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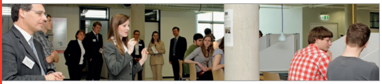

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DESIGN CONSIDERATIONS AND FUNCTIONAL ANALYSIS OF LOCAL RESERVE ENERGY MARKETS FOR DISTRIBUTED GENERATION

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FCN | Future Energy Consumer Needs and Behavior

RWTHAACHEN UNIVERSITY

Design considerations and functional analysis of local reserve energy markets for distributed generation

Von der Fakultät für Wirtschaftswissenschaften der Rheinisch-Westfälischen Technischen Hochschule Aachen zur Erlangung des akademischen Grades einer Doktorin der Wirtschafts- und Sozialwissenschaften genehmigte Dissertation

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Chapter 1

Introduction

Nowadays, everyday life would be inconceivable without electrical energy. It is ubiquitously relevant to the products we use, to the food we consume, and, of course, to the houses we live in. With permanent and reliable availability it fuels the engine of modern society. It has influenced our social interactions and opened up new channels of communication. A lack of supply would, therefore, endanger not only our lifestyle, but also threaten the basic *functionality of society*. Over the last century, the relevance of electricity has drastically increased and its usage has widened. At the same time, sources for generation have multiplied, starting with mainly fossil fuels in the very beginning, moving on to nuclear, and recently including more and more renewable sources. Among these, solar and wind power have experienced the most important upsurge. The *increasing share of renewables* in energy generation offers great opportunities in many areas. In the coming years, they will enable increasing political and economic independence from fossil fuels, and will secure the energy supply in case fuel imports should cease. Also, since abundant sun and wind are available, renewables will provide an affordable basis for production as well as a *sustainable future*. However, the growing presence of renewables also imposes challenges on the current energy system, on grids and on market mechanisms, which have all evolved over many years to cater for conventional, centralized technologies. The *security of supply* might suffer, and new concepts to ensure a *reliable grid operation* are needed.

While the topic has found its way into almost all disciplines in research, its societal relevance is proven by its high media coverage. During the liberalization of the electricity market in Germany in the 1990s, newspapers of record primarily discussed the economic consequences and daily events related to the expected developments. The focus hereby was on the future of local utility companies as well as on the larger merger and acquisition activities of the time (e.g. FAZ, 1999a, 2000a,b; ZEIT, 2000). Simultaneously, political and economic discussions on the implementation of the European energy exchanges (such as the EEX in Leipzig, which emerged in 2002 from two precedents founded in 2000) provided the basis for public discussions with an emphasis on market-design issues (e.g. FAZ, 1999c; Welt, 1999). The newly to be organized competition on the electricity market nurtured observations of the development in legislative and industrial processes (e.g. FAZ, 1999b, 2000a, 2002b,a). Shortly after this, media attention shifted towards the sustainability of energy generation and the first nuclear phaseout, which had been promoted from 1998 onwards by the then red-green government (e.g. taz, 2009; SZ, 1999; FAZ, 2003a,c, 2004c, 2005a). Already in those days, the security of supply found wide interest and concern in the public. On the one hand, due to the planned nuclear phaseout an upcoming supply gap was perceived. On the other hand, the coming into force of the German Renewable Energy Act signalized a dramatic change in the energy mix (e.g. SZ, 2005; FAZ, 2003b, 2004a,b, 2005a, 2006b). Also, other alternatives for energy generation, such as the construction of new coal power plants with integrated heat production (combined heat and power, CHP), made it into public discussion. While much attention was still focused on the daily developments of utility companies, in the same period there was just as much a fundamental discussion of the generation technologies and possible ways to a higher share of the so-called renewables (e.g Welt, 2006; FAZ, 2004b, 2005b, 2006a). In later years, political as well as public discussion in the field of energy shifted towards the topic of climate change and global warming (e.g. taz, 2005). While rising electricity prices and their consequences for energy-intensive industries have been scrutinized during the first amendment to the German Renewable Energy Act, rising electricity prices for private households gained in public interest shortly afterwards (e.g. Welt, 2009).

In conclusion, one can say that there was not only enthusiasm about the new political and technological developments, but also critical reviews, especially concerning the *financial burden* resulting from the great number of promotion and subsidy schemes as well as regulation for “green” energy. While some newspapers still express the fascination that a future with renewable energy can spark, most German newspapers tend to worry about rising costs for public transport, the affordability of building refurbishments, and Germany as a location for energy-intensive industries.

With the goal and the reality of an increasing share of (distributed) renewable energy generation, many of the recent research efforts in the field concern possible ways of adequately integrating them into the existing energy system or, alternatively, adapting the existing system to the requirements of this type of energy. Approaches hereby can be manifold. They are not only influenced by political decisions on many levels (international, national, regional), but also by the latest developments in the areas of electrical and mechanical engineering (one can think of grids, transformers, and turbines), chemistry (batteries), geophysics (geothermal energy) as well as the information and communication sciences (grid protocols, smart grids/meters). Above all this, there are resourceful entrepreneurs, who constantly come up with fresh ideas and business models that shape the energy landscape.

There are two related solution concepts that have found particular attention, namely *microgrids* and *virtual power plants*. A lot of technical issues concerning their installation have been examined. Some authors consider a multi-agent system that determines the timing and the extent of power sales or acquisition "jointly", according to the parameters set by the system, i.e. the system is controlled using a multi-agent approach. These agents have similar or opposing interests, which are solved in negotiations (cf. Dimeas and Hatziargyriou, 2007). However, it is not clear what the negotiations look like and which rules they follow. One way to organize such negotiations is by introducing a market. For microgrids or virtual power plants, it can be called a "local" market due to its scope. When being implemented in a microgrid, it can be limited geographically, while its application in a virtual power plant would mean a limit in terms of the number of participants. The concepts of microgrids and virtual power plants are closely related, because in both cases a target value for energy production needs to be defined. The main difference is that in a microgrid, this value is determined from an internal optimization, whereas for a virtual power plant, it is given by the sales volume, which results from external processes. Especially in Europe, the idea of microgrids has been promoted by islands with decentralized generation equipment that do not have an external grid connection and, therefore, do not profit from grid balancing mechanisms. In this "islanding mode", microgrids can thus sustain themselves, which has been recognized as being an advantageous feature also for areas connected to the general grid. In the case of grid disturbances, such as black-outs, a microgrid can encapsulate itself and remain stable (cf. Lasseter et al., 2002; Katiraei et al., 2005; Pecas Lopes et al., 2001, also for solutions that support such operation). Under normal conditions, it can operate as an open microgrid, i.e. interchanging as much electricity with the grid on the next higher level as desired. On the other hand, a virtual power plant is the aggregation of a fleet of generation devices that are operated to behave like a single large power plant. The main difference is that a virtual power plant is used to export electricity, for example for trading. Assuming that sufficient generation capacity is available, a microgrid can, therefore, be transformed into a virtual power plant by adjusting the target value.

This thesis builds upon the idea of a microgrid which connects households with and without electricity generation equipment and introduces a local reserve energy auction market, where such self-produced electricity can be traded. For evaluating and analyzing the proposed design, a simulation study and two experimental studies have been conducted. In the present chapter, the regulatory background, information on the current market framework, and some considerations that led to the chosen design of the local market are presented.

1.1 Perceived need for local energy markets

The need for local energy markets has previously been expressed in a number of articles. Hvleplund (2006) refers to the situation in Denmark, where wind turbines produce a lot of renewable, but fluctuating electricity. So far, during windy hours there was no other option than to sell the immense surplus electricity at low prices to other countries. While depressing payoffs of wind-farm operators, it can reduce acceptance of further fluctuating renewable energy in the long-term, which is counterproductive in the strive for more green energy and for the achievement of the *20-20-20 goals* set by the European Commission (20% reduction in greenhouse gas emissions, 20% increase in energy efficiency, 20% increase in renewable energy; (European Commission, 2008; a discussion can be found in e.g. Vasconcelos, 2008). Therefore, the author suggests introducing a decentralized market system that mirrors the decentralized nature of energy production and consumption, as opposed to the current centralized market system that mirrors the conventional centralized production procedure. In a decentralized system, local generators and consumers should be able to trade directly and without barriers with each other, thereby solving the issues related to renewable power fluctuations immediately in their own market. The reduced impact on the grid system and possible delays in expensive grid expansions are apparent.

Cardell (2007) even goes a step further. Her main objective is to enable the involvement of distributed resources in the power system. Changes in coordination and operations seem inevitable. Beyond recognizing the need for local markets, she proposes a price-based mechanism that could serve to coordinate the distributed power generation facilities. Her design is similar to the traditional load-based demand side management, where prices are used to trigger a response in load and thereby shave peak load demand. These time-of-use tariffs have been discussed in the context of the possibilities that a smart meter can offer upon roll-out (Siderius et al., 2004; Siderius and Dijkstra, 2006). However, for balancing, extensive data acquisition and processing is needed. This is used to calculate the price signals necessary to reach energy balance in an orchestrated way. The mechanism works via determining the market clearing price from the energy demand or the occurred difference to the balanced state and then sending it as a signal to the participating generators, which produce the required amount of energy accordingly.

Lund and Münster (2006) model the Danish market for the case of increased investments into wind power. They find that by embedding it in a system of micro-CHP plants, boilers and heat pumps, the supportable share in total power generation can be significantly increased. Even more interestingly, using this system intelligently to balance supply and demand, profits can be raised, yielding a total rate of return for the system of several hundred percent in their study.

The above mentioned studies show that local markets have been perceived as a necessary institution for a high share of distributed energy generation. So far, a solid mechanism for such a market as well as an analysis thereof are missing. This thesis aims at filling that gap by providing both a market design that fulfills the requirements of decentralized generation and the needs of the human market participants who run the equipment.

1.2 Regulatory framework for local energy supply and use in Germany

As already mentioned during the discussion of media coverage in the first section, the German energy market is highly regulated. Although *energy market liberalization* is also known as deregulation, this does not mean that the amount of regulations in the form of laws, acts, and rulings is really decreasing. In some areas, there is direct public involvement (such as the system usage fee), in other areas, there is indirect involvement through legislative provisions (such as unbundling), while in yet other areas, the involvement is limited to the usual antitrust efforts that apply to all sectors equally. In the following, I shall discuss how the current situation has evolved and what possibilities for the future result from this.

1.2.1 Historic development and current situation

The energy market liberalization in 1998 was meant to be the first step towards an internal market in electricity, which was agreed upon in the EC directive 96/92/EC (European Parliament and Council, 1996). To enable the European market, the formerly regulated markets of each country first needed to introduce a competitive basis. One of the cornerstones to achieve this has been the unbundling of vertically integrated undertakings. This means that enterprises engaged in generation cannot also be involved in distribution or grid operation. Specifically, the directive requires that the management and accounting for these activities be separate (Articles 7 and 14). The goal of this separation is to support competition by ensuring non-discriminating network entry, i.e.

use of the electricity grid. In Germany, the grid usage conditions are determined by individual negotiations.

These requirements entailed many changes for the German energy sector. Its foundation is the amendment of the *German Energy Industry Law* (Energiewirtschaftsgesetz EnWG, 1998, 2005)[1], a regulatory framework developed that is favorable for establishing local markets. Especially the introduction of *balance groups* in 2001 by a working group of six associations to enable fair competition on the then recently liberalized electricity market has supported this idea (BDI - Bundesverband der Deutschen Industrie e.V. et al., 2001). The concept of balance groups was transferred to the Electricity Grid Access Ordinance (Stromnetzzugangsverordnung StromNZV, 2005), which came into force in July 2005. The law states that within each control area, one or more grid users need to create balance groups. These can be utilities, industry, traders, and other entities. Each balance group needs a balance group responsible party who takes care of balanced drain and injection of electrical current in every quarter of an hour. Grid operators on every voltage level are obligated to deliver all data concerning billing and possible reductions in imbalances immediately. The balance group is created by the transmission grid operator upon request from a balance group responsible party. The balance groups can be established along one of the three contract modules referring to the grid, the end users, and trading.

