordance with the TFEU in form of the first energy package, i.e., liberalization directive 96/92/EC concerning common rules for the internal market in electricity (EPEC 1997). The directive emphasizes the importance of cross-border transmission capacities and trading between EU member states towards an

IEM. In 2003, the directive was replaced by the second energy package, directive 2003/54/EC. In context of this directive, the emphasis is on improving operations and competition within the IEM by focusing on network, tarification, and cross-border market opening issues (EPEC 2003a). The third and most recent energy package, directive 2009/72/EC, again replacing the second package, points out challenges of non-discriminatory network access in each member state as well as requires improvements upon cross-border interconnections and access to ensure security of supply. In addition, the importance of a well-functioning IEM to stimulate investments into RES and to provide appropriate incentives and to ensure competitive prices is highlighted (EPEC 2009c).

The first and second energy packages were implemented in Germany in 1998 and 2005, respectively. With the most recent amendment to the German Energy Industry Act (EnWG) in 2011, the requirements of the third energy package were put into German legislation. According to the EU's latest progress report on its IEM, the EU-wide transition to comply with the unbundling requirements of the third energy package is almost complete. This includes Germany, which has fully implemented grid restructuring measures along the transmission and distribution levels (EC 2014c).

2.2.2.2 Electricity Markets in Germany

Electricity markets in Germany can be classified into wholesale markets and ancillary services as illustrated in figure 2.8 (Judith et al. 2011). While ancillary services cover short-term balancing power, i.e., control (or operating) reserve, and other services to ensure security of supply, wholesale markets consider long-term as well as short-term products. Moreover, electricity market types can be distinguished by participants, e.g., the market for balancing power provides a platform for TSOs and large generators while TSOs do not participate in wholesale markets (Bundesnetzagentur and Bundeskartellamt 2014).

The wholesale market in Germany is segmented into interconnected over-the-counter (OTC) and exchange markets with the European Energy Exchange (EEX) and the European Power Exchange (EPEX SPOT). Within the OTC markets, bilateral contracts, or forwards, are traded continuously. These contracts have a time horizon of up to 6 years. In combination with similar products traded on the EEX futures market, these long-term products represent the main share in today's total trading volume (Bundesnetzagentur and Bundeskartellamt 2014). Moreover, these forward transaction usually are fulfilled financially, i.e., in general,

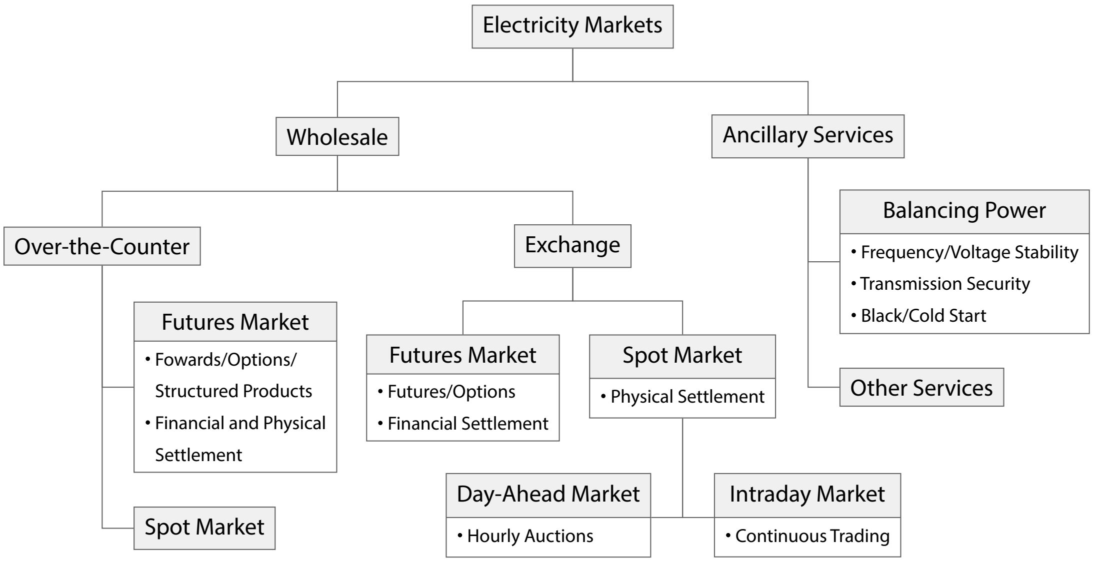


Figure 2.8: Structure of electricity markets with products and services in Germany (based on Judith et al. (2011) and Stoft (2002))

a financial settlement is favored as opposed to a physical settlement by settling the cash difference of the forward/future product and the spot market price (Bundesnetzagentur and Bundeskartellamt 2014).

Nevertheless, trading on the EPEX SPOT markets remains fundamentally important as resulting prices represent a reference point for OTC and EEX futures markets (Ockenfels, Grimm, and Zoettl 2008). The interconnection between the markets becomes apparent as buyers and sellers can negotiate and trade on both OTC and exchange markets at the same time. Clearly, possibilities for arbitrage exist. Therefore, prices are similar, e.g., no buyer would accept an offer from the OTC market if an outcome of an exchange market would be more beneficial. However, prices might still deviate given different understandings and availability of information and risk (Ockenfels, Grimm, and Zoettl 2008).

Besides the EEX futures market, the EPEX SPOT market consists of a day-ahead and an intraday market. On the EPEX SPOT day-ahead market, a uniform price auction is held once a day. Bids and asks for hourly products, standardized blocks or a combination of individually selectable hours (i.e., custom blocks) must be submitted to be cleared at 12:00 p.m. the day before the actual supply period (Bundesnetzagentur and Bundeskartellamt 2014). In contrast, trading by auction on the EPEX SPOT intraday market for similar standardized or custom 15 minute blocks is continuous in order to allow for short-term corrections of power shortages or surplus from contracted forwards/futures given the current power grid and market situation

(BMWi 2015b).

Moreover, to procure power for the control reserve, TSOs can announce their demand on the German control reserve market (Bundesnetzagentur 2011a; 50Hertz Transmission GmbH et al. 2015). Products on the control reserve markets comprise the primary and secondary control reserve as well as the minute reserve. They are designed based on technical and regulatory requirements (Ockenfels, Grimm, and Zoettl 2008; Bundesnetzagentur 2011a).

Market Clearing Clearing on most EEX and EPEX SPOT markets is based on a sealed-bid uniform price auction (Ockenfels, Grimm, and Zoettl 2008). The price and in turn the generation dispatch is determined by the order of increasing marginal generation cost represented by bids as well as availability and ramping constraints (Schweppe et al. 1988; Stoft 2002). In particular, the price is set by the so-called merit order, which ensures that the generator in the market with the lowest marginal cost is relevant for the price determination (Erdmann and Zweifel 2008). With the increasing share of RES, a merit order effect which captures the shift of expensive generators in favor of RES out of the market and therefore resulting decreased wholesale prices, can be observed. An analysis of the merit order and the aforementioned complex effect can be found in Sensfuß, Ragwitz, and Genoese (2008). In contrast, clearing on the control reserve market is performed by means of a pay-as-bid auction (Ockenfels, Grimm, and Zoettl 2008; Frontier Economics 2014).

Market Timeline As mentioned before, all markets are subject to a chronological order. On the day-ahead market, the auction clears at 12:00 p.m., on the intraday market, clearing is performed continuously. Moreover, trading on the intraday market is allowed up to 30 minutes before the actual supply period. This point in time is also referred to as *gate closure*. Afterwards, TSOs take responsibility for balancing demand and supply using the control reserve procured beforehand on the control reserve market. Finally, at a later point in time, utilized control reserve is settled financially. This process is illustrated in the following figure 2.9.

2.2.2.3 Latest Developments

Even though the previous section focuses on electricity markets in Germany, their design and regulation is also influenced actively by European guidance. Therefore, this section first

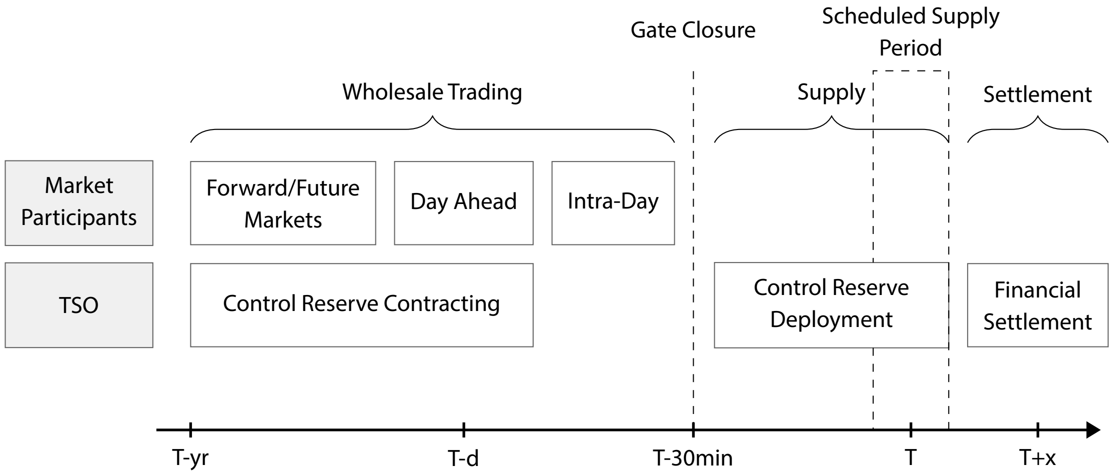


Figure 2.9: Timeline of electricity markets in Germany (based on (Frontier Economics 2014; BMWi 2015b))

highlights current trends, i.e., (consultation) processes and communications, originating from within the EU. Next, national efforts in Germany towards a new electricity market design are emphasized.

Electricity Market Design in Europe The EU called for a major revision of the current market design in mid-2015. According to the recent EU communication *COM (2015) 340* (EC 2015a), Europe's electricity system is undergoing profound changes with growing wholesale competition and cross-border electricity flow, while at the same time faced with the integration of an increasing share of RES. The current market design needs to be adapted to (i) fully integrate RES and promote their participation on par with conventional generation; (ii) integrate more active players such as flexible demand, energy service providers, innovative companies, and reliable intermediaries to facilitate consumer savings and security of supply; (iii) support cross-border competition and power flow; (iv) provide the right (financial) incentives for investments in light of RES; and (v) promote enabling technologies, e.g., smart grids, smart metering, and self-generation as well as storage technologies (EC 2015a).

In essence, an updated market design needs to be more flexible and consumers should be perceived as active as opposed to previously inactive. In particular, the concept of short-term markets, which need to be at the core of a new energy market design, is highlighted. Here, improved pricing mechanisms to foster DR, shorter trading intervals, and gate closure times closer to real time are desired market characteristics. Additionally, ensuring security of supply by leveraging (demand side) flexibility and storage technologies, represent best measures towards an effective and efficient market design (EC 2015a).

Adjacent to the current process on a new energy market design, the EU additionally calls to remove obstacles currently hindering consumers from benefiting from the energy transition (EC 2015b). In particular, *COM(2015) 339* postulates that all types of consumers need to be able to control their consumption, lower their bills, and actively participate in markets. However, current obstacles include (i) the lack of information on cost and consumption; (ii) limited transparency in offers to be able to asses the market situation and opportunities; (iii) increasing grid charges; and (iv) insufficiently developed markets for local energy services and DR (EC 2015b).

Therefore, a strategy resting on three pillars to deliver a new deal for energy consumers has been identified. Firstly, it demands to empower consumers to act by (i) providing better, real-time information on consumption data; (ii) giving a wide choice of suppliers and energy service companies (aggregators); (iii) realizing the value of flexibility through DR; and (iv) increasing consumer participation through intermediaries (aggregators) and collective schemes (communities) (EC 2015b). Secondly, promoting smart homes and networks should simplify access to new retail markets and enable (automated) participation. A complete set of EU technology and communication standards has already been delivered to support this goal. Finally, smart meter data needs to be protected in terms of data security and privacy, yet on the other hand needs to be available to metering, billing or other services in the market given their value for a new energy market.

Electricity Market 2.0 in Germany In 2014, the German Federal Ministry for Economic Affairs and Energy (BMWi) published its discussion paper (green paper) on designing an electricity market for the energy transition in Germany (*Energiewende*) (BMWi 2015b). Following a consultation period, the official outcome (white paper) was published in late 2015 (BMWi 2015a). Shortly afterwards, the initial drafts for the resulting laws were passed by the federal cabinet (BMWi 2015c) and are expected to become effective in 2016.

As suggested by its name, electricity market 2.0, the current market design needs to be refined and thus reformed. Security of supply remains central to an enhanced market design, where the main goal is to efficiently integrate RES. Suggested measures for an enhanced electricity market include, but are not limited to, (i) ensuring that price formation is not restricted and can lead to price signals that can incorporate supply scarcity factors that may entail higher prices; (ii) paying particular attention to the accounting of suppliers and retailers for a balanced grid by allocating cost resulting from positive or negative imbalances to the responsible party; (iii) the integration of flexibility from generation, DR, and storage technologies and therefore support grid stability; (iv) a continuous grid monitoring with regard to security of supply; and (v) reducing of grid expansion cost; and (vi) a stronger connection to the EU's IEM (BMWi 2015a, 2015c).

Moreover, DSOs are confronted with new challenges and need to coordinate advanced tasks and responsibilities in their grids. Specifically, the increasing share of generation capacities from fluctuating RES in residential grids results in more complex power flows in their own and eventually upper transmission grids. In turn, DSOs need to shift from passive to a more active grid management and make use of markets to procure flexibility or flexibility services from aggregators or consumers to cope with yet unseen critical grid situations. Current market designs such as the spot market or control reserve market as well as feed-in management or redispatch measures cannot accommodate these short-term requirements and need to be extended or complemented by other markets that allow the coordination of retailers, aggregators, DSOs, and possibly TSOs (BMWi 2015a).

2.3 Smart Grid

Smart grids facilitate monitoring and control of electrical power systems on a local level in real time in order to ensure an efficient, robust, and sustainable grid operation in light of an increasing share of decentralized and less predictable RES (DoE 2003). More specifically,

Definition 2.1 (Smart grid (US)). *[A smart grid] is a fully automated power delivery network that monitors and controls every customer and node, ensuring 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 (DoE 2003).*

More generally defined in the context of the EU and serving as basis for the remainder of this work,

Definition 2.2 (Smart grid (EU)). *A smart grid is an electricity network that can cost efficiently integrate the behaviour and actions of all users connected to it – generators, consumers, and those that do both – in order to ensure economically efficient, sustainable power system with low losses and high levels of quality and security of supply and safety (EC 2011).*

In order to enable detailed supervision and control on low voltage distribution grid levels, capabilities already present in the infrastructure of high and extra-high voltage grids and therefore modern information and communication technology (ICT) are required (Farhangi 2010; Varaiya, Wu, and Bialek 2011). Hence, sophisticated methods need to transform a "blind" and manually operated system into a complex system (Ipakchi and Albuyeh 2009). This enables grid operators to improve overall efficiency by achieving a better balance of supply and demand at all times. In particular, Sarvapali D. Ramchurn et al. (2012) argue that for the successful realization of the full potential of smart grids, several key components of a smart grid, i.e., (i) DSM; (ii) electric vehicles (EVs); (iii) virtual power plants (VPPs); (iv) the emergence of prosumers; and (v) self-healing networks need to interact and be smart. That is, novel algorithms and mechanisms, including from the field of artificial intelligence (AI), for solving large-scale problems with heterogeneous actors in a highly uncertain and dynamic environment are required (Sarvapali D. Ramchurn et al. 2012). Moreover, the historic rule that flexible supply follows inflexible demand gradually changes more into a system with both sides playing an active and flexible role as a result of DSM and DR measures (Strbac 2008).

2.3.1 Flexibility of Supply and Demand

It is central to electricity grid operation that supply and demand have to be balanced at all times, given the core condition that electricity consumption is instantaneous and cannot be stored efficiently without high losses as of today (Stoft 2002). Flexibility on both supply and in particular the demand side is seen as a key enabler for a cost and economically efficient smart grid that needs to accommodate an increasing share of volatile RES and mitigate potential issues of an infrastructure that is becoming older every day (SGTF 2015). On a European level, the EU Smart Grid Task Force (SGTF) defines flexibility as follows:

Definition 2.3 (Flexibility). *On an individual level, flexibility is the modification of generation injection and/or consumption patterns in reaction to an external signal (price signal or activation) in order to provide a service within the energy system. The parameters used* *to characterize flexibility include: the amount of power modulation, the duration, the rate of change, the response time, the location etc. [...] Flexibility can be provided by both supply and demand on a large scale, for example by CCGT plants, industrial ad commercial consumers, aggregated smaller household load, distributed generation, and energy storage (SGTF 2015).*

That is, flexibility can be provided by both demand and supply side and covers voluntarily or mandatory changes in consumption or generation of electricity from/to the power system from their usual patterns in response to certain signals (SG-CG 2014a; SGTF 2015).

Supply Flexibility Until today, the supply side provides the flexibility to dispatch its generation plants according to forecast and real-time demand in order to ensure a stable voltage and frequency in the grid. In particular, the flexibility is determined by the generation mix and the electricity market structure (Ockenfels, Grimm, and Zoettl 2008). For example, base load plants have restrictive ramping constraints as ramping in any direction may reduce the lifetime of plant components and conflict with high investment cost (Stoft 2002). In more detail, the value of a flexible supply resource can be determined by activation time, length of reservation period, and capacity (Petersen, Hansen, and Mølbak 2012). Moreover, electricity market interrelations need to be considered where for example the control reserve market in Germany can contract plants that may be of use on the spot market (C. Weber 2010). In particular in Germany, current supply flexibility resources for the control reserve encompass the primary, secondary, and tertiary reserves, which are distinguished by their activation time (Klobasa 2010). In more detail, the primary control reserve is used within 30 seconds, the secondary control reserve is activated thereafter but within five minutes and the minute reserve is accessed within 15 minutes (50Hertz Transmission GmbH et al. 2015).

Demand Flexibility Early research by Schweppe et al. (1988) already suggests that demand should be more adaptive to current supply conditions by means of pricing strategies. These strategies may flatten peak demand and in turn result in cheaper long-term contracting as well as benefits for grid operators. Moreover, Schweppe, Daryanian, and Tabors (1989) introduce the notion that electricity should be a service and suggest a taxonomy to classify device flexibility in terms of thermal storage, devices that can or cannot be rescheduled as well as are periodically used. More recently, Petersen, Hansen, and Mølbak (2012) define demand flexibility as "the ability to deviate from the plan" and subsequently provide a taxonomy focused on flexible demands smart grids which is comprised of three generic and domain

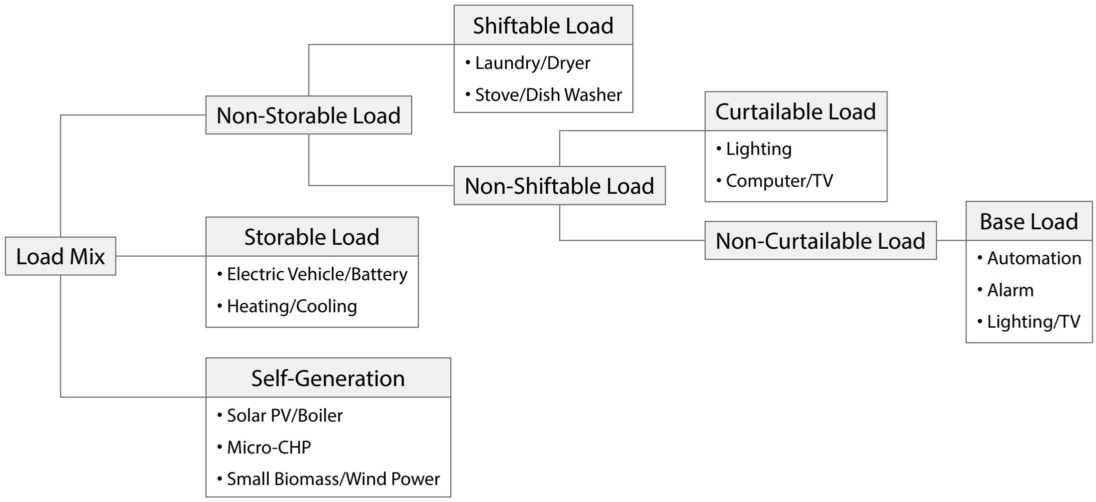


Figure 2.10: Demand side flexibility categories (based on He et al. (2013))

specific flexibility models: buckets, batteries, and bakeries (Petersen et al. 2013). Specifically, in hierarchical order of quality, i.e., in terms of less restrictive to most restrictive, the models are defined as follows: (i) buckets, which integrate power and energy constraints, e.g., a heat pump; (ii) batteries, which additionally impose a temporal constraint, i.e., a deadline by which the battery must be charged (e.g., for EVs); and (iii) bakeries, which extend previous models by a continuous and constant power consumption for a specified time interval (Petersen et al. 2013). Similarly and in a more general fashion, He et al. (2013) classify the demand (or load) mix of consumers into five hierarchical categories based on the degrees of flexibility which can be expected from consumers as illustrated in figure 2.10: (i) storable load (e.g., heating or cooling); (ii) shiftable load (e.g., dryer or dish washer); (iii) curtailable load (e.g., lighting or computer); (iv) base load (e.g., standby or alarms); as well as (v) self-generation (He et al. 2013).

In the following, the key concepts DSM and DR to foster new and inherent demand flexibility are detailed. Both DSM and DR are intrinsically linked to flexibility (SGTF 2015).

2.3.2 Demand Side Management and Demand Response

Demand side management (DSM) refers to a portfolio of primarily utility-driven measures that aim at improving the efficiency of the demand side (Palensky and Dietrich 2011; Strbac 2008). In particular, direct load control (DLC) or interruptible/curtailable load programs represent the most prominent kind of programs where utilities can remotely control or shut down devices to compensate for fluctuations of demand and supply (Albadi and El-Saadany 2008).

Definition 2.4 (Demand side management). *Demand side management (DSM) [...] aims to reduce energy consumption and improve overall electricity usage efficiency through the implementations of policies and methods that control electricity demand. Demand side management (DSM) is usually a task for power companies / utilities to reduce or remove peak load [...]. The commonly used methods [...] are: [a] combination of high efficiency generation units, peak-load shaving, load shifting, and operating practices facilitating efficient usage of electricity, etc. DSM is therefore characterized by a "top-down" approach [...] (SG-CG 2014a).*

In contrast, demand response (DR) focuses on a bottom-up approach to change consumer behavior and using consumer flexibility based on monetary and non-monetary incentives yet follows the same goal of improving system efficiency (Strbac 2008; SG-CG 2014a). Often, DSM and DR are used synonymously (Albadi and El-Saadany 2008; Faruqui, Hledik, and Sergici 2010), however, in context of smart grids and the remainder of this work, the term DR is more commonly used (Albadi and El-Saadany 2008; Strbac 2008; Siano 2014). Following Albadi and El-Saadany (2008) and SG-CG (2014a), DR is defined as follows:

Definition 2.5 (Demand response). *Demand response implies a "bottom-up approach" (SG-CG 2014a) [and] 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 (DoE 2006). DR includes all intentional electricity consumption pattern modifications by end-use customers that are intended to alter the timing, level of instantaneous demand, or total electricity consumption (International Energy Agency 2003).*

More specifically, DR programs need to engage the flexibility of consumers in such a way as to enable them to adapt their demand to the current supply situation. DR programs can be classified into price-based, i.e., tariffs with real-time pricing, (extreme day) critical peak pricing or time of use components, and incentive-based programs, i.e., market-based programs that reward consumers based on their performance (Albadi and El-Saadany 2008).

Central to a successful employment of DR is the engagement and empowerment of the flexible consumer. The choice and understanding of new options and markets and their functions together with the necessary tools, information, and knowledge will allow consumers to actively participate in DR (Sarvapali D. Ramchurn et al. 2012; SGTF 2015). For a comprehensive overview and discussion of DR programs and their benefits, the reader is referred to Siano (2014).

2.3.3 Aggregator Concept

In order to benefit from DR measures and/or the individual provision of flexibility, consumers need to be able to participate in electricity market environments (Sarvapali D Ramchurn et al. 2011). However, consumers from residential areas and small and medium-sized enterprises (SME) are faced with entry barriers such as market rules, cognitive cost, transaction cost, and risk (He et al. 2013). Moreover, a lack of incentives and regulatory issues hinder consumers in market participation (EC 2015a). To fully enable consumers to deliver their flexibility potential to markets in context of DR, intermediaries, i.e., aggregators, which act on behalf of consumers are required (EC 2015a). An aggregator first needs to procure critical mass of consumers from small groups of residential, commercial or industrial consumers into a larger power unit in order to enhance their value for the power system (Hashmi, Hanninen, and Maki 2011). Thereafter, an aggregator can act, trade, deliver the pooled flexibility potential on markets. Finally, the aggregator financially settles with its contracted consumers (Subramanian et al. 2013; SGTF 2015). The role of an aggregator can be captured by different entities such as supply companies, retailers, or new emerging service companies (He et al. 2013; SG-CG 2014a). Therefore, novel business models for incumbents as well as new service companies need to be created. Furthermore, an aggregator can also fill the role of a balancing responsible party (BRP), which plays a crucial role in ensuring system stability and security of supply (SGTF 2015).

As of today, literature lacks a clear definition of an aggregator. Aggregators are sometimes synonymously referred to as VPPs (Awerbuch and Preston 1997; Pudjianto, Ramsay, and Strbac 2007; Asmus 2010; Sarvapali D. Ramchurn et al. 2012) or flexibility operators as well as flexibility aggregators (SG-CG 2014b). In the context of this work, an aggregator is defined as follows:

Definition 2.6 (Aggregator). *An aggregator is a market participant which acts as an intermediary between markets and consumers to (i) facilitate individual consumer participation in DR; and (ii) maximize local flexibility potential, by pooling, or aggregating, a critical mass* *of heterogeneous supply and demand flexibility from consumers. The responsibilities of an aggregator include consumer procurement, contracting, and settlement, trading on markets, portfolio management, and complying with balancing requirements if needed.*

The service provided by aggregators can be of particular utility for DSOs in order to ensure security of supply depending on the current grid state (SGTF 2015). This work proposes a market-based approach, which allows a DSO to ensure security of supply by procuring demand flexibility in short-term critical grid situations.

2.3.4 Standardization

Smart grids are comprised of a heterogeneous and interconnected landscape in the value chain from generators to industry or household appliances on different levels such as voltage and (inter)nationality. Moreover, interests of various stakeholders on each level need to be accounted for. Hence, in order to securely and robustly integrate all associated actors, the EU SGTF assigned mandate M/490 on standardization to support the European smart grid deployment to European Standardization Organizations (ESOs), i.e., CEN, CENELEC, and ETSI in 2011 (EC 2011). In coordination with relevant stakeholders, ESOs formed the Smart Grid Coordination Group (SGCG) to develop a framework consisting of a technical reference architecture, consistent standards as well as sustainable processes (EC 2011). By the end of 2014, the SGCG delivered extensive and corresponding reports on (i) a set of standards; (ii) methodologies (i.e., models, architectures, and flexibility management); (iii) interoperability; and (iv) information security (SG-CG 2014b).

Concepts related to flexibility management are of particular relevance for the scope of this work. Firstly, flexibility management introduces the flexibility concept which comprises a range of methods that cover the flexibility of demand, RES, and storage technology with the goal of integrating RES into and optimizing the efficiency of the power system (SG-CG 2014a). The concept identifies functional, technical, and commercial use cases and architectures for both possible dimensions of grid and market. Moreover, flexibility management introduces the traffic light concept (TLC) which allows BRPs such as DSOs to maintain grid stability, i.e., the balance of supply and demand, in critical situations through marked-based coordination and allocation of flexibility (SG-CG 2014a). The concept stems from a definition by the German association of energy and water industries (BDEW) and is recommended to be implemented within a regulatory framework in each member state. The TLC framework is explained in detail in a later section in this work.

3

Market Design

Market design is the discipline that concerns itself with "the creation of a venue for buyers and sellers, and a format for transactions. (A market as a 'pure venue' can be seen in perhaps its clearest form in internet auctions, where some of the questions that arise about the location of a market are almost purely conceptual)" (Roth 2002).

Moreover, Roth (2002) highlights the importance that the aforementioned creation process should include a design element, rather than only a conceptual analysis. Hence, traditional methods that build upon game theoretic models must be complemented with new methods, guidelines, and frameworks that can deal with this additional complexity. Consequently, he notes that "[...] in the service of design, experimental[,] and computational economics are natural complements to game theory" (Roth 2002). In this context, the mechanism design approach represents a central engineering element of market design (Parkes 2001; M. O. Jackson 2003; P. Milgrom 2011). Mechanism design concerns itself formally with the design of institutions which satisfy certain objectives and with the question of how these institutions affect outcomes under the assumption that participating agents act strategically and hold private information about their preferences (Parkes 2001). As noted by Roth (2002), "[...] market design calls for an engineering approach" that goes beyond simple models and theoretic insights. Moreover, the engineering process must represent a conscious undertaking which ensures attention to detail of the underlying market mechanism and purpose (Roth

2002). market engineering (ME) represents a prime example for this process (Weinhardt, Holtmann, and Neumann 2003; Weinhardt and Gimpel 2007).

This chapter firstly introduces the holistic and integrated view of market engineering and its derived forms *agile* market engineering and *continuous* market engineering. Secondly, the mechanism design approach which is central to the proposed model in this work is highlighted. Finally, an overview of auctions as a prominent example of market mechanisms is provided.

3.1 Market Engineering

Following Weinhardt and Gimpel (2007), a market is defined as follows:

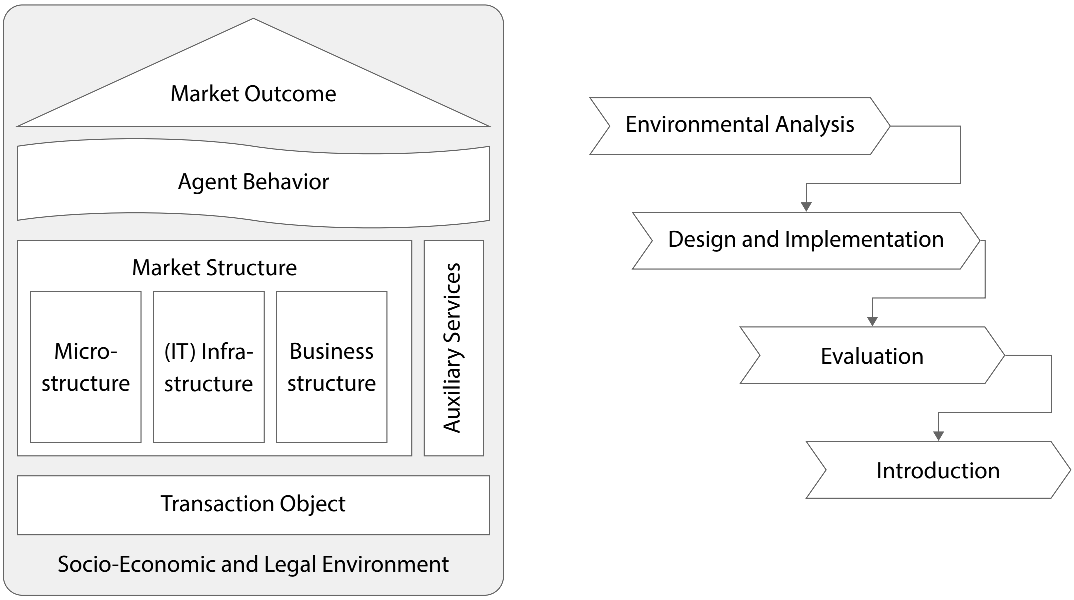
DEFINITION 3.1 **(Market).** *A market is a set of humanly devised rules that structure the interaction and exchange of information by self-interested participants in order to carry out exchange transactions at a relatively low cost (Weinhardt and Gimpel 2007).*

In 2003, Weinhardt, Holtmann, and Neumann (2003) coined the term *market engineering*, which describes a structured, systematic, and theoretically founded procedure of designing, implementing, evaluating, and introducing markets. Market engineering can be defined according to Weinhardt and Gimpel (2007) 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).*

This definition takes a more holistic approach as opposed to traditional market design, which in terms of market engineering is part of the market microstructure (Weinhardt, Schnitzler, and Luckner 2007). In order to consciously design markets, the market engineering framework, sometimes also referred to as the market engineering object, and market engineering process are proposed as shown in figure 3.1. While the market engineering framework depicts pivotal elements of a market that a market engineer is supposed to keep in mind, the market engineering process structures the engineering process of a market (Weinhardt and Gimpel 2007).

In more detail, the objective of a market engineer is to achieve a desired market outcome, i.e., an allocation or payments, or performance, in a socio-economic and legal environment.



(a) Market engineering framework **(b)** Market engineering process

Figure 3.1: Market engineering framework and process (Weinhardt, Holtmann, and Neumann 2003; Neumann 2004; Gimpel et al. 2008)

3.1.1 Market Engineering Framework

Within the market engineering framework (Weinhardt, Holtmann, and Neumann 2003), the socio-economic and legal environment encompasses applicable laws as well as social norms which cannot be directly influenced. In order to accomplish this objective, the transaction object, market structure, and auxiliary services can be designed. The market structure comprises the components microstructure, (IT) infrastructure, and business structure as interdependent elements. The microstructure defines the market mechanism, e.g., bidding language, allocation and pricing rule of an auction. Moreover, the (IT) infrastructure addresses technical system and information and communication technology (ICT) details. Finally, the business structure deals with business and pricing models, e.g., trading fees. It should be noted that the elements of the market structure cannot be designed independently, given the strong interdependencies among them. Additionally, auxiliary services, e.g., decision support systems (DSSs), reputation systems or hidden market design elements (Seuken, Jain, and Parkes 2010) adjacent to the market structure represent supporting elements for participants. Auxiliary services and the aforementioned design elements transaction object and market structure only indirectly effect the market outcome as the main link lies in the exogenous behavior of participating agents. It is therefore critical to asses the impact of the market structure on agent behavior and anticipate it accordingly by means of theoretical models from game theory, auction theory, and mechanism design (Weinhardt and Gimpel 2007; Gimpel et al. 2008).

3.1.2 Market Engineering Process

The market engineering process provides a structured procedure to design and implement markets and serves as a basis for this work. The process consists of four stages: Environmental analysis, design and implementation, evaluation (or testing), and introduction (Neumann 2004; Weinhardt, Neumann, and Holtmann 2006).

Firstly, the environmental analysis phase defines the environment, market segments and participant characteristics, objectives, and strategies. Subsequently, requirements for the transaction object and market structure are derived. Thereby, the environment is thoroughly characterized, a fundamental step towards the success of market design. Within this work, the environmental analysis is performed in section 4.2.

Secondly, the design and implementation phase covers the actual market design and mechanism design process, based on previously identified requirements. The design process consists of a conceptual design phase, followed by a less abstract embodiment and finally a concrete yet prototypical implementation phase. Within the conceptual design and embodiment phase, this work defines the auction process, mechanism, and bidding language in chapter 5. Subsequently, pricing rules are introduced in chapter 6. A prototypical implementation is introduced in chapter 7.

Thirdly, following the design and implementation phase, the evaluation phase stipulates the testing upon the technical and economic mechanism requirements defined beforehand. This phase of the market engineering process is performed in chapters 7 and 8.

Finally, the introduction phase launches the market into its operation cycle after possible refinements are incorporated.

Alternatively, the market engineering process can be described in a slightly modified five stage model: Environmental analysis, design, evaluation, implementation, and introduction (Weinhardt and Gimpel 2007; Gimpel et al. 2008).

3.1.3 Current Trends and Applications

In order to adapt to recent trends and developments in the (software) engineering domain such as rapid, iterative, and test-driven development, enhancements of the market engineering process have been proposed (Block 2010; Kranz 2015). More specifically, Block (2010) introduces agile market engineering, which suggests to bridge the gap between business concepts and running markets by building "[...] on short, incremental market development cycles and frequent user feedback in order to develop and to continuously refine and improve the electronic market platform". More recently, Kranz (2015) highlights "the importance of continuity in operating, monitoring, and re-designing markets" and in turn advances the original and agile market engineering process towards continuous market engineering, an approach which focuses on "[...] aspects of continuous operation, monitoring, and refinement".

In addition, both the market engineering framework and process have been recently applied in several domains. For instance, the allocation of computing grid resources is presented by Schnizler (2007) and Schnizler et al. (2008). Similarly, the coordination and allocation of services in service value networks is described by Blau (2009). Moreover, several types of forecasting and prediction markets have been studied by Luckner, Kratzer, and Weinhardt (2005), Teschner, Stathel, and Weinhardt (2011), Teschner (2012), Kranz, Teschner, and Weinhardt (2014), and Kranz (2015).

3.2 Mechanism Design

Mechanism design provides a profound and elegant framework that aims to design institutions — or *mechanisms* — which determine decisions based on information about individuals in the interest of achieving certain objectives (Myerson 1988). Individuals — or *agents* — are assumed to be rational and self-interested, i.e., to hold private information and act strategically for the decision at hand. Using methods from game theory, the goal of a mechanism is to provide incentives for agents not to communicate incomplete or untruthful information but to instead truthfully reveal complete information about their preferences, allowing the mechanism to determine an optimal system-wide solution (Parkes 2001).

Definition 3.3 (Mechanism Design). *The mechanism design problem is to compute an optimal and socially desirable outcome based on private information on individual preferences from rational and self-interested agents (Parkes 2001).*

3.2.1 Agents, Games, and Strategies

Mechanism design is profoundly informed by game theory. Game theory provides methods to study systems of self-interested agents in conditions of strategic interaction, i.e., at least one agent has an impact on the strategy of at least one other agent (Rasmusen 2006; Parkes 2001). The following important concepts and definitions provide the foundation for methods used in this thesis.

Commonly known in game theory as *players* in games (Rasmusen 2006), *agents* represent individuals or users in mechanism design research (Nisan et al. 2007). An agent's *type* abstracts from private information about its utility for different outcomes and also defines the preference structure of the agent. An agent's *strategy* defines its complete and contingent plan, which allows the agent to select different actions depending on every unique state of the game (Parkes 2001; Rasmusen 2006). The set of all strategies of an agent is defined by its *strategy profile*. An *equilibrium* is the combination of strategies chosen by each agent. It allows the mechanism designer to observe what actions result from the agents' plans, therefore to study the *outcome* of the mechanism (Rasmusen 2006). Agents are assumed to be *rational*, therefore only care about maximizing their utility (Nisan et al. 2007).

Definition 3.4 (Outcome). *Let $o \in \mathcal{O}$ be an outcome in the set of all possible outcomes $\mathcal{O}$ of a mechanism.*

Definition 3.5 (Agent). *Let agent i be the index of an agent in the set of agents $\mathcal{I}$, where agents are indexed $i = 1, \ldots, N$, with $N = |\mathcal{I}|$.*

Definition 3.6 (Agent type). *Given agent $i \in \mathcal{I}$, let agent i's private information be denoted by agent type $\theta_i \in \Theta_i$, where Θ_i denotes the set of all potential agent types. Agent type θ_i determines agent i's preferences over different outcomes $o \in \mathcal{O}$.*

Definition 3.7 (Strategy). *Given agent $i \in \mathcal{I}$, let $s_i(\theta_i) \in \mathcal{S}_i$ denote the strategy of agent i given agent type θ_i, where $\mathcal{S}_i \subseteq \mathcal{S}$ denotes set of all available strategies to agent i. A more convenient notation implicitly assumes an agent's type, therefore alternatively, let $s_i \in \mathcal{S}_i$ denote agent i's strategy given its type θ_i.*

Definition 3.8 (Strategy profile). *Given the set of agents $\mathcal{I}$, let vector $s(\theta) = (s_1(\theta_1), \ldots, s_N(\theta_N))$ denote the strategy profile for all agents, containing all agent strategies. Implicitly assuming an agents' type, alternatively let $s = (s_1, \ldots, s_N)$ denote the joint strategies of all agents, and $s_{-i} = (s_1, \ldots, s_{i-1}, s_{i+1}, s_N)$ denote the strategies of all gents except agent i.*

3.2.2 Utility and Preferences

Recall that agents in game theory are assumed to act rational. Agents therefore follow a strategy to maximize their individual utility. They express their preferences over different alternative outcomes, i.e., over their own strategy and the strategies of other agents, by means of a utility function (Parkes 2001). In more detail, objectives of agents are compiled into preference relations, i.e., a binary relation that allows a comparison between two alternatives. It is the general assumption in microeconomic theory that individual preferences are rational and therefore can be represented by a utility function (Mas-Colell, Whinston, and Green 1995). In other words, any rational agent possesses a utility function (Russell and Norvig 1995).