The grid module has as its primary objective the introduction of grid balance groups for implementing federal regulation (StromNZV, 2005). These special balance groups are used for managing energy losses due to grid operation and for the transmission of energy that is fed-in from renewable sources. The most important task in these balance groups is to capture deviations of actual consumption from forecast consumption with the help of standardized load profiles.

The end user module regulates the distribution of energy. This way, the balance group responsible party can distribute energy from his own power plants or contracted power plants to end users within the control area of the transmission grid operator. He can also import energy from other balance groups or abroad. Note that this is completely independent from the grid in the sense of the unbundling regulation and rather refers to the accounting purposes necessary for distribution.

The trading module enables trading with other balance groups domestically, abroad, and at the stock exchange.

Beyond the creation of balance groups, the transmission grid operator compensates any irregularities that may occur. These may, for example, be due to the usual *stochastic*

[1] Please note that all laws are cited with the date they came into force. The dates they were agreed upon can be found in the bibliography.

imbalances of demand and supply irrespective of schedules or due to malfunctioning of power plants within a certain balance group. In order to prevent a black-out, the balance group responsible party receives help from the transmission grid operator. Compensation takes the form of reserve energy, which is procured centrally via the reserve energy market. The need to implement such a central market stems from the coming into force of the second EnWG and the StromNZV in July 2005. With only few guidelines given in these laws, further regulation has been necessary and falls within the remit of the Federal Network Agency ("Bundesnetzagentur"). Hereby, Ruling Chamber 6 ("Beschlusskammer 6") decides upon the details. An overview of the rulings that are relevant for balance groups or (local) reserve energy markets can be seen in Tables 1.1 and 1.2. These and all other rulings including their attachments can also be found on the website of the German Federal Network Agency (www.bundesnetzagentur.de).

The most important variables that have been determined are the timing and the procedure of the tendering process, including minimum bid sizes and increments, as well as the specifications about information to be published before and after the bidding. Besides the details of the market, also associated issues concerning the forecasting methods, the usage of reserve energy, the data exchange between the individual parties, and the billing have been sorted. In particular, the average price of each measuring period is billed to the balance group responsible party according to usage, which means that everyone pays the same price per kWh.

From the tables, one can also see the developments that have taken place. Although a common reserve energy market was already introduced in 2006, it took almost four more years before all transmission grid operators actually procured their reserve energy via that market (see Table 1.2, BK6-08-111). Once this had been achieved, the prevailing market rules were adjusted to ease the bidding process, while keeping in mind the interdependence of the reserve energy markets with other energy markets, such as the intraday and the day-ahead market.

In a long process involving many stakeholders, the German Federal Network Agency has worked towards an improvement of the billing procedures for balance groups by determining in more detail who has to provide which data at what point in time. This has been a result of the on-going complaints especially from grid users who asked for more detailed and binding specifications concerning data exchange, deadlines, data formats, as well as contract-related regulations (see Table 1.1, BK6-07-002).

Since 2012, the balance groups and reserve energy markets seem to be working well and remain free of complaints. This is at least the conclusion one can draw when looking at the rulings. In fact, a remarkably large portion of the rulings in 2013 and 2014 concern problems with grid access, especially for offshore wind farms.

Table 1.1: Rulings by the German Federal Network Agency in order of their reference number: Part 1/2

Reference no.	**Date**	**Contents**	**Details**
BK6-06-012	29-08-2006	Determination of procurement rules for tertiary reserve energy	Common procurement on a daily basis; further details for the procedure: gate closure times, minimum bid sizes (15 MW) and increments (1 MW), settlement rules, time slices, and requirements for publication of information about forecasts, demand, and bidding results
BK6-06-065	31-08-2007	Determination of procurement rules for primary reserve energy	Monthly procurement (dates to be determined for an entire year in advance), no time slices, minimum bid size (5 MW) and increments (1 MW), settlement rules, and requirements for publication of information about demand and bidding results
BK6-06-066	31-08-2007	Determination of procurement rules for secondary reserve energy	Monthly procurement (dates to be determined for an entire year in advance), two time slices, minimum bid size (10 MW) and increments (1 MW), settlement rules, and requirements for publication of information about demand and bidding results
BK6-07-002	10-06-2009	Determination of market rules for balance group clearance	Data exchange using EDIFACT, time series in MSCONS, consistent descriptions of business processes
BK6-08-006	21-10-2008	Procurement of compensation energy for grid losses and approach for determining grid losses	Procurement once a year, bidding procedure for the long-term component (can be forecast), short-term component contracted after bidding procedure (pricing with a variable pay determined by the EEX and a fixed pay); alternatively, both components can be procured via the energy exchange
BK6-08-226	12-05-2009	Regulation for balance groups according to the German Renewable Energy Act (EEG)	Rules for trading energy from renewables; procurement of “EEG”-reserve energy to overcome forecasting errors when there is not sufficient liquidity on the energy exchange: monthly procurement of positive and negative reserve, minimum bid size of 15 MW, publication of all details of the transactions

TABLE 1.2: Rulings by the German Federal Network Agency in order of their reference number: Part 2/2

Reference no.	**Date**	**Contents**	**Details**
BK6-08-111	16-03-2010	Employment of reserve energy for secondary and tertiary control	Integration of the last TSO in the common reserve energy market, coordination to prevent using opposing reserve energy types in different zones, adjustment of the amount of required reserve energy to the joint needs, calling the winners of the joint bidding process according to the merit-order of the energy prices
BK6-10-097	12-04-2011	Determination of procurement rules and publication requirements for primary reserve energy	Common weekly procurement every Tuesday for the following week for all control areas (dates to be determined for an entire year in advance), no time slices, minimum bid size (1 MW) and increments (1 MW), pooling, settlement rules, and requirements for publication of information about demand and bidding results
BK6-10-098	12-04-2011	Determination of procurement rules and publication requirements for secondary reserve energy	Common weekly procurement every Wednesday for the following week for all control areas (dates to be determined for an entire year in advance), two time slices, minimum bid size (5 MW) and increments (1 MW), pooling, settlement rules, and requirements for publication of information about demand and bidding results
BK6-10-099	18-10-2011	Determination of procurement rules and publication requirements for tertiary reserve energy	Common daily procurement for the following day for all control areas (dates to be determined for an entire year in advance), gate closure times, time slices, minimum bid size (5 MW, with indivisible chunks of up to 25 MW) and increments (1 MW), pooling, settlement rules, and requirements for publication of information about demand and bidding results
BK6-06-013	29-06-2011	Standard contract for balance groups	Avoidance of tedious negotiations with all individual balance group responsible parties; builds upon BK6-07-002
BK6-12-024	25-10-2012	Advancement of the billing system for the balance energy price	Specifications for the reBAP (balance energy price to be employed in all control areas), publication of calculations and billing details

1.2.2 Identification of regulatory amendment possibilities

The aforementioned balance groups can be seen as the current *administrative groundwork* for local energy markets. The idea here is that a balanced group does not need the services of the transmission grid operator and thereby might be able to save money as well as help renewable energy sources reach a wider diffusion. This also makes sense in terms of the cost of learning, as distributed resources are mainly locally operated. This means that operators, such as city utilities, are re-empowered and given a greater degree of self-determination.

Although one could argue that the local procurement of reserve energy does not comply with the unbundling regulation, it is actually an expansion of the procurement of compensation energy for grid losses, which all grid operators with more than 100,000 customers already need to organize for themselves (StromNZV, 2005, §10; BK6-08-006). From a legislative point of view, only utilities with a similar size should be required to establish a local market. This also means that the additional administrative burden can be well estimated, as experience with the operation of compensation energy markets has already been accumulated. However, this should not suggest that only local utilities are eligible as local market operators. Other players, such as locally owned energy service companies, can serve the same purpose.

Recent studies have brought forward similar ideas. Corn et al. (2014), for example, suggest implementing an internal market in balance groups, where the balance group responsible party can control producers and consumers of energy to keep his group in balance. For this purpose, the producers and consumers are assumed to submit flexible offers that cover a certain period of time during which the cheapest are called whenever necessary. A related concept is presented in Ridder et al. (2011), who analyze several business cases to better integrate decentralized energy. They also follow the idea of clustering consumers and producers who trade their demand and supply first among themselves and subsequently (if no match can be found) on a higher level market.

The United Kingdom recently has also taken a step in that direction. The Department of Energy and Climate Change has launched the "Community Energy" strategy[2], which aims for communities to take on more responsibility in energy usage and procurement. There is a £15 million fund (approximately €19) open for rural communities and a £10 million fund (approximately €12.7) for non-rural communities. Energy projects can take many forms, such as the installation of equipment for renewable energy, building insulation, the use of smart technologies, and collective purchases of energy. But most

[2]https://www.gov.uk/community-energy

importantly, this strategy is also meant to facilitate local trading of energy, supporting the ideas delivered in this thesis.

1.3 Markets and other ways to keep the system balanced

The dilemma with electricity from renewables is that it is not always produced when it is needed. Photovoltaics provide electricity when it is sunny, meaning that other sources need to be tapped during evening and night hours. Wind turbines produce energy when it is windy - a weather condition which cannot reliably be predicted until one or two days ahead - and therefore without balancing mechanisms, are not useful as a main energy source. Altogether, productivity of many renewable energy sources depends on external conditions, cannot be controlled for and, therefore, needs compensation mechanisms.

1.3.1 Options to balance fluctuations

One possibility would be the extensive use of *storage*. Scenarios include load management at the generation site or within the grid, load shaving at the consumers' sites, as well as frequency control and integration of renewables. In the course of an enhanced diffusion of electric vehicles with large storage batteries, flexible storage could be handled in a distributed way and could offer an additional advantage of electric fleets (Raths et al., 2013). For stand-alone applications, however, due to the currently high investment costs for such batteries, only the employment as primary reserve energy is profitable, at least at the current price level for (reserve) energy (e.g. Ohler and Chartouni, 2007). Lund et al. (2012) even completely oppose the use of electrical storage due to economic reasons and rather promote the application of system solutions including several technologies that can adjust their production or consumption.

Hydropower would be an optimal option, but capacities in Germany are not sufficient for this purpose and it is uncertain in how far they can be extended, mainly in terms of geographical possibilities, but also in terms of social acceptance (cf. debates at Rursee, North-Rhine Westphalia, rettet-den-rursee.de). However, a promising study has been conducted in Baden-Württemberg. While considering ecological, technical, and economic constraints, it has been found that the existing 68 MW can be extended by another 25 to 32 MW. On the one hand, this includes retrofitting existing plants and, on the other hand, building new plants at suitable sites (Heimerl et al., 2010). The main potential is, however, in small hydro power plants, which are also subsidized by the Renewable Energy Act.

1.3.2 Market design of the general reserve energy market

Before examining the possible design of a local market, it is useful to understand how the superordinate reserve energy market works. Since all analyses in this thesis have been developed and conducted within the context of the German legislation, and therefore, the German reserve energy market, this section only deals with the German design. It should be noted though that all European markets have similar properties and that all need to comply with the regulation put forward by the Union for the Co-ordination of Transmission of Electricity (2004).

The general reserve market uses a *multi-unit auction* design with *discriminatory pricing*. This means that in each separate auction, several units of the same (identical) good are procured and remunerated with varying prices. Each bidder submits a vector of bids, stating his willingness to supply a certain amount of energy at a certain price. Payment occurs according to the individual bid (pay-as-bid rule). The unique design in the German market is that two bids are submitted, one stating the energy price and one stating the capacity price. Winning bidders are determined according to a merit order rule. They are, thus, sorted in decreasing order of their capacity bids until the required amount of capacity is procured. Once their services are needed, they are called up in decreasing order of their energy bid. This bears some opportunity for strategic bidding, as a relatively low capacity bid combined with a high energy bid can bring income without the need to actually deliver, i.e. without incurring other costs than opportunity costs for withholding capacity. More information on this issue can be found on the joint website of the Transmission Grid Operators (www.regelleistung.net) and in Chapter 2.

Fortunately, the number of suppliers participating in the markets rose. As of July 2014, twenty suppliers completed the prequalification process for primary reserve, 27 for secondary reserve, and 38 for minute reserve. The situation was much denser in the past, with evidence that the four big German players (E.ON, RWE, EnBW, and Vattenfall) were able to exert their market power in the minute reserve market. Growitsch et al. (2010) found that these four dominate the market in all products (different time slots, positive and negative reserve) with a combined market share of 69% to 94%, respectively. The then only 24 fringe suppliers sharing a quarter of the revenues of the entire market had no means to exert market power. An indication for the fact that the four big players could abuse their position has been found in the frequency with which they gained higher revenues than the fringe players. Due to a change in the data policy, which prohibits the publication of information that can be used to trace back the identity of the bidders, there are no recent studies available on this issue.

A general criticism of the reserve energy market is that *entry barriers* are high, which induces low levels of liquidity in the markets. Before 2007, all transmission grid operators procured their own reserve energy, each using a separate platform. This made the markets nontransparent and prone to collusion as well as other strategic behavior, for example resulting from different market closing times (cf. Swider and Weber, 2003). Although the situation has improved since then, the qualification procedure is still deemed to be complicated, taking too much time and therefore being very costly.

1.3.3 Properties of local energy markets

To date, the local energy market is a theoretical construct. Nevertheless, it has some definite characteristics that result from the specific technologies and their users. The predominant attribute is the involvement of households, i.e. end customers without much expertise in the field of energy or trading. Rules need to be very clear-cut and understandable to create something comparable to an *"energy-eBay"*.

The participants can be described as "prosumers", which is a combination of producer and consumer. The term was coined by Toffler (1980), who predicts a sharp decrease in importance of the markets as we know them. A reason for this is that people are no longer willing to pay for products and services which they can easily produce themselves with or without guidance. Ritzer and Jurgenson (2010) claim that this is not a recent phenomenon, but had started to develop in the 1950s and 1960s with the rise of shopping malls and fast-food restaurants. Here, the consumer is actively involved in the production process by taking over certain tasks, such as filling up his glass with a soft drink. This is, of course, a very early and different form of what we are observing today. Since the start of Web 2.0, prosumption has experienced a great spurt. Prosumers have become more independent from producers - who used to be required for the necessary infrastructure - and are beginning to see themselves on the same level.

Related concepts are discussed in Sauter and Watson (2007). They describe the fact that consumers also produce energy as "co-construction", "co-production", and "co-provision". The latter term was also coined during the 1980s, when the American government had to sharply cut back fiscal spending. With an upcoming discussion about privatization, it became clear that several tasks and services that had formerly been carried out by governmental agencies now had to be delivered by individuals or groups of citizens in the sense of co-provision or co-production (Ferris, 1984; Mattson, 1986; Brudney, 1987). Humphreys and Grayson (2008) add "co-creation" to the list and argue that there is potential for a fundamental change in the organization of the economy, much along the lines of Toffler (1980), but with a critical view on capitalism.

There are also technically-oriented definitions of the "prosumer". Kanchev et al. (2011) describe a prosumer as a home application that produces power during some hours of the day and consumes power during others. The home application then consists of a number of individual entities, such as solar panels, storage systems, and controllable loads. While Karnouskos (2011) sees the residential prosumer as the most important stakeholder in a smart grid and related markets, he also points out the commercial prosumer. According to his definition, these are large facilities, such as factories, that both produce and consume energy. Once a local energy market is operational, these larger players can be allocated to one of the markets for collaboration.

The market described in this thesis is defined by a possibly small number of participants, which can be expected to grow in the case of profitability, with a natural limit in the size of the balance group. This becomes even more prevalent if investment costs can be recouped quickly. However, the market's appeal also depends on the development of household energy prices, as it is certainly not profitable to use the equipment for reserve energy only. The main use should remain the *self-supply of energy* for the individual household. Legislation and incentive programs can also have a great influence. They make investment more attractive by offering advantageous financing conditions and often direct remuneration. In 2009, the self-consumption rule was introduced to the German Renewable Energy Act (EEG, 2009, §33, 2). This made externally purchased energy non-competitive, and also rendered storage more attractive. Since 2012, this special compensation is no longer available, because grid parity of solar power has been reached, and PV owners would otherwise be paid to consume energy (EEG, 2012). Instead, the EEG 2012 introduced the market premium scheme in §33g, which is meant to incentivize prosumers to sell their self-produced energy directly to a third party, for example at the energy exchange (EEX) or in a local market. Since August 2014, the feed-in tariffs have been drastically cut back (EEG, 2014), such that one should start thinking about new ways to incentivize investments in distributed renewable energy generation. A local market that offers some remuneration for self-produced energy might be a suitable instrument. Beyond the financial incentive, the political support inherent in such a market (or any other support mechanism) enhances a positive attitude towards specific technologies, making their adoption more likely.

Entry barriers should be constructed to be low, especially when compared to the superordinate reserve energy market. This is given by short lines of communication, which ensure that the qualification procedure will take less time and be less complicated. In fact, the balance group responsible party could develop standard procedures that are easy to check on a supra-regional basis. As reserve providers are thought to be mainly private households, short catalogs could mention technologies and manufacturers that are generally eligible for balancing. In some cases, additional information technology might be needed to fulfill communication needs, especially for calling the reserve energy when needed. This can be solved by providing a list of standard equipment that needs to be installed before market participation can be allowed. With proceeding roll-out of smart meters, some of the information and communication needs can be readily provided with a minor software update. Additionally, a business case could develop for contracting or at least retailing equipment, especially when the balance group responsible party is a utility having considerable experience in customer support and service.

Substitutes for the locally procured reserve energy are the reserves from the superordinate reserve energy market. As these are expected to be more expensive, they can be disregarded in the analysis. Should they become competitive, it might be of ecological interest to give priority to distributed resources by law. This could be done in an amendment to the existing law for feed-in of energy from renewable resources, which would then need to be expanded to reserve energy (on this issue, cf. Chapter 2, modeling part). Although significant interdependencies can be expected to arise between the local reserve energy market (especially upon a widespread roll-out) and the superordinate reserve energy market, these impacts are not part of the current analysis. Their evaluation requires a joint model of the superordinate market and the local market, which is beyond the interest and the scope of this thesis, as it also needs to incorporate strategic behavior and market positioning issues of energy companies. So far, these companies have not played a significant role in the analysis of a suitable local market for household producers.

1.3.4 Auction design for a local market

While the auction design for our particular market is explained at length in Chapters 2 and 4, some general issues and considerations leading to the choices made should be already introduced here.

For multi-unit or divisible good auctions, there exist multiple pricing mechanisms, which all have their particular advantages and disadvantages. The most common ones are uniform and discriminatory pricing. While bidders receive exactly what they bid under discriminatory pricing, uniform pricing ensures that most receive a higher payment than what they bid. The disadvantages are apparent, however: Bidding stops being cost-revealing, which means that not necessarily the least cost-intensive and most efficient plants win the auction. In the context of ameliorating the incentive situation for small-scale power production within households, this might be just a minor drawback.

In order to generate some profit for the suppliers on the one hand, but induce them to bid sincerely on the other hand, the Vickrey auction design has been proposed. For the multi-unit case, this means that the bidder is paid the last bids that would have been accepted if he had not taken part in the auction (Berninghaus et al., 2006). This is often described as the lowest losing bid(s), which is not correct, as this is not supposed to be a unit-price auction with a pay-out table. An alternative with similar properties is the Ausubel auction (Ausubel, 2004). However, both auction designs might not be very well understood. Even for the relatively straightforward second-price auction, it has been found that bidders do not bid according to their (theoretically) dominant strategy, because it is too difficult for them to see what this strategy might be (Kagel and Levin, 1993). In addition, being paid a price that differs with a non-constant value from the amount bid, even if this value is positive, might lead to distrust against the bidding system and a lower rate of acceptance impacting the participation in reserve provision.

Drawing together the evidence, we find that the optimal auction would be a discriminatory first-price auction. In comparison to the uniform-price auction design it also has the advantage of reducing the possibility of collusion, as price manipulation can be more easily detected. For further discussion of the pricing rules, please also consult the literature review in Chapter 2.

In the superordinate reserve energy procurement auctions, bidders do not only bid with a certain amount of capacity, but also with two types of prices. These are used to remunerate the opportunity cost of reserving capacity on the one hand and, in the case of being called up, to remunerate the cost of producing energy. In this case, the opportunity cost is just the cost of not selling energy somewhere else for sure (for example at the spot market) minus the cost of production plus the cost of keeping the plant on standby to be quickly operational when the reserve is actually needed.

A household has a similar cost structure except that it would not necessarily sell the energy on a different market, but might use it itself. The *opportunity cost* is thus determined by the availability of energy or the amount of discomfort a household might experience when giving up some of the energy that was meant to be used within the household. The second component differs with the technology in use, but also with its respective efficiency. For battery storage systems, this would be wear-out cost and, if connected to a distributed generation device in the same household, energy production cost from this device, otherwise procurement cost of external energy to be stored. Beyond this, the battery can also be used for primary reserve, which is the most expensive reserve category. Considerable gains can, thus, be expected in this form of application.

For a CHP unit, wear-out costs, as well as maintenance cost, also applies, while energy production cost is determined from fuel prices. The size of the CHP unit is typically about 1 kW electrical capacity.

Using a PV system for reserve energy entails some risk, as energy production at a particular point in time is uncertain. To prevent consequences for the system, high penalties should apply for violating the reserve contract. This means that a risk-averse PV owner should only participate in the market when he also possesses a storage system. The bid for power from such a system would, therefore, encompass not only the usual wear-out and maintenance costs, but also a risk premium in case the battery needs to be used, as battery power is more expensive. A risk-neutral PV owner can bid without a risk premium when weather forecasts are favorable. A very important difference when trying to determine the efficient market outcome is that it is not necessary or required to find those units that incur the lowest generating costs, but to find those bidders to whom it is the least costly to provide energy at a certain point in time. The objective is, thus, not to save as much fuel as possible, but to support some level of *comfort*, which is valued very highly by consumers (cf. Siderius and Dijkstra, 2006). The ecological impact does not suffer from this, as all technologies in use are energy-efficient and/or renewable, and are to be supported by their additional use as reserve energy providers.

Furthermore, the technologies that can be and are applied in households have very unequal cost structures. It might, therefore, be useful to have separate auctions for each technology in order to foster fair competition. The downside is, of course, that the already low expected number of participants drops even further. However, if the bidding process is not adjusted to the individual technology, returns might not cover costs any longer, let alone give an appropriate profit premium. Comparing this to the current incentive scheme for solar panels in the Renewable Energy Act, it can be expected to be well-received by households. This is also supported by the survey that we did after conducting the experiments (results can be found in Chapter 5).

Also, the policy of *information disclosure* can have a significant impact on the efficiency and effectiveness of a market. For the local reserve energy market, a similar approach as for the grid loss energy market can be recommended.

Concluding, the general goal of this thesis is to find the optimal auction design for a local reserve energy market. This can be broken down into more specific *research questions* on the respective impacts of

- the amount of feedback information,
- the amount of competition,
- and the number of bids that can be submitted

on the auction outcome and on the bidding behavior. As mentioned before, the focus is always on small prosumers, i.e. private households with their own generation equipment, and the research questions are to be answered in the context of their specific characteristics.

1.4 Impact on parties involved

The introduction of local markets would have important consequences for several stakeholders. The main *stakeholders* are the government, private households, the transmission grid operators, the distribution grid operators, and utilities or energy service companies.

The *government* plays a crucial role in establishing the market, determining its conditions, and mediating the interactions. If the market works fine, it might make sense to reduce the subsidies to rely more and more on competitive forces. However, it is necessary to always control for the financial reliability that consumers experience with the set-up. If this cannot be achieved with a pure market mechanism, some form of intervention might be required.