Definition 3.9 (Utility function). *Given agent $i \in \mathcal{I}$, its preferences over different outcomes θ_i and strategy profile s, let utility function $u_i(s, \theta_i) \in \mathcal{U}$ denote the utility of agent i. More clearly, utility function $u_i(\cdot)$ determines agent i's preferences over its own strategy and the strategy of all other agents.*

Example 3.1 (Utility function and preferences). Let outcomes $o_1, o_2 \in \mathcal{O}$. Agent i's utility function defines a preference ordering $\succ_i$ with

$$o_1 \succ_i o_2 \Leftrightarrow u_i(o_1, \theta_i) > u_i(o_2, \theta_i) \tag{3.1}$$

That is, agent i strictly prefers outcome o_1 over outcome o_2 (Parkes 2001).

In game theory, preferences of agents are commonly assumed to be quasi-linear (Parkes 2001; M. O. Jackson 2003). Therefore, for quasi-linear preferences, an agents' utility function is denoted as follows:

Definition 3.10 (Quasi-linear preferences). *Given agent $i \in \mathcal{I}$ and its preferences over different outcomes θ_i, let agent i's utility from quasi-linear preferences*

$$u_i(o, \theta_i) = v_i(o, \theta_i) - p_i \tag{3.2}$$

where $v_i(o, \theta_i)$ is agent i's value for an alternative outcome o and p_i is agent i's payment to the mechanism (Parkes 2001; Nisan et al. 2007).

The assumption of quasi-linear preferences for agents also holds for the work at hand. For a detailed discussion on quasi-linear preferences, the reader is referred to Mas-Colell, Whinston, and Green (1995) and Parkes (2001).

3.2.2.1 Social Choice

The core of mechanism design is the implementation of social choices in a strategic setting, where agents with private information about their preferences are assumed to act rationally (Nisan et al. 2007). A social choice function is implemented by a mechanism in order to select an optimal outcome o^* given each possible combination of agent types and other characteristics (Dasgupta, Hammond, and Maskin 1979). In other words, by aggregating the preferences of all agents, a system-wide social choice is selected (Parkes 2001). For example, in market-based environments, each agent has its own preferences, yet the outcome, i.e., the reallocation of goods and money, represents a single social choice. Auctions constitute another prominent example, where the social choice is defined by the auction rules and yields the identity of the winner(s) (Nisan et al. 2007).

Definition 3.11 (Social choice function). *Given agent types $\theta = (\theta_1, \ldots, \theta_N) \in \Theta$, social choice function $f : \Theta_1 \times \cdots \times \Theta_N \to \mathcal{O}$ selects an outcome $f(\theta) = o \in \mathcal{O}$ from the strategy profile $s(\theta) = (s_1(\theta_1), \ldots, s_N(\theta_N))$.*

3.2.2.2 Pareto Optimality

An outcome selected by social choice function f is *pareto optimal* (or pareto efficient) if there is no other outcome that would improve an agent's utility without decreasing the utility of at least one other agent (Parkes 2001).

Definition 3.12 (Pareto optimality). *An outcome of social choice function $f(\theta) = o$ is pareto optimal, if and only if*

$$u_i(o', \theta_i) > u_i(o, \theta_i) \quad \Rightarrow \quad \exists j \in \mathcal{I} : u_i(o', \theta_i) < u_i(o, \theta_i) \qquad (3.3)$$
$$\forall o' \neq f(\theta), \theta \in \Theta$$

3.2.2.3 Nash Equilibrium

A strategy profile is a Nash equilibrium (NE) if no agent has an incentive to deviate from its strategy, given that the other agents do not deviate (Nash 1950; Rasmusen 2006). A NE is widely accepted in game theory and more often applicable than a dominant-strategy equilibrium (Rasmusen 2006).

Definition 3.13 (Nash equilibrium). *A strategy profile $s = (s_1, \ldots, s_N)$ is a NE if and only if*

$$u_i(s_i, s_{-i}, \theta_i) \geq u_i(s'_i, s_{-i}, \theta_i) \quad \forall u_i \in \mathcal{U}, \forall s'_i, \neq s_i \tag{3.4}$$

3.2.2.4 Social Welfare

Social welfare is a global mechanism evaluation criterion. Therefore, it allows the comparison of alternative mechanisms by comparing their outcomes. It determines a preference aggregation over all participating agents and thus can be denoted as the sum of the payoffs or utilities of all agents (T. W. Sandholm 1999). While several notions of social welfare exist (Sen 1970; Arrow, Sen, and Suzumura 2011), this work applies the concept of *utilitarian social welfare*, which denotes the sum of the utilities of all agents.

Definition 3.14 (Social welfare). *Given a set of agents $\mathcal{I}$ and mechanism outcome o, let social welfare $sw(\cdot)$ denote the aggregation of all participating agent preferences as*

$$sw(o) = \sum_{i \in \mathcal{I}} u_i(o, \theta_i) \tag{3.5}$$

3.2.3 Mechanism Implementation and Properties

Having established the basic concepts of agents, utility, preferences, and social choice, a mechanism is defined as follows (Parkes 2001; Nisan et al. 2007):

Definition 3.15 (Mechanism). *A mechanism $\mathcal{M} = (\mathcal{S}_1, \ldots, \mathcal{S}_N, m(\cdot))$ defines the sets of possible strategies $\mathcal{S}_i \subseteq \mathcal{S} \forall i \in \mathcal{I}$ and an outcome function $m : \mathcal{S}_1 \times \cdots \times \mathcal{S}_N \rightarrow \mathcal{O}$ that maps the strategy profiles to outcomes.*

That is, a mechanism defines the available strategies to each agent and the function to determine the outcome, based on these strategy profile of all agents. In settings with quasi-linear preferences, the outcome function $o(s)$ can be split into a combination of a choice or allocation function $\kappa(s) \in \mathcal{O}$ and a transfer or payment function $\rho_i(s)$ (Parkes 2001).

As noted in definition 3.3 before, the objective of mechanism design is to compute an optimal social choice to a problem where rational and self-interested agents act with private information and individual preferences. Consequently, agents follow a strategy that maximizes their individual utility (Nisan et al. 2007). The concept of an *equilibrium*, i.e., an optimal strategy profile comprised of an optimal strategy for each agent, describes the desired outcome of a mechanism (Rasmusen 2006). Hence, a mechanism *implements* a social choice function if its equilibrium outcome, i.e., the outcome computed with equilibrium agent strategies, correspond to the outcomes of the social choice function for all possible agent preferences (Parkes 2001).

Definition 3.16 (Mechanism implementation). *Mechanism $\mathcal{M} = (\mathcal{S}_1, \ldots, \mathcal{S}_N, m(\cdot))$ implements social choice function $f(\theta)$ with outcome $o^* \in \mathcal{O}$, if $m(s_1^*(\theta_1), \ldots, s_N^*(\theta_N)) = f(\theta), \forall(\theta_1, \ldots, \theta_N) \in \Theta_1 \times \cdots \times \Theta_N$, where strategy profile $(s_1^*, \ldots, s_N^*)$ is an equilibrium solution induced by $\mathcal{M}$.*

A mechanism, or the social choice function it implements, has several desired properties as detailed in the following. While these properties are formally properties of the implemented social choice function, they are often referred to as properties of the mechanism (Nisan et al. 2007). Throughout the remainder of this work, this notion of mechanism properties is adhered to.

3.2.3.1 Allocative Efficiency

A mechanism $\mathcal{M}$ is allocative efficient if it maximizes the total utility, or social welfare, over all agents types. Note that the mechanism simply asks the agents to report their types. In such a basic setting, agents have no reason, or incentive, to report their *true types*, since the strategic manipulation of preferences may lead to a better individual outcome (Parkes 2001; Nisan et al. 2007).

Definition 3.17 (Allocative efficiency (AE)). *Mechanism $\mathcal{M} = (\mathcal{S}_1, \ldots, \mathcal{S}_N, m(\cdot))$ with $m(s(\theta)) = o$ and reported agent types $s(\hat{\theta})$ is allocative efficient, if and only if*

$$\sum_{i \in \mathcal{I}} u_i(o, \hat{\theta}_i) \geq \sum_{i \in \mathcal{I}} u_i(o', \hat{\theta}_i) \tag{3.6}$$

$$\Leftrightarrow \quad sw(m(s(\hat{\theta}))) = sw(o) \geq sw(o') \tag{3.7}$$

$$\forall s(\hat{\theta}) \in (\mathcal{S}_1, \ldots, \mathcal{S}_N), o' \in \mathcal{O}$$

3.2.3.2 Incentive Compatibility

Mechanism $\mathcal{M}$ is incentive compatible if it is rational for agents to report truthful information about their types (preferences) in equilibrium. In particular, under an incentive compatible mechanism, agents have no incentive to misreport their types to the mechanism in order to increase their utility (Parkes 2001). An incentive compatible mechanism can also be referred to as *strategy-proof* or *truthful* (Nisan et al. 2007).

Definition 3.18 (Incentive compatibility (IC)). *Given true agent types $\theta = (\theta_1, \ldots, \theta_N) \in \Theta$ and reported type $\hat{\theta}_i$ of agent $i \in \mathcal{I}$, a mechanism $\mathcal{M}$ is incentive compatible if and only if*

$$u_i(m(\theta_i, \theta_{-i})) \geq u_i(m(\hat{\theta}_i, \theta_{-i})) \quad \forall \hat{\theta}_i \in \Theta_i \tag{3.8}$$

3.2.3.3 Individual Rationality

A mechanism $\mathcal{M}$ is individually rational if no agent is worse off by participating in the mechanism than by not participating. More specifically, participating agents always receive non-negative utility which is greater or equal to their utility than under no participation (Parkes 2001).

Definition 3.19 (Individual rationality (IR)). *Given the utility $u_i(m(\hat{\theta}_i, \hat{\theta}_{-i}))$ of agent $i \in \mathcal{I}$ if agent i participates and the utility $\overline{u}_i(m(\hat{\theta}_i, \hat{\theta}_{-i}))$ if agent i does not participate. A mechanism $\mathcal{M}$ is (ex-post) individually rational if and only if*

$$u_i(m(\hat{\theta}_i, \hat{\theta}_{-i})) \geq \overline{u}_i(m(\hat{\theta}_i, \hat{\theta}_{-i})) \quad \forall i \in \mathcal{I} \tag{3.9}$$

This definition holds for *ex-post* individual rationality, where agents must have knowledge about the mechanism outcome. However, in mechanisms where agents must decide on participating or not before they know their preferences and hence are not able to observe the outcome, the weaker concept of *ex-ante* individual rationality is more appropriate. Ex-ante individual rationality, or interim individual rationality, uses the concept of expected agent utility (Parkes 2001). However, a requirement for ex-ante individual rationality is the knowledge of distributional information about the preferences $\hat{\theta}_{-i}$ of all other agents (Parkes 2001; Nisan et al. 2007).

Definition 3.20 (Ex-ante individual rationality). *Given the expected utility of agent $i \in \mathcal{I}$ if agent i participates, $E(u_i(m(\hat{\theta}_i, \hat{\theta}_{-i})))$, and the expected utility if agent i does not participate, $E(\overline{u}_i(m(\hat{\theta}_i, \hat{\theta}_{-i})))$, a mechanism $\mathcal{M}$ is ex-ante individually rational if and only if*

$$E(u_i(m(\hat{\theta}_i, \hat{\theta}_{-i}))) \geq E(\overline{u}_i(m(\hat{\theta}_i, \hat{\theta}_{-i}))) \quad \forall i \in \mathcal{I} \tag{3.10}$$

3.2.3.4 Budget Balance

Recall that for quasi-linear preferences, the outcome function $o(\cdot)$ can be split into a combination of a choice or outcome function $\kappa(\hat{\theta})$ and a transfer or payment function $\rho_i(\hat{\theta})$ (Parkes 2001). In a *(strong) budget balanced* mechanism, no net transfers into or out of the mechanism are required, i.e., payments are redistributed among the agents (Parkes 2001; Nisan et al. 2007).

Definition 3.21 (Budget balance (BB)). *Given mechanism $\mathcal{M}$ and outcome function $m(\hat{\theta}) = (\kappa(\hat{\theta}), \rho_1(\hat{\theta}), \ldots, \rho_N(\hat{\theta}))$, a mechanism $\mathcal{M}$ is budget balanced if and only if*

$$\sum_{i \in \mathcal{I}} \rho_i(\hat{\theta}) = 0 \tag{3.11}$$

The combination of allocative efficiency and budget balance implies pareto optimality (Parkes 2001). Additionally, the concept of *weak* budget balance allows net transfers from agents to the mechanism, but not the reverse case, i.e., no net payments from the mechanism to the agents (Parkes 2001; Nisan et al. 2007).

Definition 3.22 (Weak budget balance). *Given mechanism $\mathcal{M}$ and outcome function $m(\hat{\theta}) = (\kappa(\hat{\theta}), \rho_1(\hat{\theta}), \ldots, \rho_N(\hat{\theta}))$, a mechanism $\mathcal{M}$ is weakly budget balanced if and only if*

$$\sum_{i \in \mathcal{I}} \rho_i(\hat{\theta}) \geq 0 \tag{3.12}$$

3.2.3.5 Computational Complexity

The subject of complexity, or (in)tractability, considers both computational complexity and communication complexity (Garey and Johnson 1979). In particular, two different levels of a mechanism's complexity can be distinguished. Firstly, the mechanism infrastructure and secondly, the agents (Parkes 2001; Kalagnanam and Parkes 2004).

Computational complexity in mechanism design is concerned with the computational resources required to compute the outcome of a mechanism (Parkes 2001). In mechanisms that centrally determine an outcome, such complexity might break the usefulness of a mechanism due to its intractability (Dash, Jennings, and Parkes 2003). Moreover, computational complexity covers the problem that agents are faced with the difficulty to determine optimal or dominant strategies and to compute their preferences (Parkes 2001). As agents are assumed to have limited computational power, calculating preferences for all possible outcomes or determining equilibrium strategies might present a major limitation (Dash, Jennings, and Parkes 2003). The challenge of lowering this complexity has led to the emerging fields of research computational (or algorithmic) mechanism design (Dash, Jennings, and Parkes 2003; Nisan et al. 2007).

Communication complexity is concerned with the amount of information that agents have to provide and subsequently report to the mechanism (Parkes 2001; Nisan and Segal 2006). In order to reduce this complexity, providing compact and structured bidding languages represents a promising approach (Parkes 2001; Kalagnanam and Parkes 2004; Endriss and Maudet 2005; Goetzendorff et al. 2015). Ideally, a compact bidding language structure should be exploited throughout the mechanism (Parkes 2001).

For the case of (combinatorial) auctions, both computational and communication complexity play important roles (Nisan et al. 2007) and are covered in the remainder of this work.

3.2.4 Direct-Revelation Mechanisms

As noted before, the mechanism design problem is to compute an optimal and socially desirable outcome based on private information on individual preferences from rational and self-interested agents. In order to achieve this goal, it is key to provide appropriate incentives to agents so that they will choose their strategies as a function of their private information

(Parkes 2001). In situations where agents clearly have best strategies, these strategies are referred to as dominant strategies. Once the notion of dominant strategies is defined, the concept of a direct mechanism and its characteristics can be devised appropriately.

3.2.4.1 Dominant Strategies

Given all possible strategies of other agents, a dominant strategy is the best response of an agent to any available strategies other agents might choose (Parkes 2001). More specifically, a dominant strategy will always maximize the agent's expected utility, whatever strategies other agents may pick (Rasmusen 2006). Note that in most games, no dominant strategy exists and agents therefore must analyze each others' actions to choose their own (Rasmusen 2006; Nisan et al. 2007).

Definition 3.23 (Dominant strategy). *Given agent $i \in \mathcal{I}$, i's strategy s_i and all strategies of other agents s_{-i}, s_i is a dominant strategy, if and only if*

$$u_i(s_i, s_{-i}, \theta_i) \geq u_i(s_i', s_{-i}, \theta_i) \quad \forall s_i' \neq s_i, s_{-i} \in \mathcal{S}_{-i} \tag{3.13}$$

3.2.4.2 Revelation Principle

It is important to first emphasize the significant difference of direct and indirect mechanisms. A direct mechanism allows agents to simultaneously report their preferences only once and subsequently computes an outcome. On the contrary, an indirect mechanism allows agents to report several preferences and does not immediately determine an outcome but presents agents with individual feedback instead. An agent can integrate this feedback into its strategy afterwards and report updated preferences. For this reason, an indirect mechanism is sometimes also referred to as an iterative mechanism (Parkes 2001; Nisan et al. 2007). The design space for possible mechanisms is large, which poses the problem of determining the best mechanism given individual design requirements. Using the revelation principle, an important simplification towards this question can be made. The revelation principle as detailed below states that it is sufficient to focus on incentive compatible direct-revelation mechanisms (Kalagnanam and Parkes 2004). Throughout the remainder of this work, the focus is therefore restricted to direct mechanisms.

Definition 3.24 (Direct-revelation mechanism (DRM)). *A direct-revelation mechanism $\mathcal{M} = (\Theta_1, \dots, \Theta_N, m(\cdot))$ restricts agent strategies $\mathcal{S}_i = \Theta_i \forall i \in \mathcal{I}$, and has outcome function $m : \Theta_1 \times \dots \times \Theta_N \rightarrow \mathcal{O}$ which determines an outcome $m(\hat{\theta}) = o$ based on reported preferences from all agents $\hat{\theta}$.*

That is, the only available strategy, or action, to an agent is to directly report its (true or untrue) preferences $\hat{\theta}_i = s_i(\theta_i)$ (Parkes 2001).

If an agent reports true information about its preferences, the agent is said to have a truth-revealing, or truth-telling, strategy (Nisan et al. 2007). If truth-revelation is a dominant-strategy equilibrium, a mechanism is referred to as strategy-proof (Parkes 2001). The last prerequisite to the revelation principle represents the definition of an incentive compatible mechanism implementation, which states that the social choice function is computed in equilibrium, i.e., the outcome function equals the social choice function (Parkes 2001). Additionally, a mechanism is denoted as strategy-proof if truth-revelation is a dominant strategy equilibrium, i.e., the mechanism is dominant strategy incentive compatible (Parkes 2001).

Definition 3.25 (Truth-revelation). *Strategy $s_i \in \mathcal{S}_i$ of agent $i \in \mathcal{I}$ is truth-revealing if and only if $s_i(\theta_i) = \theta_i, \forall \theta_i \in \Theta_i$*

Definition 3.26 (Strategy-proof). *A direct-revelation mechanism $\mathcal{M}$ is strategy-proof, if and only if truth revelation is a dominant-strategy equilibrium.*

Definition 3.27 (Incentive compatible implementation). *Given outcome function $m(\theta)$, an incentive compatible direct-revelation mechanism $\mathcal{M}$ implements social choice function $f(\theta) = m(\theta)$.*

The well-known revelation principle (Gibbard 1973; Green and Laffont 1977; Myerson 1979, 1981) states that any direct or indirect mechanism can be transformed into an equivalent incentive compatible direct-revelation mechanism with the same social choice function (Parkes 2001). The major implication of this principle is that in order to find social choice functions that can be implemented in dominant strategies, the focus can be restricted to the set of direct-revelation mechanisms (Parkes 2001). Thus, it is sufficient to define functions that map agent types to outcomes, based on the constraints that ensure that the mechanism is incentive compatible (Kalagnanam and Parkes 2004).

Definition 3.28 (Revelation principle). *If any mechanism $\mathcal{M}$ implements social choice function $f(\cdot)$ in dominant strategies, then the direct mechanism f is dominant strategy incentive compatible, i.e., in a strategy-proof mechanism.*

3.2.4.3 Vickrey-Clarke-Groves Mechanisms

Among the class of direct-revelation mechanisms, the Vickrey-Clarke-Groves (VCG) mechanisms (Vickrey 1961; Clarke 1971; Groves 1973) are the only mechanisms that are allocative efficient and strategy-proof for agents with quasi-linear preferences and general valuation functions (Green and Laffont 1977; Parkes 2001). The VCG mechanisms represent a version of the Groves mechanisms and are commonly referred to as such (Parkes 2001).

Recall that for quasi-linear preferences, the outcome function $o(\hat{\theta})$ can be split into a combination of a choice or allocation function $\kappa(\hat{\theta}) \rightarrow \mathcal{K} \in \mathcal{O}$ and a transfer or payment function $\rho_i(\hat{\theta})$. The choice function in a Groves mechanism computes the selection, i.e., choice κ^*, which maximizes the total reported valuations over all agents:

$$\kappa^*(\hat{\theta}) = \arg\max_{\kappa \in \mathcal{K}} \sum_{i \in \mathcal{I}} v_i(\kappa, \hat{\theta}_i) \tag{3.14}$$

The payment function in a Groves mechanism introduces the degree of freedom that defines the class of Groves mechanisms by means of an arbitrary function on reported agent types or a constant $h_i : \Theta_{-i} \rightarrow \mathbb{R}$:

$$\rho_i(\hat{\theta}) = h_i(\hat{\theta}_{-i}) - \sum_{j \neq i} v_j(\kappa^*, \hat{\theta}_j) \tag{3.15}$$

Groves mechanisms are allocative efficient and strategy-proof, i.e., truth revelation is a dominant strategy for each agent, independent of the reported types of other agents (Green and Laffont 1977). Therefore, reporting its true types $\hat{\theta}_i = \theta_i$ aligns agent i's incentives with the goal of achieving allocative efficiency (Kalagnanam and Parkes 2004). Additionally, Groves mechanisms are unique in the sense that they are the only allocative efficient and strategy-proof mechanisms (Green and Laffont 1977). For detailed proofs, the reader is referred to Green and Laffont (1977) and Parkes (2001).

The Vickrey-Clarke-Groves, or Pivotal or Clarke (Clarke 1971), mechanism represents a special case of the Groves mechanisms. It maximizes the payments by the agents to the mechanism for all strategy-proof and allocative efficient mechanisms and is ex-post individual rational as well as weakly budget balanced (Parkes 2001). The additional choice function of a VCG mechanism is defined as

$$h_i(\theta_{-i}) = \sum_{j \neq i} v_j(\rho^*_{-i}(\hat{\theta}_{-i}), \hat{\theta}_j) \tag{3.16}$$

where $\rho^*_{-i}(\hat{\theta}_{-i})$ is defined as the optimal outcome without agent i (Clarke 1971):

$$\rho^*_{-i}(\hat{\theta}_{-i}) = \arg\max_{\kappa \in \mathcal{K}} \sum_{j \neq i} v_j(\kappa, \hat{\theta}_j) \tag{3.17}$$

That is, function $h_i(\theta_{-i})$ internalizes the externality imposed by agent i on all other agents in the system (Kalagnanam and Parkes 2004). For a non-participating agent, the agents' externality is assumed to be zero (Parkes 2001). Consequently, the payment function $\rho_{\text{vcg},i}(\hat{\theta})$ of a VCG mechanism is defined as follows (Kalagnanam and Parkes 2004):

$$\rho_{\text{vcg},i}(\hat{\theta}) = \sum_{j \neq i} v_j(\rho^*_{-i}(\hat{\theta}_{-i}), \hat{\theta}_j) - \sum_{j \neq i} v_j(\kappa^*, \hat{\theta}_j) \tag{3.18}$$

The VCG mechanism provides the foundation for proofs of the following impossibility theorems in mechanism design.

3.2.4.4 Impossibility Results

Based on the characterization of Groves and the VCG mechanisms, mechanism design theory has established a fundamental way of showing which economic constraints, i.e., AE, IC, IR, and BB, can be realized for direct-revelation mechanisms. Nevertheless, not all constraints can always be achieved simultaneously, introducing impossibility results for mechanism design. These impossibility results are derived from showing a conflict between different mechanism constraints and in turn generalizing the results by means of the revelation principle (Krishna and Perry 1997; Parkes 2001).

Theorem 3.1 (Hurwicz-Green-Laffont). *There does not exist an efficient, budget balanced, and strategy-proof mechanism implementation in an exchange for agents with quasi-linear preferences (Hurwicz 1972; Green and Laffont 1977; Hurwicz and Walker 1990; Parkes 2001).*

That is, if AE and BB are mechanism constraints, a dominant-strategy solution is impossible to find by means of the revelation principle (Parkes 2001). In a more general fashion, the previous theorem of can be extended to include Bayesian-Nash implementation for the additional condition of (intermin) individual rationality.

Theorem 3.2 (Myerson-Satterthwaite). *There does not exist an efficient, weakly budget balanced, (interim) individual rational, and Bayesian-Nash incentive compatible mechanism in an exchange for agents with quasi-linear preferences (Myerson 1983; Parkes 2001).*

Consequently, at most two of AE, IR, and BB constraints can be achieved in a market with agents with quasi-linear preferences. A detailed list of possibility and impossibility results is provided by Parkes (2001).

4

Markets for Smart Distribution Grids

The goal of this chapter is to bring together previously discussed fields of smart grids, market engineering, and market design in order to elaborate on the emerging necessity of markets in smart grids. While the design space for markets in smart grids has a great potential on several levels, the work at hand focuses on local, i.e., residential, markets which are inherently positioned in distribution grids. As identified by policy makers, new and updated markets which are able to reliably integrate (demand side) flexibility and renewable energy sources (RES) in a more real time manner on such local levels are key to the success of smart grids (EC 2015a; BMWi 2015a).

Central to ensuring security of supply in a distribution grid, the distribution system operator (DSO) is confronted with new challenges in managing RES and flexible consumers. In order to successfully meet the requirements imposed on the DSO, the DSO needs to perform a more active grid management and make use of markets to procure flexibility or flexibility services from consumers or intermediaries that manage groups of consumers, i.e., aggregators. Therefore, this chapter first discusses the role of the aggregator in the current environment in section 4.1. For this purpose, an overview of current research approaches, real world industry projects, and aggregator business models structured along the market engineering framework in the spirit of Weinhardt (2012) is presented. All components of the market engineering framework are mapped to current developments in research, politics, and industry, followed by a classification of emerging projects within each framework element. Moreover, future research opportunities for each element in the market engineering framework are highlighted. Subsequently, section 4.2 outlines the corresponding research environment for the DSO. That is, the requirements for a market mechanism which can be employed by a DSO to procure load flexibility from aggregators are identified. Finally, existing market mechanisms are examined towards the identified requirements. Henceforth, the role of the DSO remains central for the remainder of this work. Parts of this chapter are adapted from the following previously published papers:

- David Dauer, Paul Karaenke, and Christof Weinhardt. 2015. "Load Balancing in the Smart Grid: A Package Auction and Compact Bidding Language." In *Proceedings of the Thirty Sixth International Conference on Information Systems.* Fort Worth, TX.
- David Dauer, Frederick vom Scheidt, and Christof Weinhardt. 2016. "Towards Smart Distribution Grids: A Structured Market Engineering Review." In *Proceeings of the Second Karlsruhe Service Summit Research Workshop.* Karlsruhe.

4.1 A Market Engineering Overview of Aggregators

New proposals for energy market designs on both national (BMWi 2015a) and EU level (EC 2015a) call for a better integration of the increasing share of RES as well as opening the market to more actors in order to utilize their flexibility. In particular, DSOs and aggregators could leverage flexibility from consumers to avoid more costly options such as using the control reserve and to further generate revenue from new business models. Moreover, flexibility products and services as well as other measures beneficial to the grid, and therefore beneficial to security of supply, are necessary.

In the following, this section gives a structured overview and analysis of current research approaches and real world industry projects in Germany regarding aggregators in distribution grids along the elements of the market engineering framework, which is introduced in section 3.1 and illustrated in figure 3.1a. Moreover, all components of the market engineering framework are analyzed and illustrated by examples. In addition, future research opportunities are highlighted for each framework element.

It is important to note that this section broadens the focus from the perspective of the market engineer to additionally highlight and incorporate the role of market intermediaries, or aggregators. Aggregators can also take the role of a market engineer, where their market environment currently depicts a one-sided market, sometimes with a fixed price strategy. Nevertheless, engineering a business structure and designing appropriate transaction objects towards a market outcome still remains a valid and important task.

4.1.1 Economic and Legal Environment

Both on a European Union (EU) as well as on a national level, efforts towards achieving ambitious energy targets, such as the EU 2030 targets (EC 2015a) or the exit from nuclear power generation (BMWi 2015a), are driving changes to the current legal and economic environment which governs energy markets. Most recently, the EU started working on proposals for a new energy market design, which envisions a market design that should allow innovative companies to provide for the electricity needs of consumers by using new technologies, paradigms, products, and services (EC 2015a). The proposed framework should not only deliver suitable EU-wide electricity markets that allow for new incentives to integrate RES, but also to promote the coordination of energy policies as well as to ensure the security of supply. In more detail, opening the market to more actors, therefore allowing access to flexible demand and new electricity service providers, e.g., aggregators, remains a priority. Moreover, it is encouraged to establish better flexible and integrated short-term markets to allow more players on the supply and demand side to compete with conventional generators. In addition, removing obstacles for consumers represents a further item on the EU's agenda (EC 2015b). In particular, obstacles such as the lack of information on cost and consumption, grid charges, insufficient competition in retail markets and the absence of markets for residential electricity services as well as demand response (DR) must be addressed.

In late 2015, German policy established measures that target the development of an advanced electricity market – the *electricity market 2.0* (BMWi 2015a). In part driven by EU policy, but mainly specific to national issues, the electricity market 2.0 draft tackles issues concerning the improvement of market mechanisms, fostering the market participants' flexibility, as well as the integration into the EU's internal energy market (IEM). Of particular interest is that DSOs, faced with a growing integration of RES, are required to perform new tasks such as feeding electricity back to higher voltage levels, expanding the grid, and monitoring security of supply under new conditions. In order to ensure security of supply, the integration and coordination of markets and distribution grids is of high significance (BMWi 2015a).

Clearly, both EU and national agenda in Germany require actions to strengthen the role of DSOs. By leveraging flexibility from consumers, more costly options in expectation such as re-dispatching, balancing, or feed-in-management can be avoided. Above all, it is necessary to use flexibility services and other measures beneficial to the grid and security of supply.

4.1.2 Market Outcome

Markets are designed to achieve a desired outcome, i.e., an allocation and pricing result. The performance of a market can be measured based on the market structure and in particular based on the agent behavior, i.e., their preferences and actions, as well as the market outcome (Weinhardt, Holtmann, and Neumann 2003). Well-known global economic performance criteria are social welfare and (allocative) efficiency (T. W. Sandholm 1999). Concerning the design of markets for distribution grids, market efficiency is crucial in order to ensure a continuous balance of supply and demand. Shortages on either side can result in costly emergency measures. Considering system stability, incentives of agents should be aligned with security of supply in mind to prevent market failure. Moreover, the following suggestions for outcome objectives of secondary nature represent promising, yet important goals towards the success of local markets in smart grids.

- Consumer privacy needs to be protected in light of the large amount of high-resolution data collected by smart meters. Suitable arrangements in the IT infrastructure can support this outcome goal.
- Market mechanisms need to be efficient in terms of computational cost. Waiting times for consumers regarding feedback needs to be kept at a minimum and basically not perceivable whenever possible.
- In order to integrate consumers into such markets, entities such as aggregators are required. These in turn will only operate given viable business models. Thus, a market outcome needs to consider the (maximization of) revenue streams not only for the market engineer but also for its participants.

These criteria can be achieved by designing the market structure and transaction object in an adequate manner. Focusing on aggregators, the main market outcome is to allocate and in turn provide balancing power to ensure grid stability by efficiently controlling small power plants or to manage a pool of consumer batteries efficiently. For example, by connecting a small plant via Next Kraftwerke's Next Box to a virtual power plant (VPP), consumers can gain a share of revenue generated from the commercialization of balancing power by offering flexibility to the market mechanism (Next Kraftwerke 2015b). Beegy Solar pursues a similar approach, but focuses on solar generation while providing strong incentives such as guaranteed savings (Beegy 2015).

4.1.3 Agent Behavior

Agent behavior results from the transaction object and market structure. Therefore, it is not the goal of the market engineer to influence this behavior, but instead to analyze and anticipate the behavior and characteristics of agents (Weinhardt, Holtmann, and Neumann 2003; Weinhardt and Gimpel 2007). In context of the smart grid, agents, or consumers, are expected to offer their flexibility to a market or market intermediary, i.e., an aggregator (Albadi and El-Saadany 2008). It is therefore key to identify flexibility among consumers. Accordingly, Strbac (2008) describes flexibility as deferring or reducing loads over time. He et al. (2013) classify consumer load types into storable, shiftable, curtailable, and base load as well as self-generation. Similarly, Petersen, Hansen, and Mølbak (2012) and Petersen et al. (2013) present a taxonomy for different quality levels of flexibility. Current research approaches suggest DR programs (Albadi and El-Saadany 2008; Palensky and Dietrich 2011) that should incentivize consumers to shift their various load types. In addition, other approaches to stimulate agent behavior might include:

- Gamification, i.e., using game design elements such as rankings in non-game contexts (Deterding et al. 2011) to support the consumers' value creation (Huotari and Hamari 2012). By stimulating consumer participation in smart grids, they are more likely to offer their preferences on flexibility to the market or market intermediaries.
- Taking up the last point on user participation, hidden markets (Seuken, Jain, and Parkes 2010) and market user interface design (Seuken et al. 2012) can influence and mediate user behavior with the graphical user interface of a market. Hence, they facilitate consumer participation.
- In light of the rising sharing economy (Belk 2007; Hawlitschek, Teubner, and Gimpel 2016), peer-to-peer (P2P) platforms present an opportunity to communicate and share different transactions objects with close neighbors or friends. Communities

can share generation capacity and increase self-consumption of their electricity. The increased purchasing power allows larger generation provisioning while at the same time decreasing grid fees (buzzn 2015).

When looking at real world examples of aggregators, the strategy of employing hidden markets can be named. Seuken, Jain, and Parkes (2010) state that "the complexities of the market must be hidden and the interaction for the user must be seamless" in cases where users participate in markets in everyday life without being experts in the field. Since this is clearly the case for a lot of potential consumers of, e.g., solar power plants and intelligent energy management software, it makes sense not to inform consumers about the details behind the aggregators' business models. Private owners of small power plants probably would not want to have to actively make decisions about when and how to sell their electricity on the market. Instead they prefer to hand over the responsibility to a so-called aggregator who acts and trades in their favor. Existing companies putting this approach into practice are for example Next Kraftwerke, Caterva, LichtBlick, and Beegy. Some aggregators go as far as positioning themselves as full-line providers which take care of the whole installation process, connection to the grid, all legal formalities, and the constant monitoring and management. This minimizes efforts and increases consumer participation.

4.1.4 Market Structure

Central to a functioning market structure are active market participants. Focusing on distribution grids, strengthening the role of DSOs in markets and enabling the participation of flexible users and aggregators, i.e., businesses that facilitate the participation of flexible users in (new) markets, represent a key challenges (BMWi 2015b). New transaction objects and market microstructures are emerging, while IT infrastructure considerations on privacy and security need to be addressed.

4.1.4.1 Microstructure

The market microstructure describes the mechanism under which resources are allocated and priced. It consists of a market's trading rules and systems, considers structural characteristics of markets and researches into the process through which prices and volumes are determined. Central elements of market microstructure are therefore the market model or auction type, the execution system, the trading mechanism, and the degree of transparency (O'Hara 1998). Moreover, the form in which information is exchanged, i.e., the bidding language, is defined in the microstructure (Weinhardt, Holtmann, and Neumann 2003).

Sarvapali D Ramchurn et al. (2011) present a decentralized mechanism to manage demand in smart grids. The mechanism manages agents through a pricing mechanism that tries to avoid peak loads. Höning and Poutré (2014) introduce a combination of an ahead market and a last-minute balancing market. Their ahead market supports both binding ahead-commitments and reserve capacity bids. Lamparter, Becher, and Fischer (2010) present a market mechanism that incentivizes agents to reveal their true preferences, therefore allowing an efficient solution for coordinating demand and supply. They note that the platform is suitable even for single local energy exchanges. Moreover, Samadi et al. (2012) propose a mechanism for demand side management (DSM) which aims at maximizing social welfare of all agents while minimizing total generation cost.

When applying the microstructure element of the framework to aggregators (which can be viewed as markets on their own), several differences to classical markets become visible. First of all, the market mechanism corresponds to the general terms and conditions of the respective aggregator. These terms and conditions basically define the rules of the trade, such as the delivery of the product and the payment period. Furthermore, usually no auction type can be specified since auctions are rarely utilized as opposed to fixed prices. Consumers do not submit bids but rather inquire (customized) offers. As can be seen in table 4.1, some examined companies offer customized products and services with individual pricing, while others have a general fixed price product portfolio.

4.1.4.2 IT Infrastructure

Apart from the physical grid infrastructure, IT infrastructure, or information and communication technology (ICT), is considered to be a fundamental and at the same time critical component in the smart grid as it is responsible for ensuring a reliable system operation. Several issues that need to be addressed are as follows:

- Resilient cybersecurity systems that ensure data integrity, reliable data delivery and communication, authentication, confidentiality protection, and monitoring as well as performance stability throughout the infrastructure are necessary. Hardware-based as well as software-based solutions, e.g., firewalls and encryption mechanisms, respectively, must ensure a reliable system operation (Moslehi and Kumar 2010). Encryption and authentication solutions (Metke and Ekl 2010; Khurana et al. 2010), approaches that extend current architectures with methods from trusted computing (Paverd, Martin, and Brown 2014) as well as complete system architectures (Moslehi and Kumar 2010) have been proposed.

- Following the previous claim, privacy issues arise from the vast amount of collected data from smart meters. Most recently, Goel and Hong (2015) note that a breach of data privacy is among the most prevalent threats to the operation and safety of the grid. Prominent approaches include the anonymization of smart meter data. In particular, by aggregating frequently measured smart meter data, billing, account management, and marketing measures must still be possible (Efthymiou and Kalogridis 2010). Other approaches include the encryption of individual measurements (Mármol et al. 2012). Moreover, designing mechanisms that enhance privacy while at the same time ensuring properties of market mechanisms such as allocative efficiency constitute an important research direction at the interface of market microstructure and IT infrastructure (Kessler, Flath, and Böhm 2015).
- Industry standards for ICT are required to integrate a heterogeneous landscape of devices, e.g., intelligent appliances, smart meters or renewable generation, and to facilitate the real-time information flow between them in a smart grid system (Gungor et al. 2011). Moreover, technical issues such as low-latencies and limited bandwidth must be addressed. An overview of current standardization efforts is provided in Gungor et al. (2013).

When examining existing aggregators, the importance of the IT infrastructure becomes evident. For VPPs for example, the communication between the distributed power plants plays a crucial role and mostly happens via internet connection or mobile (GSM) communication. Besides, the communication between aggregator and consumers often is done completely through IT means such as web portals and mobile applications. The individual characteristics of each of the surveyed companies are summarized in table 4.1 below.

4.1.4.3 Business Structure

Business structure in terms of Weinhardt, Holtmann, and Neumann (2003) concerns the charges for accessing the market, as well as fees for using the communication means (e.g., for placing bids), and for executing orders. In other words, when examining the business structure, the central question deals with how revenues for a market operator are generated. Important revenue streams of current electricity markets include fees for connectivity and trading. For example, the European Energy Exchange (EEX), charges its traders for the connection to the exchange as well as for the trading itself. Different qualities of connection – "internet", "virtual private network (VPN)", and "leased line" – are offered. The trading fees consist of a fixed and a variable component, i.e., annual fees, technical fees and transaction fees (EEX 2015). For future local markets, similar business structures are conceivable, since current models have proven their value. However, the particular characteristics of local markets have to be considered. Contrary to the existing wholesale markets, it is crucial for local markets to integrate a large number of distributed consumers or agents. This can be achieved by loosening the regulative restrictions regarding market participation. A logical proposal would therefore be to decrease single payments that have to be made to get initial access to the market. Instead, subscription models could be offered.