In general, however, local energy markets are a way to empower consumers and to make household investments in distributed generation more attractive. Economic benefits should not be overstated, though. Selling reserve energy does not mean great fortunes can be earned. It is only meant to support the maintenance of a device that has already been bought and to make an investment in such a device more attractive upfront by offering different, additional uses.

For *balance group responsible parties*, the biggest change would happen. Of course, it is much easier to have reserve energy procured by a third party. Nevertheless, there might be some real economic benefits in procuring it locally. So far, utilities and energy service companies were only able to offer contracting models for generation equipment, with which they could participate in the superordinate reserve energy markets. Also, even here application has been very limited and mainly been available for industrial consumers, such as hospitals[3]. This is because investment costs are still very high and each customer needs to undergo an individual application procedure. With a general framework and easy-to-use catalogs, as presented above, these costs can be significantly reduced.

Beyond their activities as balance group responsible parties in their grid subsidiaries, which is also the traditional core business for *utilities*, the operation of district heating

[3]cf. Stadtwerke Düsseldorf, program for emergency units "Notstrom effizient", more information can be found on their website: http://www.swd-ag.de/geschaeftskunden/contracting/contracting_produkte/minutenreserve.php

grids and heat supply as well as supply of electricity and gas are likely to be affected. This is due to the expected growth in diffusion of distributed generation, which implies extended home energy production. Their role as energy suppliers could be reduced to providing electricity for heat pumps and gas for combined heat and power generators only. Another traditional field of activity is customer support, service, and advice. As demand for assistance in finding the right combination of energy saving measures and distributed generation possibilities or arrangements can be expected, this would also be an area of growth for utilities.

Focusing on the role as *distribution grid operator* only, they become decisive in local markets. As balance group responsible parties, they gain from not calling on control energy from the superordinate market, which is expensive. Furthermore, they need to send the signal for starting production of reserve energy. The communication between the generation devices and the auctioning process could be done by the grid operator himself or by an independent service company, subcontracted to the grid operator, much like the way metering is done nowadays.

The responsibility and the trade volume that are taken over by balance groups are at the same time subtracted from the superordinated reserve energy market. This means that transmission grid operators lose part of their influence. When local markets are used to counterbalance wind power parks, as suggested by Lund and Münster (2006), grid expansions might be reduced, which further diminishes the role transmission grid operators play in the energy system.

1.5 Contributions

In this doctoral thesis, a local market for reserve energy is proposed and evaluated. It can complement the existing market and help to better integrate decentralized generation. Hereby, the general idea of a multi-agent system persists, i.e. there are independent agents that try to maximize their individual payoffs. Germany, which has a leading position in the advancement of renewable energy, seems to be an appropriate model setting. In the following chapters, all of which are based on *journal articles* that have already been either published or submitted for review, distinct aspects of a local market are considered. Using the simulation study and two laboratory experiments, the optimal amount of information provision and the optimal number of bids have been analyzed. The underlying auction mechanism embraces the specific characteristics of a small market as well as the needs of household-producers, a group that is also known as prosumers.

The first paper, *"An Auction Mechanism for Local Reserve Energy Markets"*, explains the basic theoretical framework and the underlying design choices made. The focus is hereby on creating a market that is accessible and easy to understand for private households. Using a simple agent-based simulation program, the theoretical predictions of the proposed market are evaluated. The contribution of this paper is therefore twofold. On the one hand, it adds to the theoretical literature on energy market design by offering an auction design that takes into account a number of features specific to energy as a good and the prosumer as a market participant. On the other hand, it adds to the literature on agent-based energy market simulation, which has been dominated by technically-driven simulation platforms that model generation units in detail, but lack a sound economic basis. In this paper, the opposite approach has been taken by modeling the market and the behavior of the bidders in detail, but disregarding technological features of the equipment in use. Bidders can submit partially differentiable bid functions and react to the given information by adjusting this function. The findings suggest that the lack of information has a long-term effect on the market. With limited information, the convergence to the cost level not only takes longer, but also ceases on a higher price level. This price is then sustained indefinitely.

The effect of information is further addressed in the second paper, *"The Role of Information Feedback in Local Reserve Energy Auction Markets"*. Beyond the direct effect on prices, more insight is given on the issue of learning in repeated auctions. There already exist a number of theoretical and experimental studies in this field, but their application has so far been limited to single-unit first price auctions. This paper adds to the literature by dealing with this topic in the context of divisible good auctions. Using existing theories, most of the bidding behavior can be accurately predicted. However, the learning direction theory can only be partially confirmed for the divisible good auction. It offers good insights into the general movements of bids, but there seem to be other forces or strategies at work as well. At least with information displayed, behavior can also be explained by signaling efforts and anchoring on published prices. Despite the substantial amount of rounds and even with extensive feedback, no signs of successful collusion can be detected.

While building upon the same idea and the same basic theoretical framework, the third paper, *"Multiple vs. Single Bids in Reserve Energy Auctions: An Experimental Analysis"*, is broader in scope and derives results that are in principle applicable to all divisible good auctions. The theoretical framework is adapted in such a way that it allows for discrete bids. This results not only from its contribution to the auction literature, but also from the observation that in most real-world auctions rules often require minimum bid sizes. Even in an experimental setting, the submission of continuous bid functions is hardly possible. Given the complexity of deriving the necessary parameters, participants cannot be expected to adjust entire bidding functions in a way to increase their pay-offs. When decisions cannot be properly linked to outcomes, an experiment risks producing unreliable results, which do not help to give insights into theories or to understand human behavior. Theoretical considerations suggest that bidders should submit only one bid to maximize their profit, also given the opportunity of submitting multiple bids. Nevertheless, in most cases, bidders take the opportunity and submit two non-identical bids. Markets which allow multiple bids are less volatile, but offer lower profits for bidders.

The contributions of this thesis can be summarized as follows:

- modeling and analysis of an innovative local reserve energy market
- economically motivated agent-based energy market simulation
- experimental evaluation of the effect of the number of discrete bids on the auction outcome
- experimental confirmation of the learning direction theory in the context of divisible good auctions
- identification of the role of signaling and anchoring in the same context

1.6 Limitations

The major limitation lies in the auction design itself. It needs to be kept simple to be easily conveyable to non-expert consumers. Therefore, there might be room for welfare-enhancement through adjusting the process. Moreover, there is political pressure to extend the *district heating* network in Germany. The envisaged goal is a coverage of 60% of households. This leaves only 40% as possible locations for micro-CHP, because the heating demand of all other households would be fulfilled. Micro-CHP is important for balancing, because the engines can be turned on whenever necessary. From an ecological point of view, there is not necessarily a difference: District heating often uses the heat from large CHP plants. Furthermore, it should be obvious that a strong preference for local generation might be welfare distorting. This is because competition can only occur within very limited frames, which means that since it is not necessarily the plant with the lowest overall cost producing energy, this decreases global efficiency. On the other hand, with large power plants there are also economies of scale, which are foregone when switching to smaller, decentralized generation plants.

A further limitation may be found in the way the experiments were conducted. Participants were mainly students, who might not represent the attitudes and preferences of the actual market participants, i.e. homeowners with decentralized generation equipment. It is therefore possible that these would have reacted differently (this issue is also discussed in Chapter 5). In general, an experiment can only be used to examine certain features of a market. A real-world implementation of the proposed auction might therefore produce different results and encounter issues not thought of before.

These limitations can also be understood as further scope for research in several disciplines. With empirical models, the diffusion of the technologies used for local generation and the acceptance of homeowners can be analyzed. This can be extended by an estimation of the chances for a local market and the possible number of participants in different regions. Hereby, also the effects of restrictions due to district heating can be evaluated. In a simulation using standard or historic load profiles and the feed-in of the (potential) participants in a region, it can be evaluated whether there is a sufficient match of demand and supply. In terms of the necessary infrastructure to implement a local market in a specific area, much can be learned from recent smart grid efforts. It would therefore be interesting to put the local market to practice in a field test. In this context, communication protocols and other safety critical aspects can be examined. While doing so, it is also important to protect the data privacy of the participants.

1.7 Structure of the dissertation

In the following, three essays are presented, each of which has either been published by or submitted for review by high quality journals.

Chapter 2 is based on a paper published in 2013 in *Decision Support Systems*, 56:1, 168-179. It describes the auction design in more detail and tests it in an agent-based simulation. This way, several degrees of information can be investigated for many bidders over a longer period of time. I find that when no information is provided, the market outcome remains on a higher level indefinitely. To further examine the validity of this finding and to find out how human bidders react to the proposed design, I conducted several experiments.

Chapter 3 is based on a paper published in the FCN Working Paper Series (*FCN Working Paper No. 15/2013, revised May 2014*). It deals with the same question as Chapter 2, i.e. how information feedback makes a difference, but with human bidders instead of simulated agents.

A more fundamental design question is answered in Chapter 4, which evaluates the impact of allowing bidders to submit one or two bids in a divisible good auction. The chapter is based on a paper published in the FCN Working Paper Series (*FCN Working Paper No. 8/2013, revised November 2013*).

Chapter 5 provides some insights into socio-demographic differences in bidding and evaluates the chances of a local market in a real-world setting.

Please note that some of the chapters have individual appendices, which are referred to in the chapter and might be necessary for understanding some of the details within that specific chapter. At the end of this thesis, there is also a general Appendix. It contains the material used for conducting the experiments, i.e. both versions of the instructions and the questionnaire. These are not essential for understanding the individual chapters, but should be provided for completeness.

Chapter 2

An Auction Design for Local Reserve Energy Markets

Abstract

In this paper we develop an auction mechanism that is designed for a local energy market. It aims to enable regionally or virtually restricted trading of ancillary services, which enhances the position of the balance group responsible party beyond that of simple accounting. Furthermore, it makes local market participants somewhat more independent from the transmission grid operator, but at the same time provides incentives for investments in distributed generation technologies. A wider spread of these technologies can help to save CO_2 emissions, while at the same time a part of them can also be used to counter the fluctuations of energy from volatile renewable sources, such as wind and solar power. Because of their relatively high margins and small share in total production, ancillary services are well-suited for a remuneration scheme. Participants in the auction are, thus, private households, which impose specific design characteristics on the auction. Most importantly, it needs to be transparent and easy to understand, as homeowners will typically not have the insights of a professional trader as well as lack a similar position and motivation. Also, the confinement to a single balance group, i.e. a local market, means that especially in the beginning of the trading only a small number of bidders can be expected. Therefore, competition will initially be limited, so that the auction design needs to be adapted accordingly. In order to test the performance of the proposed auction market design under varying information policies, a simple agent-based simulation program has been developed. We find that the theoretical predictions hold and that competition quickly leads to price convergence.

2.1 Introduction

In recent years ancillary services in electricity markets and especially such providing reserve energy have received increasing attention. This is due to several facts. First of all, the increase of the share of unpredictably fluctuating renewable energy in total energy production has led to a higher demand for reserve capacities to buffer those fluctuations. Secondly, new technological and societal developments have started to offer new ways of meeting this demand. Smaller and larger consumers can offer some of their loads and capacities to external control or even offer load adjustments at certain times of the day themselves. They can further participate in virtual power plants (VPPs) to sell power produced in large numbers of small-scale, distributed home devices, such as micro combined-heat-and-power (CHP) plants or photovoltaics. So far, this has been limited to the trade of real power. Balancing energy market mechanisms have only been examined in pilot projects with microgrids, i.e. only under these special circumstances has household energy been used as reserve energy.

The purpose of this paper is to show how in current circumstances decentralized generation can be used beneficially for a regional energy system with an appropriate auction design. In particular, this paper aims at determining a valid auction mechanism that suits a local reserve energy market with all its special needs and characteristics, as discussed below. Once this mechanism is defined, it needs to be evaluated as to how bidders in such a market behave over time. The details with respect to how this mechanism can eventually be implemented optimally are side issues and will, therefore, only be treated briefly.