Looking at the business structure of emerging aggregators, the focus lies on their business model. VPP operators and electric vehicle (EV) aggregators constitute examples of current fields of research and already existing real world business models. Firstly, Asmus (2010) sees VPPs to either become smart grid enablers by providing an ICT network or to expand the sale of electricity towards other services such as heat, cooling, or lighting. Schulz, Roder, and Kurrat (2005) present a business model for a VPP of combined heat and power (CHP) units, yet note that as prices may not be able to compete with conventional plants, contract solutions are necessary. Werner and Remberg (2008) highlight that the regulatory framework needs to be considered in a deregulated market environment such as Germany. As recently shown by Knorr et al. (2014), VPPs are not only technically capable of supplying all of Germany with renewable energy, but are also able to offer ancillary services to the grid. Therefore the fundamental prerequisites for (profitable) business models for VPPs are given. Further, Pandžić et al. (2013) examine the case of a VPP consisting of a wind power plant, a quick response conventional power plant and a pumped hydro storage plant. Their results indicate that by participating in both the day-ahead and the balancing market, the coordinated aggregate of generators performs (financially) better than independent generation units.

Besides, the aggregation increases the overall operational flexibility.

Another promising use case for aggregator business models is the pooling and centralized management of EVs. Ensslen et al. (2014) examine the business model of a smart charging manager which aggregates load shifting potential offered by EVs and coordinates their charging process. Their results from simulation experiments indicate considerable potential for the profitable operation of their proposed business model. Moreover, they shows that appropriate grid integration can avoid new peaks in electricity consumption due to increased demand by electric mobility. Also, it explicitly mentions the possibility of the smart charging manager to help DSOs avoid critical situations in distribution grids. Additionally, Jargstorf and Wickert (2013) analyze the business case of providing balancing power on the German market with pooled EVs as an example for vehicle to grid (V2G) services. Their simulation reveals comparably low revenues per EV, leading to the argument that either larger units are required or that other markets with lower entry barriers need to be addressed. Similarly, Dallinger, Krampe, and Wietschel (2011) suggest that a pool size of 10 000 EVs is required in order to balance in-pool individual driving behavior. The still relatively low penetration rate of EVs hinders the profitability of business models regarding aggregated EVs. However, depending on the future development of the EV market and market access requirements, they might become more relevant in the future. Through integration into larger pools of consuming and producing units, EVs can help stabilizing distribution grids in the near future. In this context, Dauer et al. (2014) evaluate the economic potential of tariffs and coordination models for concurrent EV charging. Based on "concurrency factors", they suggest that aggregators can coordinate EV charging accordingly. Moreover, Kießling et al. (2015) introduce the concept of aggregating EV flexibility and provide a functional architecture for the coordination of EV flexibility. Moreover, they highlight the need for a communication architecture based on EU standards.

A real world example for an actively operating and already profitable aggregator company is the 2009 founded and Germany based Next Kraftwerke. Aggregating over 2600 power plants – biogas, solar, wind, water, combined heat, and power and emergency generators – the company has traded over 5.3 TWh on the spot and balancing market in 2015 (Next Kraftwerke 2015a). Next Kraftwerke has two major revenue streams. One is the price for the hardware component "Next Box", which consumers have to install in order to be connected to the virtual power plant. This corresponds to a one-time connection fee from a market operator point of view. The other revenue source is a share of the profits generated from trading activities (Next Kraftwerke 2015b). The joint venture Beegy has a slightly different focus and business model. On the one hand, the company offers solar panels and the intelligent management and monitoring thereof for private consumers while guaranteeing certain financial savings (BEEGY Solar and BEEGY Care). Moreover, Beegy integrates existing heat pumps and storage heaters and also offers batteries in a partnership with the battery storage manufacturer ads-tec (BEEGY Solar + Powerstore). On the other hand, Beegy offers services like energy management and monitoring and marketing of electricity and flexibility for businesses and the housing industry. The revenue streams include the price for the installation of solar panels or batteries and the BEEGY Gateway (i.e., a one-time connectivity fee) as well as a yearly fee for monitoring, savings guarantee, and supplementary services (subscription model) (Beegy 2015). In order to avoid high one-time cost that can deter smaller consumers, companies like the VPP operator Caterva offer a subscription model in addition to a purchase model. Here, consumers can rent a battery and thus become a part of the VPP without having high investment cost. Experience shows that consumers clearly prefer the subscription model (L. Weber 2015). This supports the above statement that replacing one-time access fees by subscription fees can help aggregators to attract additional consumers.

4.1.5 Transaction Object

The transaction object is the product or service traded between parties in a market. In the case of markets available to actors on the distribution grid level, relevant transaction objects are currently limited to retailers acting and trading on electricity wholesale markets (Judith et al. 2011). In particular, while over-the-counter (OTC) products (futures) represent bilateral contracts between generators and retailers (Growitsch and Nepal 2009), the exchange model in Germany allows trading bid functions for individual hours and block bids for standardized block hours in so-called spot markets (Erdmann and Zweifel 2008; Ockenfels, Grimm, and Zoettl 2008). Grid operators do not interact with these markets. Due to policy requirements, changed market structures and new technological options, these goods might be redesigned and complemented by new ones (BMWi 2015b).

The early research of Schweppe et al. (1988) suggests to differentiate products, i.e., tariffs, along temporal and spacial components. Similarly, Hayn, Bertsch, and Fichtner (2015) develop a concept for quality of service (QoS) level indicators for (residential) electricity tariffs, which they define as a service. Moreover, Flath et al. (2015) perform an extensive and structured analysis to derive new transaction objects. In particular, they suggest product differentiation based on different levels of security of supply, tariff components and additional use cases of power, such as for electric mobility. In line with this research, it becomes clear that while electricity will remain a homogeneous good regarding its technical properties like voltage and frequency, a product differentiation along non-functional quality attributes of electricity services presents an emerging approach. In particular, temporal flexibility, curtailment flexibility and reliability requirements constitute promising characteristics to further raise efficiency not only on the local but global electricity market level. Schuller et al. (2015) present a framework and design options for quality differentiated electricity products and related services. They suggest that product differentiation can foster self-selection of consumers and thus support activating the flexibility potential of DSM in smart grids. R. Sioshansi (2012) and Flath (2014) evaluate different tariffs for EVs, e.g., time of use (TOU) tariffs, and find that trade-offs between tariff complexity and efficiency are to be accounted for. Existing aggregators in smart grids offer various sorts of transaction objects, like hardware products for the connection and integration into the swarm, intelligent management software and a wide range of different services. Table 4.1 shows an aggregated overview of the types of offered transaction objects.

4.1.6 Market Overview

As detailed before, aggregator concepts and solutions from the industry exist already today. The findings are summarized in table 4.1, structured according to the market engineering framework. Here, due to their clear importance, the two aspects of improving grid stability and generating additional revenues through the marketing of electricity and flexibility are chosen as representatives for evaluating the market outcome. Regarding agent behavior, the target consumers are divided into the two groups of private and industry consumers, where the ownership of solar or wind generation units are further differentiated. With respect to the microstructure, especially the availability of custom prices is of interest. When looking at the (IT) infrastructure of aggregators, the three most relevant categories are internet access, mobile access and the offering of a mobile application. With regards to the business models, the revenue streams of the existing companies differ in particular and are therefore subdivided into one-time fee (sale), subscription model, and brokerage fee. The latter is synonymous to the aggregators keeping a share of the generated revenue. Last, the particular transaction objects are grouped into products and services.

Table 4.1: Overview of aggregator companies with products and services (● = Fulfilled, ○ = Not fulfilled or unknown)

	Next Kraftwerke	Beegy	LichtBlick SchwarmEnergie	Sonnenbatterie	Tesla	Caterva
Market outcome						
Ensure grid stability through efficient allocation	●	●	●	●	●	●
Generate revenues through flexibility marketing	●	●	●	○	○	●
Agent behavior						
Private households	●	●	●	●	●	●
Industry consumers	●	●	●	○	●	○
Solar generation installed	●	●	●	○	○	●
Wind generation installed	●	○	○	○	○	○
Microstructure						
Custom prices	●	●	●	○	○	○
(IT) infrastructure						
Internet access required	○	●	●	○	○	●
Mobile (GSM) access available	●	○	○	●	○	●
Provides mobile application	●	●	○	●	○	●
Business structure						
One-time sale	●	●	●	●	●	●
Subscription	●	●	●	○	○	●
Brokerage fee/shared revenue	●	●	○	○	○	●
Transaction object						
Physical product	●	●	●	●	●	●
Service	●	●	●	○	○	●

Source: Own data from 2015/12.

4.2 Environmental Analysis and Related Work

Having provided an overview of aggregators within the market engineering framework, this section focuses on the DSO, which constitutes an aggregator's potential counterpart in future local markets. This section first elaborates on the idea and necessity for DSOs to employ market mechanisms to ensure grid stability in critical and near real-time situations by allocating flexibility from aggregators. Afterwards, requirements upon a market mechanism for a DSO in context of the smart grid from an economic and technical perspective are defined. Based on the identified requirements, related work with regard to existing market mechanisms is identified and described. Subsequently, limitations with regard to the requirements are highlighted.

4.2.1 The Need for Market-Based Allocation of Flexibility

Today's regulatory framework in Germany leaves DSOs two options for a reliable and secure grid management in light of an increasing share of RES. Firstly, DSOs can expand their grids in the traditional sense, or secondly, DSOs can temporarily reduce the feed-in from RES.

Activities of regulatory and legislative nature on both the national level in Germany and European level highlight the importance of a market-based allocation of flexibility from local consumers to support the integration of RES. More specifically, the grand challenge of efficiently integrating RES from local levels into the smart grid requires flexibility management, i.e., the combination of flexibility of demand and storage technology from consumers or prosumers, to support grid stability. As highlighted in chapter 2 and section 2.3, in order to avoid critical grid situations, calls for market-based coordination and allocation of flexibility by DSOs have emerged (SG-CG 2014a; SGTF 2015; BMWi 2015a). Such market-based approaches allow the integration of new, local, and so far inactive players which can provide flexibility services (EC 2015a; SGTF 2015).

Particularly responsible for grid stability, DSOs in Germany are faced with new tasks and challenges with the increasing share of RES. Such new responsibilities need to include the short-term and market-based allocation of flexibility from local aggregators in critical grid situations as current market designs do not allow the short-term coordination of retailers, aggregators, and DSOs (BMWi 2015a). While this is an ongoing process, requirements for DSOs in context of an updated electricity market scenario in Germany have already been formulated (BMWi 2015b, 2015a, 2015c). However, a detailed proposal and implementation for such a market-based process remains unavailable as of today. This absence highlights the relevance of this work.

The proposed market mechanism is supposed to represent an extension to the transformative process in the electricity grid, which should not only foster competition but also actively integrate consumers or prosumers. In contrast to current market designs, the proposed mechanism needs to account for current (critical) local grid situations where existing flexibility can represent a cost-efficient solution compared to emergency measures and nonessential grid investments cost.

4.2.2 Traffic Light Concept

The traffic light concept (TLC) represents the suggested basis for the market-based allocation of flexibility by DSOs in Germany and on a European level (SG-CG 2014a; SGTF 2015). Using the TLC, DSOs can define different system states depending on potential critical grid situations (SGTF 2015). In turn, a system state can enable DSOs to use mechanisms, such as the procurement of flexibility, to maintain the balance of supply and demand (SG-CG 2014a). Possible TLC states, which are visible to other market parties, constitute the red, yellow, and green states.

Green State The green state of the TLC reflects a normally operating grid state. Existing markets can competitively operate freely, i.e., the green state yields no restrictions for trading on markets (SG-CG 2014a). Within this state, a DSO does not need to employ the mechanism proposed in this work.

Yellow State The yellow state specifies a situation where a local critical grid state, which typically does not affect higher transmission grids, exists or is about to exist. The DSO then actively tries to resolve the critical situation by means of market-based allocation of flexibility free from discrimination. The yellow state indicates to potential market participants that there exists demand for local flexibility to stabilize the grid. Participation within the market mechanism is clearly not mandatory. However, should the DSO not be able to resolve the situation at hand while the critical situation remains, the TLC dictates the switch to the red state (SG-CG 2014a).

Red State The red state represents a last resort for the DSO to stabilize the grid to avoid a blackout situation. By means of temporary and specific actions, the DSO can and needs to engage in current market operations and override existing delivery contracts while at the same time executing direct control over generation or demand units (SG-CG 2014a).

4.2.3 Classification in the Current Market Environment

The proposed mechanism can be classified as part of the yellow TLC state to be available to the DSO in order to (i) ensure grid stability and guide the grid from the yellow to the green TLC state and (ii) to avoid emergency measures needed in case a switch to the red TLC state is required. In contrast to the existing control reverse markets, the proposed mechanism focuses on the local grid level where aggregators can bundle consumer and prosumer flexibility into portfolios and market this flexibility accordingly in a cost-efficient manner. The local nature of the mechanism is important as flexibility and their location denote important aspects of future distribution grids (SG-CG 2014a; EC 2015a). Following the timeline of electricity markets in Germany as illustrated in figure 2.9, the proposed mechanism can be integrated after the operating reserve contracting is completed and in particular in short-term situations before the scheduled supply period.

4.2.4 Requirements

In contrast to the existing control reverse markets, the proposed mechanism focuses on the local grid level where aggregators can bundle consumer and prosumer flexibility into portfolios and market this flexibility accordingly in a cost-efficient manner. The local nature of the mechanism is important as flexibility and their location denote important aspects of future distribution grids (SG-CG 2014a; EC 2015a). Following the timeline of electricity markets in Germany as illustrated in

Requirement 1 (Allocative efficiency). *A mechanism is allocative efficient if it maximizes the total utility over all agents, i.e., for the DSO and all other participants. That is, the mechanism maximizes social welfare.*

Allocative efficiency represents the main objective the mechanism needs to achieve. An efficient allocation implies for the DSO that the best flexibility offers from aggregators have been chosen according to a predefined objective. The objective in this work is to efficiently allocate flexibility from aggregators for minimum cost.

REQUIREMENT 2 (Incentive compatibility). *A mechanism is incentive compatible if it is rational for agents to report truthful information about their preferences. Under an incentive compatible mechanism, agents have no incentive to misreport their preferences to the mechanism in order to increase their utility.*

Incentive compatibility ensures that aggregators truthfully report the flexibility from their portfolios to the DSO. Not only is incentive compatibility (IC) a requirement for allocative efficiency (AE), it also eliminates the need for aggregators to consider different strategies as to which portfolios to report in order to increase individual revenue. However, IC cannot always be ensured for all types of possible mechanisms. Moreover, IC should contribute to grid stability, as it minimizes the contingency risk of aggregators for the DSO, e.g., due to unavailable yet allocated flexibility.

REQUIREMENT 3 (Individual rationality). *A mechanism is individually rational if no agent is worse off by participating in the mechanism than by not participating. More specifically, participating agents always receive non-negative utility which is greater or equal to their utility than under no participation.*

Individual rationality constitutes an important requirement for the mechanism employed by the DSO. If individual rationality (IR) is not satisfied by the mechanism, the voluntary participation of aggregators cannot be ensured as they are confronted with the risk of being worse off than under no participation. Instead, aggregators would be better of offering their flexibility to other businesses or mechanisms.

REQUIREMENT 4 (Budget balance). *A mechanism is weakly budget balanced if no net transfers into the mechanism, i.e., from an external subsidization, are required. That is, there can be net payments by agents to the mechanism but not vice versa. Hence, payments are redistributed among the agents.*

Budget balance ensures an economically feasible business case for the DSO, as the mechanism must not be externally subsidized in order to be able to pay flexibility offers from aggregators.

A mechanism for allocating flexibility from aggregators in context of the smart grid must fulfill the following domain-specific requirements.

Requirement 5 **(Flexibility characteristics).** *A mechanism supports flexibility characteristics (FC) if its allocation rule and bidding language account for domain-specific flexibility characteristics. More specifically, the mechanism needs to account for flexibility (i) types (i.e., consumption or production); (ii) ranges (i.e., intervals); (iii) portfolios (i.e., bundles); and (iv) valuations per unit (i.e., unit prices).*

In detail, a *flexibility type* constitutes either consumption or production capability of an individual consumer or a pool of aggregated consumers. For example, a consumer can have consumption devices such as an EV, a washing machine, a (laundry) dryer, and other appliances. At the same time, the same consumer can provide production capability from devices such as solar panels on a rooftop or a stationary battery storage. Both consumption or production activities can be offered in part or completely to an aggregator operate. With a heterogeneous pool of consumers, an aggregator can then bundle many consumption or production capabilities into an arbitrary number of *flexibility portfolios* which can be offered to the market mechanism employed by the DSO. The heterogeneity within such a portfolio allows the aggregator to specify *flexibility ranges*. That is, the aggregator can internally determine minimum and maximum amounts for a given point in time that are available for consumption or production and offer such range to the mechanism. Additionally, given the different cost structures of flexibility types, an aggregator requires the ability to specify *flexibility valuations per unit* within a flexibility portfolio. For example, offering generation from solar panels can be perceived as less costly than generation from conventional generators. Also, offering consumption from household appliances can represent an entirely different issue given that a potential risk of (non-)fulfillment may need to be accounted for.

Requirement 6 **(Compact bidding language).** *A mechanism supports a compact bidding language (CBL) if the domain-specific bidding language allows an aggregator to express a flexibility offer in a concise and succinct manner in order to reduce an aggregator's internal computational complexity as well as the communication complexity between the DSO and aggregators.*

More specifically, for an aggregator's portfolio to be economically feasible, it may be required that consumption or generation activities last a predefined amount of time. Reasons may be of a manifold nature. For example, a minimum runtime may be required in order to avoid battery deterioration and associated cost. Similarly, a minimum runtime may be required given an aggregator's internal cost structure for consumer flexibility management.

In addition, a linear cost structure would allow to omit the repeated specification of the same monetary bid. While a standard bidding language requires a full expression of preferences, i.e., an aggregator would need to redundantly specify the same information multiple times over the minimum runtime horizon, a compact bidding language can reduce this complexity.

Requirement 7 (Outside option). *A mechanism supports an outside option (OO) if it allows the DSO to fall back to an emergency alternative in case the requested flexibility cannot be allocated from the provided flexibility offers.*

Recall the initial statement that the DSO needs to ensure grid stability by using local flexibility in a short-term scenario. However, due to the short-term nature and/or unfortunate aggregator portfolio compositions, the DSO may not be able to allocate required flexibility at all times. For this reason, an outside option is required which can ensure the balance of supply and demand. Similar to the control reserve mechanism, an emergency outside option is associated with higher cost, yet can ensure a stable grid.

Requirement 8 (Price fairness). *A mechanism provides price fairness (PF) if the perceived fairness of prices for both the DSO and aggregators is ensured.*

More specifically, some pricing rules may result in situations where the DSO pays allocated aggregators too much. For example, an aggregator's received payment may exceed its minimum requested monetary value for flexibility by far under a certain pricing rule, resulting in unacceptably high payments, or cost, for the DSO. At the same time, some aggregators which are not part of the allocation may exist. In some cases, these aggregators may offer their flexibility for a lower compensation. Such aggregators would then object, or block, the outcome of the mechanism as there exists a more beneficial allocation for both the aggregators and the DSO. In order to adjust this imbalance and thus to improve the perceived fairness of prices so that the blocking aggregators would not object, the pricing rules of the mechanism need to enable fair and balanced prices.

The requirements are summarized in the following table 4.2.

4.2.5 Related Work

The work at hand applies rigorous methods from auction and mechanism design theory to address problems in the smart grid domain. To position this research in these research

Table 4.2: Market mechanism requirements

Requirement	Origin	Description
1	Allocative efficiency (AE)	Mechanism design
2	Incentive compatibility (IC)	
3	Individual rationality (IR)	
4	Budget balance (BB)	
5	Flexibility characteristics (FC)	Domain-specific
6	Compact bidding language (CBL)	
7	Outside option (OO)	
8	Price fairness (PF)	

communities, this section briefly surveys relevant contributions. That is, research approaches which are closely related to the work at hand are investigated. Moreover, their limitations regarding the previously identified requirements are highlighted.

Hobbs et al. (2000) describe an electricity auction which uses the Vickrey-Clarke-Groves (VCG) mechanism for supply and demand bidding with the goal of efficiently allocating resources in order to maximize social welfare. Bids can contain information on start-up cost, minimum runtime, running levels, and maximum ramp rates. The authors formulate an optimization problem where the goal is to maximize the sum of accepted demand bids minus the sum of accepted supply bids. Based on the accepted bids, VCG prices are determined. They show that in settings with high market concentration, there exists a risk of market power being present and that the VCG scheme employed is vulnerable to collusion. However, the proposed bidding language is not compact and the auction does not support flexibility characteristics or fair prices. In addition, an outside option is not incorporated.

Penya and Jennings (2008) propose a reverse combinatorial auction for electricity which determines an optimal outcome where the auctioneer maximizes its payoff. Bids are represented by demand or supply functions in a compact manner, yet do not allow to capture flexibility characteristics. In order to prevent strategic bidding, prices are determined using a VCG mechanism. Moreover, optimal clearing algorithms for their scenarios are introduced to allow the winner determination to be solved in polynomial time. In addition, the bid input is constrained to also mitigate worst case runtime scenarios. However, neither an outside option nor a method for determining fair prices is considered.

Ausubel and Cramton (2010) propose an auction design for VPPs in order to facilitate electricity market entry, improve liquidity, and reduce market power in electricity spot markets. The auction format is a simultaneous ascending-clock (forward) auction with discrete rounds. The auctioneer announces available supply with an interval of valid prices. Each bidder can submit a demand curve as a sealed bid. The pricing rule in their auction design is either uniform pricing or pay-as-bid (PAB). However, the auction focuses on larger (spot) markets and therefore does not consider flexibility characteristics or other domain-specific requirements such as an outside option or price fairness.

Torrent-Fontbona, Pla, and López (2014) describe a multi-attribute combinatorial auction in context of a manufacturing process where the goal is to minimize energy consumption subject to resource price, delivery time, and consumed energy. The proposed bidding process partly incorporates flexibility characteristics such as the ability to specify bids for task bundles. However, they do not solve the winner determination problem (WDP) optimally but instead propose a genetic algorithm, which cannot ensure AE. Moreover, by proposing a modified VCG mechanism which reduces payments if a task is performed in worse conditions than agreed, they forfeit IC but it could be argued that this denotes a small increase in prices fairness.

Schnizler et al. (2008) propose a multi-attribute combinatorial exchange for computing services. While the bidding language accounts for specific service characteristics, it does not allow auction participants to specify bids in a compact representation. The auction mechanism is AE, while IC, which is ensured through VCG prices, holds. However, a novel approximated VCG mechanism is introduced which is computationally more efficient but relinquishes the economic properties of AE and IC. Moreover, by employing k-pricing as an additional pricing mechanism, the distribution of payments can be considered fair for certain parameter specifications.

Table 4.3 highlights the limitations of the works described above. While several authors are concerned with combinatorial electricity auctions, various gaps concerning domain-specific flexibility requirements and pricing rules still exist and are addressed in the scope of this work.

Table 4.3: Summary of related work with requirement fulfillment (● = Fulfilled, ◑ = Partly fulfilled, ○ = Not fulfilled or unknown)

	Requirement							
	Mechanism Design				Domain-specific			
Reference	AE	IC	IR	BB	FC	CBL	OO	PF
Hobbs et al. (2000)	●	●	●	○	○	○	○	○
Penya and Jennings (2008)	●	●	●	○	○	●	○	○
Ausubel and Cramton (2010)	●	◑	●	○	○	◑	○	○
Torrent-Fontbona, Pla, and López (2014)	◑	◑	●	○	◑	○	○	◑
Schnizler et al. (2008)	◑	◑	●	●	○	○	○	◑
This work	●	◑	●	●	●	●	●	●

Part II

Design

5

Smart Grid Flexibility Auction Model and Allocation Problem

Recall from the previously reviewed related work in section 4.2.5 that no market mechanism exists which supports the requirements identified in section 4.2.4. That is, no market mechanism supports flexibility characterisitcs, a compact bidding language, an outside option, and tries to improve the perceived fairness of prices. The current and the following chapter address these limitations and introduce the smart grid flexibility auction for allocating short-term flexibility in local distribution grids along the design science research (DSR) framework. This chapter in particular contributes the central model and the allocation problem, whereas the succeeding chapter focuses on different pricing rules for the auction.

As the proposed artifact constitutes an auction, section 5.1 firstly and briefly introduces auctions as well as the underlying research method DSR, which guides the design of the auction. Subsequently, the main contributions of this work are introduced. Therefore, section 5.2 focuses on the formal auction model, section 5.3 describes and illustrates the auction process and section 5.4 introduces the compact bidding language. Then, section 5.5 extends the model definition. Finally, section 5.6 describes the winner determination problem (WDP). Parts of this chapter are adapted from the previously published paper: David Dauer, Paul Karaenke, and Christof Weinhardt. 2015. "Load Balancing in the Smart Grid: A Package

Auction and Compact Bidding Language." In *Proceedings of the Thirty Sixth International Conference on Information Systems.* Fort Worth, TX.

5.1 Preliminaries

5.1.1 Auctions

Auctions are a widely used market mechanism for determining both resource allocations and prices based on bids from auction participants (McAfee and McMillan 1987). Auction participants can also be denoted as bidders, or buyers and sellers (P. R. Milgrom 2004). The resource allocation, i.e., the winner determination in an auction, is specified by a set of auction rules which can also restrict participation and bids (i.e., bid amounts or increments) to the auction as well as enforce a certain behavior of auction participants (Wolfstetter 1999). Auctions are used in various settings for many transactions. For example, auctions are employed to sell private resources in (online) consumer environments. In addition, more complex auctions can be found in corporate (e.g., financial markets, logistics, food industry), technical (e.g., bandwidth or processing power allocation) and government (e.g., spectrum rights) environments (Shoham and Leyton-Brown 2009). Today, auctions are mainly used for reasons of (i) speed of sale; (ii) revelation of information about valuations of buyers; and (iii) prevention of untruthful dealings between sellers and buyers (Wolfstetter 1999).

5.1.1.1 Standard Auction Types

There exists an infinite number of possible auction types as the auction mechanism and its rules for allocation and pricing can be specified freely in accordance with any situation at hand (Shoham and Leyton-Brown 2009). A number of independent auction properties have been identified in order to provide a holistic auction classification. In particular, auctions can be (i) single or multi-dimensional; (ii) single-sided or double-sided; (iii) open-cry or sealed-bid; (iv) first price or k-th-price; (v) single-unit or multi-unit; or (vi) single-item or multi-item (Parsons, Rodriguez-Aguilar, and Klein 2011). Yet, four standard auction types which focus on settings with one good for sale from one seller and multiple potential buyers are generally used and investigated (Klemperer 2004). Such settings are called single-sided, as there is only one seller on one side and multiple buyers on the other side of the market (Wurman, Wellman, and Walsh 2001; Shoham and Leyton-Brown 2009). The standard auction types can be classified as follows (McAfee and McMillan 1987; Parsons, Rodriguez-Aguilar, and Klein 2011; Klemperer 2004):

1. Ascending-bid auction. This auction is also referred to as the English auction. Beginning with a starting price from the auctioneer, buyers submit successive bids which are ascending in the bid price. The auction ends when only one bidder remains, who is by definition the winner and has to pay the price of the final bid.

2. Descending-bid auction. This auction is also referred to as the Dutch auction. In contrast to the English auction, the auctioneer sets a high start price and continues to announce incrementally lower prices. The auction ends when a buyer calls out to accept the current price.

3. First-price sealed-bid auction. This auction is also referred to as first-price auction. Contrary to the ascending and descending-bid auctions, where bids are submitted publicly (open-cry), bidders do not see the other bidders' bids in sealed-bid auctions as bids are submitted in a closed fashion. Once all bids are submitted, the bidder with the highest bid wins.

4. Second-price sealed-bid auction. This auction is also referred to as second-price, or Vickrey, auction. Analogous the the first-price sealed-bid auction, bids are submitted in a concealed fashion. Also, the winner is the bidder with the highest bid. However, the winning bidder does not pay the price of its own bid but rather that of the second-highest bid.

While the four described auction types seem different, some equivalences exist (Krishna 2002). Firstly, the Dutch auction is strategically equivalent to the first-price sealed-bid auction. That is, bidding in a first-price sealed-bid auction is strategically equivalent to placing a bid for the same amount in a Dutch auction for the same good. Secondly, there exists a weak notion of equivalence between the English and the second-price sealed-bid auction. That is, they are not strategically equivalent but have the same optimal strategy if values are private. A detailed analysis on this notion is provided by Krishna (2002).

In contrast to single-sided auctions, double-sided, or double, auctions allow multiple buyers and sellers to exchange goods (Friedman and Rust 1993; Wurman, Walsh, and Wellman 1998). The two common variations of double auctions are the periodic double auction, also referred to as call markets (McCabe, Rassenti, and Smith 1990), and the continuous double auction.

The underlying mechanism of both the periodic and continuous auction is the identical with the exception that the periodic auction clears at predetermined time intervals whereas the continuous auction clears matching bids immediately (Wurman, Walsh, and Wellman 1998). A comprehensive overview of double-sided auction can be found in Wurman, Walsh, and Wellman (1998). Within the scope of this work, a single-sided auction is designed and evaluated.

5.1.1.2 Reverse Auctions

In contrast to single-sided auctions where there is only one seller and multiple buyers, i.e, forward auctions, an opposite setting models one buyer and multiple sellers, i.e., reverse auctions. A forward auction can usually be transformed into a reverse auction by substituting the words "seller" and "buyer" as well as negating all numbers related to bid prices and amounts (Shoham and Leyton-Brown 2009). Hence, in a reverse auction, the buyer wants to acquire one or more goods at the lowest possible cost. Sellers submit bids, i.e., asks, in which they specify the minimum requested price they "ask" for a good (Sandholm et al. 2002).

Reverse auctions are commonly referred to as procurement auctions as they are employed in procurement settings in various domains. For example, governments use procurement auctions to sell access to public resources such as the electromagnetic spectrum (Shoham and Leyton-Brown 2009; Cramton 2013). Moreover, procurement auctions can be found in corporate (Bichler, Pikovsky, and Setzer 2005; Cramton, Shoham, and Steinberg 2006), supply chain and logistics (Chen et al. 2005; Cramton, Shoham, and Steinberg 2006), electronic market (Bichler, Kaukal, and Segev 1999), electronic services (Blau, Conte, and Dinther 2010), and computational (Brewer 1999; Bichler and Kalagnanam 2006) settings. The auction designed within this work constitutes a reverse auction.

5.1.1.3 Multi-Unit Auctions

Multi-unit auctions represent an extension of single-unit auctions as there is no longer a single good to allocate but rather multiple instances of the same good (Shoham and Leyton-Brown 2009). While such an extension can normally be made by adjusting some part of the auction mechanism, there are a few details regarding pricing rules, bid placement, and tie-breaking that have to be considered (Parsons, Rodriguez-Aguilar, and Klein 2011; Shoham and Leyton-Brown 2009). Specifically, the problem of determining payments of bidders given different bid amounts arises. Following the example in Shoham and Leyton-Brown (2009), assume three goods are for sale with the best three bids requesting one unit. Then, one good will be assigned to each bid. As each bid generally will have a different bid price, the auctioneer has to determine the pricing for each bidder. Two pricing rules are emplyed, namely the discriminatory pricing rule ("pay-your-bid" or "pay-as-bid") where each bidder pays its own bid, and the uniform pricing (non-discriminatory) rule where each bidder pays the same price for the same amount of identical goods. The uniform price can either be the lowest accepted price among the winning bids or the highest among the losing bids (Shoham and Leyton-Brown 2009).

5.1.1.4 Combinatorial Auctions

In combinatorial auctions, sometimes referred to as package auctions (Ausubel and P. R. Milgrom 2002; P. Milgrom 2007), bidders can place bids on an arbitrary number of combinations of heterogeneous goods that can be either complements or substitutes (Cramton, Shoham, and Steinberg 2006). Hence, bidders can express their complex preferences for sets, or bundles of goods, supporting the underlying idea that the value of a bundle might be different from the sum of the values of the single goods (Shoham and Leyton-Brown 2009). This contributes to a potential increase of economic efficiency in combinatorial auctions with a low risk for bidders at the cost of computational difficulty (Andersson, Tenhunen, and Ygge 2000; De Vries and Vohra 2003).

Combinatorial auctions are widely studied and applied in practice. Initially proposed for spectrum rights (C. L. Jackson 1976) and airport time slot allocation (Rassenti, Smith, and Bulfin 1982), recent applications extend spectrum auctions (Cramton 2002, 1997, 2013), and include treasury securities (Bikhchandani and Huang 1993; Ausubel et al. 2014) as well logistics (Ledyard et al. 2002; Chen et al. 2005), transportation (Caplice 1996; Schmidt 1999; Sheffi 2004), and industrial settings (Bichler, Pikovsky, and Setzer 2005; Bichler et al. 2006). Moreover, emerging applications of combinatorial auctions can be observed in the context of electronic markets (Brewer 1999; Bichler, Kaukal, and Segev 1999), grid services (Schnizler et al. 2008), and electricity markets (Hobbs et al. 2000; Fabra, Fehr, and Harbord 2002; Maurer and Barroso 2011; Torrent-Fontbona, Pla, and López 2014). An extensive overview of combinatorial auctions from economic, optimization, and computer science perspectives can be found in De Vries and Vohra (2003) and Cramton, Shoham, and Steinberg (2006).

The design of combinatorial auctions requires the market engineer to solve several complex problems, in particular those of bid expression, winner determination, payment, and strategy (Nisan 2000; De Vries and Vohra 2003).

Bid Expression As bidders are allowed to bid on arbitrary combinations of bundles, issues regarding valuation and communication complexity arise (De Vries and Vohra 2003). Valuation complexity is related to the required amount of information on a bidder's preferences and the required complexity of bidders to internally compute and express these information in form of bids (Parkes 2001). Communication complexity deals with the required amount of communication between bidders and the auctioneer in terms of frequency and amount (Parkes 2001; Nisan and Segal 2002; De Vries and Vohra 2003). In order to overcome these complexities, De Vries and Vohra (2003) suggest the use of oracles and Boutilier and Hoos (2001) proposes logical bidding languages, whereas the more common approach is to specify a bidding language that encodes the bidder's preferences in an efficient and compact manner (Nisan 2000; Parkes 2001). Bidding languages in combinatorial auctions need to allow for a more succinct and convenient way to express bids as an auction with m goods generally requires a bidder to specify a valuation for each of the possible $2^m - 1$ non-empty subsets (Nisan 2000, 2006). Common bidding languages range from standard atomic bids, OR-bids or XOR-bids to more complex combinations of OR and XOR bids such as OR-of-XORs, XOR-of-ORs or OR/XOR-formulae (Nisan 2006). A detailed analysis of these languages can be found in Nisan (2000, 2006). De Vries and Vohra (2003) note that a computationally efficient bidding language relies upon rules that either restrict the preferences or the combinations of bundles that bidders can specify and bid on.

Winner Determination The problem of identifying the allocation of goods to bidders in combinatorial auctions according to a predefined objective by the auctioneer, usually the maximization of social welfare, is called the WDP (Shoham and Leyton-Brown 2009). The challenge of determining such an efficient outcome is also referred to as the combinatorial auction problem (CAP). CAP is generally formulated as a mixed integer problem (MIP) (Rothkopf, Pekeč, and Harstad 1998; T. Sandholm 2002). For the single-unit case, the CAP is formulated as follows (Shoham and Leyton-Brown 2009): Let $\mathcal{I}$ be the set of bidders and $\mathcal{G}$ be the set of goods. The reported valuation of bidder i for a subset of goods, or bundles, $S \subseteq \mathcal{G}$, is constant and denoted as $\hat{v}_i(S)$. The decision variable indicating whether a bundle S

is allocated to bidder i is given by $x_i(S)$, where $x_i(S) = 1$ denotes that bundle S is allocated to bidder i and $x_i(S) = 0$ denotes that bundle S is not allocated to bidder i.

$$\text{CAP}(\mathcal{I}) = \max_{x} \sum_{i \in \mathcal{I}} \sum_{S \subseteq \mathcal{G}} \hat{v}_i(S) x_i(S) \tag{CAP}$$

$$\text{s. t.} \sum_{S \supseteq \{g\}} \sum_{i \in \mathcal{I}} x_i(S) \leq 1 \qquad \forall g \in \mathcal{G} \tag{5.1a}$$

$$\sum_{S \subseteq \mathcal{G}} x_i(S) \leq 1 \qquad \forall i \in \mathcal{I} \tag{5.1b}$$

$$x_i(S) \in \{0,1\} \qquad \forall i \in \mathcal{I}, S \subseteq \mathcal{G} \tag{5.1c}$$

The objective of the combinatorial auction problem (CAP) is to maximize the social welfare over all bidders in (CAP). Constraint (5.1a) ensures that no overlapping bundles are assigned, i.e., any good is assigned at most once. Constraint (5.1b) ensures that no bidder receives more than one bundle, which represents an XOR constraint. Constraint (5.1c) defines that no bundle can be partially assigned to a bidder. An extended version of the single-unit CAP to a multi-unit CAP is provided by De Vries and Vohra (2003).

While a combinatorial auction contributes to an economically favorable allocation, the CAP imposes computational difficulties (Shoham and Leyton-Brown 2009). Specifically, the CAP is an instance of the weighted set packing problem (SPP) which is known to be NP-hard (Lehnmann, Müller, and Sandholm 2006; Rothkopf, Pekeč, and Harstad 1998; Garey and Johnson 1990; Karp 1972). In order to address this problem, several heuristic solutions to approximate the CAP have been proposed (Fujishima, Leyton-Brown, and Shoham 1999; T. Sandholm 2002; Andersson, Tenhunen, and Ygge 2000; Günlük, Ladányi, and De Vries 2005; Sandholm and Suri 2003; Sandholm et al. 2005). Despite many of these algorithms promising computational improvements, they often target specialized cases and do not always perform better than generalized MIP solvers (Andersson, Tenhunen, and Ygge 2000; Günlük, Ladányi, and De Vries 2005; Sandholm et al. 2005; T. Sandholm 2006). Hence, for an optimal winner determination, MIP solvers are recognized as viable alternatives to solve the CAP (Lehnmann, Müller, and Sandholm 2006). Solving the CAP in an optimal fashion also motivates truthful bidding (T. Sandholm 2006).

Payment and Strategy In forward auctions, the amount each winner of a bundle has to pay as well as the revenue of the auctioneer is determined by pricing rules (Nisan 2000).

Consequently, in reverse auctions, pricing rules determine the amount the auctioneer, or buyer, has to pay as well as the revenue of the bidders. With no strategic bidding, bidders are assumed to report their true valuations to the auction. Otherwise, with strategic bidding under consideration, pricing mechanism such as Vickrey-Clarke-Groves (VCG) can be employed to ensure that bidders act non-strategically (Nisan 2000; Parkes 2001).

5.1.1.5 Multi-Unit Combinatorial Reverse Auctions

Multi-unit combinatorial reverse auctions are particularly common in procurement scenarios (Sandholm et al. 2002). By combining the previously introduced auction formats, an extended WDP can be formulated. Following Hsieh (2010), let $i \in \mathcal{I}$ be the set of agents and $\mathcal{G}$ be the set of goods. The buyer that requests a set of goods is given by $i = 0$, all other bidders, i.e., sellers, are given by $i \in \{1, 2, \dots, N\}$. The number of requested goods is denoted as T and the desired units for the t-th good as a_0^t, where $t \in \{1, 2, \dots, T\}$. The bids of bidder $i > 0$ are given by $\mathcal{J}_i$. The j-th bid submitted by a bidder $i > 0$ is represented by vector $e_{i,j} = (a_{i,j}^1, \dots, a_{i,j}^t, \dots, a_{i,j}^T, b_{i,j})$ where $a_{i,j}^t \geq 0$ denotes the offered quantity for the t-th good and $b_{i,j}$ denotes the monetary value of the bid $e_{i,j}$. The decision variable indicating whether the j-th bid $e_{i,j}$ is allocated to bidder i is given by $x_{i,j}$, where $x_{i,j} = 1$ denotes that bid $e_{i,j}$ is allocated to bidder i and $x_{i,j} = 0$ denotes that bid $e_{i,j}$ is not allocated to bidder i.

$$\mathrm{RCAP}(\mathcal{I}) = \min_{x,a} \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}_i} b_{i,j} x_{i,j} \tag{RCAP}$$

$$\text{s. t.} \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}_i} a_{i,j}^t x_{i,j} \geq a_0^t \qquad \forall t = 1, 2, \dots, T \tag{5.2a}$$

$$\sum_{j \in \mathcal{J}_i} x_{i,j} \leq 1 \qquad \forall i \in \mathcal{I} \tag{5.2b}$$

$$x_{i,j} \in \{0, 1\} \qquad \forall i \in \mathcal{I}, j \in \mathcal{J}_i \tag{5.2c}$$

The objective of the reverse combinatorial auction problem (RCAP) is to minimize the overall cost over all bidders in (RCAP). Constraint (5.2a) ensures that the received quantities $a_{i,j}^t$ must be greater than or equal to the requested quantities a_0^t of the buyer. Note that this formulation assumes free disposal, i.e., surplus of the offered quantities can be disposed of at no cost. Constraint (5.2b) ensures that no bidder is assigned more than one bid, which represents an XOR constraint. Finally, constraint (5.2c) defines that no bid can be partially assigned to a bidder.

5.1.1.6 Electricity Auctions

Almost all of today's electricity auctions are organized as multi-unit auctions with either a first-price, i.e., uniform, or a pay-as-bid (PAB), i.e., discriminatory pricing rule (Fabra, Fehr, and Harbord 2002; Maurer and Barroso 2011). Both the uniform and the discriminatory pricing rule are subject to extensive discussions in literature as to which one is deemed a better fit for electricity markets considering strategic criteria such as possible collusion among suppliers (Kahn et al. 2001b, 2001a; Fabra, Fehr, and Harbord 2002; Cramton 2003). However, in order to guarantee efficiency independent of industry players and market data, the Vickrey auction should be a regulator's choice (Fabra, Fehr, and Harbord 2002). Nevertheless, within these auctions, bids usually include information about minimum supply prices from generators as well as the available capacity at the named price. In addition, more complex two-sided auctions can be found in several countries, e.g., the European Energy Exchange (EEX). Such auctions broaden the focus from an electricity procurement setting towards a more competitive setting which can also increase welfare (Maurer and Barroso 2011).

Auctions in context of the German control reserve markets, where the main objective is to ensure security of supply, can be characterized as single-sided, multi-unit procurement auctions. The procurement of balancing power by grid operators is performed in advance and not in real-time (Müsgens, Ockenfels, and Peek 2014; Bundesnetzagentur 2011b). Generators submit bids with information on their capacity price as well as their energy price. The capacity price compensates the provisioning of the balancing power, whereas the energy price is paid for actually retrieved balancing power. Auction winners are determined based on the capacity price and are paid using the PAB rule. In case the provisioned and thus available balancing power needs to be retrieved, previously determined winners are required to increase or decrease generation or consumption of electricity and are paid according to their energy price bid, again using the PAB rule (Müsgens, Ockenfels, and Peek 2014).

An extensive overview of electricity auctions which deals with procurement, exchanges, and energy policy related aspects, market contexts, auction design and implementation issues as well as investigates auction participants and the role of renewable energy sources (RES) can be found in Maurer and Barroso (2011).

5.1.2 Research Method

The research in the work at hand follows the DSR approach proposed by Hevner et al. (2004). The DSR paradigm – based on engineering and the sciences of the artificial (Simon 1996) – is a problem-solving paradigm. It targets the *construction and evaluation* of information technology (IT) artifacts, enabling organizations to address information-related tasks (Hevner et al. 2004; Gregor and Jones 2007). IT artifacts are defined as constructs (vocabulary and symbols), models (abstractions and representations), methods (algorithms and practices), and instantiations (implemented and prototype systems). The method, model, and instantiation artifacts proposed in this research are: (i) a smart grid auction that constitutes an approach for allocating load flexibility from consumers and prosumers via aggregators to address the local grid load balancing problem; (ii) a compact bidding language that allows bidders to express minimum and maximum amounts of electric flexibility (production or consumption) along with unit prices in single bids for time periods of different size; and (iii) the prototype implementation.

DSR relies upon the application of rigorous methods in both the construction and evaluation of the design artifact. Therefore, the theories that inform the construction and evaluation of the proposed artifact are described in the following. The utility, quality, and efficacy of a design artifact must be rigorously demonstrated via well-executed evaluation methods (Hevner et al. 2004). In this work, simulation experiments based on real-world data are applied and provide evidence that load flexibility auctions can reduce distribution system operator (DSO) cost and that procurement combinatorial/package auctions are well-suited to address the grid load balancing problem. This chapter follows the structural guidelines for presenting DSR proposed by Gregor and Hevner (2013). Table 5.1 summarizes the mapping of the approach against the DSR guidelines.

The rationale for the selection of auction and game theory to inform the construction of the artifact is as follows: The problem of balancing supply and demand by DSOs is in fact a problem that is naturally addressed by a market. While the demand side is currently rather inflexible (i.e., there are hardly any truly dynamic pricing schemes for consumers), the supply side has been subject to energy exchanges for over a decade. However, these exchanges consider large amounts of energy to balance supply and demand on a different grid level. In contrast, the DSOs have to balance comparatively rather small amounts, though the timely balance is not only a matter of economics, but also of grid stability. Mechanism design and

Table 5.1: Mapping against design science research guidelines

Guideline (Hevner et al. 2004)	Contribution
Design as an artifact	The research outcomes (i) smart grid load flexibility auction; (ii) compact bidding language; and (iii) prototype implementation constitute method, model, and instantiation artifacts.
Problem relevance	The addressed research problem responds to the grand challenge of grid load balancing with the growth of fluctuating wind and solar generation as well as with the emergence of flexible loads.
Design evaluation	Utility, quality, and efficacy of the design outcomes are demonstrated in an experimental simulation study.
Research contributions	The design artifacts and design construction knowledge extend and improve the knowledge of electricity market design.
Research rigor	Auction theory is used for artifact construction and for design evaluation. Literature on simulation analysis informs the evaluation of the artifact.
Design as a search process	The discovery of an effective solution in the form of the proposed smart grid auction and iterative improvements and extensions in future work constitute the search process in electricity market design.
Communication of the research	The formal models and technical details inform technology-oriented audiences, implications, and opportunities inform management-oriented audiences.

auction theory provide mature and rigorous methods to build and analyze market designs (Nisan et al. 2007).

The evaluation of the proposed artifact is informed by the literature on simulation analysis. The simulation of technical and economic systems is a well-established method to evaluate complex artifacts and can be used to numerically analyze the artifact to estimate the true systems characteristics (Kelton and Law 2000). The artifact is evaluated with respect to both the estimated implications for smart grid coordination as well as the computational complexity of different instantiations.

5.2 Auction Model

In the following, the smart grid load flexibility auction is described by first presenting relevant fundamental model assumptions and definitions, followed by introducing the proposed bidding language. Subsequently, the WDP is formulated. Different pricing rules are presented in the next chapter.

5.2.1 Model Assumptions

The auction design rests upon fundamental and common assumptions of mechanism design and auction theory (Krishna 2002; Sandholm et al. 2002). Agents are assumed to be risk neutral, i.e., they strive to maximize their expected profits. Following definition 3.10, agents are furthermore assumed to have quasi-linear utility. Moreover, valuations of bidders are independently distributed, that is, a bidder's information and value is independent of all other bidders' information. The buyer is assumed to have no budget constraints, i.e., the buyer is always able to pay the sellers for all considered pricing rules. Furthermore, as demand has to equal supply at all times, no free disposal is assumed. Moreover, a successful allocation is perceived as a contract. That is, not delivering the allocated balancing power results in strong penalties for the responsible party. Finally, agents are assumed to truthfully report to the mechanism, that is $\theta = \hat{\theta}$.

5.2.2 Model Description

The model comprises the DSO, who needs to procure short-term balancing power from aggregators. Therefore, the DSO represents the buyer in the proposed auction, whereas aggregators represent sellers. Furthermore, the DSO needs to resort to an outside option in case the requested balancing power cannot be allocated from participating sellers. All auction participants are referred to as agents.

Definition 5.1 (Auction format). *The auction (artifact) constitutes a procurement, or reverse, combinatorial auction. Thus, in contrast to the forward case, the auctioneer represents the buyer whereas the bidders represent sellers.*

Definition 5.2 (Time). *The auction format is characterized through discrete time slots. Let $T \in \mathbb{N}$ denote the time horizon under consideration. Let $t \in \mathcal{T} = \{1, 2, \ldots, T\}$ denote the time slots. The time slots are of equal length. To ensure generalizability, the length of a time slot is described by means of a time unit (TU).*

The good, or product, in the auction is defined as follows: The product to be procured is defined as balancing power for discrete time slots $t \in \mathcal{T}$ over time horizon T. Balancing power can denote both positive or negative balancing power.

Definition 5.3 (Product). *Let $g \in \mathcal{G}$ be the product in the set of all available products to be procured. Let $g = (g^1, \ldots, g^t, \ldots, g^T)$ with $g^t \in \mathbb{R}$ denote the product, i.e., balancing power, requested for time slot t. For reasons of generalizability, the unit of balancing power is defined as energy unit (EU). A concrete specification could resolve EU to, e.g., kW or MW.*

Definition 5.4 (Agent). *Following definition 3.5, the set of agents is defined as $\mathcal{I}$, with an agent in the set of agents denoted as $i \in \mathcal{I}$. The number of agents participating in the auction is given by $N = |\mathcal{I}|$. Agents $i \in \mathcal{I}$ are differentiated into buyer and sellers as follows.*

Definition 5.5 (Agent type). *Following definition 3.6, let $\theta = (\theta_1, \ldots, \theta_i, \ldots, \theta_N) \in \Theta$ denote all agents' private information in the set of all potential agent types of all agents. Let agent i's private information, be denoted by agent type $\theta_i \in \Theta_i$, where Θ_i denotes the set of all potential agent types of agent i. Moreover, let $\theta_{-i} = (\theta_1, \ldots, \theta_{i-1}, \theta_{i+1}, \ldots, \theta_N)$ denote the set of all agent types without agent i.*

Definition 5.6 (Bundle). *Let bundle $S \subseteq \mathcal{G}$ denote a subset of the available goods or products and $S_i \subseteq \mathcal{G}$ denote an awarded bundle to agent i.*

As noted in definition 5.3 the DSO requests balancing power. Hence, the DSO announces the auction as the auctioneer in order to buy positive or negative balancing power. Note that the DSO is not required to conduct the auction as an intermediary could be appointed for this task. However, for reasons of simplicity, the DSO is assumed to conduct the auction for the remainder of this work.

Definition 5.7 (Buyer). *Following definition 5.4, let agent $i \in \{0\}$ be the buyer for balancing power in the auction. The buyer in this work is a single DSO.*

Definition 5.8 (Auctioneer). *The auctioneer $i \in \{0\}$ in this work represents the buyer, or DSO.*

Note that outside of this work, the role of an auctioneer can also be assumed by a separate external entity and need not necessarily be the DSO.

Addressing requirement 7, the DSO needs to ensure a balance of supply and demand at all times. Therefore, in case less than the required balancing amount from aggregators can be allocated, the DSO needs to be able to resort to other more expensive emergency solutions that can guarantee the balance of supply and demand. In this work, such an emergency solution is represented by an outside option as follows:

Definition 5.9 (Outside option). *Let $\psi^t = (\psi^t_+, \psi^t_-) \in \Psi$ denote the positive and negative (i.e., production and consumption) outside option amounts with $\psi^t \in \mathbb{R}^2$. Let ψ^t_+ denote the positive balancing power amount, i.e., outside option, allocated in case no less expensive bids can be allocated for time slot t. Similarly, let ψ^t_- denote the negative outside option amount allocated. Exogenous prices for both positive and negative amounts from the outside option prices are denoted as $\gamma^t \in \mathbb{R}^2$, i.e., $\gamma^t = (\gamma^t_+, \gamma^t_-) \in \Gamma$ where γ^t_+ and γ^t_- represent the price for positive and negative balancing power prices.*

Note that the outside option is assumed to be available in unlimited quantities in the remainder of this work.

Definition 5.10 (Outside option provider). *The outside option is provisioned and sold by separate agents $r \in \mathcal{R} \subseteq (\mathcal{I} \setminus \{0\})$.*

In order to ensure budget balance (BB), the outside option provider is explicitly modeled as an agent, as payments therefore stay within the auction mechanism. Conforming to definitions 5.11 and 5.13, the cost of an outside option provider can be comprised of investment, trading, or power plant operation cost. An outside option provider offers its real cost and is compensated based on a first-price/pay-as-bid procedure.

Sellers, represented by aggregators or outside option providers, act as balancing power suppliers.

Definition 5.11 (Seller). *Following definition 3.5, let agents $i \in \mathcal{I} \setminus \{0\}$ be sellers in the auction.*

Definition 5.12 (Bidder). *Following definition 5.11, let agents $i \in \mathcal{I} \setminus (\{0\} \cup \mathcal{R})$ be bidders (i.e., aggregators) in the auction.*

Moreover, bidders are characterized by having cost for provisioning their portfolio of flexible consumers or loads for each $t \in \mathcal{T}$.

Definition 5.13 (Cost). *Let cost function for each bidder $i \in \mathcal{I} \setminus (\{0\} \cup \mathcal{R})$ be denoted as $c_i : \Theta \to \mathbb{R}$ with*

$$c_i(\theta) = \sum_{t \in \mathcal{T}} c_i^t(\theta). \tag{5.3}$$

Definition 5.14 (Valuation). *Let valuation function for buyer $i \in \{0\} \subset \mathcal{I}$ be denoted as $v_i : \mathcal{G} \to \mathbb{R}$ where*

$$v_i(g) = \sum_{t \in \mathcal{T}, g^t \in g} v_i^t(g^t). \tag{5.4}$$

Definition 5.15 (Bids and bid indices). *The bidders place bids e_j, for which the bid index in the set of bid indices is denoted as $j \in \mathcal{J} = \{1, 2, \ldots, M\}$. The number of bid indices $M = |\mathcal{J}|$ is partitioned into subsets of bid indices of the bidders $i \in \mathcal{I} \setminus (\{0\} \cup \mathcal{R})$ such that*

$$\forall i \in \mathcal{I} \setminus (\{0\} \cup \mathcal{R}) \; \exists! \, \mathcal{J}_i \tag{5.5}$$

with

$$\bigcup_{i \in \mathcal{I} \setminus (\{0\} \cup \mathcal{R})} \mathcal{J}_i = \mathcal{J} \;\wedge \bigcap_{i \in \mathcal{I} \setminus (\{0\} \cup \mathcal{R})} \mathcal{J}_i = \varnothing. \tag{5.6}$$

Definition 5.16 (Allocation). *Let $\mathcal{X} = \{x_j\}_{j \in \mathcal{J}_i}$ denote whether a bidder i's bid e_j with $x_j \in \{0, 1\}$ is allocated to bidder i ($x_j = 1$) or not ($x_j = 0$), i.e., whether positive or negative balancing power could successfully be procured by the DSO from an aggregator, or bidder i.*

Definition 5.17 (Allocation function). *Let allocation function $\kappa : \Theta \to \{0, 1\}^{|\mathcal{J}|}$ determine an allocation based on the agent types Θ and outside option prices γ, that is $\kappa : \Theta = \mathcal{X}$.*

Definition 5.18 (Auction pricing function). *Let pricing function $p_i : \Theta \to \mathbb{R}^N$ define the price of bidder $i \in \mathcal{I} \setminus (\{0\} \cup \mathcal{R})$.*

Definition 5.19 (Auction transfer function). *Let transfer, or payment, function $\rho_i : \Theta \to \mathbb{R}^N$ denote the positive or negative transfer for auction participants $\mathcal{I}$. Note that due to incentive compatibility (IC) considerations, the transfer function is identical to the pricing function for all agents $i \in \mathcal{I} \setminus (\{0\} \cup \mathcal{R})$.*

$$\rho_i(\theta) = \begin{cases} -p_i(\theta) - \sum\limits_{t \in \mathcal{T}} (\gamma_+^t \psi_+^t + \gamma_-^t \psi_-^t) & i = 0 \\ p_i(\theta) & i \in \mathcal{I} \setminus (\{0\} \cup \mathcal{R}) \\ \sum\limits_{t \in \mathcal{T}} (\gamma_+^t \psi_+^t + \gamma_-^t \psi_-^t) & i \in \mathcal{R} \subseteq \mathcal{I} \end{cases} \tag{5.7}$$

5.3 Auction Process

Following the formal model description in section 5.2, this section illustrates main parts of the process of the flexibility auction. Figure 5.1 shows the sequence of interactions by using the example of a single aggregator with the DSO and the flexibility auction. More specifically, the aggregator initially is assumed to constantly contract flexibility from consumers and prosumers and to manage its portfolio accordingly. Note that this assumption constitutes a precondition and is not in scope of this work. Following section 4.2.3, the auction is part of the yellow traffic light concept (TLC) state. That is, the auction is not repeated but invoked only when a critical grid situation is detected. For this reason, the DSO needs to continuously monitor its local grid. In case a critical grid situation is detected, the DSO determines the required amount of flexibility and initiates and announces the flexibility auction with the identified flexibility demand. Aggregators are notified and can then submit their bids, i.e., offers, for flexibility. Subsequently, the auction determines the optimal allocation and sets prices, i.e., payments to aggregators, according to a predefined pricing rule. With the information on winners and the amount of allocated flexibility from the flexibility auction, the DSO then settles the payments with the aggregators, which are required to deliver the allocated flexibility in return. In case the amount of allocated flexibility is less than the announced required amount, the difference is fulfilled by means of an outside option. The complete sequence of the auction process is illustrated in the following as an Unified Modeling Language (UML) sequence diagram (Rumbaugh, Jacobson, and Booch 2004).

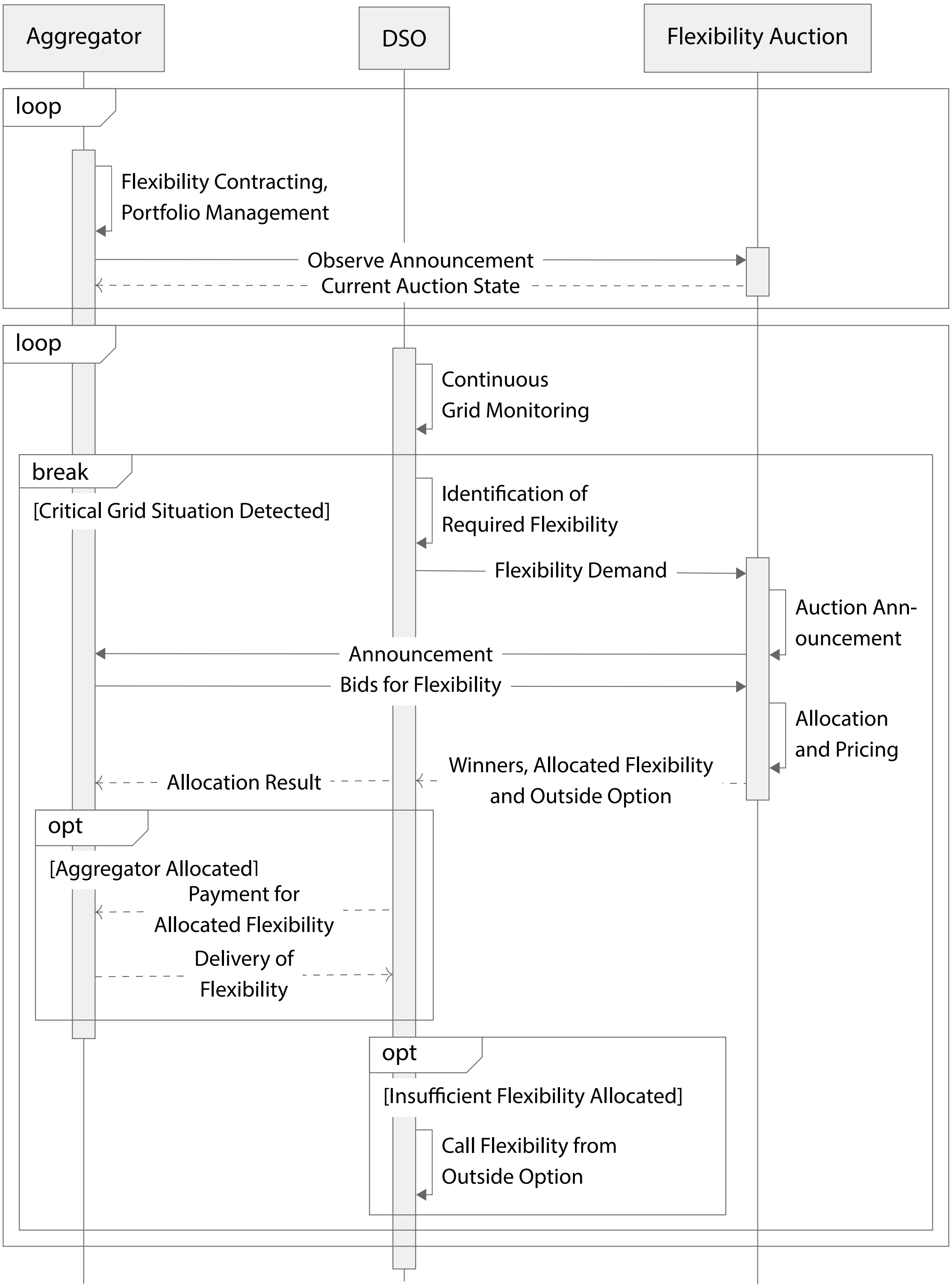


Figure 5.1: Process of the flexibility auction

5.4 Bidding Language

Following section 5.2.2 and definition 5.15, the bids e_j with $j \in \mathcal{J}$ each consist of several atomic bids. Hence, for each $t \in \mathcal{T}$, an atomic bid can be specified within a unique, distinct bid e_j. Within a bid e_j, bidders do not have to explicitly declare an atomic bid for each $t \in \mathcal{T}$. Instead, the preceding atomic bid implicitly remains valid until succeeded by an atomic bid with a subsequent time slot. An atomic bid allows the bidder to express the possible delivery time of balancing power. Furthermore, bidders can indicate the type of balancing power, i.e., energy consumption or production. Moreover, minimum and maximum delivery amounts can be specified. Finally, the monetary bid per EU can be expressed. These parameters provide bidders with a compact yet flexible means to communicate aggregated consumer load flexibility.

More formally, let e_j consist of n atomic bids. Then, the n-th *delivery start time* of bid e_j is denoted by $\sigma_{j,n} \in \mathcal{T}$.

Definition 5.20 (Bid start time). *Let $\sigma_{j,n} \in \mathcal{T}$ denote the bid start time of the n-th atomic bid in bid e_j.*

The n-th *delivery direction* of bid j is denoted by $\phi_{j,n} \in \{-1, 1\}$. Here, $\phi_{j,n} = -1$ denotes *energy consumption* (negative balancing capability) by the bidder and $\phi_{j,n} = 1$ *energy production* (positive balancing capability) by the bidder.

Definition 5.21 (Bid direction). *Let $\phi_{j,n} \in \{-1, 1\}$ denote the bid delivery direction of the n-th atomic bid in bid e_j, where $\phi_j = -1$ denotes energy consumption by the bidder and $\phi_j = 1$ energy production by the bidder.*

Moreover, the *minimum* and *maximum delivery amounts* of the n-th start time (or atomic bid) in bid j are specified by $\underline{a}_{j,n}$ and $\overline{a}_{j,n}$.

Definition 5.22 (Bid amount). *Let $\underline{a}_{j,n} \in \mathbb{R}_{\geq 0}$ denote the minimum bid delivery amount and $\overline{a}_{j,n} \in \mathbb{R}_{\geq 0}$ the maximum delivery amount of the n-th atomic bid in bid e_j.*

Minimum and maximum delivery amounts constitute interval $[\underline{a}_j, \overline{a}_j]$, which describes the flexibility of a bidder with regard to the bid amount. Thus, a flexible bidder bids $\underline{a}_j < \overline{a}_j$ whereas a completely inflexible bidder bids $\underline{a}_j = \overline{a}_j$.

The *monetary bid* (minimum requested price) *per EU* (production or consumption) of the n-th start time in bid j is given by $b_{j,n} \in \mathbb{R}_{\geq 0}$.

Definition 5.23 (Bid price). *Let $b_{j,n} \in \mathbb{R}_{\geq 0}$ denote the bid price of the n-th atomic bid in bid e_j. The bid price constitutes a unit bid price and is therefore defined by means of a monetary unit (MU) per EU.*

The composition of definitions 5.20 to 5.23 results in a complete, atomic bid which is defined as follows:

Definition 5.24 (Atomic bid). *Let bidder i's n-th atomic bid of bid e_j with $j \in \mathcal{J}_i$ be denoted as a 5-tuple*

$$(\sigma_{j,n}, \phi_{j,n}, \underline{a}_{j,n}, \overline{a}_{j,n}, b_{j,n}) \tag{5.8}$$

where $\sigma_{j,n} \in \mathcal{T}$ is the n-th delivery start time, $\phi_{j,n} \in \{-1, 1\}$ the n-th delivery direction, $\underline{a}_{j,n} \in \mathbb{R}_{\geq 0}$, and $\overline{a}_{j,n} \in \mathbb{R}_{\geq 0}$ the n-th minimum and maximum delivery amounts, and $b_{j,n} \in \mathbb{R}_{\geq 0}$ the n-th valuation per EU.

Note that the atomic bids of bid e_j are subject to a logical AND constraint. Therefore, bid e_j can only be allocated in its entirety or not at all. This enables a bidder to specify dependencies resulting of atomic bids, e.g., to ensure that consecutive atomic bids constitute a minimum runtime. The bidders $i \in \mathcal{I} \setminus (\{0\} \cup \mathcal{R})$ can submit zero or more bids e_j.

Definition 5.25 (Bid). *Let bidder i's bid e_j with $j \in \mathcal{J}_i$. Bid e_j is denoted as $5 \times n$ matrix*

$$e_j := \begin{pmatrix} \sigma_{j,1} & \phi_{j,1} & \underline{a}_{j,1} & \overline{a}_{j,1} & b_{j,1} \\ \sigma_{j,2} & \phi_{j,2} & \underline{a}_{j,2} & \overline{a}_{j,2} & b_{j,2} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \sigma_{j,n} & \phi_{j,n} & \underline{a}_{j,n} & \overline{a}_{j,n} & b_{j,n} \end{pmatrix} \tag{5.9}$$

where $\sigma_{j,n} \in \mathcal{T}$ is the n-th delivery start time, $\phi_{j,n} \in \{-1, 1\}$ the n-th delivery direction, $\underline{a}_{j,n} \in \mathbb{R}_{\geq 0}$, and $\overline{a}_{j,n} \in \mathbb{R}_{\geq 0}$ the n-th minimum and maximum delivery amounts, and $b_{j,n} \in \mathbb{R}_{\geq 0}$ the n-th valuation per EU.

Example 5.1 (Extensive bid). Given time horizon $T = 4$, suppose that bidder $i = 1$ wants to submit a single bid with $\mathcal{J}_i = \{1\}$. The bidder has determined its optimal consumer portfolio which allows to submit a bid as follows. The bid should include a possible positive balancing power (supply) between 5 and 10 EU over the first two TU. Additionally, the

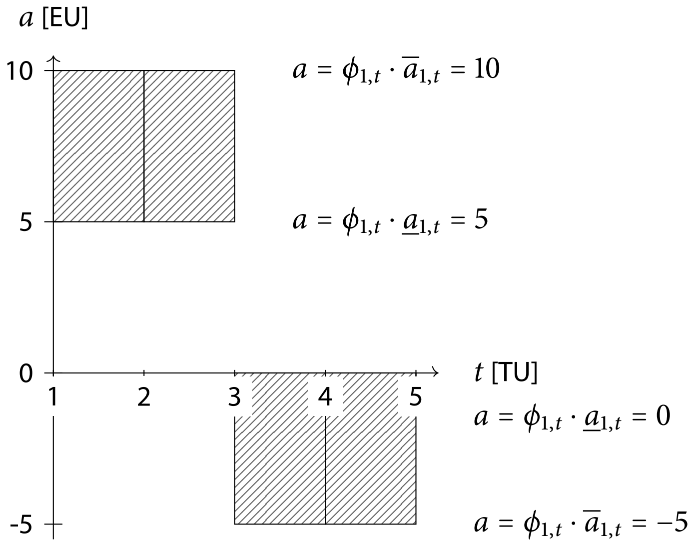


Figure 5.2: Bid amounts of extensive bid from example 5.1.

valuation per EU is set at 20 MU/EU. Therefore, $\sigma_{1,t} = t$, $\phi_{1,t} = 1$, $\underline{a}_{1,t} = 5$, $\overline{a}_{1,t} = 10$, and $b_{1,t} = 20\ \forall t \in \{1, 2\}$, i.e., $\sigma_{1,1} = 1$, $\sigma_{1,2} = 2$, $\phi_{1,1} = 1$, $\phi_{1,2} = 1$, $\underline{a}_{1,1} = 5$, $\underline{a}_{1,2} = 5$, $\overline{a}_{1,1} = 10$, $\overline{a}_{1,2} = 10$, $b_{1,1} = 20$, and $b_{1,2} = 20$. Moreover, the bidder offers negative balancing power (demand) between 0 and 5 EU over the last two TU with a valuation of 30 MU/EU, i.e., $\sigma_{1,t} = t$, $\phi_{1,t} = -1$, $\underline{a}_{1,t} = 0$, $\overline{a}_{1,t} = 5$, $b_{1,t} = 30\ \forall t \in \{3, 4\}$, i.e., $\sigma_{1,3} = 3$, $\sigma_{1,4} = 4$, $\phi_{1,3} = -1$, $\phi_{1,4} = -1$, $\underline{a}_{1,3} = 0$, $\underline{a}_{1,4} = 0$, $\overline{a}_{1,3} = 5$, $\overline{a}_{1,4} = 5$, $b_{1,3} = 30$, and $b_{1,4} = 30$. Then, the submitted bid in its complete and extensive form is specified as follows.

$$e_1 = \begin{pmatrix} \sigma_{1,1} & \phi_{1,1} & \underline{a}_{1,1} & \overline{a}_{1,1} & b_{1,1} \\ \sigma_{1,2} & \phi_{1,2} & \underline{a}_{1,2} & \overline{a}_{1,2} & b_{1,2} \\ \sigma_{1,3} & \phi_{1,3} & \underline{a}_{1,3} & \overline{a}_{1,3} & b_{1,3} \\ \sigma_{1,4} & \phi_{1,4} & \underline{a}_{1,4} & \overline{a}_{1,4} & b_{1,4} \end{pmatrix} \tag{5.10}$$

$$= \begin{pmatrix} 1 & 1 & 5 & 10 & 20 \\ 2 & 1 & 5 & 10 & 20 \\ 3 & -1 & 0 & 5 & 30 \\ 4 & -1 & 0 & 5 & 30 \end{pmatrix} \tag{5.11}$$

Moreover, the bid is illustrated in figure 5.2. As noted before, the bid can only be allocated if all atomic bids can be matched to demand.

Example 5.2 (Compact bid). Suppose bidder $i = 2$ wants to submit a single bid with

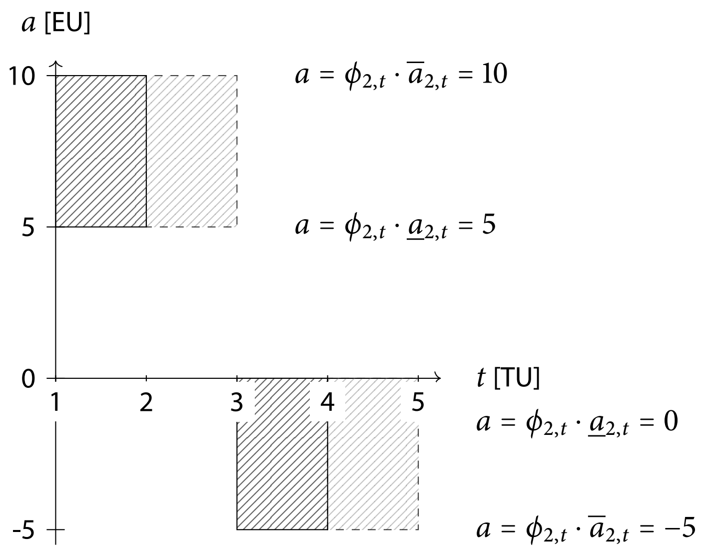


Figure 5.3: Bid amounts of compact bid from example 5.2. Grayed out bids reflect implicitly assumed atomic bids.

$\mathcal{J}_i = \{2\}$ given the same scenario specification as in example 5.1. The compact bid form allows the omission of atomic bids with identical values in all but the delivery start time element σ_j. Thus, the preceding atomic bid implicitly remains valid until succeeded by an atomic bid with a subsequent time slot. This is in particular highlighted in figure 5.3. The resulting compact bid submitted by bidder i is therefore specified as follows:

$$e_2 = \begin{pmatrix} \sigma_{2,1} & \phi_{2,1} & \underline{a}_{2,1} & \overline{a}_{2,1} & b_{2,1} \\ \sigma_{2,2} & \phi_{2,2} & \underline{a}_{2,2} & \overline{a}_{2,2} & b_{2,2} \end{pmatrix} \tag{5.12}$$

$$= \begin{pmatrix} 1 & 1 & 5 & 10 & 20 \\ 3 & -1 & 0 & 5 & 30 \end{pmatrix} \Leftrightarrow e_1 \tag{5.13}$$

That is, bid e_2 is equivalent to bid e_1 from example 5.1.

For the remainder of this work, the compact form is utilized.

In the bidding language, bids e_j are combined with logical XORs operators $(\oplus)$. This describes the combinatorial nature of the auction and allows bidders to express bid alternatives. Such alternatives capture the claim from requirements 5 and 6 that a bidder is faced with a complex and heterogeneous smart grid consumer portfolio. In order to maximize the allocation of contracted consumers to current DSO demand as well as to minimize the internal risk of changes in consumer behavior, a bidder needs to be able to take advantage of a great number of possible consumer scheduling combinations.

Example 5.3 (Combinatorial bid). Given time horizon $T = 10$, suppose that bidder $i = 3$ wants to submit two bids with $\mathcal{J}_i = \{3, 4\}$. In the first bid e_3, a positive balancing power (supply) between 5 and 10 EU for 20 MU/EU over the first 5 TU is offered, i.e., $\sigma_{3,1} = 1$, $\phi_{3,1} = 1$, $\underline{a}_{3,1} = 5$, $\overline{a}_{3,1} = 10$, and $b_{3,1} = 20$. Furthermore, positive balancing power of 12 to 13 EU for 24 MU/EU beginning at $t = 6$ is offered, i.e., $\sigma_{3,2} = 6$, $\phi_{3,2} = 1$, $\underline{a}_{3,2} = 12$, $\overline{a}_{3,2} = 13$, and $b_{3,2} = 24$. Alternatively, in the second bid e_4, bidder $i = 3$ offers a constant supply of 0 to 2 EU for 10 MU/EU over the complete time horizon T. While bid e_3 may represent power supply from a number of combined heat and power (CHP) plants, the power source of bid e_4 may be a single battery storage. The submitted bid in its compact and combinatorial form is then specified as follows and further illustrated in figure 5.4:

$$e_3 \qquad \oplus \qquad e_4 \tag{5.14}$$

$$= \begin{pmatrix} \sigma_{3,1} & \phi_{3,1} & \underline{a}_{3,1} & \overline{a}_{3,1} & b_{3,1} \\ \sigma_{3,2} & \phi_{3,2} & \underline{a}_{3,2} & \overline{a}_{3,2} & b_{3,2} \end{pmatrix} \oplus \begin{pmatrix} \sigma_{4,1} & \phi_{4,1} & \underline{a}_{4,1} & \overline{a}_{4,1} & b_{4,1} \end{pmatrix} \tag{5.15}$$

$$= \begin{pmatrix} 1 & 1 & 5 & 10 & 20 \\ 6 & 1 & 12 & 13 & 24 \end{pmatrix} \oplus \begin{pmatrix} 1 & 1 & 0 & 2 & 10 \end{pmatrix} \tag{5.16}$$

Definition 5.26 (Winning bid). *Let bid price $b_i^* = \sum_{t \in \mathcal{T}} b_i^{t*}$ and bid amount $a_i^* = \sum_{t \in \mathcal{T}} a_i^{t*}$ denote the winning bids and amounts of winning bidder i from the set of winners $\mathcal{W} \subseteq \mathcal{I}$.*

Clearly, the winning bid amount a_i^* and price b_i^* is influenced by outside option amounts ψ^t and prices γ^t.

Definition 5.27 (Winning coalition). *A winning coalition $\mathcal{C} \subseteq \mathcal{I}$ is the result of an allocation with $\mathcal{C} = \{i \in \mathcal{I} : \exists j \in \mathcal{J}_i : x_j = 1\}$.*

Definition 5.28 (Demand). *Let $a_0 = (a_0^1, \dots, a_0^t, \dots, a_0^T)$ denote the demand of flexibility, i.e., balancing power, from buyer $i \in \{0\}$. Moreover, let $g^* = a_0$ denote the product that completely fulfills the amounts of the demand.*

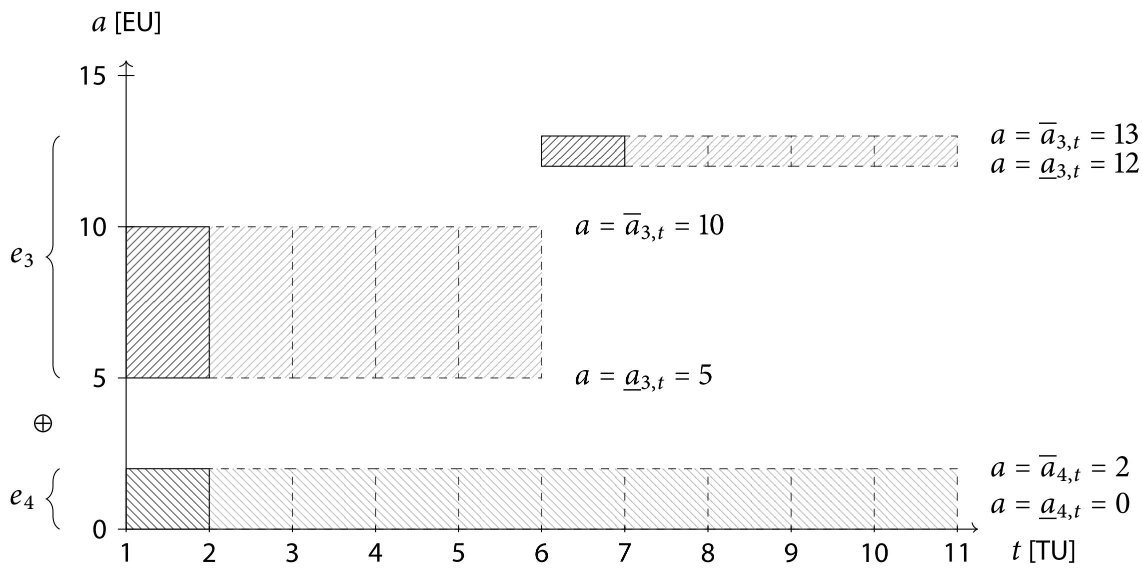


Figure 5.4: Bid amounts of combinatorial bid from example 5.3. Grayed out bids reflect implicitly assumed atomic bids.

5.5 Utility Functions and Social Welfare

Definition 5.29 (Buyer utility function). *The utility function of buyer i with $i \in \{0\}$ is determined by buyer i's valuation (v_i) for balancing power requested for each $t \in \mathcal{T}$, plus the payments (ρ_i) for allocated balancing power to bidders. Thus, the utility function of buyer $i \in \{0\}$ is given by:*

$$u_0(\theta) = v_0(g^*) + \rho_0(\theta) \tag{5.17}$$

The valuation of buyer i represents its opportunity cost for having to fall back to an outside option and is assumed to be fixed.

Definition 5.30 (Seller utility function). *The utility function of seller i with $i \in \mathcal{I} \setminus \{0\}$ is determined by the payments received for providing positive or negative balancing power, less the cost c_i for provisioning, contracting, and managing its portfolio of flexible consumers or loads for each $t \in \mathcal{T}$. For an outside option provider, the cost can encompass investment, trading or operational cost. Then, the utility function of a seller agent i is given by:*

$$u_i(\theta) = \rho_i(\theta) - c_i(\theta) \tag{5.18}$$

Definition 5.31 (Social welfare). *The social welfare is given by the sum of equations* (5.17) *and* (5.18) *over all participating agents:*

$$
\begin{aligned}
sw(\theta) &= \sum_{i \in \mathcal{I}} u_i(\theta) && (5.19)\\
&= u_0(\theta) + \sum_{i \in \mathcal{I} \setminus \{0\}} u_i(\theta) && (5.20)\\
&= v_0(g^*) + \rho_0(\theta) + \sum_{i \in \mathcal{I} \setminus \{0\}} (\rho_i(\theta) - c_i(\theta)) && (5.21)\\
&= \sum_{t \in \mathcal{T}, g^{*,t} \in g} v_0^t(g^{*,t}) + \rho_0(\theta) + \sum_{i \in \mathcal{I} \setminus \{0\}} (\rho_i(\theta) - \sum_{t \in \mathcal{T}} c_i^t(\theta)) && (5.22)\\
&= \sum_{t \in \mathcal{T}, g^{*,t} \in g} (v_0^t(g^{*,t}) - \sum_{i \in \mathcal{I} \setminus \{0\}} c_i^t(\theta)) && (5.23)
\end{aligned}
$$

Note that the valuation of sellers is zero, as they will not deliver, i.e., start generating or consuming balancing power, unless successfully allocated. In addition, the utility of the buyer is given through its valuation for balancing power.