Keeping in mind the characteristics of bidders in a local energy auction, the problem that needs to be solved is, thus, to find an adequate and reliable remuneration for each provider of reserve capacity and energy. At the same time, the auction mechanism needs to be as simple and easily understandable as possible in order not to turn down potential participants, while reducing opportunities for strategic behavior to a minimum. Moreover, transaction costs in a market with such small quantities need to be low in order to leave room for at least a minimal profit. The analysis of an auction for such a matter entails many parts. Electricity auctions are a specific type of auction because the good is perfectly divisible and non-storable, which means transactions need to happen in real time or at least at a predefined point of time in the future. This type of auction can be compared to the treasury auction, which has received considerable scientific attention in the past. So far, game-theoretic analyses of reserve auctions with the properties needed in a local market are very limited.

The remainder of the paper is structured as follows: In Section 2.2, the literature on theoretical analysis, electricity auctions, and reserve energy auctions is reviewed. In Section 2.3, the market is briefly described as a preparation of the auction model, which is explained in the same section. It is presented for both the asymmetric and the symmetric case and solved accordingly. Section 2.4 introduces the simulation and theoretical considerations of the strategies implemented, and the results of the simulation. Section 2.5 explains the technical backgrounds of the simulations well as the results obtained. Section 2.6 provides a conclusion and some suggestions for future research.

2.2 Literature review

The liberalization of the electricity sector has fueled the desire to analyze markets and the behavior of market participants. Due to the complex nature of the good itself, each individual market and the interaction of several markets for different energy products have set strong limitations on analytical methods. Therefore, simulations have very quickly gained acceptance in this field.

Many different kinds of electricity market models are possible. Ventosa et al. (2005) classify them as optimization models, equilibrium models, and simulation models, whereby simulation models can either be derived from equilibrium models or formulated as agent-based models. The main difference between these two is the static nature of the approach in the first case and the dynamic approach in the second. Sensfuß et al. (2007) categorize these agent-based models as tools to analyze market power and market design, agent decisions and learning, and the interdependence of short-term and long-term decisions. At least for wholesale electricity markets, Weidlich and Veit (2008) offer a very different way of distinguishing agent-based models, namely with regard to their algorithms. According to the authors, these may be model-based adaptation algorithms, genetic algorithms, and algorithms applying the reinforcement learning approach by Erev and Roth (1998).

From an economic point of view, the major problem with most of the recent electricity market modeling is the overemphasis on detailed modeling of generation equipment (Contreras et al., 2001; Martini et al., 2001) or individual agents representing several interest groups (Praca et al., 2003; Vale et al., 2009), whereas a sound market model has rarely been analyzed. Two exceptions are the analysis of Wilson's design (1997) by Otero-Novas et al. (2000) and the comparison of uniform-price to discriminatory-price auctions by Bower and Bunn (2001).

The remaining part of this section is used to review the literature on auction design in general and for our local market in particular. Especially research on treasury auctions and its accommodation of a small number of bidders or diverse technologies, as well as the literature on electricity and ancillary services auctions is of interest.

From a theoretical point of view, a reserve energy auction is a multi-unit (or share auction, i.e. an auction of a divisible good, with equivalent characteristics; Wilson, 1979) as well as a multi-part auction. In the multi-unit part it resembles a treasury auction, which is an auction of a divisible good. A very important topic in this field is whether uniform pricing or discriminatory pricing, whereof the Ausubel auction (Ausubel, 2004) is treated as a special case, yields more favorable outcomes. A downside of uniform pricing is that bidders have an incentive to understate their demand for the second and following units in order to win those at lower prices in case of a demand auction. Transferred to a procurement auction like the one at hand, this means that bidders understate their supply, thereby creating an artificial scarcity, and are able to extract price premiums (Ausubel and Cramton, 2002; Engelbrecht-Wiggans and Kahn, 1998). Back and Zender (1993) describe this mechanism as “collusive”, meaning that each bidder colludes with himself while trying to maximize his profit. Even more important is that this does not change with the number of bidders, i.e. no real competition may emerge. Discriminatory pricing does not exhibit these downsides, but helps to limit market power (Hudson, 2000), which is especially prevalent in local markets. A disadvantage, however, is that revenues for the auctioneer are generally lower in discriminatory auctions (Wang and Zender, 2007). Put differently, one could say that “competition needs to be bought with higher prices” (i.e. bids). Furthermore, Rassenti et al. (2003) find that price volatility is reduced in discriminatory price auctions, which is an important feature for markets with household participation, as fluctuating prices can easily alienate this kind of participant and thereby reduce participation rates. Haghighat et al. (2008), however, find no differences between the two auction formats under imperfect competition, i.e., for example, when bidders can exercise market power or are able to collude.

The model primarily meant for treasury auctions in Wang and Zender (2007) represents, in principle, a situation very similar to the one at hand. Besides simply equating demand and supply, the authors also allow for non-competitive bids, which reduce the quantity available. The size of this reduction, however, is not endogenous but random. Furthermore, their model uses common values with private signals, which is very straightforward for financial goods that are acquired in the hope that they will increase in value, determined by subsequent trading, which affects all holders of such items equally in a common market. This is very different for an energy auction, which comprises several differentiated units and technologies and, therefore, exhibits private values, or rather cost.

Burke and Auslander (2009) specifically consider a residential electricity auction. While the design is directed at acquiring electricity by residential bidders and should, therefore, entail consumer behavior, it needs only one bid, composed of the maximum quantity desired and the maximum price to be paid. The mechanism then determines how much each bidder can obtain and what price he will need to pay. This is done by using uniform pricing and soft budget constraints, meaning that allocated quantities are reduced for increased prices, but the overall amount being paid remains the same.

Chao and Wilson (2002) suggest an auction design with a robust incentive mechanism. Similar to the design currently in use, they require two bids, one for capacity and the other for energy. The capacity bids are used to construct a merit order in which the units are called. Upon being called, they are remunerated with the real-time spot price, which is thus outside their range of influence. As this seems to be a promising approach to limiting gaming in the auction process, the basic idea of independence between energy price and bid will be followed in the model presented in Section 2.3.

Swider and Weber (2007) analyze the bidding behavior in the German minute reserve auction market, using a decision-theoretical framework. They are among the first to analyze the bidding behavior in the actual market as it occurs in reality. In particular, they address the difficulty of defining a probability density function for the price and thereby the expected price itself, by deriving it from historic time series. However, their investigation can only be applied to a limited extent to a local market, as they look at the behavior of one individual bidder and describe the rest of the market by a probability function. In a small market, this generalization cannot be justified due to the lack of statistical validity.

Another approach with a similar goal is presented in the work by Block et al. (2007). They describe a scenario of a microgrid where households can act as energy consumers and producers in an alternating fashion. For this purpose, they introduce a combinatorial double auction. While it is efficient and welfare-maximizing in theory, they do not examine possible gaming strategies or cooperation inherent in the auction design that the bidders might pursue. Also, it is not sensible to use this design in situations with only one buyer.

Hao (2000) focuses on simple electricity auctions. While his design allows the usage of probabilities of other bidders bidding less or more, in our case it is too simple to be applied, as it uses fixed MWh blocks combined with a single price bid. The auction is then cleared at the price of the last accepted bid. As concluded in the paper itself, this leads to untruthful bidding and overstatement of costs.

Bernard et al. (1998) compare the outcomes of several uniform auction designs with varying numbers of bidders. Similar to the theoretical result derived in our paper later on, they find empirical evidence for growing supply reduction with growing group sizes. Unfortunately, their design does not allow the drawing of final conclusions from this phenomenon, as it could also be a result of the information given to bidders, namely that not all of their capacity will be used under all circumstances. The auction form chosen was apparently less significant, which hints at the fact that it might be transferable to other forms than those examined by the authors, including pay-as-bid auctions.

However, none of the work presented deals with small, local markets. Therefore, this paper can be seen as an extension to Chao and Wilson's design (2002), but with discriminatory pricing instead of uniform pricing and allowing for endogenous demand reduction of the central buyer. From a mechanism design point of view, our work most closely relates to Back and Zender (1993) and Wang and Zender (2007), who were inspired by the treasury auctions. From the authors cited here, they are the only ones considering continuous bidding functions, while all others focus on discrete bids. In both papers, they chose a theoretical approach, such that their reflections on bidding behavior in discriminatory price auctions give important insights into expected outcomes in our local market. The uniqueness of our auction design lies more within the application and the adjustment to the local energy market. Furthermore, the approach of using historic prices in the simulation is inspired by Swider and Weber (2007), with bidders adjusting their strategies accordingly. The market and the auction design are presented in the following section. For a better overview of the auction designs examined in previous studies, a table has been produced with a selection of the cited literature. It can be found in the Appendix to this chapter, Part A.

2.3 Auction design

2.3.1 Getting to know the market

In an electricity grid it is paramount to always have exactly as much power input as consumption. If this is not sustained, blackouts or other major distortions will occur. While commercial energy providers do their best to forecast the demand of the consumers they supply, it can never be perfectly predicted. At the same time, supply from most renewable energy sources (such as wind and solar power) as well as the possibility of power plant outages contributes to unforeseen fluctuations in the power grid. This is the reason why reserve energy for balancing purposes is such a crucial element of the energy system. Most countries have a regime distinguishing between several qualities of reserve energy (cf. Singh, 1999, for an extensive discussion of the ancillary services market in California). They are activated in hierarchical order in different degrees of automation, after different time spans, and depending on whether there is an energy shortage or surplus. This poses corresponding requirements on the availability of reserve energy and technological infrastructure. In a local market, we assume that the different kinds of reserve energy can all be met by using different types of technologies. For the highest quality batteries seem appropriate as they can almost instantly provide the necessary energy.

Currently, the dimensioning of the capacity needed depends on the forecasts submitted as schedules to the transmission system operator (TSO). It is responsible for the large, transnationally interconnected grids on the highest voltage levels. These grids absorb energy produced by large power stations and transmit as well as distribute it over long distances. The schedules are produced on a lower level by the balance group responsible parties with the help of the commercial suppliers active in their balance group. The lower voltage levels encompass the medium and low voltage grids, where smaller power plants can feed in their energy, and larger and smaller customers extract their demand. Taking Germany as an example, there are four TSOs, but more than 600 balance group responsible parties, who all report to the TSO that supervises their geographical region. Within each balance group, supply needs to equal demand. The balance group responsible party needs to arrange for this by forecasting loads, adjusting supply, and submitting the schedules to its TSO. Using these, the exact amount of capacity needed and the implementation are determined using the regulations put forward by the European Network of Transmission System Operators for Electricity (ENTSO-E) (Union for the Co-ordination of Transmission of Electricity, 2004). This means that the demand for reserve capacity is known in advance and perfectly inelastic. On the contrary, the amount of reserve energy that actually needs to be supplied is uncertain and depends on stochastic events. This is why the central auction requires a three-part bid consisting of a capacity price, an energy price, and the amount of capacity offered. The reserve energy is then not used by the TSOs themselves, but again by the balance group responsible parties in their balance group. Due to the stochastic nature of electricity demand and partly also of the supply an exact match is never possible. The balance group responsible party is, therefore, billed by the TSO according to the share of reserve energy it uses in the area that it supervises. Typically, a balance group responsible party is either a local utility, a large industrial consumer with own energy supply or a trader at the energy exchange, or a combination of the aforementioned. It should be noted that due to the unbundling process the balance group responsible party in the function described here does not possess any generation capacity itself, but is just an administrative entity.

In the current market regime, it is very difficult for households to participate in the reserve energy market. The barriers to enter the central market are high and the threshold capacities for the lowest quality are still 5 MW, which most households cannot easily spare. The only way they are affected by the market is through the costs of the reserve energy that are transferred to them by their energy provider as part of their regular bill.

The local market that is proposed in this paper makes the balance group responsible party more independent. Via an online auction platform it can itself ask private households or small businesses that dispose of decentralized generation units (or flexible loads, which is analogous and, therefore, not explicitly treated here) to submit bids to cover its reserve energy needs. Those that win the auction need to reserve the allocated capacity and are automatically called when needed. The auction takes place weekly for the following week for each hour of the day. For renewable sources, it is assumed that reliable forecasts are available. Note that for micro-CHP plants and batteries, this uncertainty is not relevant. As these have higher unit costs, the market price is likely to be driven by these technologies, providing for a risk premium for participants with solar panels. The advantages of a local market for reserve energy are reduced grid losses and reduced market power of the large providers in the central market. Due to the implemented reserve price from the control area level of the TSOs, prices are always lower or equal to the current level. Furthermore, local trading of reserve energy is a necessary complement to trading of real power by private households.

2.3.2 Pricing mechanism

The buyer of reserve energy is, thus, the local balance group responsible party with total demand Q. Q is measured in kW (kilowatt) as only the capacity to be reserved is known. Sellers are market participants that bid within an auction. In this case they are households that dispose of devices that are capable of energy production or provision. These would typically be single- or multi-family homes with solar panels, micro-CHP plants, or storage batteries. Furthermore, small businesses with similar equipment that does not exceed 50 kW of installed capacity might also be included. Note that this threshold is not arbitrary, but specified in the EU Directive 2004/8/EC (European Parliament and Council, 2004) and is also the upper threshold for the highest remuneration (disregarding the option of heat-driven operation, which has been treated differently since the latest amendment, cf. KWK, 2012) for electricity from CHP plants according to the German CHP Act, where §7, Art. 4 (KWK, 2008) regulates that for an installed capacity of 50 kW_{el}, a subsidy of 5.11 Euro-ct per kWh is paid.

There are n bidders. Each bidder $i \in I$, with I being the set of potential bidders, can submit a set of offers $q_i(p)$, which consists of an arbitrary number of $(l_i + 1)$ bids.

A bid $x_{i,k}$ is composed of a price $p_{i,k}$ [€/kW] and the amount of capacity to be reserved $q_{i,k}$ [kW]. Index k with $k \in 0, 1, ..., l$ hereby denotes the rank of an individual bid among all bids submitted by bidder i. Each bidder may submit l_i of these bids altogether plus a mandatory nil-offer (0;0). This gives the above-mentioned total number of bids $q_i(p) = \begin{pmatrix} x_{i,0}, & x_{i,1}, & ..., & x_{i,l} \end{pmatrix}$.

The bids are ranked with $x_{i,0}$ being the lowest offer and $x_{i,max}$ $(= x_{i,l})$ being the highest offer. A continuous set of offers thereby constitutes an offer function. Each bidder knows his cost as a function of quantity $c_i(q)$. Per bidder and auction only one contract is concluded and the successful bid is denoted by x_i^*. The balance group responsible party can further buy the amount q_R at price p_R from the transmission grid operator. Obviously, it does not make sense for the buyer to procure reserve energy in the local market if it costs significantly more than in the global market. Article 29 (3) of the European Council Directive 90/531/EEC (Council of the European Communities, 1990) sets the price difference up to which offers can be regarded as equivalent to 3%, giving preference to local offers.

Let p be the vector of prices that the balance group responsible party faces due to the submitted sets of offers and let q be the corresponding quantity vector, as emerging from the bids x_i. The total costs for the grid operator are, thus,

$$Y(p, q_R) \colon \mathbb{R}^{n+1} \to \mathbb{R} \text{ with } Y(p, q_R) = p^T q + q_R p_R. \tag{2.1}$$

Successful bids and the capacity to be reserved via the TSO can be determined by solving the minimization problem $\min_{p,q_R}[Y(p, q_R)]$. The sum of the power bought from bidders and the grid operator must be at least as much as total demand Q, where Q is defined as the capacity that needs to be reserved times the time slot considered, which is one hour: $\sum_i q_i \geq Q$. Q can either be determined in a separate optimization problem or might be defined in some future amendment to the current ENTSO-E procedures. Both possibilities will not be discussed further at this point and, therefore, Q will be viewed as externally given, i.e. fixed and inelastic. Furthermore, the price constraint in acknowledgment of the EU Council Directive 90/531/EEC needs to be obeyed: $p_i \leq 1.03 p_R$.

The solution to this optimization problem describes the pricing mechanism. The complete optimization problem is, thus,

$$\begin{aligned} & \min_{p,q_R}(Y(p,q_R)) \\ \text{s.t.} \quad & \sum_i q_i - Q \geq 0 \\ & 1.03p_R - p_i \geq 0 \; i \in I. \end{aligned} \tag{2.2}$$

From here, the solution $(p^*; q_R^*)$ follows with $p^* = \left(p_1^*, \; p_2^*, ..., \; p_n^* \right)$, whereas the successful bid of bidder i is given as $x_i^* = [p_i^*, q_i^*(p_i^*)]$. The bidder's profit, taking into account his cost function $c_i(q)$, is $\pi_i = q_i^* p_i^* - c_i(q_i^*)$.

In case of discrete bids $q_i(p)$, a situation of ties may emerge. This situation arises with price equality of several quantities offered and when each quantity as such is sufficient to fulfill the constraint, i.e. each quantity is at least as large as the missing amount up to total demand. In this case, the bid with higher quantity is preferred. If prices as well as quantities among bidders are equal, the winner is determined randomly with equal probabilities.

The information flow starts with the determination of the required quantity according to UCTE requirements. The balance group responsible party can then publish the beginning and the end of the auction as well as invite participants to submit bids. After determining their free capacity and evaluating the competition to optimize their bids, these may then send their offers. From the prices and quantities the balance group responsible party can estimate whether it is able to procure enough reserve energy at a reasonable price. If there is not enough reserve energy offered, or if prices exceed those on the global market, i.e. the market at the transmission grid level, it should be able to register its residual needs with the TSO. Such a mechanism is currently not available in the market, but should require only a small change in the current regulation. At the same time, successful bidders are informed about the quantities they are obliged to reserve and prepare to be called.

2.3.3 Bidder's strategy

2.3.3.1 Asymmetric case

In principle, each bidder tries to maximize his expected profit. The expected profits are the sum of all bids less the respective costs weighted by the respective probability of winning. Costs are hereby a very general term and do not only include technology-related costs like fuel expenses, but also opportunity costs that rise with quantity as some of the available capacity might be needed for consumption within the household. In this sense the cost variable is equivalent to an individual reservation price. In the discrete case the expected profit can be expressed as

$$\begin{aligned} E_d(\pi_i) &= \sum_k (Pr(q_{i,k})(p_{i,k} - c_i(q_{i,k}))q_{i,k}) \\ \text{with} \quad \sum_k Pr(q_{i,k}) &= 1. \end{aligned} \tag{2.3}$$

In the continuous case, the probabilities are expressed by a function $f(q)$, giving the following formula for expected profit:

$$E_c(\pi_i) = \int_0^{q_{i,l}} f(q)(p_i(q) - c_i(q))qdq \tag{2.4}$$

Note that in both cases, $p_i(q) = q_i^{-1}(p)$. The problem is that unlike in Hao (2000) the probability is not dependent on a simple figure, but on a function or at least the association of price and quantity. Therefore, it cannot be assumed to exhibit continuity and is intractable analytically *ex ante*. In the current setting, there is thus no easy way to work with it.

To complete the analysis of the auction and the expected profit to be gained from it, the energy that is actually being called and remunerated separately should also be considered. As the necessary reserve energy per time slot cannot be known *a priori*, it can only be embraced in stochastic terms. The reserve energy being called, w_i, is, thus, a function of the capacity reserved.

In order to prevent gaming and market power, it is advisable to ensure equal chances for each participant in the calling process, much unlike the current procedure of arranging a merit order. In other words, the process needs to ensure that the probability of being called exhibits a uniform distribution. Let the expected value thereof be γ. The expected profit of an individual bidder then becomes

$$E(\pi_i) = \int_0^{q_i,l} (q \cdot p_i + \int_{t_s}^{t_f} \gamma q dt p_W - c - c_W) f(q)dq, \tag{2.5}$$

where c_W is the additional cost that is incurred for generating the power called. Under the condition that p_W is greater than c_W, risk-averse bidders should not add this additional stochastic profit to their certain profit during the strategy-planning phase at the auction stage. This means that they would never understate their costs for reserving capacity to increase their chances of winning the auction in the expectation of making up for it by being called and receiving additional payment for delivering energy.

Summing over all q_i^*, total costs of the balance group responsible party become

$$Y = p^T q + p_R q_R + \int_{t_s}^{t_f} \gamma Q p_W dt \tag{2.6}$$

for each time slot, where p_W [€/kWh] is the constant energy price for reserve energy called. As this energy price as well as Q, the total capacity to be reserved, and γ, the expected value of the portion of power actually called, are all independent from the bid sets $(p_i, q(p_i))$, the solution of the optimization problem remains identical to the solution from eq. (2.2). It can clearly be seen that the price and the amount of energy being called do not influence the pricing mechanism. Please also note that this structure makes the auction mechanism very robust, as truthful bidding is the dominant strategy.

2.3.3.2 Symmetric case

In the case of a symmetric market, the bid functions of all bidders are identical, i.e. $q_1 = q_2 = ... = q_n$. This could happen when all bidders have identical technologies, for example when solar panels are especially popular in a city quarter. Furthermore, the symmetric case gives a first benchmark for the behavior in an asymmetric market.

The total costs of the buyer are, thus,

$$\begin{aligned} & Y_\xi = n p_\xi q_\xi + q_R p_R \\ \text{s.t.} \quad & p_\xi = p_1 = p_2 = ... = p_n \\ & q_\xi = q_1 = ... = q_n = q_\xi(p_\xi), \end{aligned} \tag{2.7}$$

i.e., the price received by each bidder is p_ξ and the corresponding power offered is q_ξ. From this, the optimization problem can be written as:

$$\begin{aligned} & \min_{p, q_R} (n p_\xi q_\xi + q_R p_R) \\ \text{s.t.} \quad & n q_\xi - Q \geq 0 \\ & 1.03 p_R - p_i \geq 0 \qquad\qquad i \in I. \end{aligned} \tag{2.8}$$

As competition rises, a transition phase begins. During this phase, bidding is according to the Cournot equilibrium, where quantities are endogenously determined while understating capacities. As soon as capacities significantly outrange total demand, a situation of perfect competition is reached. This motivates bidders eventually to bid their marginal (economic) costs $c_i(q)$.

In order to find out the point up to which it makes sense for the bidder not to deviate from the collusive bid, i.e. from which point onwards convergence to competitive bidding can be assumed one needs to compare bidder *j's* profit under each bidding regime:

$$\pi_i = \frac{Q}{n}(p_R - c). \tag{2.9}$$

When deviating, the profit becomes

$$\pi_j = q_j(p_R - c - \varepsilon). \tag{2.10}$$

Letting $p_R - c = m$ and rearranging terms, one obtains from $\pi_i = \pi_j$ that

$$\varepsilon = \frac{q_j n - Q}{q_j n} m. \tag{2.11}$$

Note that q_j, Q, and m are all fixed. The only changing parameter is, thus, n, i.e. the number of bidders participating in the auction. For a growing number of participants, ε grows as well. This is in line with theoretical considerations of market movements, as it says that the greater the competition, the faster prices drop to marginal costs. This is because once someone has deviated, the other bidders will follow in the coming round until equilibrium is reached and everyone bids marginal costs. This already implies that m or rather p needs to be updated for every round, meaning $p_{j,t} = p_{j,t-1} - \varepsilon$ or, reformulating

$$\begin{aligned} p_{j,t} &= \frac{q_j n - Q}{q_j n} c + \frac{Q}{q_j n} p_{j,t+1} \\ \text{until} \quad p_{j,t+z} &= c. \end{aligned} \tag{2.12}$$

Note that ε is the upper limit of the amount by which the price should be reduced. If it were a little more, the bidder would be better off sticking to the old price and strategy. In order to get the strategy working, a much smaller amount of reduction might suffice. However, this is only true for the symmetric case. For the asymmetric case, the undercutting will stop as soon as the most costly generators bid their marginal costs. Therefore, less cost-intensive generators can sustain a higher profit forever, at least if total demand Q cannot be met by them alone. This higher profit margin equals the marginal costs of expensive generators less the marginal costs of cheaper generators. If, however, demand can be met by the reduced number of less cost-intensive generators, more cost-intensive generators are driven out of the market, as competition continues until the price has reached marginal costs of less expensive generators, at least as long as there are no regulatory measures to prevent such an outcome. This also means that none of the bidders has an incentive to underbid costs, who might have a motivation in a commercial setting, for example to secure a higher market share. In the household setting at hand, and with such limited capacities, strategic actions in terms of marketing activities are not relevant.