5.6 Winner Determination Problem

Given the bidding language, the WDP can be formulated. In the following, two versions of the WDP are introduced. The first version of the WDP exclusively considers the allocation of bids that match the requested delivery direction ϕ_j^t (production or consumption) for a given time slot t. Extending this conservative and restrictive approach, the second version of the WDP relaxes the restriction on unidirectional bid acceptance to allow the matching of both delivery directions (production and consumption) bids at the same time for a given time slot. This bidirectional WDP approach represents the foundation for further evaluations.

In accordance with literature on combinatorial (reverse) auctions (Rassenti, Smith, and Bulfin 1982; T. Sandholm 2000; Sandholm et al. 2002; T. Sandholm 2002; Cramton, Shoham, and Steinberg 2006; T. Sandholm 2006; Hsieh 2010), the winner determination problem is formulated as a MIP in the following.

5.6.0.1 Unidirectional WDP

Following definitions 5.20 to 5.23, let ϕ_j^t, $\underline{a}_j^t$, $\overline{a}_j^t$, and b_j^t be the direction, minimum/maximum amount, and monetary bid submitted in the jth bid that are valid in t ($\phi_j^t, \underline{a}_j^t, \overline{a}_j^t, b_j^t$: $(\sigma_{j,n}, \phi_j^t, \underline{a}_{j,n}, \overline{a}_{j,n}, b_{j,n},) \in e_j \wedge \sigma_{j,n} = \max(\{\sigma_{j,n} : \sigma_{j,n} \leq t\})$).

The amount of balancing power requested by the auctioneer for time slot t is denoted as a_0^t. The accepted delivery amount of bid j in time slot t is specified by $a_j^t \in \mathbb{R}_{\geq 0}$. From definition 5.9, the positive and negative amount of balancing power purchased using an outside option are denoted as ψ_+^t and ψ_-^t at prices γ_+^t and γ_-^t, respectively.

As noted in definition 5.31, the valuation of the buyer is assumed to be fixed, and the cost by the sellers are subtracted therefrom. That is, the social welfare is the difference of the buyer valuation and the seller cost. Therefore, the WDP can be formulated as the following minimization problem.

$$
\begin{aligned}
\mathrm{UWD}(\theta) = \min_{x,a,\psi_+,\psi_-} \sum_{t\in\mathcal{T}} \sum_{j\in\mathcal{J}} & b_j^t a_j^t + \gamma_+^t \psi_+^t + \gamma_-^t \psi_-^t && && \text{(UWD)} \\
\text{s. t.} \sum_{j\in\mathcal{J}} & a_j^t + \psi_+^t - \psi_-^t = a_0^t && \forall t \in \mathcal{T} && \text{(5.24a)} \\
\sum_{j\in\mathcal{J}} & a_j^t \geq \sum_{j\in\mathcal{J}} \underline{a}_j^t x_j && \forall t \in \mathcal{T} && \text{(5.24b)} \\
\sum_{j\in\mathcal{J}} & a_j^t \leq \sum_{j\in\mathcal{J}} \overline{a}_j^t x_j && \forall t \in \mathcal{T} && \text{(5.24c)} \\
\sum_{j\in\mathcal{J}} & \phi_j^t x_j \phi_0^t \geq 0 && \forall t \in \mathcal{T} && \text{(5.24d)} \\
& \psi_+^t \phi_0^t \geq 0 && \forall t \in \mathcal{T} && \text{(5.24e)} \\
& -\psi_-^t \phi_0^t \geq 0 && \forall t \in \mathcal{T} && \text{(5.24f)} \\
& \psi_+^t, \psi_-^t \geq 0 && \forall t \in \mathcal{T} && \text{(5.24g)} \\
\sum_{j\in\mathcal{J}_i} & x_j \leq 1 && \forall i \in \mathcal{I} && \text{(5.24h)} \\
& x_j \in \{0,1\} && \forall j \in \mathcal{J} && \text{(5.24i)}
\end{aligned}
$$

The objective of the WDP is to minimize the sum of accepted bids and of the outside option for the buyer and is given in UWD. The commonly known WDP (Rassenti, Smith, and Bulfin 1982; T. Sandholm 2000; Sandholm et al. 2002; T. Sandholm 2002; Cramton, Shoham, and Steinberg 2006; T. Sandholm 2006; Hsieh 2010) is extended by minimum and maximum amounts, unit prices, a combination of balancing power production and consumption potential, and a fixed price outside option. In order to guarantee a constant balance of supply and demand, constraint (5.24a) ensures that the DSO's requested balancing power amount a_0^t is fulfilled in every time slot t. This constraint also includes the positive and negative outside options ψ_+^t and ψ_-^t as a backup solution. Moreover, constraint (5.24b) limits the accepted amount a_j^t to the minimum amount $\underline{a}_j^t$ specified in each bid $j \in \mathcal{J}$ for all $t \in \mathcal{T}$. Similarly, constraint (5.24c) limits the accepted mount to the maximum amount $\overline{a}_j^t$ specified in each bid. Constraint (5.24d) ensures the delivery direction ϕ_j^t, i.e., production or consumption, matches the requested delivery direction ϕ_0^t. Correspondingly, constraints (5.24e) and (5.24f) limit the delivery direction of the positive and negative outside options ψ_+^t and ψ_-^t to the requested delivery direction ϕ_0^t. Moreover, constraint (5.24g) ensures the non-negativity of an allocated outside option ψ_+^t or ψ_-^t. Furthermore, constraint (5.24h) models the XOR relation of the single bids and ensures that at most one bid can be accepted per bider. Finally, constraint (5.24i) describes the binary structure of a bid allocation, i.e., a bid j can either be allocated ($x_j = 1$) or not ($x_j = 0$).

5.6.0.2 Bidirectional WDP

In order to allow for a more flexible allocation of balancing power from aggregators, the previously introduced version of the winner determination problem in UWD, which requires bid directions ϕ_j^t to match the requested direction ϕ_0^t for all $t \in \mathcal{T}$, is extended by relaxing the relevant constraint from 5.24d. Henceforth, a requested direction ϕ_0 can be matched with a combination of positive or negative balancing power amount bids from aggregators. Therefore, for each time slot t, the accepted bid amount a_j^t is split up into bidirectional components a_{j+}^t and a_{j-}^t which denote positive and negative balancing power accepted for each $t \in \mathcal{T}$. For the remainder of this work, the following bidirectional version of the WDP is used.

Analogous to section 5.6.0.1, let ϕ_j^t, $\underline{a}_j^t$, $\overline{a}_j^t$, and b_j^t be the direction, minimum/maximum amount and monetary bid submitted in the jth bid that are valid in t ($\phi_j^t, \underline{a}_j^t, \overline{a}_j^t, b_j^t$: $(\sigma_{j,n}, \phi_j^t, \underline{a}_{j,n}, \overline{a}_{j,n}, b_{j,n},) \in e_j \wedge \sigma_{j,n} = \max(\{\sigma_{j,n} : \sigma_{j,n} \leq t\})$).

The amount of balancing power requested by the auctioneer for time slot t is denoted as

a_0^t. Extending the previous WDP, the accepted positive and negative delivery amounts of bid j in time slot t are specified by $a_{j+}^t \in \mathbb{R}_{\geq 0}$ and $a_{j-}^t \in \mathbb{R}_{\geq 0}$ ($a_{j+}^t a_{j-}^t = 0$). The positive and negative amount of balancing power purchased using an outside option are denoted as ψ_+^t and ψ_-^t at prices γ_+^t and γ_-^t, respectively.

$$\mathrm{WD}(\theta) = \min_{x,a_+,a_-,\psi_+,\psi_-} \sum_{t\in\mathcal{T}} \sum_{j\in\mathcal{J}} (b_j^t a_{j+}^t + b_j^t a_{j-}^t) + \gamma_+^t \psi_+^t + \gamma_-^t \psi_-^t \tag{WD}$$

$$\text{s. t.} \sum_{j\in\mathcal{J}} (a_{j+}^t - a_{j-}^t) + \psi_+^t - \psi_-^t = \phi_0^t a_0^t \qquad \forall t \in \mathcal{T} \tag{5.25a}$$

$$\sum_{j\in\mathcal{J}} a_{j+}^t \geq \sum_{j\in\mathcal{J}} \underline{a}_j^t x_j \phi_j^t \qquad \forall t \in \mathcal{T} \tag{5.25b}$$

$$\sum_{j\in\mathcal{J}} a_{j-}^t \geq - \sum_{j\in\mathcal{J}} \underline{a}_j^t x_j \phi_j^t \qquad \forall t \in \mathcal{T} \tag{5.25c}$$

$$\sum_{j\in\mathcal{J}} a_{j+}^t \phi_j^t \leq \sum_{j\in\mathcal{J}} \overline{a}_j^t x_j \qquad \forall t \in \mathcal{T} \tag{5.25d}$$

$$- \sum_{j\in\mathcal{J}} a_{j-}^t \phi_j^t \leq \sum_{j\in\mathcal{J}} \overline{a}_j^t x_j \qquad \forall t \in \mathcal{T} \tag{5.25e}$$

$$\sum_{j\in\mathcal{J}} a_{j+}^t \phi_j^t \geq 0 \qquad \forall t \in \mathcal{T} \tag{5.25f}$$

$$- \sum_{j\in\mathcal{J}} a_{j-}^t \phi_j^t \geq 0 \qquad \forall t \in \mathcal{T} \tag{5.25g}$$

$$\psi_+^t, \psi_-^t \geq 0 \qquad \forall t \in \mathcal{T} \tag{5.25h}$$

$$\sum_{j\in\mathcal{J}_i} x_j \leq 1 \qquad \forall i \in \mathcal{I} \tag{5.25i}$$

$$x_j \in \{0,1\} \qquad \forall j \in \mathcal{J} \tag{5.25j}$$

Since the load flexibility auction is a procurement auction, the objective is to minimize the cost of accepted bids in addition to the cost of the outside option in WD. As before, the general WDP is extended by minimum and maximum amounts, unit prices, a combination of power production and consumption potential, and a fixed price outside option.

Constraint (5.25a) ensures that the DSO's requested balancing amount a_0^t is fulfilled in every time slot $t \in \mathcal{T}$. In particular, balancing is now allowed in between bids from aggregators. That is, larger and potentially less expensive bids can be allocated and immediately be counterbalanced with bids containing an opposing bid direction. This allows for a possibly cheaper and more flexible allocation of bidders, with the purpose avoiding to resort to the outside option. In addition, constraints (5.25b) to (5.25e) limit the accepted balancing power amounts to the minimum and maximum bid amounts, $\underline{a}_j^t$ and $\overline{a}_j^t$, in the bids $j \in \mathcal{J}$ for all $t \in \mathcal{T}$, in accordance with the offered delivery direction ϕ_j^t. Moreover, constraints (5.25f) and (5.25g) restrict the purchases of the DSO to the offered direction ϕ_j of bids from aggregators. Furthermore, constraint (5.25h) ensures that the accepted outside option amounts ψ_+^t, ψ_-^t are non-negative. Finally, constraint (5.25i) models the XOR relation of the single bids and ensures that at most one bid can be accepted per bidder while constraint (5.25j) is the binary variable that captures whether bid j is allocated or not.

6

Smart Grid Flexibility Auction Pricing Rules

Following the model of the flexibility auction introduced in the previous chapter 5, this chapter focuses on different pricing rules that can be applied in the auction. Firstly, section 6.1 introduces pay-as-bid (PAB) as the classical pricing rule employed in auctions. Secondly, section 6.2 provides details on the pricing rule k-pricing. Thirdly, section 6.3 introduces the application of Vickrey-Clarke-Groves (VCG) with the Clarke pivot rule to the flexibility auction. Finally, section 6.4 introduces the novel contribution of core pricing to a combinatorial reverse auction scenario as applied in the flexibility auction. Parts of this chapter are adapted from the previously published paper: David Dauer, Paul Karaenke, and Christof Weinhardt. 2015. "Load Balancing in the Smart Grid: A Package Auction and Compact Bidding Language." In *Proceedings of the Thirty Sixth International Conference on Information Systems.* Fort Worth, TX.

6.1 Pay-as-Bid

The pay-as-bid (PAB) rule represents the most basic pricing rule for pricing in auctions and is commonly employed in first-price auctions, in particular in financial, non-financial, and procurement settings (Rothkopf and Harstad 1995). In the traditional forward setting, the highest bidder wins and pays the value of his bid (Krishna 2002). This rule is also referred to as a discriminatory pricing rule. More formally,

$$p_i(\theta) = b_i^*. \tag{6.1}$$

In comparison to VCG mechanisms, PAB pricing has the benefit that it can avoid low revenue outcomes in forward auctions (or high buyer payments in reverse auctions). Section 6.3 elaborates on the limitations of VCG mechanisms. Moreover, it discourages shill bidding and collusive strategies (Ausubel and P. R. Milgrom 2002).

However, the PAB pricing rule requires to deal with strategic behavior of bidders, as there exist several incentives to misreport preferences in order to improve the individual auction outcome. For example, Day and Raghavan (2007) note that in sealed-bid combinatorial auctions, a PAB rule encourages bidders to submit bids that just about ensure an efficient outcome. Yet, uncertainty among bidders can lead to lower bids which in turn can result in inefficient auction outcomes. For a characterization on solutions to the bidders' strategic problem, the inclined reader is referred to Bernheim and Whinston (1986).

In the following, the PAB pricing rule serves as a *best case* benchmark for the distribution system operator (DSO), as it is assumed that bidders truthfully report their bids. Hence, the payments from the DSO to aggregators can be assumed to be minimal.

Definition 6.1 (Pay-as-bid pricing). *From definition 5.26, let b_i^* and a_i^* denote the winning bid and amount of winning bidder i. Then, the payment for bidder i is given by*

$$p_i^{PAB}(\theta) = \sum_{t \in \mathcal{T}} b_i^{t*} a_i^{t*} \tag{6.2}$$

That is, under PAB pricing in the reverse auction setting at hand, bidder $i \in \mathcal{I} \setminus (\{0\} \cup \mathcal{R})$ receives exactly its offered price for its allocated amounts.

6.2 k-Pricing

The k-pricing rule represents an approach which aims at distributing welfare in sealed-bid double-sided auctions between sellers and buyers according to factor k (Satterthwaite and

Williams 1989, 1993). That is, prices are determined depending on the difference of the bids from both a seller and a buyer. More specifically, given the valuation of buyer $i = 1$ as bid b_1 and the reservation price of seller $i = 2$ as offer b_2, the payment of the buyer to the seller is determined as

$$p_1(\theta) = kb_1 + (1-k)b_2, \tag{6.3}$$

where $k \in [0,1]$ if and only if $b_1 \geq b_2$ (Satterthwaite and Williams 1989). Otherwise, no allocation would exist and the price would be 0. While $k = 0$ or $k = 1$ represent a unilateral price determination for the seller or buyer, respectively, a value of $0 < k < 1$ indicates that both seller and buyer influence the price determination. Under the assumption of truthfulness, the most equitable price setting is given for both sides with $k = 0.5$. That is, the final price is located exactly midway between the valuation and reservation price.

Obviously, the advantage of of k-pricing lies within its ability to account for fairness and revenue considerations given the flexibility to set k. Moreover, considering computational runtime, k-pricing determines prices in polynomial time. However, similar to PAB pricing, k-pricing is vulnerable to strategic manipulation from bidders. That is, a trade-off between this limitation and the advantages of k-pricing is required (Stößer, Neumann, and Weinhardt 2010). k-pricing has been successfully applied in market-based settings, e.g., for double-sided combinatorial exchanges (Schnizler et al. 2008) or for distributed scheduling in grid markets (Stößer, Neumann, and Weinhardt 2010).

In context of the reverse auction setting in the work at hand, it is assumed that the opposite side compared to the double-sided auction scenario is represented by the outside option. Hence, the reservation price of the buyer is given by the outside option prices γ_+^t and γ_-^t. From definition 5.26, let b_i^* and a_i^* denote the winning bid and amount of winning bidder i and from definition 5.9, let γ_+^t and γ_-^t the prices for both positive and negative balancing power for time slot $t \in \mathcal{T}$.

Definition 6.2 (k-pricing). *The payment a bidder i receives under the k-pricing rule is given by*

$$p_i^{KP}(\theta) = k \sum_{t \in \mathcal{T}} f(\gamma_+^{t*}, \gamma_-^{t*}) + (1-k) \sum_{t \in \mathcal{T}} b_i^{t*} a_i^{t*} \tag{6.4}$$

with

$$f(\gamma_+^{t*}, \gamma_-^{t*}) = \begin{cases} \gamma_+^{t*} & \phi_0^t > 0 \\ \gamma_-^{t*} & \phi_0^t < 0. \end{cases} \tag{6.5}$$

6.3 VCG

The VCG mechanisms allow to set aside strategic considerations on determining optimal bidder strategies as the VCG mechanisms with the Clarke pivot rule are incentive compatible, i.e., strategy-proof. (Green and Laffont 1977). Therefore, the best strategy of each player is to report its true valuations to the auction mechanism. Moreover, the family of VCG mechanisms also maximizes social welfare, i.e., the mechanism is allocative efficient for quasi-linear utility functions. Additionally, the mechanism is ex-post individual rational and weakly budget balanced as described in section 3.2.4.3 (Nisan et al. 2007; Shoham and Leyton-Brown 2009). There is no other mechanism satisfying these properties in a combinatorial setting (Green and Laffont 1977). As shown in section 3.2.4.3, the VCG mechanisms are a family of mechanisms because there is a freedom of selecting the function which determines the payments of agents. In these direct mechanisms, the agents' payments do not depend on their declarations (bids) and they are paid the sum of every other agent's declared valuation for the mechanism's choice (Nisan et al. 2007; Shoham and Leyton-Brown 2009). That is, prices reflect the externality imposed on other participants by a given agent. The general functioning of VCG mechanisms is described in section 3.2.4.3. In the following, VCG is described for the load flexibility auction introduced in section 5.2. Subsequently, this section elaborates on the limitations of the VCG mechanisms.

6.3.1 Definition

Following definition 5.26, let b_i^* and a_i^* denote the winning bid and amount of winning bidder i. In addition, let $\mathrm{WD}^*(\cdot)$ denote the optimal solution to WD.

The VCG payments a bidder $i \in \mathcal{I} \setminus (\{0\} \cup \mathcal{R})$ receives are defined as

$$p_i = h_i(\theta_{-i}) - (\mathrm{WD}^*(\theta) - \sum_{t \in \mathcal{T}} b_i^{t*} a_i^{t*}). \tag{6.6}$$

The function $h_i(\cdot)$ is independent bidder i's bids and the possibility of different functions explains why VCG is a family of mechanisms. The term $\mathrm{WD}^*(\theta) - \sum_{t \in \mathcal{T}} b_i^{t*} a_i^t$ denotes the valuations of all bidders except i of the efficient outcome plus the price for using the outside option for the optimal allocation. For the Clarke pivot payment, $h_i(\cdot)$ is defined as the valuation of all other participants of an outcome when agent i does not participate, i.e.,

$$h_i(\theta_{-i}) = \mathrm{WD}^*(\theta_{-i}). \tag{6.7}$$

Hence, the payment that bidder $i \in \mathcal{I} \setminus (\{0\} \cup \mathcal{R})$ receives is calculated as

$$p_i(\theta) = \mathrm{WD}^*(\theta_{-i}) - (\mathrm{WD}^*(\theta) - \sum_{t \in \mathcal{T}} b_i^{t*} a_i^{t*}) \tag{6.8}$$

$$= \sum_{t \in \mathcal{T}} b_i^{t*} a_i^{t*} - (\mathrm{WD}^*(\theta) - \mathrm{WD}^*(\theta_{-i})). \tag{6.9}$$

That is, prices reflect the externality imposed on other participants by a given agent.

Note that the winning bid is empty and the $\mathrm{WD}^*(\cdot)$ terms cancel for non-winning bidders and are therefore zero. The buyer pays

$$p_0(\theta) = -\sum_{i \in \mathcal{I} \setminus (\{0\} \cup \mathcal{R})} p_i(\theta) - \sum_{t \in \mathcal{T}} (\gamma_+^t \psi_+^t + \gamma_-^t \psi_-^t). \tag{6.10}$$

That is, VCG payments are only applied for the bidder side. Moreover, payments are bounded by the outside option prices γ^t as these are available for all $t \in \mathcal{T}$. Therefore, every bidder can at most receive a payment of

$$p_{i,\max} = \sum_{t \in \mathcal{T}} \gamma_{\max}^t a_i^{t*} \tag{6.11}$$

where

$$\gamma_{\max}^t = \max(\{\gamma_+^t, \gamma_-^t\}) \quad \forall t \in \mathcal{T}. \tag{6.12}$$

This follows from the observation that the product of winning bids and amounts cannot exceed the optimal value of WD, i.e.,

$$\sum_{t \in \mathcal{T}} b_i^{t*} a_i^{t*} \leq \mathrm{WD}^*(\theta), \tag{6.13}$$

since they are part of a sum that gives the resulting value. Then,

$$p_i(\theta) \leq \mathrm{WD}^*(\theta) - (\mathrm{WD}^*(\theta) - \mathrm{WD}^*(\theta_{-i})) = \mathrm{WD}^*(\theta_{-i}) \tag{6.14}$$

With

$$\mathrm{WD}^*(\cdot) \leq \sum_{t \in \mathcal{T}} \gamma^t_{\max} a_i^{t*} \tag{6.15}$$

this yields

$$p_i(\theta) \leq \sum_{t \in \mathcal{T}} \gamma^t_{\max} a_i^{t*}. \tag{6.16}$$

6.3.2 Limitations

As shown before, the VCG mechanisms for determining pricing in combinatorial auctions have the advantage of being the only mechanisms that are efficient and dominant-strategy incentive compatible (Green and Laffont 1977). That is, winners are selected with the objective to maximize the combined value of allocated bundles and it is the dominant strategy of bidders to truthfully bid their valuations for each bundle of goods.

However, there exist several well-known limitations of the VCG mechanisms (Ausubel and P. R. Milgrom 2002; Ausubel and P. Milgrom 2006; Rothkopf, Teisberg, and Kahn 1990; Rothkopf and Harstad 1995), e.g., low revenue, fairness, and disqualification problems as well as the possibility of shill-bidding and collusion. These limitations are illustrated along the following examples.

Revenue The first limitation as noted by Ausubel and P. R. Milgrom (2002) represents that generated seller revenues can be very low or zero in forward auctions.

Example 6.1 (Revenue in forward auctions). Following Day and Milgrom (2008), consider an auction scenario with two identical goods for sale and three bidders which bid their true valuations, i.e., the maximum price they are willing to pay, as shown in table 6.1 as follows: Notice that the outcome of the auction determines bidders 2 and 3 as winners. VCG with the Clarke pivot rule assigns the payments of bidders 2 and 3 to

$$p_i = \hat{v}_i - (\mathrm{CAP}(\mathcal{I}) - \mathrm{CAP}(\mathcal{I}_{-i})) \Leftrightarrow \tag{6.17}$$

$$p_2 = p_3 = 10 - (20 - 10) = 0. \tag{6.18}$$

Hence, the revenue for the seller would be 0, while it could be at least 10 as any bidder would pay 10 for the bundle AB.

Table 6.1: Bids resulting in low seller revenue

	Bundle		
Bidder	A	B	AB
1	0	0	10
2	0	10	10
2	10	0	10
3	0	10	10
3	10	0	10

Table 6.2: Bids resulting in high buyer payments

	Bundle		
Bidder	A	B	AB
1	10	0	0
2	0	10	0
3	0	0	30

In reverse auctions on the other hand, the low revenue problem can be referred to as the high payments problem as buyer payments can be too high.

Example 6.2 (Payments in reverse auctions). Consider an auction scenario with two goods to procure and three bidders with their reported valuations, i.e., the minimum price they request, in table 6.2 as follows: Notice that the outcome of the auction determines bidders 1 and 2 as winners since the goal of the buyer is to minimize its cost. VCG with the Clarke pivot rule assigns the payments to bidders 1 and 2 to

$$p_i = \hat{v}_i - (\mathrm{CAP}(\mathcal{I}) - \mathrm{CAP}(\mathcal{I}_{-i})) \Leftrightarrow \tag{6.19}$$

$$p_1 = p_2 = 10 - (20 - 30) = 20. \tag{6.20}$$

Hence, the buyers pays $\sum_{i \in \{1,2\}} p_i = 40$ in total. However, the losing bidder $i = 3$ would have sold the item for 30. Therefore the buyer pays too much.

Fairness A direct implication of the low revenue problem is that the outcome is not a core allocation (Day and Raghavan 2007). This in turn implies that there exists an outcome provided by a coalition of bidders and the seller which is favorable but was rejected, yet could be formed through a renegotiation, i.e., collusion, among the corresponding coalition of the seller and bidders. Such a favorable outcome could have been between non-winning bidders who are willing to pay more than the winning bidders and the seller. In particular in auctions that involve the public sector, such an outcome can be perceived as unfair (Day and Raghavan 2007; Day and Cramton 2012). Following the previous example 6.2 with table 6.2, note that while the buyer pays 40 in total, bidder 3 would object to this outcome due to it being unfair as a renegotiation could produce a more favorable outcome for both the buyer and bidder 3. That is, the buyer would pay less in total and bidder 3 would be allocated. Another notion of fairness is introduced by Ausubel and P. R. Milgrom (2002), which refers to the effect of a discriminatory pricing rule on the outcome where two bidders may have to pay different prices for the same allocation based on the same bids. However, the notion by Day and Raghavan (2007) is followed henceforth.

Disqualification The VCG mechanism with the Clarke pivot rule provides incentives for sellers to exclude qualified buyers, known as the disqualification problem (Day and Milgrom 2008).

Example 6.3 (Disqualification problem). Following example 6.1 and table 6.1 therein, notice that by disqualifying bidder 3, the outcome of the auction determines either bidder 1 or 2, according to a predefined tie-breaking rule, as winner. Assuming bidder 1 wins, the price bidder 1 has to pay is set to

$$p_i = \hat{v}_i - \left(\mathrm{CAP}(\mathcal{I}) - \mathrm{CAP}(\mathcal{I}_{-i})\right) \Leftrightarrow \tag{6.21}$$

$$p_1 = 10 - (10 - 10) = 10. \tag{6.22}$$

Therefore, the seller has raised the VCG price from 0 to 10 and in turn its own revenue.

Shill Bidding By misrepresenting their valuations and identity and therefore participating as multiple entities (“shills”) in the auction, bidders can lower their payments in forward auctions (Ausubel and P. R. Milgrom 2002) and increase their revenue in reverse auctions. As this drawback is not of relevance for this work, an example is omitted but can be found in Day and Milgrom (2008).

6.4 Core Pricing

Core pricing aims at tackling the central issue associated with VCG mechanisms: Low seller revenue in forward auctions (or high buyer payments in reverse auctions) and the associated perceived fairness of prices (Day and Raghavan 2007). This section first introduces core pricing for the combinatorial forward auction case. Subsequently, a novel application of core pricing as a pricing rule in the flexibility auction is introduced.

6.4.1 Definitions

Core pricing, sometimes also referred to as a core-selecting auction or mechanism (Day and Cramton 2012), was introduced in recent years (Day and Raghavan 2007) to mitigate the limitations of VCG as identified in section 6.3.2. In particular, the goal of core pricing is to increase the perceived fairness of prices and to determining adequately large payments for bidders. Such payments need to prevent any coalition of losing bidders to propose a mutually beneficial outcome for both the bidders and the seller, thereby also addressing the low seller revenue problem (Day and Raghavan 2007). In addition to the properties of VCG, namely ex-post individual rationality and allocative efficiency, core pricing introduces the "core" property to combinatorial auctions, which ensures that the previously mentioned mutually beneficial renegotiations do not occur, i.e., that there exists no bidder who would be willing to pay more. Note that core pricing does not provide dominant-strategy incentive compatibility as VCG does. Instead, VCG prices are used as a baseline and core prices are determined in such a way as to minimize the deviation from incentive compatibility (Day and Milgrom 2008). That is, while not being incentive compatible, core pricing aims at providing incentives for bidders to reveal their bids truthfully by adjusting their payments to be as near to VCG as possible. However, incentives for manipulation can be considered minimal in larger markets, where the information on bidders and their preferences is not necessarily known (Day and Raghavan 2007). Before being able to describe how the mechanism works, it is essential to extend the auction model definitions of section 5.2.2 and therefore establish several other fundamental notions based on Day and Raghavan (2007) as follows:

Definition 6.3 (Payment). *Let $p = (p_1, \dots, p_i, \dots, p_N) \in \mathbb{R}$ denote the vector of payments for all bidders $i \in \mathcal{I}$. Furthermore, let $p^{VCG} = (p_1^{VCG}, \dots, p_i^{VCG}, \dots, p_N^{VCG})$ denote the VCG payment vector and $p^{CORE} = (p_1^{CORE}, \dots, p_i^{CORE}, \dots, p_N^{CORE})$ denote the core payments* *of all bidders $i \in \mathcal{I}$. Moreover, $p^\tau = (p_1^\tau, \ldots, p_i^\tau, \ldots, p_N^\tau)$ denotes the payment vector for all bidders at algorithm iteration τ (Day and Raghavan 2007).*

That is, the payment vector defines the payments from bidders to the seller in forward auctions. In the case of the load flexibility auction, which constitutes a reverse auction, the payment vector defines payments from the seller to bidders.

Definition 6.4 (Outcome). *Following definition 3.4, let $o \in \mathcal{O}$ denote the outcome, i.e., an allocation $x \in \mathcal{X}$ and payment vector p, of a combinatorial auction (Day and Raghavan 2007).*

Definition 6.5 (Coalition). *Following definition 5.27, let $\mathcal{C}_o$ denote the set of winning bidders determined by a feasible solution to the auction's winner determination problem (WDP), i.e., outcome $o \in \mathcal{O}$ (Day and Raghavan 2007; Day and Cramton 2012).*

Definition 6.6 (Blocking outcome and coalition). *An outcome o is called blocked if there exists an alternative outcome o' which generates strictly more revenue for the seller and for which every bidder in the corresponding coalition $\mathcal{C}_{o'}$ weakly prefers the alternative outcome o' to o. If such an alternative outcome o' exists, the corresponding coalition $\mathcal{C}_{o'}$ is called a blocking coalition (Day and Raghavan 2007).*

Definition 6.7 (Core outcome). *An outcome o which is not blocked is said to be a core outcome (Day and Raghavan 2007).*

Definition 6.8 (Bidder-Pareto-optimal outcome). *A core outcome o is called bidder-Pareto-optimal if no other core outcome exists which is weakly preferred by every bidder in the corresponding coalition $\mathcal{C}_o$ (Day and Raghavan 2007).*

That is, given an efficient allocation and payment vector p, there exists no alternative payment vector p' which is also in the core, such that $p' \leq p$ (Day and Cramton 2012).

6.4.2 Pricing Rule

Based on the fundamental concepts of core pricing, the mechanism of a core-selecting auction is described in the following. A core-selecting auction determines the allocation identical to VCG, i.e., it maximizes social welfare. However, contrary to VCG with the Clarke pivot rule,

Table 6.3: Bidder valuations for core pricing

	Bundle		
Bidder	A	B	AB
1	28	0	0
2	0	20	0
3	0	0	32
4	14	0	0
5	0	12	0

payments are chosen differently, i.e., so that they are in the core. That is, VCG payments are effectively corrected and thus substituted for core payments when the VCG payments are not in the core. Specifically, payments are chosen in such a way that no one can be made better off without making someone else worse off. Following Day and Cramton (2012), this process can be illustrated with the subsequent simple yet exhaustive example.

Example 6.4 (Core pricing). Following Day and Cramton (2012), consider an auction with two goods and five bidders with their reported valuations in bids as shown in table 6.3. Notice that the outcome of the auction determines bidders 1 and 2 as winners with VCG payments

$$p_i^{\mathrm{VCG}} = \hat{v}_i - (\mathrm{CAP}(\mathcal{I}) - \mathrm{CAP}(\mathcal{I}_{-i})) \Leftrightarrow \tag{6.23}$$

$$p_1^{\mathrm{VCG}} = 28 - (48 - 34) = 14 \tag{6.24}$$

$$p_2^{\mathrm{VCG}} = 20 - (48 - 40) = 12. \tag{6.25}$$

The constraints defined by the bidders' reported valuations $\hat{v}(\cdot)$, which in turn define the core, are shown in the following figure 6.1. Notice that in particular the lower bounds of the constraints are given considering that bidder 4 would always object a payment of bidder 1 for less than 14 on good A, therefore $p_1 \geq 14$. At the same time, bidder 5 would block if the payment of bidder 2 would be less than 12, hence $p_2 \geq 12$. Similarly, bidder 3 needs the payments of bidders 1 and 2 to be larger than his bid in order not to block, therefore $p_1 + p_2 \geq 32$. The upper bounds of the constraints are identical to the bids. Recall that $p^{\mathrm{VCG}} = (14, 12)$ and note that this vector is not in the core as bidder 3 would pay more for both goods, i.e., $\sum_{i\in\{1,2\}} p_i^{\mathrm{VCG}} = 26 \leq 32 = \hat{v}_3(AB)$. Now, to unblock bidder 3 and therefore ensure that the payments are in the core, the auctioneer determines a corrected payment vector which would be located at any point on the line segment from $(14, 18)$ to $(20, 12)$.

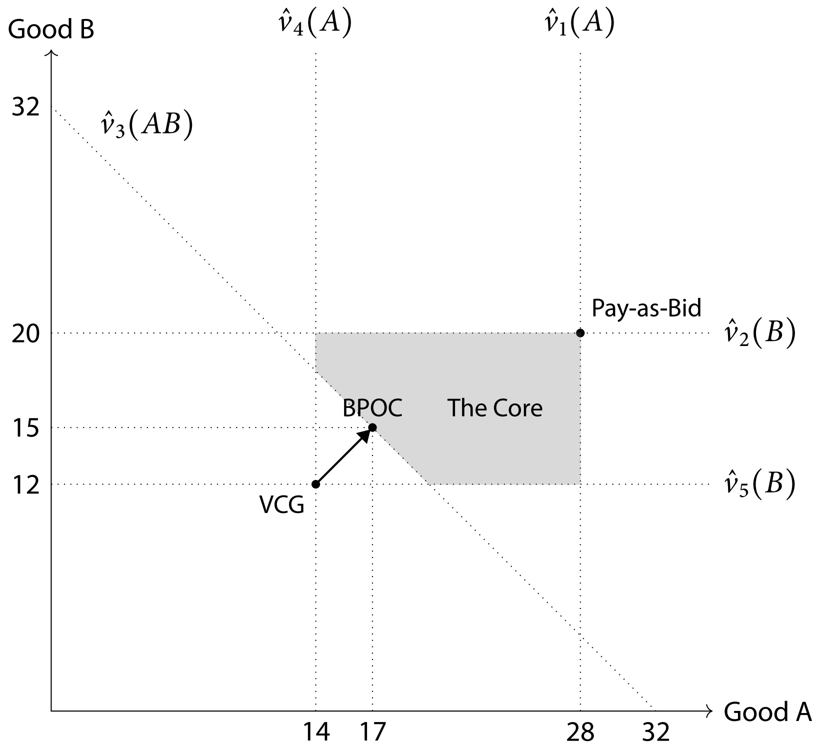


Figure 6.1: Core pricing example (based on Day and Cramton (2012))

Such a corrected payment vector is also referred to as bidder-Pareto-optimal (BPO) core payments. In figure 6.1, the point with the minimum distance from p^{VCG} (also referred to as VCG-nearest or equitable bidder-Pareto-optimal (EBPO) core payments), i.e., $(17, 15)$, is chosen and substitutes the initial VCG payments p^{VCG}.

The underlying approach that can guarantee EBPO core payments is a process presented by Day and Raghavan (2007), which is referred to as the core constraint generation (CCG) algorithm. The goal of CCG is to determine EBPO core payments as an alternative to VCG payments using a two-stage process. For that purpose, CCG takes an iteratively generated payment vector p^{τ} and thereby first determines by using a modified WDP whether there exists an alternative auction outcome o' which is weakly preferred over the current outcome o by some bidder and generates strictly more revenue for the seller. If such an alternative outcome exists, then based on the corresponding blocking coalition $\mathcal{C}_{o'}$ to which such a bidder belongs, a constraint resulting from the violating payment vector p^{τ}, is used to determine EBPO core payments relative to all coalitions found though iteration τ as a second step. More formally, the most violated core constraint, i.e., blocking coalition, if any, is found by extending the

WDP CAP using the following mixed integer problem (MIP) formulation.

The objective of SEP$^\tau$ is to maximize the social welfare over all bidders, where all winning bidders are discounted by their opportunity cost from the original allocation. Here, $\hat{v}_i^*(S_i)$ denotes the winning bid of bidder i within the set of winners $\mathcal{W}$ with awarded bundle S_i resulting from CAP. Assuming payment p_i^τ for bundle S_i in CAP, to be willing to win bundle S_i' in coalition $\mathcal{C}$, a coalitional contribution of $q_i(S_i', p_i^\tau) = \hat{v}_i^*(S_i') - \hat{v}_i^*(S_i) + p_i^\tau$ of bidder i is required. That is, the opportunity cost for the currently winning coalition, $\sum_{i \in \mathcal{W}}(\hat{v}_i^*(S_i) - p_i^\tau)$, have to be taken into account in SEP$^\tau$. More specifically, a bidder i would not voluntarily join a coalition where his surplus would be less than the opportunity cost.

$$z(p^\tau) = \max_{x,\zeta} \sum_{i \in \mathcal{I}} \sum_{S \subseteq \mathcal{G}} \hat{v}_i(S) x_i(S) - \sum_{i \in \mathcal{W}} (\hat{v}_i^*(S_i) - p_i^\tau) \zeta_i^\tau \tag{SEP$^\tau$}$$

$$\text{s. t.} \sum_{S \supseteq \{g\}} \sum_{i \in \mathcal{I}} x_i(S) \leq 1 \qquad \forall g \in \mathcal{G} \tag{6.26a}$$

$$\sum_{S \subseteq \mathcal{G}} x_i(S) \leq 1 \qquad \forall i \in \mathcal{I} \setminus \mathcal{W} \tag{6.26b}$$

$$\sum_{S \subseteq \mathcal{G}} x_i(S) \leq \zeta_i \qquad \forall i \in \mathcal{W} \tag{6.26c}$$

$$x_i(S) \in \{0,1\} \qquad \forall i \in \mathcal{I}, S \subseteq \mathcal{G} \tag{6.26d}$$

$$\zeta_i \in \{0,1\} \qquad \forall i \in \mathcal{I} \tag{6.26e}$$

A core constraint violation has been found if the sum of payment vector p^τ in the current iteration τ is less than the optimal solution $z(p^\tau)$ to SEP$^\tau$. Then, EBPO core payments, i.e., the minimum payments in the core which satisfy the core constraints found, are calculated as defined in $\omega^\tau(\epsilon)$. The objective of EBPO$^\tau$ is to determine minimum payments in the core subject to minimizing the maximum deviation from VCG payments, which is given by δ^τ.

$$\omega^{\tau}(\epsilon) = \min_{\delta} \sum_{i \in \mathcal{W}} p_i^{\text{CORE},\tau} + \epsilon \delta^{\tau} \tag{EBPO$^\tau$}$$

$$\text{s. t.} \sum_{i \in \mathcal{W} \setminus \mathcal{C}^{\tau'}} p_i^{\text{CORE},\tau} \geq z(p^{\tau'}) - \sum_{i \in \mathcal{W} \cap \mathcal{C}^{\tau'}} p_i^{\tau'} \qquad \forall \tau' \leq \tau \tag{CORE}$$

$$p_i^{\text{CORE},\tau} - \delta^{\tau} \leq p_i^{\text{VCG}} \qquad \forall i \in \mathcal{W} \tag{6.27a}$$

$$p_i^{\text{CORE},\tau} \leq \hat{v}_i^*(S_i) \qquad \forall i \in \mathcal{W} \tag{6.27b}$$

$$p_i^{\text{CORE},\tau} \geq p_i^{\text{VCG}} \qquad \forall i \in \mathcal{W} \tag{6.27c}$$

Here, $p_i^{\text{CORE},\tau}$ denotes the interim core payment vector in iteration τ. Core constraints resulting from SEP$^\tau$ extend the constraint space in CORE for each iteration $\tau' \leq \tau$. Deviations are kept sufficiently small by a small enough value of ϵ. The optimal solution of EBPO$^\tau$ yields updated payments $p_i^{\text{CORE},\tau}$ which are used in the next iteration. This iterative process is repeated until no further constraints can be found using SEP$^\tau$, i.e., while $z(p^{\tau}) > \omega^{\tau-1}(\epsilon)$ with the initial setting $\omega^0(\epsilon) = \sum_{i \in \mathcal{W}} p_i^{\text{VCG}}$.