The calculation of the expected profit of the individual including energy called is analogous to the asymmetric case.

2.4 Simulation of an asymmetric market

In the previous section we have seen the derivation of the strategy for symmetric bidders, which can be used as a reference value now. For an asymmetric market, however, an analytical solution is very hard to find, as we cannot construct the probability of winning in the auction. This leaves us with the option of simulation. In the case presented here, a learning strategy has been formulated and translated into an algorithm as presented in the coming paragraphs. The formulation of probability expectations is not necessary for the current investigation, but will be handled later on in the course of the still ongoing research project, which is running till the end of 2012 and investigates behavior of energy consumers using experimental methods.

The second part is the cognition and strategy formulation of the bidders. The basic bidding curves are characterized as partially differentiable functions of the form

$$p(q) = k(a_0 + a_1 q + a_2 e^{bq}). \tag{2.13}$$

This means that bidding curves of several shapes can be implemented, i.e. they may be linear, constant, or exponential. They might be limited by the real world boundaries, such as the corresponding cost functions, but are meant to be monotonically increasing in principle. The mathematically redundant coefficients k and k_c are used for reasons of practicality, i.e. to be able to easily shift the curves upwards or downwards if required by the implemented strategy. The cost functions are modeled accordingly and exhibit the same properties:

$$c(q) = k_c(a_{c0} + a_{c1} q + a_{c2} e^{b_c q}). \tag{2.14}$$

An example cost curve and bidding curves for the first 30 rounds of the “no information” case (see explanations further below) are shown in Figure 2.1. The cost curve is the lowest curve in the diagram, and the squares are the accepted bids.

After each auction round, the bidder is informed about his winning bid. The quantity is a point between zero and the maximum quantity bid, while the price is determined from the bid function. This means that in the following round, the bidder can react to the outcome and either increase his price (i.e. shift his bid function upwards) to increase his profit margin or lower his price (i.e. shift his bid function downwards) to increase

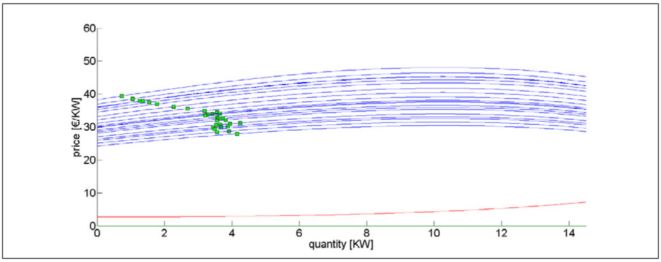

Figure 2.1: Example cost curve and bidding curves with price convergence over 30 rounds

chances of selling a higher quantity. His action space is thereby limited by the given cost function, which represents a lower limit. This algorithm is modeled according to the learning direction theory of Selten and Stoecker (1986). Hailu and Schilizzi (2004) also showed that there is no significant difference in outcome when applying a more complicated learning algorithm, like the reinforcement algorithm by Roth and Erev (1995); Erev and Roth (1998), which is why we can comfortably stick to the simpler algorithm.

Furthermore, bidders can differ in a number of ways: First of all, they own equipment of various sizes in the range from 3 kW to 50 kW, which is randomly distributed with a mean of 9 kW and a standard deviation of 6.3 kW. To illustrate this, bidding curves of all bidders in the market are shown in Figure 2.2; squares are again accepted bids. Each bidding curve stops at the maximum capacity. Secondly, their bidding curves as well as cost curves may be steeper or flatter, also randomly generated with the coefficients introduced in equations (2.13) and (2.14) above. Moreover, fixed and variable prices vary across bidders, reflecting ample technologies. The strategy used by all bidders is to increase or decrease their bids by some percentage points, depending on whether they

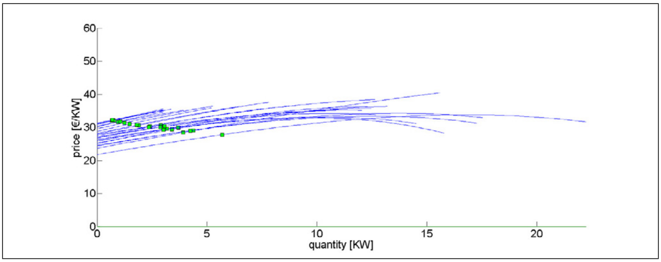

Figure 2.2: Bidding curves of all bidders in the 25th round of the "no information" case

are satisfied with the outcome or not. The boundary is hereby set to 25 % of each bidder's individually available capacity.

Three main scenarios are scrutinized, varying in the information provided to the bidders. In each scenario, 24 bidders participate in the market during 365 rounds. The idea is to test several plausible scenarios that are based on different information policies, but also on how this information is processed, i.e. how the bidder lets himself be influenced (in terms of bids for the coming round) by the information provided. Information policies are inspired by Ausubel (2004), who suggests a no-bid information, an aggregate bid information, and a full bid information policy. As Ray and Cashman (1999) report, different degrees of information provision make sense from a regulatory point of view, especially in markets where perfect competition cannot be guaranteed and market power might be an issue. In an early phase of the market introduction scarce information can, thus, spur competition and disencourage collusion, which is why regulators employed this strategy in New South Wales (Australia) when restructuring the electricity market (Ray, 1997). This leads us to the following scenarios subject to our analysis:

1. Total supply and aggregated price curve of accepted bids;
2. All accepted bids;
3. No information.

In each scenario, the bidder's bid may or may not be accepted. In the case where it is not accepted, the bidder will adapt his strategy as long as he can still generate a profit, i.e. as long as he is not bidding his cost curve. In the case where it is accepted, the bidder might be content with the outcome and not change anything. However, he might also want to gain more profit by increasing the capacity sold. In this case, strategy adaptation might happen under the condition that the previous profit margin is maintained, but stretched to more units.

Together with the cost function, the information can be used to find the most profitable response to the actions of the other bidders. This also means that the implemented strategies do not necessarily force the bidder to lower prices, but may also push him to increase prices when competition allows it.

The aggregated price curve is constructed by summing up the inverse of all submitted bid functions, whereas total supply is a vertical curve at the quantity desired. From the intersection the market price, i.e. the highest price paid per kW in this market, can be determined:

$$\sum_{i=1}^{n} p_i^{-1}(q) - Q = 0. \tag{2.15}$$

At the same time, p^* solves the inverse of the above-mentioned equation and is the highest price any bidder can obtain and beyond which chances of winning dramatically decrease. It is, therefore, most sensible for a bidder to bid flat at this price to achieve the highest profit margins while assuring the maximal sales volume. In case his sales volume drops too low, he can choose to adapt his strategy by bidding just below the market price. At any point in time, he will not bid more than the reserve price because the balance group responsible party would never accept such a bid and he will bid his cost curve whenever the flat bid would not cover the expenses for a certain amount of energy reserved. His bid function, thus, looks like:

$$p_i(q) = \begin{cases} p_R & \beta p^* \geq p_R \geq c_i(q) \\ \beta p^* & p_R \geq \beta p^* \geq c_i(q) \\ c_i(q) & \beta p^* < c_i(q). \end{cases} \tag{2.16}$$

Note that β is equal to one as long as the bidder is satisfied with the quantity sold. If it drops too low, β becomes a discount factor for the bid function, which is randomly chosen from a normal distribution with a mean of 0.98 and a standard deviation of 0.01. It has an upper limit, as risk-averse bidders will not become more expensive.

When the information provided is very detailed, the bidder can look at the individual price/quantity-pairs and might, for example, adjust his curve to intersect all the winning points or to lie just below them. Otherwise, he might simply identify the point that is most profitable to him and adjust his bid curve to have this profit margin for all possible quantities. As this kind of extensive information supports a variety of strategies, we exemplarily implement two possible reactions. In the first, as mentioned above, the most profitable winning point is identified and the bid is adjusted to ensure the same amount of profit for all quantities larger than the one in this point. Below this limiting quantity, bids are flat on the price in the optimal point. The most profitable bid

$$\tilde{x}_s = [p_s, q_s] \tag{2.17}$$

is, thus, determined from:

$$\max_{\tilde{x}_k} (p_s - c_i(q_s))q_s. \tag{2.18}$$

His bidding curve is then:

$$\tilde{p}_i(q) = \begin{cases} \frac{(p_s - c(q_s))q_s}{q} + c(q) & q > q_s \\ p_s & q \leq q_s. \end{cases} \tag{2.19}$$

In other words, he bids his costs plus the most suitable relative profit margin for large quantities and the optimal price for low quantities. In case he does not sell enough with these bids, he can shift his bid functions downwards with the same randomly distributed discount factor β as in the previous section.

In the second reaction, bids are flat at the most profitable point until they hit the cost curve.

$$\tilde{p}_i(q) = p_s \tag{2.20}$$

This can be regarded as an easier strategy from the point of view of the household bidder and has also been put forward by Wang and Zender (2007), among others, as an equilibrium strategy. Discounts are assumed to be given by β again. As bidding above the reserve price does not make any sense, we can summarize the bid curves for both alternatives as follows:

$$p_i(q) = \begin{cases} p_R & \beta\tilde{p}_i(q) \geq p_R \geq c_i(q) \\ \beta\tilde{p}_i(q) & p_R \geq \beta\tilde{p}_i(q) \geq c_i(q) \\ c_i(q) & \beta\tilde{p}_i(q) < c_i(q). \end{cases} \tag{2.21}$$

In the "no information" case, the bidder does not receive any information on what happened during the auctioning process and what the outcomes of the other bidders were. He has only the feedback if at all and how much he was able to sell from his capacity offered. This input added he can decide whether he is happy with his personal result or whether he would like to sell more. If he concludes that the quantity sold should be increased, he needs to lower the price. He does so in a similar manner as in the first and in the second case, i.e. by pushing down his bid curve with the discount factor β. However, he does not change the shape of his original bid curve determined in equation (2.13).