In summary, the entire core constraint generation process is described in algorithm 6.1.

Algorithm 6.1: Core Constraint Generation (CCG) (Day and Raghavan (2007))

$\mathcal{W}, \hat{v}^*(S) \leftarrow$ solve the winner determination problem CAP to find winners $\mathcal{W}$ and winning bids $\hat{v}^*(S)$;
foreach $i \in \mathcal{W}$ **do**
  $p_i^{\text{VCG}} \leftarrow$ compute VCG price $\hat{v}_i^*(S_i) - (\text{CAP}(\mathcal{I}) - \text{CAP}(\mathcal{I}_{-i}))$;
$p^1 \leftarrow p^{\text{VCG}}$;
$\omega^0(\epsilon) \leftarrow \sum_{i \in \mathcal{W}} p_i^{\text{VCG}}$;
$\tau \leftarrow 1$;
while *true* **do**
  $\mathcal{C}^\tau \leftarrow$ solve the core constraint separation problem SEP^τ;
  if $z(p^\tau) > \omega^{\tau-1}(\epsilon)$ **then**
    add constraint $\sum_{i \in \mathcal{W} \setminus \mathcal{C}^\tau} p_i^{\text{CORE},\tau} \geq z(p^\tau) - \sum_{i \in \mathcal{W} \cap \mathcal{C}^\tau} p_i^\tau$ to EBPO^τ and solve EBPO^τ;
    $p^{\tau+1} \leftarrow p^{\text{CORE},\tau}$ from EBPO^τ;
  else
    $p \leftarrow p^\tau$;
    break;
  $\tau \leftarrow \tau + 1$;

6.4.3 Application to the Load Flexibility Auction

As the load flexibility auction constitutes a reverse auction, the principle of core pricing is in the following firstly illustrated for an exemplary reverse setting. The subsequent example constitutes a novel use case and should provide a clear understanding of the differences between (forward) core pricing and the reverse case.

Example 6.5 (Reverse core pricing). Consider a reverse auction where a single buyer wants to procure two goods and five bidders report their valuations in bids, i.e., the minimum price requested, as shown in table 6.4. In the given scenario, the goal of the auction is to minimize cost for the buyer. Therefore, the outcome of the auction determines bidders 1 and 2 as winners with VCG payments

$$p_i^{\text{VCG}} = \hat{v}_i - (\text{RCAP}(\mathcal{I}) - \text{RCAP}(\mathcal{I}_{-i})) \Leftrightarrow \tag{6.28}$$

$$p_1^{\text{VCG}} = p_2^{\text{VCG}} = 10 - (20 - 30) = 20. \tag{6.29}$$

Table 6.4: Bidder valuations for reverse core pricing

	Bundle		
Bidder	A	B	AB
1	10	0	0
2	0	10	0
3	0	0	32
4	20	0	0
5	0	20	0

While PAB prices are clearly the prices that result in the least cost for the buyer ($\sum_{i\in\{1,2\}} p_i = 20$), they do not ensure incentive compatibility (IC) and hence facilitate that sellers could misreport their true valuations in order to game the pricing mechanism. Such incentives do not exist with VCG mechanisms. With VCG, the buyer has to pay $\sum_{i\in\{1,2\}} p_i^{\mathrm{VCG}} = 40$ in total. The following figure 6.2 shows the constraints defined by the bidders' reported valuations $\hat{v}(\cdot)$ which in turn define the core. Notice that in particular the upper bounds of the constraints are given considering that bidder 4 would always object a payment to bidder 1 of more than 20 on good A, therefore $p_1 \leq 20$. At the same time, bidder 5 would block if the payment to bidder 2 would be more than 20, hence $p_2 \leq 20$. Similarly, bidder 3 needs the payments to bidders 1 and 2 to be less than his bid in order not to block, therefore $p_1 + p_2 \leq 32$. The lower bounds of the constraints are identical to the bids. Recall that $p^{\mathrm{VCG}} = (20, 20)$ and note that this vector is not in the core as bidder 3 would request less for both goods, i.e., $\sum_{i\in\{1,2\}} p^{\mathrm{VCG}} = 40 \geq 32 = \hat{v}_3(AB)$. Therefore, to unblock bidder 3 and therefore ensure that the payments are in the core, the auctioneer determines a corrected payment vector which would be located at any point on line segment from $(12, 20)$ to $(20, 12)$. Such a corrected payment vector for the buyer is also referred to as BPO core payments. In figure 6.2, the point with the minimum distance from p^{VCG} (also referred to as EBPO core payments), i.e., $(16, 16)$, is chosen and substitutes the initial VCG payments p^{VCG} of the buyer to the bidders (sellers).

In the following, the concepts of core pricing are applied to the load flexibility allocation problem introduced in chapter 5. Furthermore, the core pricing mechanism, i.e., CCG with the core constraint separation problem (SEP) and the problem of determining EBPO core prices, is extended in order to support the specified requirements of the load flexibility auction. In particular, the contributions in this section encompass

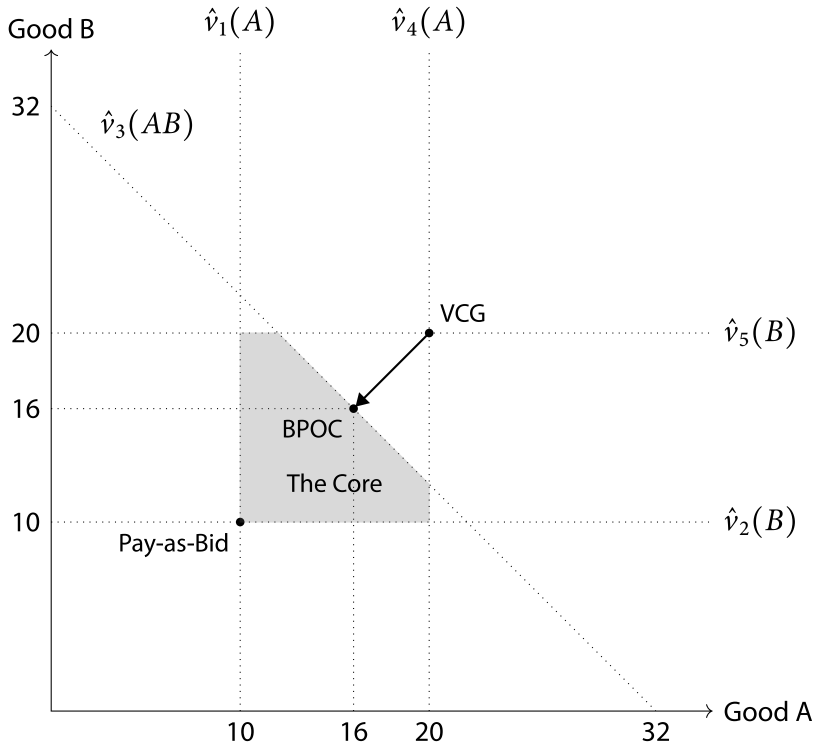


Figure 6.2: Reverse core pricing example

- the extension of SEP$^\tau$ to support the reverse auction format of the load flexibility auction as well as to support an outside option and unit prices,
- the extension of EBPO$^\tau$ to allow unit prices as well as support the reverse auction format,
- the extension of the core constraint generation algorithm to support unit prices in the reverse auction format.

Recall from definition 5.1 that the load flexibility auction constitutes a reverse auction. Additionally, as described in section 6.4 and as shown in example 6.2, VCG mechanisms can result in unacceptably high buyer payments in reverse auctions. Hence, in accordance with requirement 8, this section proposes the novel application of core pricing to a specific reverse auction format, which constitutes the load flexibility auction in this work.

Based on the previous definition of reverse core pricing, the core constraint separation problem which yields the most violated core constraint, if any, is defined as follows: In accordance with definition 5.26, let b_i^* and a_i^* denote the winning bid and amount of winning bidder i from the set of winners $\mathcal{W} \in \mathcal{I}$. In addition, let $\mathrm{WD}^*(\theta)$ denote the optimal solution to WD and $\mathrm{WD}^*(\theta_{-i})$ the optimal solution to WD without bidder i. From definition 6.3, p_i^τ denotes the payment vector of bidder i at iteration τ.

The formulation of $\mathrm{SEP}_{\mathrm{SG}}^\tau$ builds upon WD, and thus also has the objective to minimize the cost of accepted bids and the cost of the outside option. Assuming payment p_j^τ for bid e_j in WD, to be willing to win bid $e_{j'}$ in coalition $\mathcal{C}$, a coalitional contribution of

$$q_i(e_{j'}, p_j^\tau) = \sum_{t \in \mathcal{T}} (b_{j'}^t a_{j'}^t - b_j^t a_j^t) + p_j^\tau \tag{6.30}$$

is required for bidder $i : j, j' \in \mathcal{J}_i$. That is, the opportunity cost for the currently winning coalition,

$$-\sum_{i \in \mathcal{W}} \left(\sum_{t \in \mathcal{T}} b_i^{t*} a_i^{t*} - p_i^\tau\right) = \sum_{i \in \mathcal{W}} \left(p_i^\tau - \sum_{t \in \mathcal{T}} b_i^{t*} a_i^{t*}\right) \tag{6.31}$$

have to be taken into account in $\mathrm{SEP}_{\mathrm{SG}}^\tau$ for each bidder which is selected as part of a blocking coalition resulting from $\mathrm{SEP}_{\mathrm{SG}}^\tau$. More specifically, a bidder i would not voluntarily join a coalition where his surplus would be less than the opportunity cost. Therefore, each bid from a winning bidder is corrected by his opportunity cost in case the winning bidder is part of a blocking coalition.

$$
\begin{aligned}
z(p^\tau) = \min_{x,\zeta,a_+,a_-,\psi_+,\psi_-} & \sum_{t\in\mathcal{T}}\sum_{j\in\mathcal{J}}(b_j^t a_{j+}^t + b_j^t a_{j-}^t) + \gamma_+^t\psi_+^t + \gamma_-^t\psi_-^t && && (\mathrm{SEP}^\tau_{\mathrm{SG}})\\
& + \sum_{i\in\mathcal{W}}(p_i^\tau - \sum_{t\in\mathcal{T}} b_i^{t*}a_i^{t*})\zeta_i^\tau \\
\text{s. t.} & \sum_{j\in\mathcal{J}}(a_{j+}^t - a_{j-}^t) + \psi_+^t - \psi_-^t = \phi_0^t a_0^t && \forall t\in\mathcal{T} && (6.32a)\\
& \sum_{j\in\mathcal{J}} a_{j+}^t \geq \sum_{j\in\mathcal{J}} \underline{a}_j^t x_j^\tau \phi_j^t && \forall t\in\mathcal{T} && (6.32b)\\
& \sum_{j\in\mathcal{J}} a_{j-}^t \geq -\sum_{j\in\mathcal{J}} \underline{a}_j^t x_j^\tau \phi_j^t && \forall t\in\mathcal{T} && (6.32c)\\
& \sum_{j\in\mathcal{J}} a_{j+}^t \phi_j^t \leq \sum_{j\in\mathcal{J}} \overline{a}_j^t x_j^\tau && \forall t\in\mathcal{T} && (6.32d)\\
& -\sum_{j\in\mathcal{J}} a_{j-}^t \phi_j^t \leq \sum_{j\in\mathcal{J}} \overline{a}_j^t x_j^\tau && \forall t\in\mathcal{T} && (6.32e)\\
& \sum_{j\in\mathcal{J}} a_{j+}^t \phi_j^t \geq 0 && \forall t\in\mathcal{T} && (6.32f)\\
& -\sum_{j\in\mathcal{J}} a_{j-}^t \phi_j^t \geq 0 && \forall t\in\mathcal{T} && (6.32g)\\
& \psi_+^t, \psi_-^t \geq 0 && \forall t\in\mathcal{T} && (6.32h)\\
& \sum_{j\in\mathcal{J}_i} x_j^\tau \leq 1 && \forall i\in\mathcal{I}\setminus\mathcal{W} && (6.32i)\\
& \sum_{j\in\mathcal{J}_i} x_j^\tau \leq \zeta_i^\tau && \forall i\in\mathcal{W} && (6.32j)\\
& x_j^\tau \in \{0,1\} && \forall j\in\mathcal{J} && (6.32k)\\
& \zeta_i \in \{0,1\} && \forall i\in\mathcal{I} && (6.32l)
\end{aligned}
$$

Constraint (6.32a) ensures that the requested balancing amount a_0^t is fulfilled in every time slot $t \in \mathcal{T}$. In addition, constraints (6.32b) to (6.32e) limit the accepted balancing power amounts to the minimum and maximum bid amounts, $\underline{a}_j^t$ and $\overline{a}_j^t$, in the bids $j \in \mathcal{J}$ for all $t \in \mathcal{T}$, in accordance with the offered delivery direction ϕ_j^t. Moreover, constraints (6.32f) and (6.32g) restrict the purchases of the buyer, i.e., the DSO, to the offered direction ϕ_j of bids from aggregators. Furthermore, constraint (6.32h) ensures that the accepted outside option amounts ψ_+^t, ψ_-^t are non-negative. Constraint (6.32i) models the XOR relation of the single bids and ensures that at most one bid can be accepted per bidder. Notice that this constraint is limited to all bidders except for the winning bidders. For the winning bidders, a new constraint (6.32j) is introduced which ensures that in case a winning bidder is selected to be part of a coalition resulting from $\mathrm{SEP}^{\tau}_{\mathrm{SG}}$, he will be compensated his opportunity cost accordingly. Constraints (6.32k) and (6.32l) represent the binary variables which capture whether bid j is allocated or not and whether or not to consider the opportunity cost in ($\mathrm{SEP}^{\tau}_{\mathrm{SG}}$), respectively.

A core constraint violation has been found if the sum of payment vector p^{τ} and the outside option in the current iteration τ is less than the optimal solution $z(p^{\tau})$ in $\mathrm{SEP}^{\tau}_{\mathrm{SG}}$, i.e., $z(p^{\tau}) < \sum_{i \in \mathcal{W}} p^{\tau}_i + (\sum_{t \in \mathcal{T}} \gamma^{t*}_+ \psi^{t*}_+ + \gamma^{t*}_- \psi^{t*}_-)$. The blocking coalition $\mathcal{C}_{o'}$ is given by all bidders $i \in \mathcal{I}$ where $\exists j \in \mathcal{J}_i : x^{\tau}_j = 1$.

Then, EBPO core payments, i.e., the minimum payments in the core which satisfy the core constraints found, are calculated as defined in $\omega^{\tau}(\epsilon)$. In contrast to EBPO^{τ}, the objective of $\mathrm{EBPO}^{\tau}_{\mathrm{SG}}$ is to determine maximum payments in the core with the secondary objective to minimize the maximum deviation from VCG payments, which is given by δ^{τ}.

$$
\begin{aligned}
\omega^{\tau}(\epsilon) = \max_{\delta} & \sum_{i \in \mathcal{W}} p^{\mathrm{CORE},\tau}_i - \epsilon \delta^{\tau} && && (\mathrm{EBPO}^{\tau}_{\mathrm{SG}}) \\
\text{s. t.} & \sum_{i \in \mathcal{W} \setminus \mathcal{C}^{\tau'}} p^{\mathrm{CORE},\tau}_i \leq z(p^{\tau'}) && && (\mathrm{CORE}_{\mathrm{SG}}) \\
& - \Big(\sum_{i \in \mathcal{W} \cap \mathcal{C}^{\tau'}} p^{\tau'}_i + \sum_{t \in \mathcal{T}} \gamma^{t*}_+ \psi^{t*}_+ + \gamma^{t*}_- \psi^{t*}_- \Big) && \forall \tau' \leq \tau && \\
& p^{\mathrm{CORE},\tau}_i + \delta^{\tau} \geq p^{\mathrm{VCG}}_i && \forall i \in \mathcal{W} && (6.33a) \\
& p^{\mathrm{CORE},\tau}_i \geq \sum_{t \in \mathcal{T}} b^{t*}_i a^{t*}_i && \forall i \in \mathcal{W} && (6.33b) \\
& p^{\mathrm{CORE},\tau}_i \leq p^{\mathrm{VCG}}_i && \forall i \in \mathcal{W} && (6.33c)
\end{aligned}
$$

Here, $p^{\mathrm{CORE},\tau}_i$ denotes the interim core payment vector in iteration τ. Core constraints resulting from $\mathrm{SEP}^{\tau}_{\mathrm{SG}}$ extend the constraint space in $\mathrm{CORE}_{\mathrm{SG}}$ for each iteration $\tau' \leq \tau$. Constraint (6.33a) ensures that deviations are kept sufficiently small by a small enough value of ϵ. Moreover, constraint (6.33b) ensures a winning bidder's payment is at least as large as under a PAB pricing rule, which selects the minimum requested price for a given allocation. Therefore the lower bound of the core prices is set to the value of its winning bid, $\sum_{t \in \mathcal{T}} b^{t*}_i a^{t*}_i$. Similarly, constraint (6.33c) ensures that the payment is at most as high as the VCG payments. The optimal solution of EBPO^{τ} yields updated payments $p^{\mathrm{CORE},\tau}_i$ which are used in the next iteration. This iterative process is repeated until no further constraints can be found using $\mathrm{SEP}_{\mathrm{SG}}^{\tau}$, i.e., while $z(p^{\tau}) < \omega^{\tau-1}(\epsilon) + \left(\sum_{t\in\mathcal{T}} \gamma_{+}^{t*}\psi_{+}^{t*} + \gamma_{-}^{t*}\psi_{-}^{t*}\right)$ with the initial setting $\omega^{0}(\epsilon) = \sum_{i\in\mathcal{W}} p_i^{\mathrm{VCG}}$.

In summary, the entire core constraint generation process for a reverse auction is described in algorithm 6.2.

Algorithm 6.2: Core Constraint Generation (CCG) (based on Day and Raghavan (2007))

$\mathcal{W}, b_i^* \leftarrow$ solve the winner determination problem $\mathrm{WD}(\theta)$ to find winners $\mathcal{W}$ and winning bids b_i^*;
foreach $i \in \mathcal{W}$ **do**
  $p_i^{\mathrm{VCG}} \leftarrow$ compute VCG price $b_i^* - (\mathrm{WD}^*(\theta) - \mathrm{WD}^*(\theta_{-i}))$;
$p^1 \leftarrow p^{\mathrm{VCG}}$;
$\omega^0(\epsilon) \leftarrow \sum_{i\in\mathcal{W}} p_i^{\mathrm{VCG}}$;
$\tau \leftarrow 1$;
while *true* **do**
  $\mathcal{C}^{\tau} \leftarrow$ solve the core constraint separation problem $\mathrm{SEP}_{\mathrm{SG}}^{\tau}$;
  if $z(p^{\tau}) < \omega^{\tau-1}(\epsilon) + \left(\sum_{t\in\mathcal{T}} \gamma_{+}^{t*}\psi_{+}^{t*} + \gamma_{-}^{t*}\psi_{-}^{t*}\right)$ **then**
    add constraint $\sum_{i\in\mathcal{W}\setminus\mathcal{C}^{\tau}} p_i^{\mathrm{CORE},\tau} \leq z(p^{\tau}) - \left(\sum_{i\in\mathcal{W}\cap\mathcal{C}^{\tau}} p_i^{\tau} + \sum_{t\in\mathcal{T}} \gamma_{+}^{t*}\psi_{+}^{t*} + \gamma_{-}^{t*}\psi_{-}^{t*}\right)$ to $\mathrm{EBPO}_{\mathrm{SG}}^{\tau}$ and solve $\mathrm{EBPO}_{\mathrm{SG}}^{\tau}$;
    $p^{\tau+1} \leftarrow p^{\mathrm{CORE},\tau}$ from $\mathrm{EBPO}_{\mathrm{SG}}^{\tau}$;
  else
    $p \leftarrow p^{\tau}$;
    break;
  $\tau \leftarrow \tau + 1$;

Part III

Implementation and Evaluation

7

Simulation Design

This chapter empirically analyzes properties of the flexibility auction by means of a simulation-based evaluation following the definition of the auction and pricing mechanisms in chapters 5 and 6. Given the underlying complexity of electricity and power markets, large test-bed scenarios or analytical methods as proposed by the market engineering (ME) approach constitute problematic or even impossible evaluation methods given complex physical requirements of building real-world electricity grids. However, alternative evaluation methods such as simulation-based analysis exist, which allow to abstract from and model complex real-world systems and gain insight into such systems. Hence, simulation serves as an appropriate method to evaluate the proposed flexibility auction.

In the following, this chapter first elaborates on the methodology and concept of simulation in section 7.1. Section 7.2 defines the metrics which are used to analyze the simulation results. Subsequently, section 7.3 describes the simulation model for the flexibility auction. Based on the simulation model, the relevant settings consisting of input data and parametrization are defined in section 7.4. Finally, section 7.5 describes the technical implementation of the simulation.

7.1 Preliminaries

Simulations allow to model real-world or other systems using information technology (IT) and in turn to study characteristics and parameters of the model in a less complex and less detailed fashion. Moreover, simulations enable to evaluate these models numerically and over time (Banks 1998; Kelton and Law 2000). In the work at hand, the system of the flexibility auction is comprised of the economic environment, agents, and the actual market mechanism. More specifically, the economic environment can be seen as a local part of the the power system, or smart grid. The agents in the work at hand are the distribution system operator (DSO) as well as aggregators. The flexibility auction constitutes the market mechanism.

One of the main advantages of simulation is the possibility to control and adapt any parameter and input variable specific to the problem. This not only allows the comparison of different simulation settings but also to investigate the effects of changing a specific parameter on the system (Banks 1998). Moreover, simulations are less expensive compared to field experiments as no real payments to participants are required (Kelton and Law 2000). The ability to model heterogeneity is an additional benefit of simulation studies. Instead of being restricted to real-world constraints such as firm sizes, such constraints can be chosen in an arbitrary fashion (Axtell 2000). In scope of smart grids, heterogeneity plays an important role. On the local level, solar generation capacities can vary from rooftop to rooftop. Similarly, battery storage or electric vehicle (EV) capacities and cost are heterogeneous given the wide consumer model choice. In addition, consumer behavior and rationality cannot be assumed to be identical. Hence, the frequency a consumer can offer its potential flexibility to an aggregator, which in turn can market this flexibility to the proposed auction in the work at hand, needs to reflect such heterogeneity.

In contrast, simulations face some limitations. Firstly, simulations are less detailed and less complex, therefore do not identically represent real-world systems. In addition, simulation results need to be interpreted carefully (Banks 1998). Furthermore, the outcome of a simulation depends on the chosen set of input parameters and defined assumptions. Therefore, a sensitivity analysis can help to ensure the robustness of a simulation (Kelton and Law 2000).

In summary, simulations represent a helpful tool for market-based problems. While they are not completely applicable to all problems, they often represent an efficient way to evaluate systems or market designs. In the following, different simulation models are characterized and general simulation steps are outlined.

7.1.1 Simulation Characteristics

Simulation models can be characterized along three dimensions (Kelton and Law 2000). Firstly, a simulation can be either *discrete or continuous*, i.e., the state variable which contains information about the system's environment or outcome changes with respect to time. Secondly, a simulation can be either *static or dynamic*, i.e., represent a specific point in time or model systems where time plays no role, or evolve over time. Lastly, a simulation can be either *stochastic or deterministic*. This means that the simulation does or does not include probabilistic components.

In context of market-based settings, simulations are, among others, often characterized as discrete and stochastic in nature. For example, agent-based simulations constitute dynamic and stochastic simulations, whereas Monte Carlo (MC) simulations represent simulation models of static and stochastic nature. More specifically, the static and stochastic nature of MC simulations allows the empirical evaluation of computationally hard problems (Kelton and Law 2000). MC simulations in market-based settings, also in the domain of electricity markets, are widely used, e.g., by Gode and Sunder (1993), Wen and David (2001), Cai and Wurman (2005), and El-Khattam, Hegazy, and Salama (2006).

7.1.2 Simulation Steps

A simulation study generally follows a structure process consisting of the following steps (Banks 1998; Kelton and Law 2000). Firstly, in the *problem definition*, a clear understanding of the problem at hand as well an appropriate and clear formulation are established. Additionally, assumptions are formulated and evaluation metrics are defined. Secondly, the *model conceptualization* step defines the simulation model in an abstract or mathematical fashion. This step includes to define the environment, the agents and their behavior as well as their interactions with each other and/or the environment. Thirdly, the *model implementation* requires the (i) implementation, (ii) verification, and (iii) validation of the conceptual model. That is, the model is translated into a software artifact either using common frameworks or built as an individually customized software artifact. Afterwards, the artifact is verified, e.g., by means of unit testing, and validated, e.g, by using existing theories of expected outcomes. Fourthly, the *execution and evaluation* step requires to define and describe simulation settings, i.e., the simulation parametrization and relevant input data. Within this step, multiple simulation runs are performed in order to account for the stochastic nature of a simulation. Finally, the output data of the simulation is analyzed using statistical methods, e.g., by computing descriptives such as means or variances.

7.2 Problem Definition

As noted in section 7.1.2, the first step when using simulation as an evaluation method is to formulate the problem definition and evaluation metrics for the system at hand. Here, the system of the flexibility auction consists of of the economic environment, agents, and the actual market mechanism with different pricing rules.

7.2.1 Cost and Pricing Rules

The application of different pricing rules directly impacts DSO payments to winning aggregators whereas the contracted outside option price remains constant for each pricing rule. Following research question 5 and definitions 5.9, 5.10, 5.19 and 5.29, the primary metric c^λ is therefore given by the payments to winning bidders and the cost for the contracted outside option, formally as follows:

$$c^\lambda = \rho_0^\lambda(\theta). \tag{7.1}$$

The metric depends on the pricing function $\lambda \in \{\text{PAB}, \text{KP}, \text{VCG}, \text{CORE}\}$ as defined by the pricing rules in chapter 6.

The benchmark for measuring the DSO's savings is given by the outside option for the full flexibility demand. Following definitions 5.9, 5.10 and 5.28, the benchmark metric is therefore given by

$$\Upsilon = \sum_{t \in \mathcal{T}} (f(\gamma_+^t, \gamma_-^t, \phi_0^t) a_0^t) \tag{7.2}$$

with

$$f(\gamma_+^t, \gamma_-^t, \phi_0^t) = \begin{cases} \gamma_+^t & \phi_0^t > 0 \\ \gamma_-^t & \phi_0^t < 0 \\ 0 & \text{otherwise.} \end{cases} \tag{7.3}$$

The determined prices for the different pricing rules are compared to investigate possible differences among the applied pricing rules. Therefore, different ratios are compared. In detail,

1. the ratio of the core payments p_i^{CORE} to the monetary bid values $\sum_{t\in\mathcal{T}} b_i^{t*} a_i^{t*}$ (Core/Bid),
2. the ratio of the Vickrey-Clarke-Groves (VCG) payments p_i^{VCG} to the monetary bid values $\sum_{t\in\mathcal{T}} b_i^{t*} a_i^{t*}$ (VCG/Bid),
3. the ratio of the k-pricing payments p_i^{KP} to the monetary bid values $\sum_{t\in\mathcal{T}} b_i^{t*} a_i^{t*}$ (K/Bid),
4. the ratio of the k-pricing payments p_i^{KP} to the VCG payments p_i^{VCG} (K/VCG),
5. the ratio of the k-pricing payments p_i^{KP} to the core payments p_i^{CORE} (K/Core),
6. the ratio of the VCG payments p_i^{VCG} to the core payments p_i^{CORE} (VCG/Core).

7.2.2 Computational Tractability

The winner determination problem (WDP) of the flexibility auction represents an instance of the set-packing problem and is therefore NP-hard (cp. section 5.1.1.4). As VCG and the core constraint separation problem (SEP) solve a modified WDP, these pricing rules are likewise NP-hard. Hence, it is crucial to investigate the empirical computational hardness as proposed in research question 6. More specifically, the duration ξ for computing the winners of the action as well as payments under different pricing rules is measured.

7.3 Simulation Model

The simulation constitutes a Monte Carlo simulation. That is, a simulation with the same parameter configuration is repeated a predefined number of times with different random seeds. This technique is common in simulation to obtain robust results (Kelton and Law 2000).

The simulation model is composed of an environment with a predefined number of aggregators and one DSO, which initiates the flexibility auction. Simulation input data is partly based on real-world data. The flexibility demand describes the products of the flexibility auction. Once the auction is announced, aggregators submit their flexibility to the DSO, which constitutes the auctioneer. Subsequently, the winner determination problem is solved optimally and pricing rules determine payments from the DSO to aggregators.

The flowchart of the simulation is illustrated in figure 7.1. The complete simulation starts by configuring what and where to log the simulation output to. Afterwards, the simulation control draws the main simulation seed as well as a random seed for each set of parameters according to the specified number of runs. The set of parameter configurations is built in the subsequent step. Moreover, the simulation loads input data from a local database. Having finished all preparations, the simulation control begins starting individual simulation runs consecutively. Within a run, the DSO, or auctioneer, uses the previously loaded input data to randomly draw its demand for flexibility. This demand is immediately known to all aggregators. Aggregators randomly determine their flexibility, which is based on an exemplary minimum runtime constraint to indicate an aggregated (non-)availability of a portfolio. Having collected all bids, the DSO proceeds to solve the auction's WDP and to determine prices according to a number of pricing rules. All information is subsequently logged for evaluation purposes. Finally, the simulation run is repeated for each remaining parameter configuration.

Following section 5.2.2, the simulation considers a time horizon T with discrete time slots $t \in \mathcal{T} = \{1, 2, \dots, T\}$ of equal length. The set of all participating agents is given by $i \in \mathcal{I}$ where $i \in \{0\}$ is the buyer, i.e., DSO, and all other agents represent sellers. Specifically, bidders, i.e., aggregators, are given by $i \in \mathcal{I} \setminus (\{0\} \cup \mathcal{R})$. The DSO announces its demand $a_0 = (a_0^1, \dots, a_0^t, \dots, a_0^T)$ and aggregators $i \in \mathcal{I} \setminus (\{0\} \cup \mathcal{R})$ can submit bids $e_j \; \forall j \in \mathcal{J}_i$ for their pooled flexibility. Given the bids, the DSO solves WD to determine the winners of the auction and subsequently determines prices given different pricing rules.

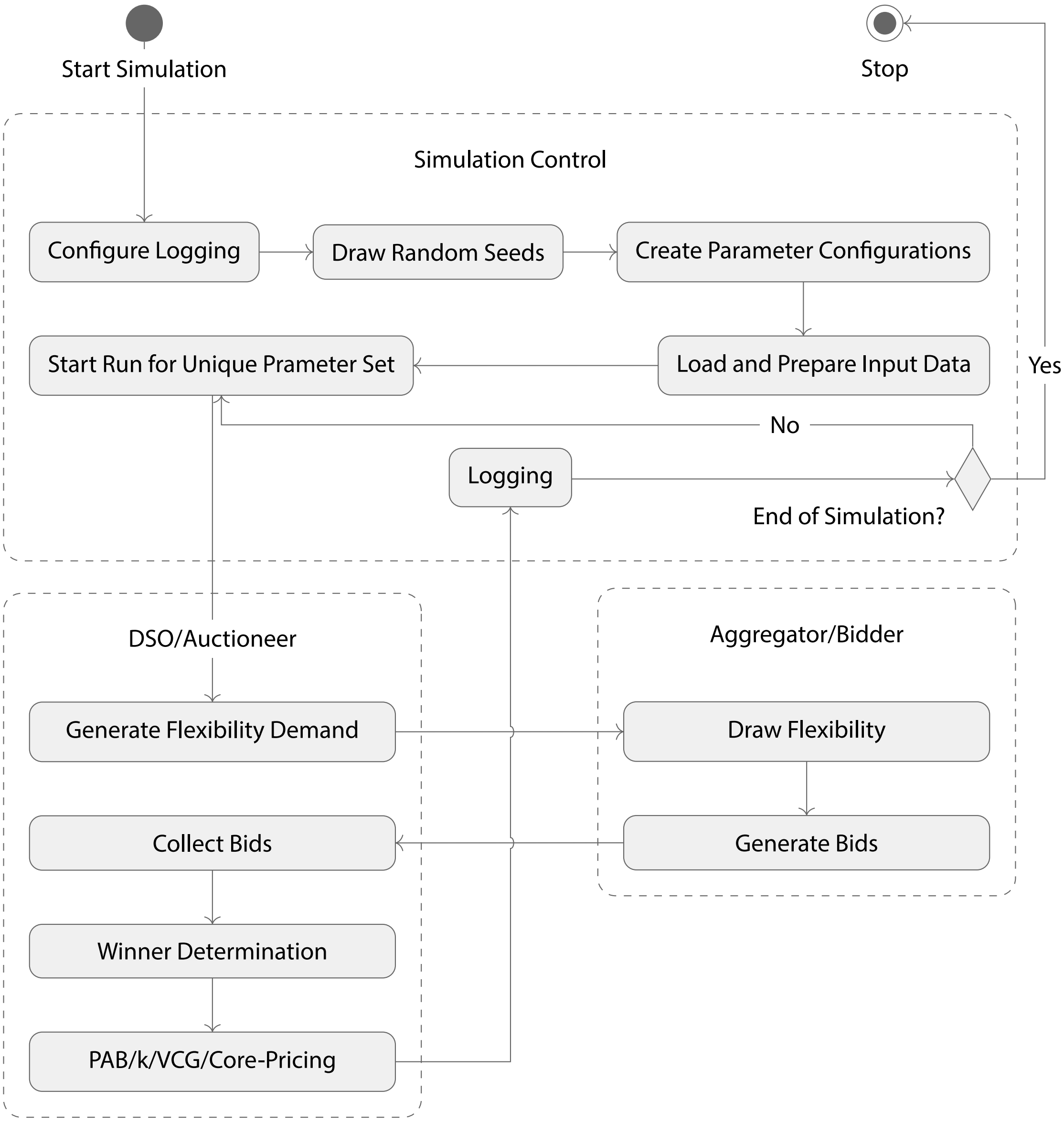


Figure 7.1: Activity diagram of the simulation flow

7.3.1 Market Mechanism

The flexibility auction constitutes the market mechanism. The flexibility auction is a reverse combinatorial multi-unit auction with an outside option. In detail, the DSO as the auctioneer $i = 0$ announces the products a_0 that describe the required flexibility demand and collects voluntary bids from aggregators as bidders. The auction is announced as necessary given the yellow traffic light concept (TLC) state, i.e., does not constitute a multi-round auction. More specifically, strategic implications of multi-round auctions are not in the scope of this work.

Following chapter 6, four distinct pricing rules are evaluated with the market mechanism. While pay-as-bid (PAB) pricing and k-pricing constitute polynomial pricing rules, i.e, are computationally tractable, VCG and core pricing are NP-hard. Therefore, the pricing rules for VCG pricing and core pricing as well as the WDP are solved optimally using the a commercial mathematical programming solver Gurobi 6 (Gurobi Optimization 2015).

7.3.2 Bidder Structure

The bidder structure can be characterized by the dimensions (i) number of bidders, (ii) bidder flexibility, and (iii) bidder heterogeneity as follows.

7.3.2.1 Number of Bidders

The number of bidders determines the size of the market. Within a local setting and given that aggregators represent a currently emerging entity in smart grids, the number of bidders is kept deliberately small to model realistic conditions. That is, groups consisting of 5 to 30 aggregators are evaluated.

7.3.2.2 Bidder Flexibility

While each individual contracted consumer or prosumer of an aggregator possesses an individual flexibility, for the purpose of this simulation, the combined flexibility is subject to certain assumptions for reasons of simplicity.

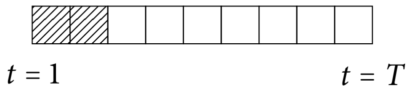


Figure 7.2: Bidder flexibility for $l = 2$ from example 7.1. Marked time slots reflect active time slots.

Firstly, the flexibility *in time* of an aggregator is given by a minimum runtime constraint. Specifically, the less constrained an aggregator, the more flexible it is, as it can provide a greater amount of bids to the DSO which in turn impacts possible allocations. In contrast, the larger the runtime constraint, a lower number of bids can be determined.

Definition 7.1 (Bidder flexibility). *Let $l_i \leq T, l_i \in \mathbb{N}$ denote agent i's flexibility.*

The minimum runtime constitutes the flexibility of an aggregator. Given a time horizon T, an aggregator has

$$T - l_i + 1 \tag{7.4}$$

possible start times for bids. Note that the number of possible placements is applied to a single bid and that an aggregator can submit an arbitrary number of bids with different flexibility placements. The following example illustrates the process of the minimum runtime constraint. For this purpose, consider a time horizon of 45 minutes and a granular time slot length of 5 minutes. Then, a DSO can announce the flexibility auction with $T = \frac{45}{5} = 9$ time slots, i.e., products.

Example 7.1 (Bidder flexibility for $l = 2$). Suppose the flexibility of an aggregator i, i.e., its minimum runtime, has been determined to be $l_i = 2$. Then, the bids of aggregator i require that at least l_i consecutive time slots are identical for the same bid amounts and monetary value. The number of possible flexibility placements is $9 - 2 + 1 = 8$. The beginning of the flexibility is determined endogenously and is from this point on forward assumed to start at $t = 1$ for reasons of simplicity. Figure 7.2 illustrates the flexibility of aggregator i with $l_i = 2$.

Example 7.2 (Bidder flexibility for $l = 7$). Suppose the flexibility of an aggregator i has been determined to be $l_i = 7$. Then, the bids of aggregator i require that at least l_i consecutive time slots are identical. The number of possible flexibility placements is $9 - 7 + 1 = 3$. Hence, aggregator i can submit only up to 3 bids assuming constant amounts. Figure 7.3 illustrates all possible flexibility placements of aggregator i with $l_i = 7$.

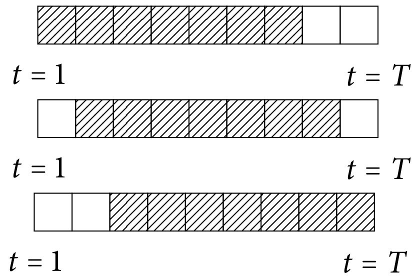


Figure 7.3: Bidder flexibility for $l = 7$ from example 7.2. Marked time slots reflect active time slots.

The flexibility *in volume* of an aggregator, i.e., the amount of consumption or production for a given time slot which can be provided, is influenced by the market share of an aggregator, which is given by a heterogeneity factor described in the following.

7.3.2.3 Bidder Heterogeneity

Recall that an aggregator portfolio can consist of a heterogeneous consumer or prosumer population. This in turn reflects on the ability of the aggregator to provide a certain amount of flexibility to the market. In order to capture this heterogeneity and provide a structure depending on the current electricity market structure with few large and many small utilities, aggregators are distinguished by their amount of balancing flexibility. To this end, Zipf's law (Axtell 2001) is leveraged. More specifically, Zipf's law allows to instantiate an empirically valid yet parsimonious model for modeling heterogeneity in (firm) size (Axtell 2001) and is defined as follows:

Definition 7.2 (Bidder heterogeneity). *Given heterogeneity level $d \in \mathbb{R}$ with $0 \leq d \leq 1$ and the total requested amount of flexibility from definition 5.28 a_0, the φ-th largest of n firms, i.e., aggregators, assumes maximum bid size $\overline{a}_j$ of*

$$a_0 \cdot \left(\frac{1}{\varphi^d} / \sum_{\eta=1}^{n} \frac{1}{\eta^d}\right) \tag{7.5}$$

Note that for $d = 0$, bid sizes are uniformly distributed, i.e., every aggregator provides the same amount of flexibility. Hence, bids can also be referred to as homogeneous. For $d \to \infty$, the largest bidder assumes the entire quantity. Figure 7.4 illustrates the distributions for a small and large number of aggregators.

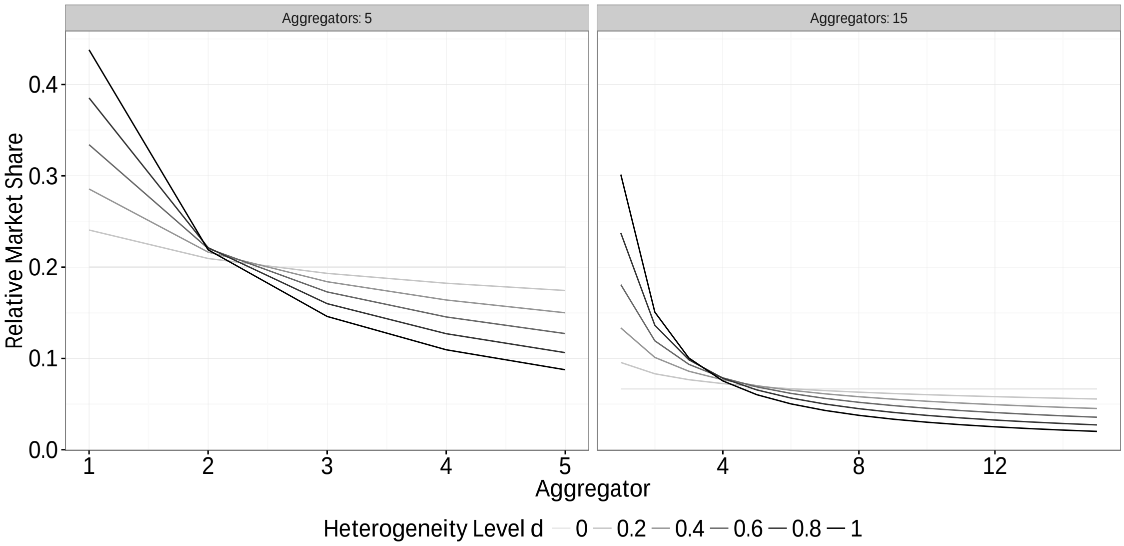


Figure 7.4: Exemplary distributions of bid sizes under Zipf's law for 5 and 15 aggregators

7.3.3 Bidding Process

An aggregator can submit up to $2^T - 1$ bids in theory. However, this upper boundary is limited by the aggregator's flexibility, which is given by a minimum runtime constraint as described before. Hence, depending on the flexibility, the amount of bids submitted by an aggregator can be substantially below the theoretical upper boundary. In context of the simulation in the work at hand, an aggregator is assumed to submit exactly

$$\left\lceil \frac{\mathcal{T}}{l_i} \right\rceil + 1 \tag{7.6}$$

bids. That is, a bid for every possible location in time is submitted. For example, following example 7.2, an aggregator i with a minimum runtime of $l_i = 7$ with a time horizon of $T = 9$, i.e., the products to bid on, submits $\lceil 9/7 \rceil + 1 = 3$ bids.

As defined by the bidding language in definition 5.25, the parameters start time, direction, minimum, and maximum delivery amount as well as a monetary value constitute a bid. The start time is given by the minimum runtime. The direction is chosen stochastically between generation and production. In order to determine the minimum and maximum bid amounts, the requested flexibility amount and bidder heterogeneity are considered. More specifically, the maximum amount is endogenously given by and scaled to the current flexibility demand and corrected by the aggregators market share, i.e., its heterogeneity as given by definition 7.2.

The minimum amount is set to exactly half of that amount. Moreover, the monetary value in terms of integer values is drawn randomly from a uniform distribution between $[1, \min \gamma^t]$ where γ^t denotes the minimal outside option price over all time slots. More technically, a single bid is generated and then split according to the minimum runtime constraint, which results in the number of bids as given by equation (7.6).

Recall from chapter 6 that PAB, k-pricing, and core pricing are not incentive compatible. Therefore, for the purpose of the simulation, it is further assumed that the submitted bids represent the truthfully reported monetary value of the bidders.

7.4 Simulation Settings

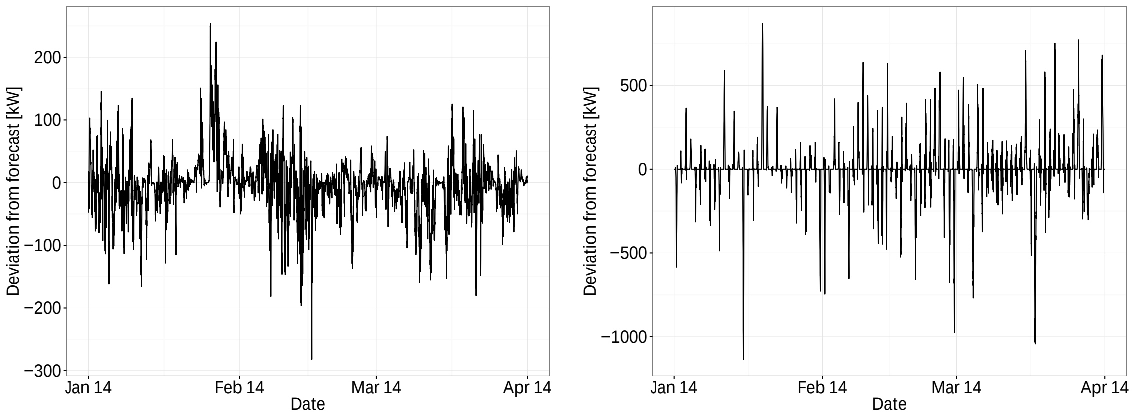
This section describes the exogenously specified simulation input data and parametrization. By using exogenous data and parameters, the simulation can be evaluated from many different perspectives which underlines and supports the validity and robustness of the model.

7.4.1 Input Data

Real-world data sets integrated in the simulation are (i) market data for solar and wind feed-in from the year 2014, (ii) data for balancing energy prices for 2014. These data sets are described in the following.

7.4.1.1 Wind and Solar Data

In order to generate the DSO's demand for flexibility, either wind or solar generation data from the European Energy Exchange (EEX) transparency market data repository for the year 2014 is used (EEX 2014). The data for both generation types has a similar structure. More specifically, the data for each generation type is available as ex-ante and ex-post time series data, which describe the expected and the actual metered power values, respectively. A data set contains information on the connecting area, which describes which grid operator area contains the generation unit. Moreover, information on the time of the data is provided. Depending on the ex-ante or ex-post nature of the data, either the expected or the actual wind or solar energy values are provided.



(a) Wind deviations **(b)** Solar deviations

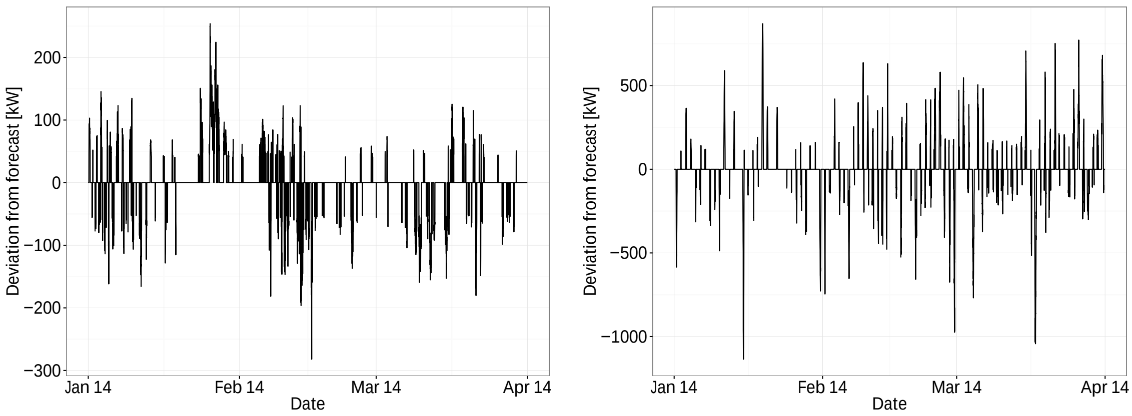
Figure 7.5: Deviations between ex-ante and ex-post wind and solar generation for the area of EnBW in Q1/2014 (*Source*: Data from EEX (2014))

In context of this simulation, deviations from the current generation schedule that result in demand for flexibility are modeled using the ex-ante and ex-post wind or solar generation data. Following Feuerriegel, Riedlinger, and Neumann (2014), the difference between ex-ante forecast and ex-post realized feed-in within the connecting area of EnBW in southern Germany constitute the basis for the demand for flexibility. That is, the difference between the ex-ante and ex-post wind or solar feed-in in time slot t is denoted as δ_t. Figure 7.5 illustrates the deviations between forecast and realized wind and solar generation for the connecting area of EnBW in Q1/2014.

Comparing both wind and solar feed-in, the deviations in solar feed-in reach a much larger extend in volume than in wind feed-in. In contrast, the frequency of deviations in wind feed-in is comparably larger than in solar feed-in. That is, for both feed-in types, weather characteristics can be observed. In the following, the auction is assumed to run for deviations exceeding a specific threshold only, as smaller discrepancies may be resolved in more cost-efficient manners by grid operators or are resolved independently due to stochastic consumer behavior. To this end, the deviations δ_t are filtered to determine the flexibility demand from definition 5.28 as follows:

$$a_0 = \delta_t \cdot \mathbb{1}_{(|\delta_t| \geq \underline{\delta})} \tag{7.7}$$

where $\underline{\delta}$ denotes the 10% quantile of the data. Figure 7.6 illustrates the filtered feed-in data which serves as the input for the simulation. More specifically, from the year 2014, a week is



(a) Wind deviations **(b)** Solar deviations

Figure 7.6: Filtered deviations between ex-ante and ex-post wind and solar generation for the area of EnBW in Q1/2014 (*Source*: Data from EEX (2014))

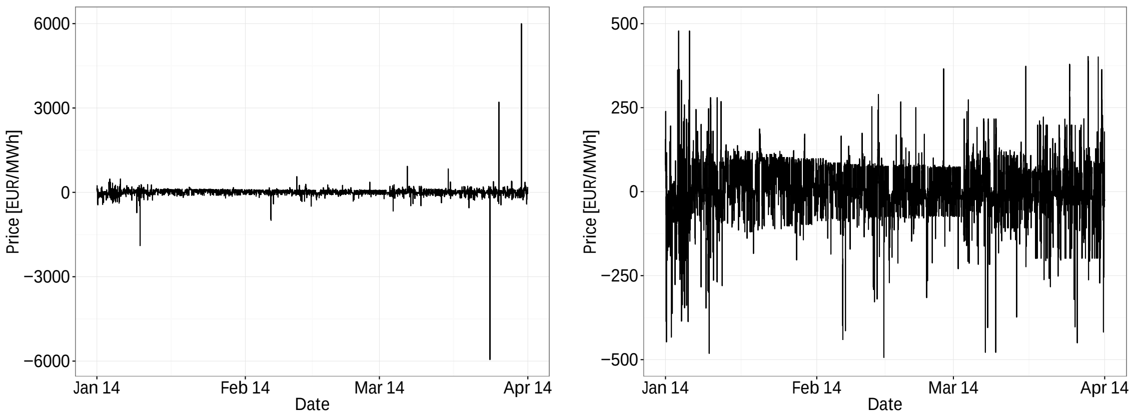
randomly picked to select the demand for flexibility.

7.4.1.2 Balancing Energy Prices

In the same way as wind and solar data serve as real-world input data for flexibility demand, prices for the outside option are based on real-world balancing energy prices. These prices can occur in today's electricity market environment when deviations need to be balanced after the gate closure for trading as described in section 2.2.2.2. As wind and solar data are considered for the grid region of EnBW, balancing energy prices are sourced from the same area and for the same year (TransnetBW GmbH 2015). Figure 7.7 shows the balancing prices for the corresponding time period. As balancing prices can sometimes reach extreme peaks in either positive or negative directions, both the original and a filtered time series within the limits of $[-500, 500]$ kW are shown. The balancing energy prices are randomly picked from the corresponding time period for wind or solar generation.

7.4.2 Parametrization

In order to analyze different scenarios, the simulation parameters are varied along multiple dimensions. Firstly, the bidder structure is described. More specifically, the number of bidders and the bidder heterogeneity are varied. The number of bidders is set from 5 to 30 and the heterogeneity from 0 to 1.0 in discrete steps. The second dimension is given by the



(a) Complete balancing prices

(b) Filtered balancing prices in limits [-500,500]

Figure 7.7: Balancing energy prices for the area of TransnetBW in Q1/2014 (*Source*: Data from TransnetBW GmbH (2015))

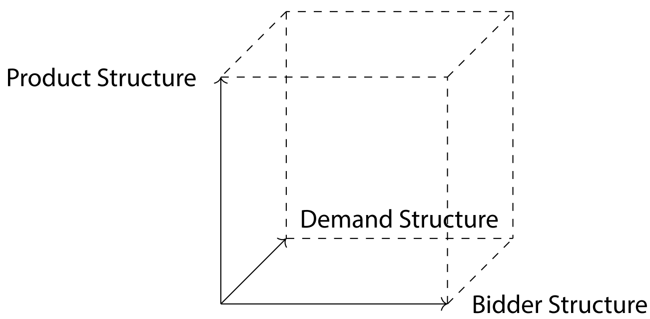


Figure 7.8: Simulation evaluation space

product structure. In more detail, the product structure defines the number of products, i.e., time slots. Given a time horizon of 45 minutes, this period is fragmented into either 15 minute or granular 5 minute time slots. This results in either $45/15 = 3$ or $45/5 = 9$ products. Thirdly, the demand for flexibility is drawn either from real-world wind or solar data, resulting in the demand type dimension. These dimensions constitute the evaluation space as illustrated in figure 7.8.

In addition, for every parameter configuration in the evaluation space, all pricing rules as defined in chapter 6 are evaluated in a further evaluation dimension. The k-pricing rule is parametrized with $k = 0.5$ to favor neither the demand nor the supply side.

Moreover, a full factorial simulation is conducted. That is, only one parameter from the evaluation space is varied while the other stay the same (Kelton and Law 2000). Random parameters for every simulation run include the aggregator's flexibility (minimum runtime),

Table 7.1: Deterministic simulation parameters

Parameter	Range
Number of bidders (N)	$\{5, 10, 15, 20, 25, 30\}$
Bidder heterogeneity (d)	$\{0, 0.5, 1.0\}$
Number of products (T)	$\{3, 9\}$
Pricing rule	{PAB, k-Pricing, VCG, Core Pricing}
Flexibility demand source	{Wind, Solar}

Table 7.2: Random simulation parameters

Parameter	Range	Distribution
Bidder flexibility (l_i)	$[1, T] \subset \mathbb{N}$	Uniform
Bid type (ϕ_j)	$\{-1, 1\} \subset \mathbb{Z}$	Uniform
Monetary bid value (b_j)	$[1, \min_{t \in \mathcal{T}} \gamma^t] \subset \mathbb{N}$	Uniform
Flexibility demand (a_0)	Day/Time from real-world data sets	Uniform

its bid type (consumption or generation), the bid price and the DSO's demand for flexibility. The complete deterministic and random simulation parameters are shown in tables 7.1 and 7.2. A large number of possible parameter combinations and their interdependencies in the context of simulation can result in extreme results. For this reason, each simulation run based on a single parameter combination is repeated 100 times in order to reduce statistical noise and improve the robustness of the results. That is, the permutations of the deterministic parameter values result in 96 simulation experiment runs. With each run repeated 100 times, the total number of simulation experiment runs results in 7200. Within each run, the prices are calculated for all pricing rules in order to avoid an artificial increase of simulation runs to 28800. After each simulation experiment run, the cost for the DSO for different pricing rules are calculated.

7.5 Simulation Implementation

The third step within a simulation constitutes the model implementation. The model is transformed into a software artifact by means of existing frameworks or customized and more effective implementations. Currently, no existing frameworks support the implementation of combinatorial auctions with all relevant aspects of solving the WDP, generating bids or determining prices with different pricing rules. Hence, the simulation is implemented as a custom software artifact using Python 2.7.11 (Python Software Foundation 2015) as part of the Anaconda distribution (Continuum Analytics 2016). Moreover, given the large number of possible simulation runs, the software artifact is implemented to support parallelization, i.e., to run on multiple cores.

Figure 7.9 illustrates the class diagram for the simulation. Note that for reasons of compactness, function arguments and types are omitted. The main class `Simulation` represents the entry point and is either launched directly with a complete configuration for all runs or as a child process of `Cluster` with a specific configuration range for a subset of runs. A `Simulation` launches an `AuctionProcessor` which initiates a `Scenario` and generates the parameter configuration. Moreover, an `AuctionProcess` prepares the HDF database, which can store data for logging purposes in a table format. A `Scenario` loads and caches wind and solar data from a local database. Additionally, it generates the set of bidders, their bids as well as the demand for flexibility. Furthermore, balancing prices are loaded from a local database. With a `Scenario` at hand, the WDP as a mixed integer problem (MIP) is generated in `Wd` and solved using the optimization engine Gurobi (Gurobi Optimization 2015). Based on the solution of the WDP from `Wd`, the pricing is calculated and solved using `KPricing`, `VcgPricing`, and `CorePricing`. PAB prices is calculated directly within `Wd`. After each run, the results are written to the local database created in a `Scenario`.

While the implemented model has been partly verified using unit tests, the external validation of the model represents a task which needs to be completed in further research as no comparable implementations with similar characteristics exist as of yet.

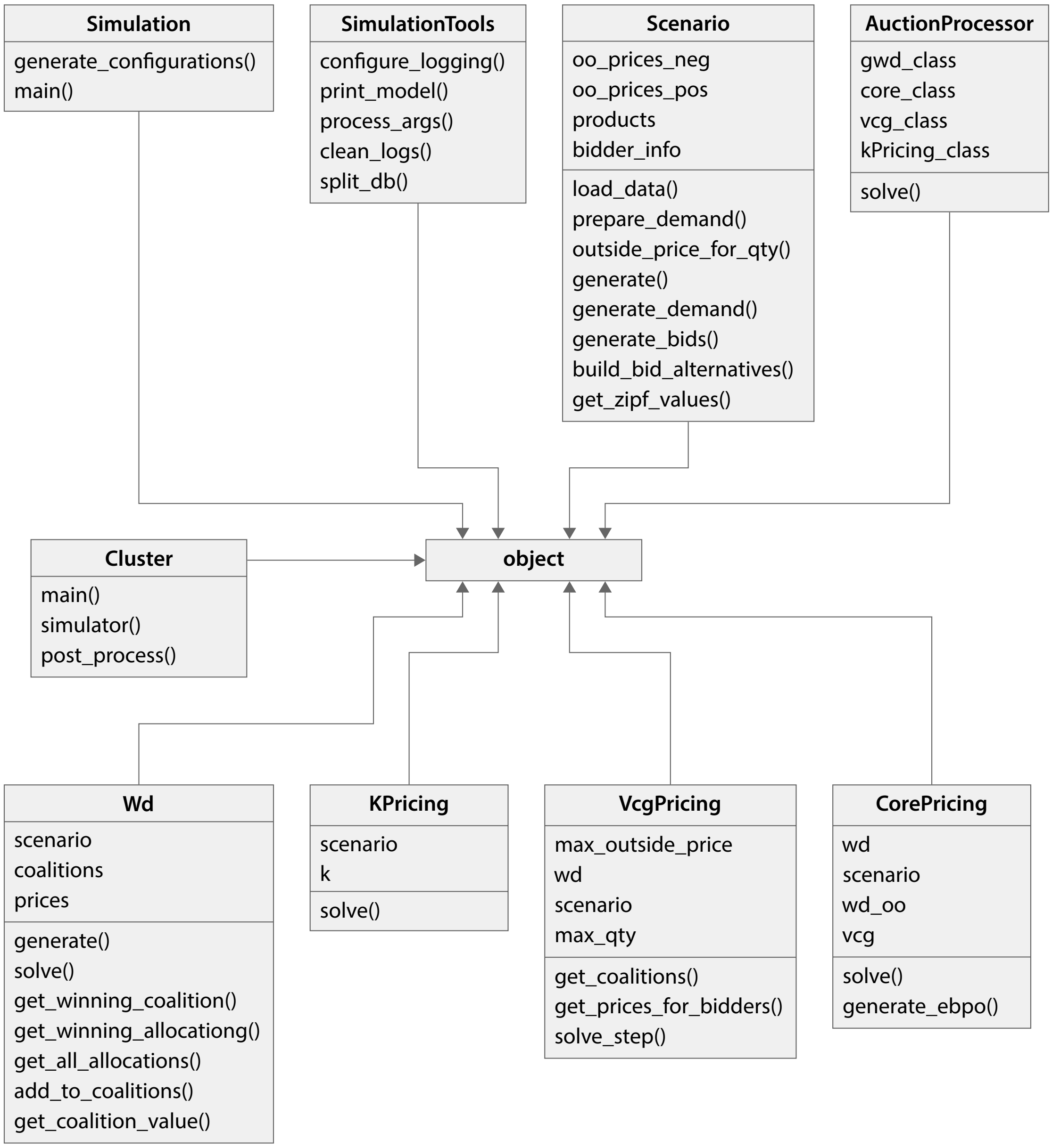


Figure 7.9: Class diagram of the simulation architecture

8

Simulation Results

Based on the previously introduced simulation model and implementation of the flexibility auction, this chapter presents, analyzes, and interprets the obtained results.

Technically, all simulations are performed on an 64-bit Intel® Xeon® server with 6 cores, with each at core operating at 1.73 GHz. The available memory amounts to 12 GB. The running system constitutes the server version of Ubuntu 14.04.3 LTS. Further system components include Python 2.7.11 from the Anaconda distribution 4.0.0 and the state-of-the-art linear optimization solver Gurobi 6.5.1 (Gurobi Optimization 2015; Continuum Analytics 2016). The process of analyzing the simulation experiment data is supported by an evaluation pipeline. That is, the simulation experiment data is written into a table-like HDF5 database (The HDF Group 2015). Subsequently, the data is read into the statistics software R 3.2.4 (R Core Team 2016). RStudio 0.99.893 (RStudio Team 2015) is used as a graphical user interface (GUI) for R. Based on scripts written in R and RStudio, the graphics and tables are generated.

Recall the simulation evaluation space as described in section 7.4.2 and shown in figure 7.8. The remainder of this chapter is structured accordingly as follows: Firstly, section 8.1 analyzes the simulation experiment results from an economic perspective for all simulation runs for the bidder structure dimension. Secondly, the product structure is analyzed in section 8.2 . Thirdly, section 8.3 investigates the demand structure. Subsequently, the technical results concerning the empirical computational tractability of the simulation are analyzed in section 8.4.

Finally, section 8.5 concludes this chapter by discussing and reflecting on the simulation experiment results.

8.1 Bidder Structure

This section analyzes the characteristics of the bidder structure, i.e., the number of bidders, the bidder flexibility as well as bidder heterogeneity.

8.1.1 Number of Bidders

Table 8.1 shows median, mean, and standard deviation of the distribution system operator (DSO) cost as a function of the number of bidding aggregators. Moreover, the difference (Δ) from the preceding experiment (i.e., line) for median, mean, and standard deviation are shown.

For an increasing number of bidders, the mean DSO cost decreases. However, the high volatility of the flexibility demand from wind and solar as well as outside option prices result in large standard deviations from EUR 17 242.97 to EUR 21 124.17. Yet, the median also decreases with an increase of bidders and remains comparatively low. For 30 bidding aggregators, more than 50 % of the simulation experiments show DSO cost at or below EUR 3413.30.

Table 8.1: DSO cost in EUR as a function of the number of bidding aggregators

N	Median	Mean	Sd	Δ_{Median}	Δ_{Mean}	Δ_{Sd}
5	5009	13 009.43	21 124.17	-	-	-
10	4053	10 801.55	17 738.99	−956	−2207.88	−3385.18
15	3779.17	10 492.72	17 638.07	−273.83	−308.82	−100.93
20	3607.50	10 156.26	17 671.43	−171.67	−336.46	33.36
25	3482.17	9996.67	17 271.50	−125.33	−159.59	−399.93
30	3413.30	9844.99	17 242.97	−68.87	−151.68	−28.53
[5,30]	3875	10 717.29	18 195.95	-	-	-

Figure 8.1 illustrates the DSO cost as a function of the number of bidding aggregators. As before, the results comprise all simulation experiments. The values are represented by box

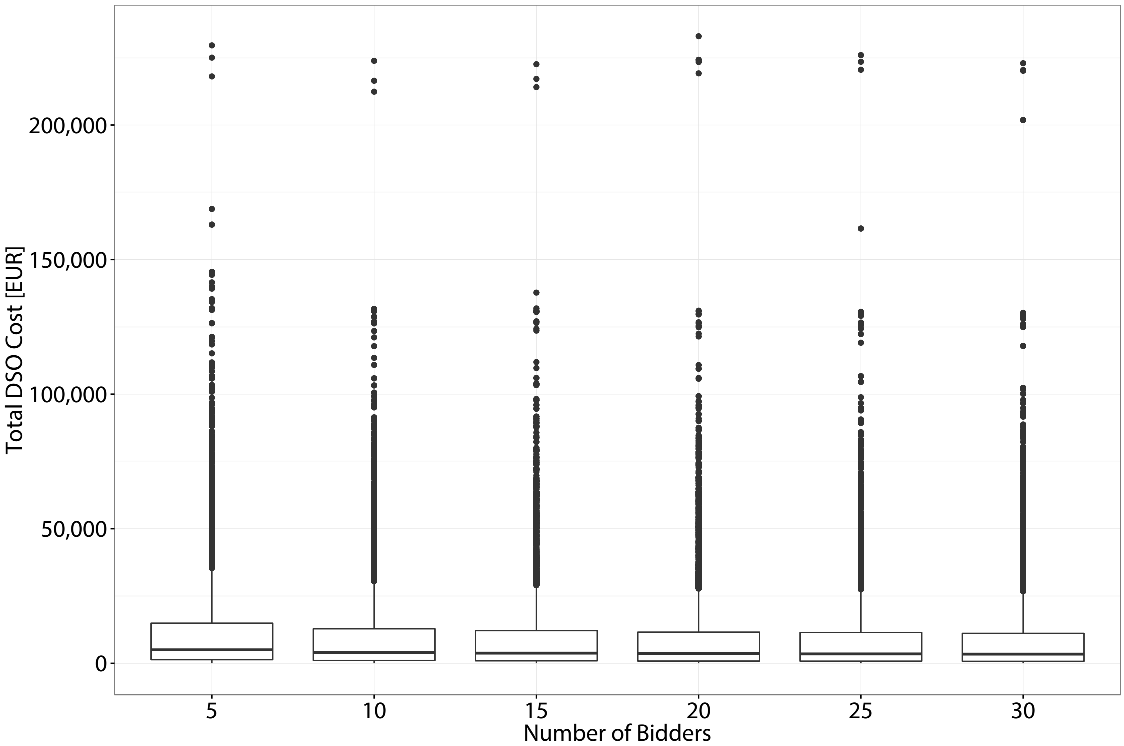


Figure 8.1: DSO cost in EUR as a function of the number of bidding aggregators

plots. A box contains 50 % of all data points and line within the box denotes the median. Moreover, the box is limited by the lower and upper quartiles. More specifically, 25 % of all data points reside above, and 25 % below the box. Within figure 8.1, the resulting cost for the DSO for all number of bidders lie below EUR 14 909.13 for 75 % of the experiments. The vertical lines above and below extending a box, also referred to whiskers, denote 1.5 times the interquartile range. That is, the interquartile range is given by the difference of the 75 % and 25 % quantile. Single dots above and below whiskers denote outliers. Despite the extreme nature of outliers as illustrated in figure 8.1, where values greater than EUR 200 000 can be observed, their effect on mean DSO cost is limited given their limited occurrence. The DSO cost can be described as reaching a convergence based on the mean values for more than 20 bidders. Hence, it can be concluded that the flexibility auction is scalable with regard to the number of bidding aggregators.

Table 8.2 shows the median, mean, and standard deviation as a function of the pricing rule over all experiments. Moreover, the difference (Δ) from the preceding experiment (i.e., line) for median, mean, and standard deviation are shown. The mean cost for the DSO is situated within the interval of EUR 6239.50 to EUR 13 479.10. Based on the most conservative pricing rule, pay-as-bid (PAB), k-pricing leads to an increase of mean cost by EUR 7239.60. Compared to k-pricing, the use of Vickrey-Clarke-Groves (VCG) leads to a decrease of median and mean prices by EUR 1308.75 and EUR 1850.93, respectively. Core pricing additionally reduces the median and mean cost under a VCG regime by EUR 58.90 and EUR 105.77, respectively. The smaller decrease of core pricing can be explained due to the fact that core pricing represents an improvement upon VCG prices for DSO in terms of lower cost. In addition, it can be concluded that VCG often leads to prices that are already in the core and do not need to be improved upon and therefore can be considered as perceived fair. The standard deviations lie between EUR 10 369.49 and EUR 22 001.52 over all experiments.

Table 8.2: DSO cost in EUR as a function of the pricing rule

Pricing Rule	Median	Mean	Sd	Δ_{Median}	Δ_{Mean}	Δ_{Sd}
Pay as Bid	2098.67	6239.50	10 369.49	-	-	-
k-Pricing	5565.58	13 479.10	22 001.52	3466.92	7239.60	11 632.03
VCG	4256.83	11 628.17	18 838.89	−1308.75	−1850.93	−3162.63
Core Pricing	4197.93	11 522.40	18 677.57	−58.90	−105.77	−161.32

Figure 8.2 shows the DSO cost as a function of the pricing rule over all experiments. It can be observed that for 75 % of all experiments the cost for the DSO are below EUR 15 584.25 over all experiments and pricing rules. All pricing rules produce outliers above EUR 100 000.00, with only PAB producing a data point slightly above that boundary. The outliers can be explained to result from the highly volatile input data for flexibility demand and outside option prices.

In order to allow for a comparison of the resulting cost for the DSO, table 8.3 shows the mean cost for the DSO, the benchmark value for the outside option, their difference (Δ) as well as the resulting relative savings of the DSO over all simulation experiments. The benchmark value for the outside option results from the assumption that all flexibility demand would be procured from the outside option. Relative savings are calculated by putting the difference of the actual cost and theoretical outside option cost in relation to the outside option cost. The difference between the actual cost and the theoretical benchmark ranges from EUR 6692.92 to EUR 13 932.52. This corresponds to savings between 33.0 % and 69.0 % over all simulation experiments. While PAB produces the highest saving, it cannot be assumed that bidding aggregators would continue to submit their true valuations. Therefore, the savings would decrease as aggregators would learn that they could get a higher reward by falsely reporting their valuations. K-Pricing leads to savings of 33.0 %, yet is subject to

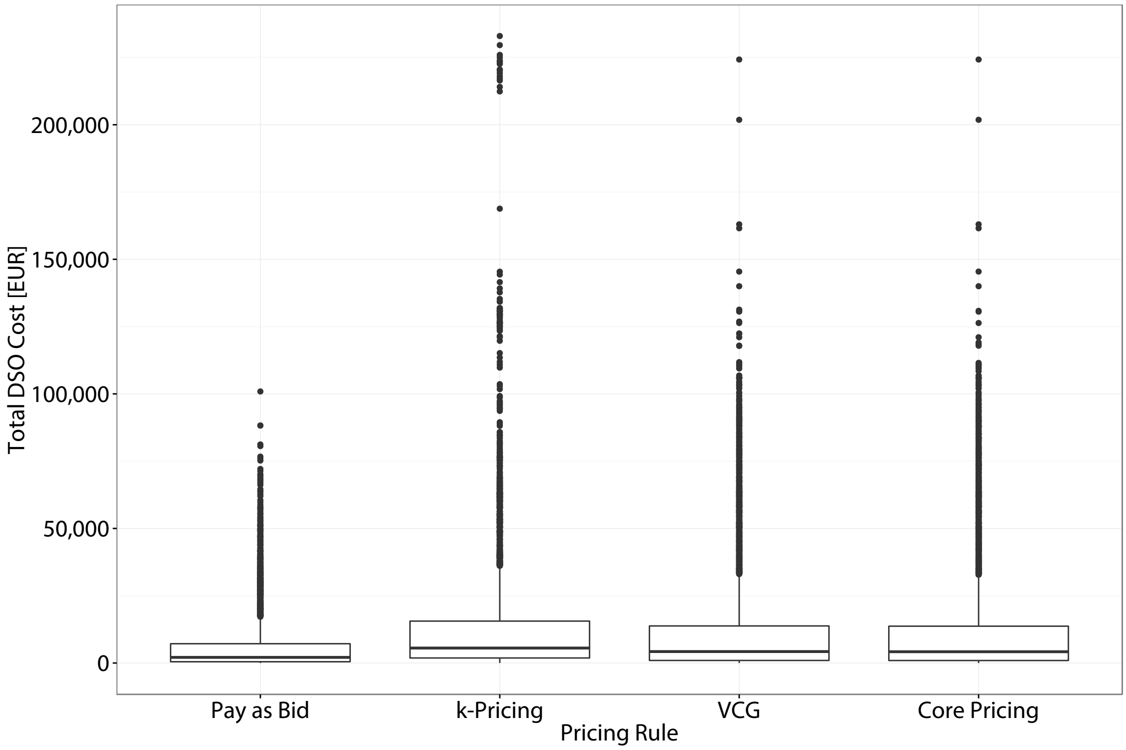


Figure 8.2: DSO cost in EUR as a function of the pricing rule

the same incentive compatibility issue. Core pricing can slightly increase the savings for the DSO compared to VCG from 42.0 % to 43.0 %. However generally speaking, the savings constitute substantial reductions upon a price taker regime in which the DSO would simply rely on an outside option.

Table 8.3: DSO cost in EUR in comparison to outside option

	Mean			
Pricing Rule	Cost DSO	Outside Option	Δ	Relative Savings
Pay as Bid	6239.50	20 172.02	13 932.52	0.69
k-Pricing	13 479.10	20 172.02	6692.92	0.33
VCG	11 628.17	20 172.02	8543.86	0.42
Core Pricing	11 522.40	20 172.02	8649.62	0.43

Table 8.4 shows the results of a linear regression analysis over all simulation experiments. The DSO's cost represents the dependent variable. The regression shows the influence of the parameters number of bidders (N), bidder heterogeneity (d), number of products (T), flexibility demand source (wind, solar) on the total cost of the DSO. All parameters have

a significant influence on the DSO's cost. In more detail, the number of bidders and the number of products have a negative effect on the cost, whereas all other parameters, i.e., bidder heterogeneity and the flexibility demand source, have a positive effect on the DSO's cost. Details on these parameter are given in the following sections.

Table 8.4: Linear regression analysis results for DSO cost

	Dependent variable:
	Total DSO cost
Number of bidders (N)	−106.241***
	(11.506)
Bidder heterogeneity (d)	602.839**
	(240.691)
Number of products (T)	−270.307***
	(32.756)
Flexibility demand source	14 371.240***
	(196.537)
Constant	6711.473***
	(336.077)
Observations	28 784
R^2	0.161
Adjusted R^2	0.160
Residual Std. Error	16 672.060 (df = 28 779)
F Statistic	1376.554*** (df = 4; 28 779)
Note:	*p<0.1; **p<0.05; ***p<0.01

8.1.2 Bidder Flexibility

Table 8.5 shows the values for median, mean, and standard deviation of the number of accepted bids as a function of bidder flexibility over all experiments. The number of accepted bids for all bidders represents a set of successfully cleared bids. The median lies between

2 and 4 and is decreasing with an increasing value for the bidder flexibility level l. That is, the more constrained the bidder's flexibility, the less of the bidder's bids are allocated. Similarly, the values for mean and standard deviations lie within 2.74 to 6.75 and 1.86 to 5.85, respectively. They decrease with an increasing limitation of the flexibility. In other words, a greater flexibility results in a greater number of allocations on average. More specifically, mean and standard deviation values support this notion, in particular for $l = 1$.

Table 8.5: Number of accepted bids as a function of bidder flexibility

Flexibility l	Median	Mean	Sd
1	4	6.75	5.85
2	3	3.39	2.20
3	3	3.19	2.11
4	2	2.74	1.86

Table 8.6 shows the results of a linear regression analysis over all simulation experiments focused on the bidder perspective. The number of allocations represents the dependent variable. The regression shows the influence of the parameters number of bidders (N), bidder heterogeneity (d), bidder flexibility (l) and number of products (T) on the number of allocations for all bidding aggregators. All parameters have a significant influence on the number of allocations, supporting the statement regarding the decreasing effect of the flexibility level from the previous paragraph. That is, the number of bidders and the bidder heterogeneity have a positive effect on the number of allocations. On the contrary, the bidder flexibility number of products have a negative effect on the number of allocations. However, recall that the greater the flexibility level, the less flexible an aggregator actually is, as the level represents a minimum runtime constraint.

Figure 8.3 illustrates the number of allocations as a function of a bidder's flexibility partitioned by the number of participating bidders. This allows a more in-depth view on the number of participating bidders. In all simulation experiments, the number of allocations increases for flexibility level $l = 1$. However, the number of allocations remains below 10 for 75 % of the experiments for all other flexibility levels $l \neq 1$. In line with the previous regression analysis, it is obvious that in particular a larger number of bidders and a low flexibility level are beneficial to the number of allocations. In particular, note that flexibility level $l = 1$ can be explained as a bids based on this flexibility often act as a fill-in for larger bids to support the overall allocation.

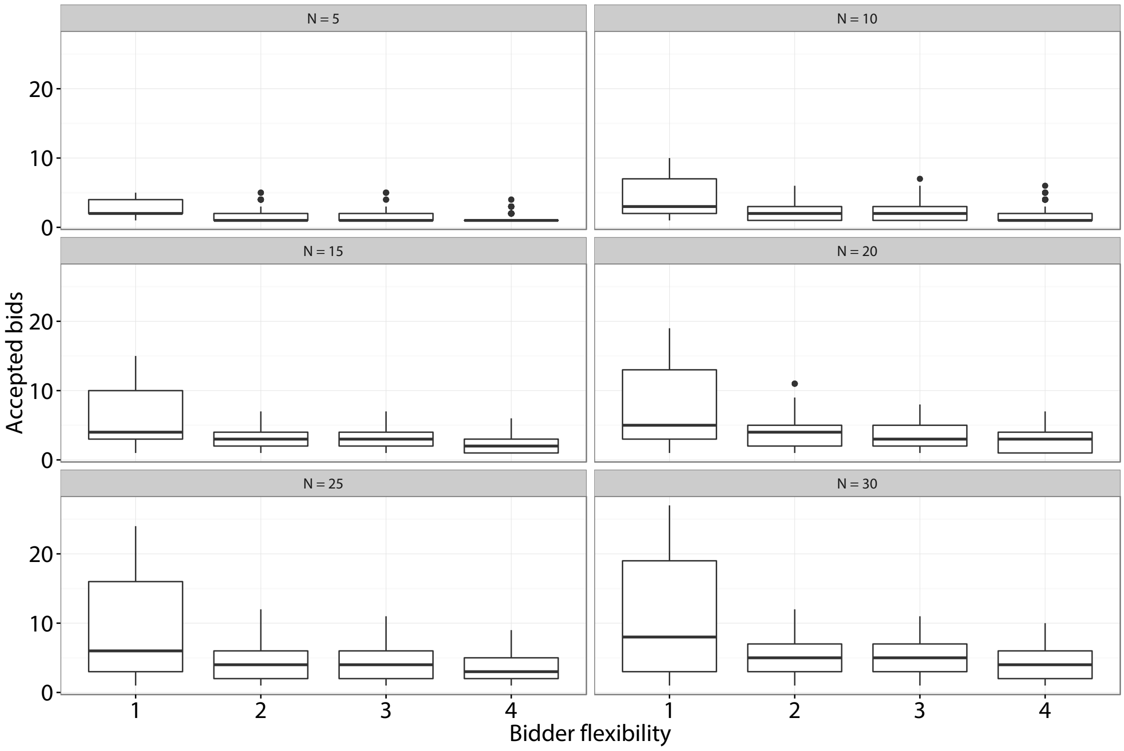


Figure 8.3: Number of accepted bids as a function of a bidder's flexibility partitioned by the number of participating bidders

Table 8.6: Linear regression analysis results for number of bidder allocations

	Dependent variable:
	Number of accepted bids
Number of bidders (N)	0.219***
	(0.003)
Bidder heterogeneity (d)	1.898***
	(0.030)
Bidder flexibility (l)	–0.524***
	(0.022)
Number of products (T)	–0.932***
	(0.010)
Constant	8.559***
	(0.080)
Observations	20 745
R^2	0.556
Adjusted R^2	0.556
Residual Std. Error	3.037 (df = 20 740)
F Statistic	6491.885*** (df = 4; 20 740)
Note:	*p<0.1; **p<0.05; ***p<0.01

8.1.3 Bidder Heterogeneity

Table 8.7 shows the DSO cost in EUR as a function of the pricing rule partitioned by bidder heterogeneity for all simulation experiments. That is, for each heterogeneity level $d \in \{0, 0.5, 1\}$, the DSO cost are shown for all pricing rules. A heterogeneity level denotes that the requested amount of flexibility demand is distributed among all bidders according to definition 7.2. The mean values for a heterogeneity level d range from EUR 5962.60 to EUR 6670.71 for PAB, from EUR 13 291.43 to EUR 13 772.39 for k-pricing, from EUR 11 325.26 to EUR 12 123.78 for VCG and from EUR 11 255.96 to EUR 11 910.06 for core pricing. The standard deviation is considerably higher with ranging from EUR 9730.31 to EUR 22 594.35 over all heterogeneity levels and pricing rules. Given that no substantial changes for median, mean, and standard deviation for each pricing rule can be observed, it can be concluded that the auction is robust with regard to different heterogeneous market structures.

Table 8.7: DSO cost in EUR as a function of the pricing rule partitioned by bidder heterogeneity

Heterogeneity Level d	Pricing Rule	Median	Mean	Sd
0	Pay as Bid	2077.67	5962.60	9730.31
	k-Pricing	5487.17	13 291.43	21 648.22
	VCG	4202.00	11 435.33	19 024.71
	Core Pricing	4164.00	11 401.07	18 993.01
0.5	Pay as Bid	2080.00	6085.13	10 000.37
	k-Pricing	5584.75	13 373.44	21 755.85
	VCG	4152.00	11 325.26	18 027.45
	Core Pricing	4112.02	11 255.96	17 954.25
1	Pay as Bid	2163.00	6670.71	11 300.11
	k-Pricing	5604.33	13 772.39	22 594.35
	VCG	4454.00	12 123.78	19 434.28
	Core Pricing	4345.65	11 910.06	19 065.90

Figure 8.4 shows the DSO cost in EUR as a function of the pricing rule partitioned by bidder heterogeneity. In more detail, 75 % of all simulation experiments yield DSO cost less than EUR 15 584.25. More specifically, for PAB, 75 % of all experiments result in cost less than EUR 7180.00, whereas VCG and core pricing yield cost less than EUR 13 783.33 and EUR 13 696.13, respectively, for 75 % of the simulation experiments. Note that no considerable effect can be observed among the heterogeneity levels. In line with previous results, this underlines the robustness of the auction model regarding homogeneous or heterogeneous market structures.

Table 8.8 shows values for the mean and standard deviation of the pricing ratios partitioned by bidder heterogeneity for all simulation experiments. The mean ratios lie within the interval of $[1.01, 5.25]$ for a homogeneous aggregator population ($d = 0$) and in the interval of $[1.07, 5.39]$ for a heterogeneous aggregator population. In more detail, while ratio of VCG prices to the bids is always more than 3 times higher, the ratio of core prices to the bids are about 2.95 to 3.10 times higher. K-Pricing performs considerably worse as the resulting prices lead to 5.25 to 5.39 times higher payments to aggregators compared to the submitted bids on average. However, compared to VCG or core pricing, k-pricing only leads to mean ratios of

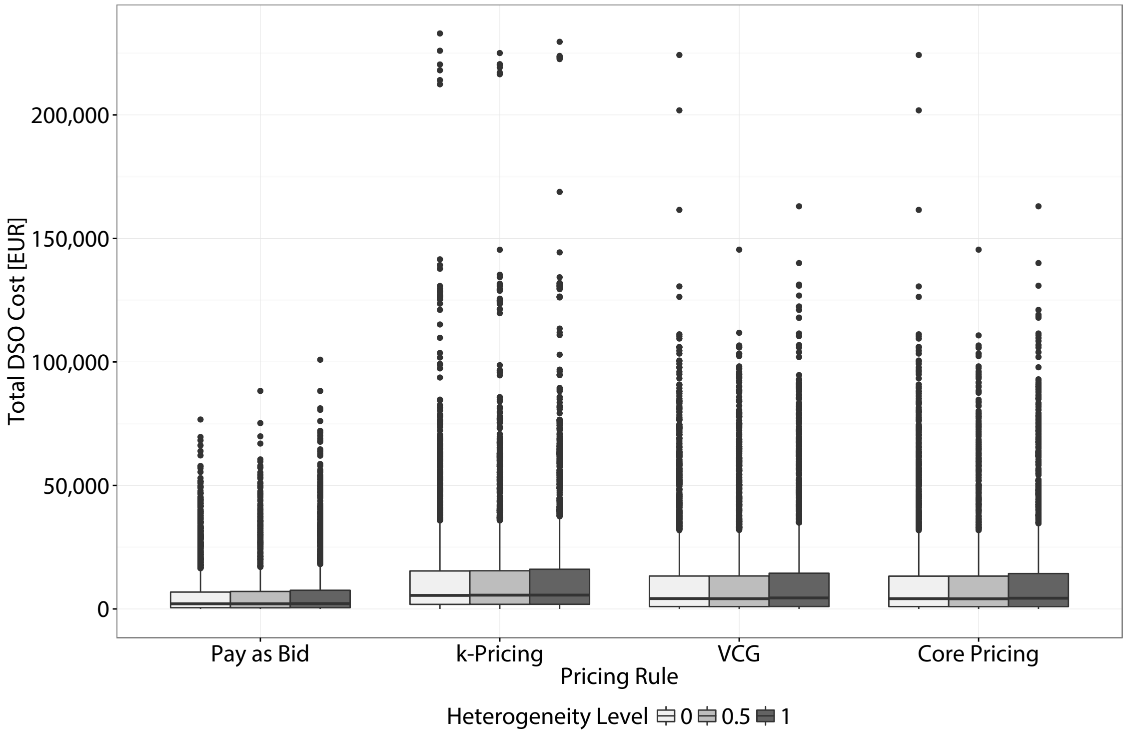


Figure 8.4: DSO cost in EUR as a function of the pricing rule partitioned by bidder heterogeneity

1.85 to 2.04. The ratio of VCG to core pricing shows that core pricing can improve about 7 % upon VCG prices.

8.2 Product Structure

Recall from section 7.4.2 that the product structure is divided into a short-term and medium/long-term horizon. That is, in the following, the effect of 3 or 9 products that indicate flexibility demand is investigated.

Table 8.9 shows the values for median, mean, and standard deviation for the DSO cost in EUR as a function of the pricing rule partitioned by the number of products for all simulation experiments. The median for 3 products lies in the interval of EUR 2205.00 to EUR 4508.50 and within the interval of EUR 1972.67 to EUR 5279.42 for 9 products. Compared by pricing rule, the cost for the DSO are in general less with more products available. This can be explained from the fact that with the same time horizon divided into more granular products, a more cost-efficient allocation becomes possible. In comparison by pricing rule, PAB yields

Table 8.8: Pricing ratios partitioned by bidder heterogeneity

	0		0.5		1	
Ratio	Mean	Sd	Mean	Sd	Mean	Sd
Core/Bid	3.10	4.53	3.02	4.33	2.95	4.11
VCG/Bid	3.13	4.56	3.08	4.39	3.11	4.33
K/Bid	5.25	8.06	5.33	8.40	5.39	8.93
K/VCG	1.85	1.66	1.88	1.70	1.88	1.79
K/Core	1.88	1.80	1.94	1.99	2.04	2.56
VCG/Core	1.01	0.10	1.02	0.19	1.07	0.43

mean reductions in DSO cost of 14.39 % under a more granular product structure. Similarly, k-pricing results in mean reductions of 16.29 %, VCG in reductions of 12.56 % and core pricing in reductions of 12.78 %. For each number of products, the relation among the pricing rules remains as before, i.e., PAB yields the lowest prices and k-pricing the highest prices. In addition, core pricing always reduces DSO prices compared to VCG prices for median, mean, and standard deviation values.

Table 8.9: DSO cost in EUR as a function of the pricing rule partitioned by the number of products

Number of Products	Pricing Rule	Median	Mean	Sd
3	Pay as Bid	2205.00	6723.48	10 686.33
	k-Pricing	6002.50	14 674.70	24 528.37
	VCG	4508.50	12 408.02	19 409.22
	Core Pricing	4459.50	12 309.63	19 215.67
9	Pay as Bid	1972.67	5756.05	10 021.19
	k-Pricing	5279.42	12 284.82	19 076.24
	VCG	4057.50	10 849.18	18 220.81
	Core Pricing	3980.41	10 736.04	18 092.63

Figure 8.5 shows the DSO cost in EUR as a function of the pricing rule partitioned by the number of products. For 3 products, the cost lie below EUR 17 331.75 in 75 % of the simulation experiments, while for 9 products, 75 % of the experiments yield cost of less than EUR 14 552.13 over all pricing rules. Contrarily, more than 75 % of experiments result in cost of more than EUR 518.00 for 3 products and in cost of more than EUR 456.67 for 9 products. In all experiments, extreme outliers can be observed, yet due to their limited occurrence, their effect on mean cost is limited.

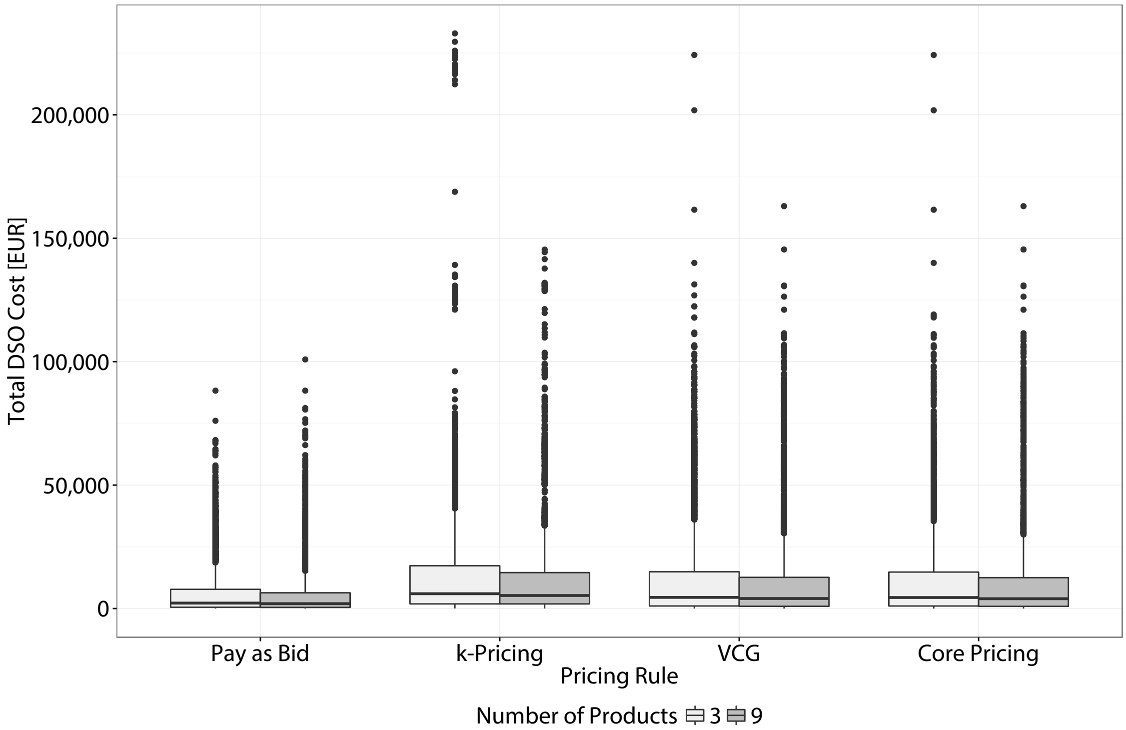


Figure 8.5: DSO cost in EUR as a function of the pricing rule partitioned by the number of products

Table 8.10 shows values for the mean and standard deviation of the pricing ratios partitioned by the number of products for all simulation experiments. The mean ratios lie within the interval of $[1.02, 5.36]$ for 3 products and in the interval of $[1.05, 5.29]$ for 9 products. For both numbers of products, the standard deviation for the ratio of k-pricing to bids is substantially larger than for all other ratios. Additionally, while the mean ratio for core pricing and VCG to bids over all experiments is about 2.83 to 3.29, k-pricing yields ratios of 5.29 and 5.36 to the bids. The ratio of VCG to core pricing shows that core pricing can improve 2 % upon VCG prices for 3 products and 5 % for 9 products. Moreover, the mean ratio of k-pricing to core pricing for both 3 and 9 products, i.e, 1.86 and 2.04, shows that core pricing can substantially improve upon prices resulting from the k-pricing regime. Therefore, the lower prices of core pricing result lower payments towards aggregators and hence lower total cost.

Table 8.10: Pricing ratios partitioned by the number of products

	3		9	
Ratio	Mean	Sd	Mean	Sd
Core/Bid	3.25	4.99	2.83	3.64
VCG/Bid	3.29	5.05	2.94	3.81
K/Bid	5.36	8.86	5.29	8.12
K/VCG	1.82	1.71	1.91	1.72
K/Core	1.86	1.89	2.04	2.33
VCG/Core	1.02	0.16	1.05	0.35

8.3 Demand Structure

This section investigates the effect of the type of generation data used on the cost for the DSO as well as also on resulting prices. As described in section 7.4.1.1, wind and solar data both constitute the basis for the demand for flexibility by the DSO.

Table 8.11 shows the values for median, mean, and standard deviation for the DSO cost in EUR as a function of the pricing rule partitioned by the flexibility demand source for all simulation experiments. The median, mean, and standard deviations for wind data are considerably lower compared to those for solar data. The median values for all prices rules using wind data lie in the range of EUR 1079.00 to EUR 3334.17 and in the range of EUR 6051.17 to EUR 2192.67 for solar data. The mean values are between EUR 1878.02 and EUR 4827.32 for wind and between EUR 10 600.98 and EUR 22 130.88 for solar data. Such substantial difference can result from the volatility which can be observed in both data sets but to a greater extend in solar deviations. In particular, deviations of the amount between ex-ante and ex-post data for solar generation span a much wider range compared to wind generation. Hence, the amount of flexibility demand increases and results in more cost for the DSO. For each flexibility demand source, the relation among the pricing rules remains as before, i.e., PAB yields the lowest prices and k-pricing the highest prices. In addition, core pricing always results in lower prices for the DSO compared to VCG prices for median, mean, and standard deviation values.

Figure 8.6 illustrates the DSO cost in EUR as a function of the pricing rule partitioned by the flexibility demand source. In 75 % of the simulation experiments, the DSO cost are less than EUR 28 244.96. Particularly for wind data, 75 % of the experiments yield cost less

Table 8.11: DSO cost in EUR as a function of the pricing rule partitioned by the demand source

Demand Source	Pricing Rule	Median	Mean	Sd
Wind	Pay as Bid	1079.00	1878.02	2539.36
	k-Pricing	3334.17	4827.32	5379.08
	VCG	2192.67	3729.39	4983.30
	Core Pricing	2159.11	3692.88	4958.93
Solar	Pay as Bid	6051.17	10 600.98	13 060.57
	k-Pricing	14 018.75	22 130.88	28 099.56
	VCG	11 583.00	19 526.94	23 669.74
	Core Pricing	11 489.86	19 351.92	23 464.27

than EUR 6041.75. Note that even the outliers do not exceed a value of EUR 100 000, whereas experiments based on solar data yield substantially more outliers.

Table 8.12 shows values for the mean and standard deviation of the pricing ratios partitioned by the flexibility demand source for all simulation experiments. The mean ratios are located within the interval of $[1.03, 5.89]$ for wind data and in the interval of $[1.04, 4.76]$ for solar data. The standard deviation values are between 0.23 and 8.74 for wind and between 0.32 and 8.17 for solar data. Core pricing and VCG can result in substantially lower prices compared to k-pricing for wind and solar data. However, no considerable difference can be observed between wind and solar data for lower DSO cost of core pricing over VCG.

Table 8.12: Pricing ratios partitioned by the demand source

	Wind		Solar	
Ratio	Mean	Sd	Mean	Sd
Core/Bid	3.01	4.24	3.03	4.40
VCG/Bid	3.10	4.35	3.12	4.50
K/Bid	5.89	8.72	4.76	8.17
K/VCG	2.08	1.73	1.66	1.68
K/Core	2.18	2.22	1.73	2.02
VCG/Core	1.03	0.23	1.04	0.32

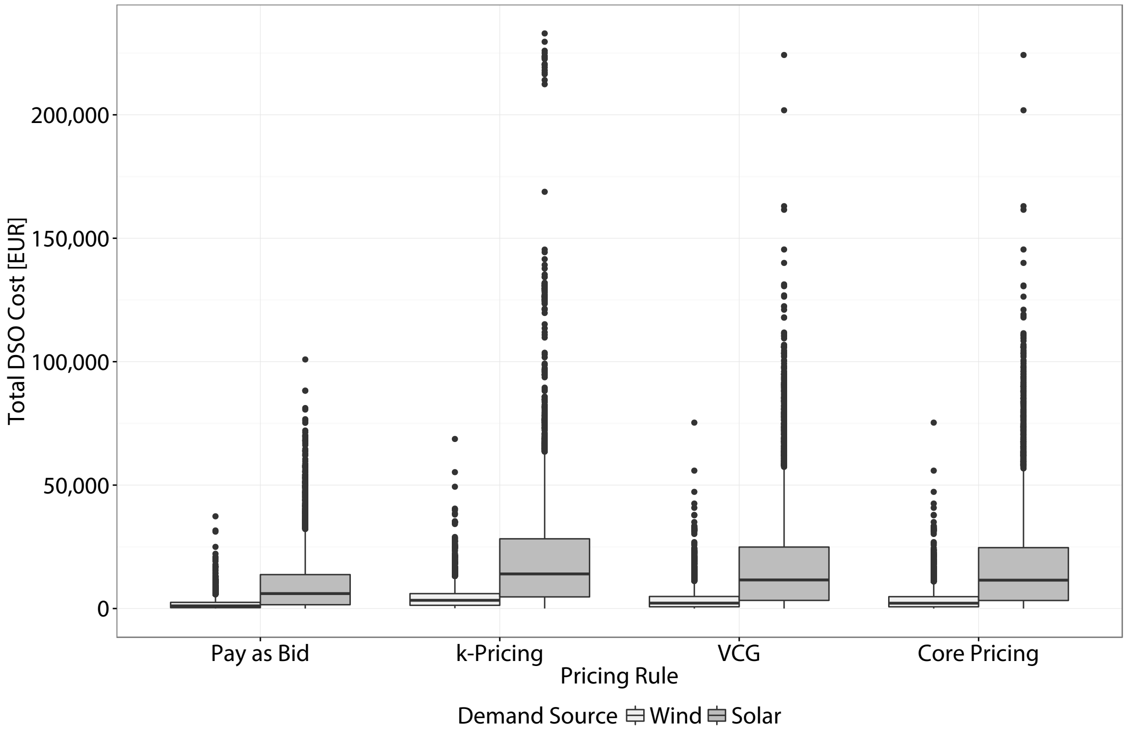


Figure 8.6: DSO cost in EUR as a function of the pricing rule partitioned by the demand source

8.4 Computational Tractability

Table 8.13 shows median, mean, standard deviations, and maximum runtimes for WD, k-pricing, VCG, and core pricing with $\text{SEP}^{\tau}_{\text{SG}}$ and $\text{EBPO}^{\tau}_{\text{SG}}$, as well as the total computation time partitioned by the number of bidders. Within the simulation experiments, no time limit is imposed on the solver, which is used to solve WD, VCG, and core pricing. The solver therefore always computes the optimal solution. On average, the winner determination and pricing rules require no more than 10 seconds for $N = 5$. With $N = 10$, the same observation holds, except for $\text{SEP}^{\tau}_{\text{SG}}$, which constitutes a 6.19 time increase of mean runtime compared to $N = 5$. In general, the mean observed empirical computation time increases with N, in particular for core pricing with $\text{SEP}^{\tau}_{\text{SG}}$. This can be explained as solving $\text{SEP}^{\tau}_{\text{SG}}$ may require several iterations. Moreover, runtimes for VCG prices also increase with N, which can be explained since calculating VCG prices requires the repeated solving of WD without each winning bidding aggregator. Hence, both problems contribute mainly to the mean total runtime.

In addition, table 8.13 also shows that there exist several instances that require a substantially increased computation time. For example, while the maximum runtime of $\text{SEP}^{\tau}_{\text{SG}}$ of 742.265 s for $N = 5$ constitutes a 89.32 time increase of the mean of 8.321 s, the maximum runtime of $\text{SEP}^{\tau}_{\text{SG}}$ of 33 314.917 s already constitutes a 265.218 time increase of the mean 125.613 s. This result is intuitive, as an increasing number of bidders results in an increasing number of submitted bids. In turn, more bids extend the DSO's space to determine the optimal combination of aggregators to support the demand for flexibility. Moreover, more bidders potentially allow for more alternatives for blocking coalitions, which need to be resolved by core pricing. In contrast, $\text{EBPO}^{\tau}_{\text{SG}}$ runtimes are close to zero for all N. This is because $\text{EBPO}^{\tau}_{\text{SG}}$ is not a mixed integer problem (MIP) and therefore faster to solve.

Figure 8.7 shows the runtimes a function of the number of bidding aggregators on a logarithmic y-scale. For k-pricing, 75 % of the simulation experiments yield a runtime of less than 0.003 67 s. Similarly, the runtimes of $\text{EBPO}^{\tau}_{\text{SG}}$ of core pricing are less than 0.004 24 s for 75 % of the simulation experiments. In contrast, the runtimes for all over problems, i.e., WD, VCG, and core pricing with $\text{SEP}^{\tau}_{\text{SG}}$, require considerably more computation time. While the computation time over all number of bidders N takes less than 22.097 53 s for VCG in 75 % of the experiments, solving $\text{SEP}^{\tau}_{\text{SG}}$ consumes 48.024 93 s in 75 % of the experiments.

8.5 Discussion

The results of the experimental simulation study provide evidence for the efficacy and usefulness of the proposed flexibility auction artifact in different settings along the bidder structure, product structure, and demand structure.

The cost of the DSO decrease with an increasing number of participating and bidding aggregators over all simulations. This result is intuitive, as more aggregators are inherently able to offer more flexibility from their prosumer portfolios to the auction. Investigating the pricing rule that can be applied, PAB results in the lowest payments of the DSO to winning aggregators. However, PAB is not incentive compatible and encourages aggregators to game the auction mechanism as soon as they realize that they can directly influence the outcome. In context of this simulation study however, it is assumed that bidders truthfully report their valuations in all scenarios. Hence, the cost for the DSO under PAB remain low. K-pricing, which allows to initially introduce a fairness component to the pricing mechanism, results in the highest prices over all experiments. In contrast, VCG prices, which are incentive

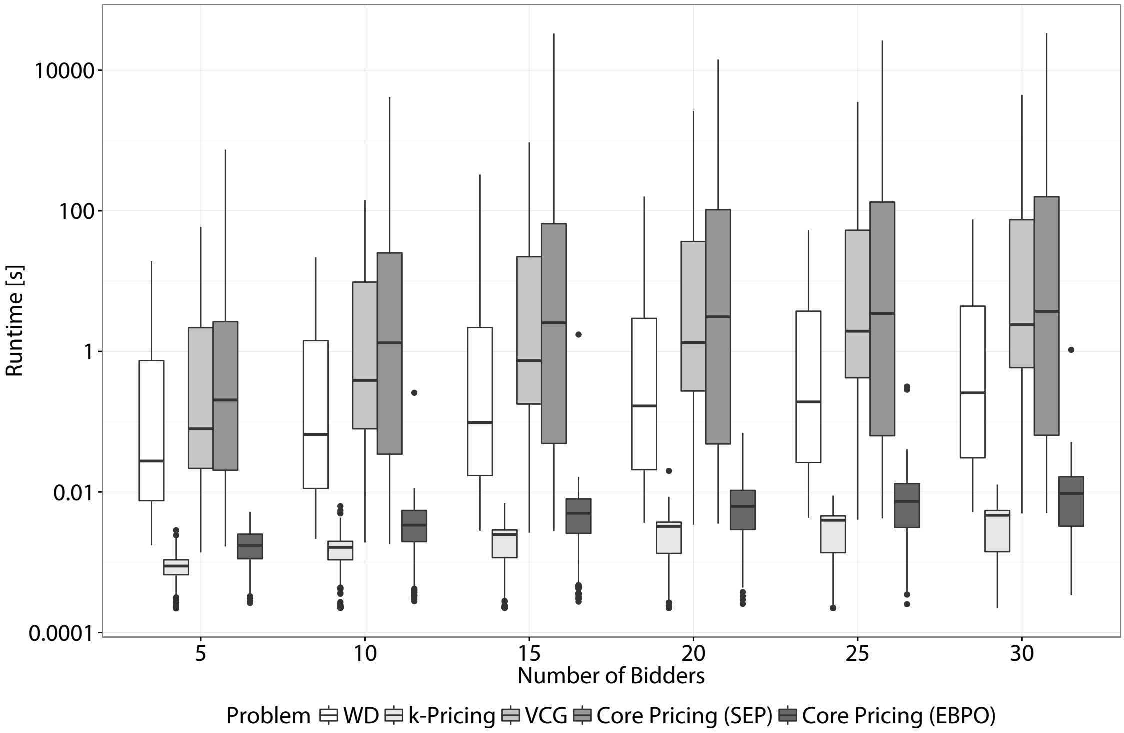


Figure 8.7: Runtimes a function of the number of bidding aggregators

compatible but can result in high DSO payments, result in less cost on average than k-pricing. Core pricing, which aims at proving the perceived fairness of prices, results in lower cost for the DSO compared to VCG prices. In terms of savings compared to a scenario where the auction would not be in place and the DSO's demand for flexibility would need to be acquired solely by means of an outside option (e.g., control reserve), k-pricing results in 33.0 % savings of DSO cost, VCG in 41.5 % and core pricing in 42.1 % savings of DSO cost.

Investigating the bidder structure with the focus on the bidder flexibility, the simulation experiments show that from the perspective of the bidding aggregators, bids with more flexibility substantially increase the number of accepted bids. Specifically, individual allocations of bids that reflect the highest temporal flexibility level ($l = 1$) are almost twice as high compared to the second highest flexibility level ($l = 2$). The reason for the considerably higher allocation of those bids can be explained as these bids often act as a fill-in for larger bids to support the overall allocation. Focusing on bidder heterogeneity, the results support the conclusion that the proposed flexibility auction is robust with regard to different homogeneous and heterogeneous market structures as no substantial changes can be observed.

Within the dimension of the product structure, the cost of the DSO decreases with an increasing number of products. This can be explained as more products constitute a more granular fashion to match supply and demand of flexibility more efficiently. Over all pricing rules, a more granular product structure yields mean reductions of the DSO cost from 12.56 % to 16.29. In addition, the simulation provides evidence from the mean pricing ratios that core pricing produces substantially more reductions to DSO payments compared to VCG and k-pricing under a more granular product structure.

The DSO cost also considerably increase for different sources of the DSO's demand for flexibility. Comparing deviations in real-world wind data to deviations in solar data, the simulation shows that the DSO's cost are driven by the extend of the volatility in each data set. More specifically, mean cost based on demand from deviations in solar data are about 5 times higher compared to demand from deviations in wind data.

The computational evaluation shows that PAB and k-pricing can be calculated in polynomial time in under 0.02 seconds. However, the problems of winner determination, VCG, and core pricing can represent a computational challenge. The empirically measured runtime is driven by the number of participating bidding aggregators. Bidders submitting more bids extend the solution space for the winner determination problem. Moreover, more bidders can potentially form more blocking coalitions, which requires to run more iterations to solve the core pricing problem.

In summary, the experimental simulation study shows the utility, quality, and efficacy of the proposed flexibility auction artifact. Moreover, the results show the robustness of the design against various parameter sensitivities. These results therefore provide evidence for a practical applicability of the flexibility auction.

Table 8.13: Runtimes in seconds

N	Problem	Median	Mean	Sd	Max
5	WD	0.028	0.590	1.284	19.223
	k-Pricing	0.001	0.001	0	0.003
	VCG	0.079	1.901	4.560	59.191
	Core Pricing (SEP)	0.203	8.321	35.253	742.264
	Core Pricing (EBPO)	0	0	0.001	0.005
	Total	0.311	10.813	41.098	820.686
10	WD	0.066	1.004	1.837	21.830
	k-Pricing	0.002	0.002	0.001	0.006
	VCG	0.388	6.751	11.970	142.745
	Core Pricing (SEP)	1.323	50.994	221.920	4176.995
	Core Pricing (EBPO)	0	0.002	0.007	0.258
	Total	1.778	58.753	235.735	4341.834
15	WD	0.097	1.678	8.505	327.110
	k-Pricing	0.002	0.002	0.001	0.007
	VCG	0.735	15.247	34.209	940.554
	Core Pricing (SEP)	2.550	125.613	953.880	33 314.917
	Core Pricing (EBPO)	0	0.004	0.043	1.736
	Total	3.384	142.545	996.639	34 584.323
20	WD	0.167	2.113	6.476	159.502
	k-Pricing	0.003	0.003	0.002	0.020
	VCG	1.331	27.117	86.298	2645.325
	Core Pricing (SEP)	3.100	165.706	655.918	14 221.596
	Core Pricing (EBPO)	0	0.004	0.005	0.070
	Total	4.601	194.942	748.699	17 026.512
25	WD	0.191	2.238	3.593	53.653
	k-Pricing	0.004	0.003	0.002	0.009
	VCG	1.938	38.095	108.133	3537.687
	Core Pricing (SEP)	3.472	266.518	1170.812	26 494.964
	Core Pricing (EBPO)	0.001	0.005	0.012	0.316
	Total	5.605	306.860	1282.553	30 086.629
30	WD	0.257	2.692	4.686	75.336
	k-Pricing	0.005	0.004	0.002	0.013
	VCG	2.391	54.341	148.534	4454.737
	Core Pricing (SEP)	3.714	353.174	1597.822	33 589.721
	Core Pricing (EBPO)	0	0.006	0.027	1.051
	Total	6.368	410.217	1751.071	38 120.859

Part IV

Finale

9

Conclusion and Outlook

To conclude the research at hand, this chapter first presents a summary of this work and recapitulates the key contributions in section 9.1. Then, section 9.2 discusses limitations of the proposed flexibility auction and provides an outlook on future research to complement the research of this thesis.

9.1 Summary and Contribution

Distribution system operators (DSOs) are presented with yet unseen challenges by the increasing share of renewable energy sources (RES) and ambitious goals on a European and German level regarding the integration of RES into power grids. One key issue is to maintain the balance of supply and demand at all times to ensure security of supply. To align the fluctuating generation from RES with consumption in a short-term manner, the flexibility potential of the demand side needs to be activated and integrated into electricity markets. In order to address this problem, market-based solutions are desired (EC 2015a). In line with this rationale, this work contributes the vision of the smart grid flexibility auction as a means for DSOs to procure flexibility from consumers via aggregators. The flexibility auction can provide a step towards more sustainable and efficient distribution grids, which in turn support the success of the smart grid.

Chapter 1 described the topic of the work at hand and provided a structured overview of the thesis. In addition, it formulated the research questions guiding this work. Chapter 2 introduced the current state and trends of today's electrical power system and gave insight into the nature and characteristics of the smart grid. Chapter 3 provided an overview of market design with market engineering (ME) and mechanism design. This was required for a subsequent classification of the market mechanism. Bringing together both previously introduced domains of the smart grid and market design, chapter 4 elaborated on the application of ME to smart grids. In addition, an environmental analysis was provided to address the requirements for market-based allocation flexibility in smart grids (research question 1). Moreover, related work was presented. Based on these fundamentals, requirements upon the market mechanism were formulated. These requirements served as a basis for further research in this work.

Chapter 5 introduced the main contribution of this work — the novel smart grid flexibility auction — as a reverse combinatorial auction with unit prices and an outside option (research question 2). Auction theory was used to design the smart grid flexibility auction as a design science research (DSR) artifact. The bidding language was formulated to allow for a compact representation of aggregator flexibility (research question 3). Furthermore, the allocation problem was formulated to attain an efficient allocation. Chapter 6 derived several pricing rules applicable to the flexibility auction (research question 4). To this end, pay-as-bid (PAB), k-pricing, and Vickrey-Clarke-Groves (VCG) with the Clarke pivot rule were applied to this domain-specific setting. In order to address the high buyer payments problem as well as the fairness of prices for sellers, core pricing was applied to the flexibility auction. The core pricing rule adapts VCG payments with the Clarke pivot rule, which can be considered unfair by a coalition of losing aggregators (bidders), to eliminate the possibility of such a coalition to object the auction outcome and to propose a mutually beneficial outcome for both the aggregators and the DSO (seller). Therefore, no losing aggregator exists which would offer its flexibility for less than any other winning aggregator. Moreover, the high buyer payments is addressed by determining adequately large payments that remain in the core of the auction while minimizing their distance to VCG payments.

Building upon the fully specified smart grid flexibility auction, chapter 7 was concerned with the design of a simulation model and its implementation into a prototypical software system for rigorous evaluation purposes. Within the simulation, scenarios of varying complexity along the dimensions of bidder structure, product structure, and demand structure were defined. Moreover, metrics for evaluation purposes were defined. Chapter 8 provided the analysis and discussion of the simulation experiment results from an economic and technical point of view. The economic analysis showed the potential of the DSO to reduce balancing cost (research question 5). More precisely, the analysis over all simulation experiments demonstrated that k-pricing results in savings of 33 % when comparing the auction outcome to potential outside option cost. In addition, VCG with the Clarke pivot rule and core pricing result in savings of 42 % and 43 %, respectively. Moreover, the results showed that the flexibility auction is scalable with regard to the number of bidding aggregators and robust to different heterogeneities of market share in the aggregator population. On an individual aggregator level, the simulation experiments showed that a greater flexibility in terms of time results in a greater number of allocations on average. Investigating the granularity of the announced products, the results revealed that the cost of the DSO can be reduced by 14.39 % on average when dividing the time horizon of the auction into 5 minute time slots as opposed to 15 minute time slots given a 45 minute time horizon. Furthermore, the volatility in the real-world data for deviations in wind or solar generation impacts the cost of the DSO. More specifically, using wind data, average DSO cost are substantially larger compared to using solar data. In addition, the technical analysis showed that the empirical computational hardness of the proposed flexibility auction given different bidder structures is high (research question 6).

9.2 Outlook

Having presented the main contributions of the smart grid flexibility auction in this thesis, future research opportunities that can complement this work are discussed in the following.

Bidding Language The introduced bidding language is designed to allow for a compact representation of an aggregator's preferences for electric load flexibility in a smart grid scenario. However, there can be scenarios in which a different degree of complexity for the bid formulation may be more beneficial to bidder requirements. For example, when individuals such as prosumers can become bidders, the bidding language may need to be simplified to account for their limited expertise and bounded rationality. Hence, future work has to consider the trade-off between expressiveness and complexity of bidding languages and to refine the proposed bidding language if necessary.

Mechanism Design The simulation experiments in this work assume that auction participants truthfully report their preferences on their flexibility to the flexibility auction. This assumption may not hold in real-world scenarios unless the mechanism is incentive compatible. Following Schnizler (2007) and Blau (2009), future work has to evaluate the effect of manipulating bidders with the auction as well as consider mechanism implementations that ensure incentive compatibility.

Moreover, alternative approaches of pricing rules to face the limitations of VCG need to be addressed. For example, deferred-acceptance auctions (Milgrom and Segal 2014, 2015; Dütting, Gkatzelis, and Roughgarden 2014) maintain strategy-proofness while at the same time sacrificing efficiency to address the low revenue problem in forward auctions or high buyer payments problem in reverse auctions. However, existing analysis for these auctions is limited to single-minded bidders. Hence, future work building upon the flexibility auction needs to investigate the application of different pricing rules to the problem of procurement of electric load flexibility.

Furthermore, the strategic aspect of repeated interaction is excluded from the scope of this work. Future research needs to evaluate the impact of multi-round auctions on agent strategies and behavior. In addition, intelligent agent behavior, e.g., learning agents, can be applied to further simulation experiments.

Simulation The simulation experiments are partly based on empiric real-world data which serve as input for the demand for flexibility as well as the outside option prices. Future simulation experiments need to extend the use of real-world data to support the validity of the smart grid flexibility auction. For example, the current bid generation process produces synthetic bids. For more realistic results, bids can be based on data resulting from empirically obtained valuations. To this end, surveys among consumers and prosumers need to be conducted. Results of such surveys allow to consider realistic bidding strategies in the simulation experiments.

Additionally, the demand for flexibility is currently based on deviations observed in solar or wind generation time series. Instead, actual measured critical values of transformer stations or grid lines on a local level could represent a promising extension to the work at hand.

Computational Hardness The results of the simulation experiments show that the empirical runtime of the non-polynomial pricing rules represent a computational challenge for a large number of auction participants. Hence, further research needs to consider computational aspects of solving the winner determination problem (WDP) as well as determining prices more quickly. Such research can be conducted in two directions. Firstly, the underlying linear programs can be optimized or different solver techniques such as constraint programming can be applied (Rossi, Beek, and Walsh 2006). Secondly, heuristics can be developed. For example, Goetzendorff et al. (2015) present the TRIM and REUSE heuristics for core pricing in order to find solutions to the WDP more quickly. In addition, Bünz, Seuken, and Lubin (2015) present an algorithm that outperforms the core constraint generation (CCG) algorithm. The increase in runtime is shown experimentally for several large combinatorial auction problems. In general, heuristics in particular need to consider mechanism design properties and the requirements defined for the flexibility auction.

Smart Grid This work focuses on economic aspects of the flexibility auction and hence abstracts from the technical properties and constraints of power networks. Future research needs to allow for incorporating technical constraints for local distribution grid areas. For example, power flow calculations and a locality component can be integrated to the balancing capabilities within the WDP. Moreover, throughout this work, flexibility is limited to the dimensions of amount and time of electricity consumption and production. Given the additional existing dimensions of flexibility such as rate of change, response time or location, further research can be complemented by considering these ample dimensions of flexibility.

Moreover, regulatory considerations are excluded from this work. In more detail, current regulation in Germany would not allow DSOs to introduce the proposed flexibility auction due to clear unbundling restrictions. However, proposals to loosen such limitations are currently being discussed (BMWi 2015b, 2015a). As soon as new legislation comes into force, this work can reflect upon and integrate proposed changes into the flexibility auction.

Hidden Market Design In the context of this work, it is assumed that auction participants are aggregators which pool and market individual consumer or prosumer flexibility. While aggregators possess specialized and domain-specific expertise to act on a market such as the flexibility auction, individual entities may be faced with large obstacles. Such obstacles may include interaction cost and cognitive cost. The research of Seuken, Jain, and Parkes (2010) proposes *hidden market design* as an attempt to "[...] find new techniques and approaches towards designing and building 'hidden markets' for non-sophisticated users [and to] find the right trade-off between hiding or reducing some of the market complexities while maximizing economic efficiency attained in equilibrium". In line with this challenge, future research on the flexibility auction has to consider abstracting from the compact bidding language and provide graphical user interfaces (GUIs) as intermediaries which take the user's cognitive cost into account and support truthful preference elicitation.

Decision Support Systems Decision support systems (DSSs) ideally represent a means to facilitate and to strengthen individual consumer or household participation in the flexibility auction. Hence, further research needs to be complemented by the design of (intelligent) DSSs. Such DSSs need to support direct market interaction as well as hidden markets. Moreover, they should avoid information overload and consequently display and query information from users in efficient ways. By means of learning algorithms based on artificial intelligence (AI), such interfaces could adjust themselves to individual user preferences and behavior such as recent interaction or electricity usage. In addition, algorithms need to account for non-stationary behavior and determine the right point in time to inquire the user about updated information on their preferences.

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