2.5 Simulation set-up and results

2.5.1 Set-up

The simulation program has been implemented on an object-oriented basis in MATLAB, version R2011b, using the MATLAB optimization toolbox. It has been run on a Windows 7 machine with a dual-core processor, taking a runtime of about 30 to 60 minutes. Each bidder behaves as an independent agent trying to maximize his own profit. He is modeled using the bid function (equation (2.13)) and the cost function (equation (2.14)) developed in Section 2.4. The exact values of the parameters in the functions are determined by a random number generator that draws values from a given distribution. The

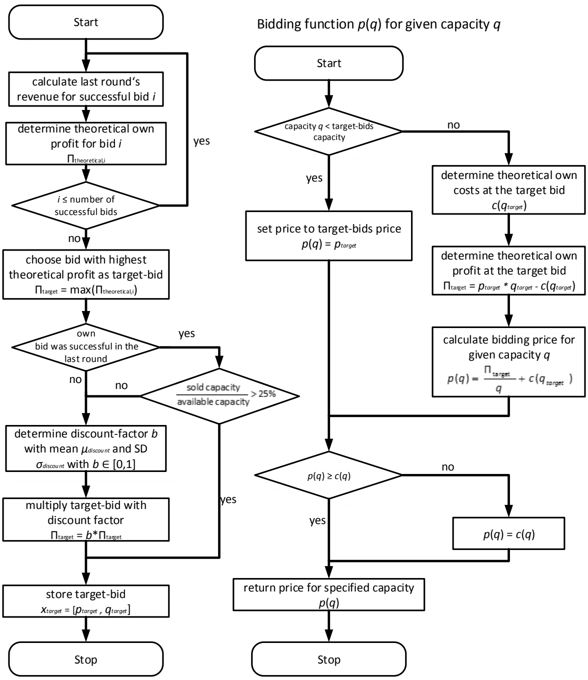

Figure 2.3: Flowchart of bidding algorithm and price determination algorithm

mean values and the standard deviations of the distributions for each parameter can be seen in Table 2.1. The capacities, for example, are set between 3 kW to 50 kW, and are randomly drawn from a distribution with a mean of 9 kW and a standard deviation of 6.3 kW. The so-constructed normal distribution is now cut off at 3 kW at the lower end and 50 kW at the upper end. Capacities of each bidder are illustrated in Figure 2.4, with the dark horizontal line describing the mean of the sample and the lighter horizontal lines describing the confidence interval of one standard deviation in the sample. Please note that the theoretical mean and standard deviation and the sample mean and standard deviation do not exactly coincide because of the small sample size and, more importantly, because of the imposed upper and lower bounds when drawing the sample. The slope is determined in a similar way with a mean of -0.8 and a standard deviation of 0.04. For computational reasons, the limits here are set at +15 and -15. Fixed costs are described by the product of k and a_0. The start price (y-intercept) of the bid function is constructed by analogy. The resulting configuration has been produced automatically

Table 2.1: Parameter values in the simulation

Variable	**Mean μ**	**Standard deviation σ**	**Min value**	**Max value**
k	8	$\frac{k}{10}$	0	$k*3$
a_0	0.3	$\frac{a_0}{10}$	-15	15
a_1	-0.8	$\frac{a_1}{20}$	-15	15
a_2	5	$\frac{a_2}{20}$	-15	15
b	0.1	$\frac{b}{10}$	-15	15
a_{c0}	-0.1	$\frac{a_{c0}}{10}$	-5	5
$a_{c1}*(qmax/lqmax)$	1	$\frac{a_{c1}}{10}$	-5	5
a_{c2}	2	$\frac{a_{c2}}{10}$	-5	5
$b_c*(qmax/lqmax)^{0.7}$	0.2	$\frac{b_c}{10}$	-5	5
$qmin$	0	-	-	-
$qmax$	9	$qmax*\frac{7}{10}$	3	50

at the beginning of the first simulation. To allow comparisons across treatments it has then been saved and served as input for all other simulations as well.

Depending on the strategy used by a bidder he adjusts original bidding curves according to equations (2.16), (2.19), and (2.21) after the first auction round.

The simulated auction round proceeds as follows: After all bidding agents have "submitted", i.e. formed their bidding curves, the resulting optimization problem is solved according to equation (2.2). This classical nonlinear programming (NLP) problem represents, thus, the role of the balance group responsible party. For determining the outcome of the pricing mechanism, an SQP Solver with an active-set method is applied.

The outcome of this optimization is then used as an input for the following auction round. This can be in the form of the aggregated price curve of accepted bids, individual price-quantity pairs, or only the information of how much of the own capacity has been sold. Bidding agents use this feedback to evaluate their bidding curve of the preceding round

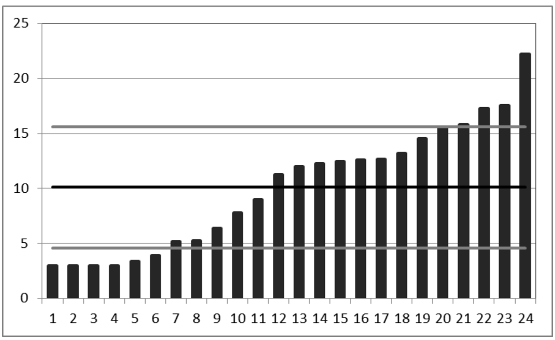

Figure 2.4: Overview of capacities of all bidders

and adjust it, if necessary, in the current round according to the strategies described before.

This procedure is repeated 365 times to cover an entire year. Output at each stage is a table with the adjusted parameters of the bidding curve of each bidder, individual profits gained, and expenditures of the balance group responsible party. Figure 2.3 shows the flowchart of the algorithm for determining the bid in general (left-hand side) and the function for determining the price of a bid in case full information is provided (right-hand side). The code for this part of the simulation can be found in the Appendix to this chapter, Part B.

2.5.2 Results

The results clearly show that the information policy in a local reserve energy market makes a difference. Generally speaking, the more information is provided, the fiercer the competition becomes.

In the "all accepted bids" case, market equilibrium is reached after only about ten rounds. Even in case the convergence process were to take longer in a real-world setting, the swiftness is remarkable and promises a reliable market. When assuming flat bid functions, convergence stretches over 100 auction rounds before equilibrium is reached. However, even this is rather quick and proves the robustness of the mechanism. The equilibrium price is only slightly higher in the second case (0.16 cents), which can be regarded as non-significant.

In the "no information" case, where bidders have only their individual feedback, competition is significantly reduced. Although bidding is according to individual bid curves that maintain their shape during the entire process, market equilibrium takes more than 180 rounds to be reached. Compared to the full information case above, the market is

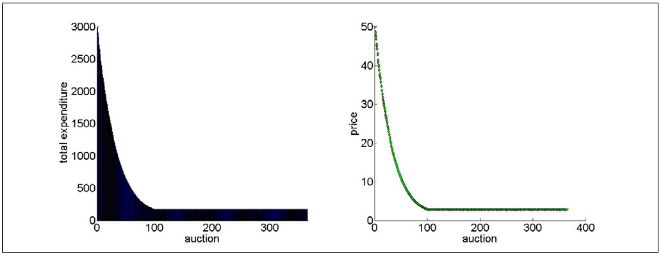

FIGURE 2.5: Expenditures of the balance group responsible party (left plot) and highest, average, and lowest price received (right plot) in "all accepted bids" information setting with flat bids

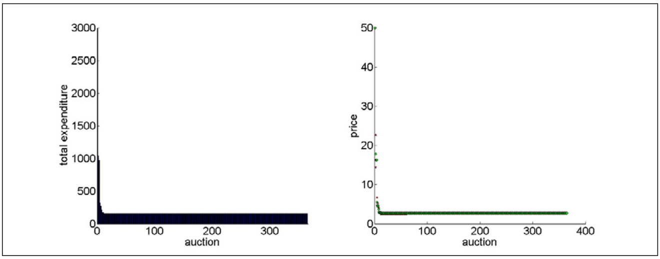

FIGURE 2.6: Expenditures of the balance group responsible party (left plot) and highest, average, and lowest price received (right plot) in "all accepted bids" information setting with individual bid functions

less efficient, and thus suffers from the typical market failure. Also, the equilibrium price is twice as high forever, providing a substantially higher profit for the households in the long run.

The case "total supply and aggregated price curve" gives a result that lies in between the informational extremes of the two other cases. When thinking about what information is given to the bidders and how they can react to it, this is not surprising. After 215 rounds, market equilibrium is reached with an equilibrium price of about the same amount as in the "all accepted bids" case with individual bid functions that are only flat on the first part. Interestingly, it is below the "all accepted bids" case with flat bids, but not significantly. The slow speed of convergence can be explained by the single point that is provided to the bidders on the one hand, and the lowering of the price in response to dissatisfaction on the other hand. Even when lowering the price in one round, the market price is still likely to remain less significantly changed. With this higher reference point, bidders can go back to the higher price in the next round, thus hindering the market dynamics.

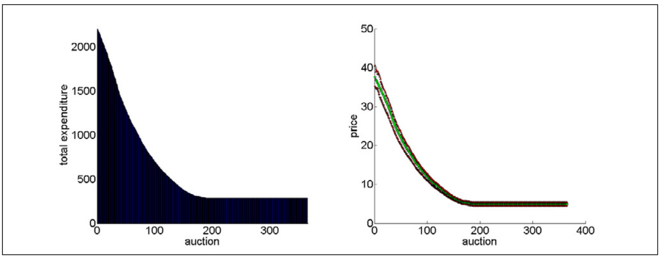

FIGURE 2.7: Expenditures of the balance group responsible party (left plot) and highest, average, and lowest price received (right plot) in a no information setting

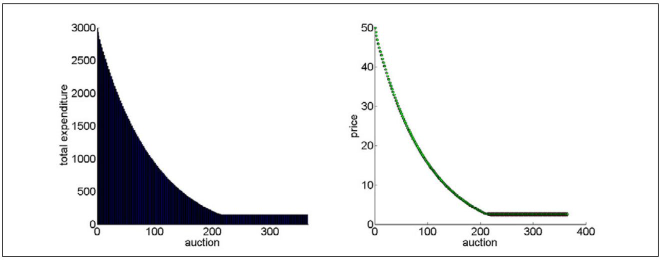

FIGURE 2.8: Expenditures of the balance group responsible party (left plot) and highest, average, and lowest price received (right plot) in aggregated information setting

The information policy chosen for such a market thus depends on what authorities would like to achieve. For energy markets, this is of special interest, as regulators usually try to achieve explicit goals with their guidelines. Considerable profits can attract more participants in the market and thereby support liquidity and competition, calling for a policy with very limited information. If, however, the objective is to run the market as efficiently as possible from the beginning, in order to benefit from low reserve energy prices immediately, a broader information policy should be put into place. These results are also illustrated in Figures 2.5 - 2.8. More detailed output data is available from the authors upon request.

2.6 Conclusion

In this paper a new auction model for a local reserve energy market has been introduced and tested in a simulation. It has been designed to accommodate the special needs of non-expert bidders such as private households. This model can be used to revolutionize the reserve energy market, as a balance group responsible party is given the chance to self-supply reserve energy. Thereby it serves several purposes as it helps to further integrate decentralized and renewable energy penetration, but can also help to lower the costs for reserve energy by cutting back the market power of the currently dominating, large-scale utility companies. Final energy consumers can profit from this twice because they are the ones providing the energy and getting paid for it as well as having to pay a lower energy bill, once the market provides cheaper reserve energy. At the same time the mechanism supports the remuneration and subsidy schemes for decentralized and renewable energy that are already in place. In the long run, when promotion schemes eventually expire, it can serve as a long-lasting incentive scheme for investments in the designated technologies. This is supported by both the results from the theoretical investigation of the symmetric case and the simulation of the asymmetric case. We found that the information policy in the market has a significant influence on the speed of convergence and also a small effect on the equilibrium market price that is finally reached. In the extreme treatment with no information provided, the effect on the equilibrium price becomes substantial and, even more importantly, is sustained indefinitely, which emphasizes the importance of the design choice.

The advantage of such a market-based incentive scheme is that it eliminates itself when it is no longer needed. This can happen under two circumstances. Firstly, as soon as further investments in the supported technologies do not enhance total welfare anymore and secondly, as soon as the slope of the learning curves for the respective technologies has reached its minimum alongside with the unit costs of the technologies, such that the acquisition happens without the need of subsidies. Furthermore, the concept can be used in a microgrid to solve the issue of remuneration of ancillary services. If a barter economy is desired in such circumstances, bids can easily be translated into amounts of energy that may be consumed at a later point in time.

Beyond energy markets the design can also be applied in other small, possibly local markets, for example those known in the financial sector, i.e. cloud financing or crowd funding. These are characterized by a rather non-professional environment (usually no banks or other financial institutions participate) and aim to gather a certain, predetermined amount of financial resources. Whether an explicit reservation price makes sense in those circumstances remains to be determined. An implicit reservation price is, however, certainly given by the prevailing conditions of the official financial sector. Moreover, competition is likely to be much more quantity-based, as market participants might like to invest a certain amount and only fine-tune according to the prices on the market.

Subsequent research will need to examine how actual human bidders react to the proposed design and whether theoretical predictions as well as simulation results hold. To this end, we plan to conduct a laboratory experiment as an empirical test of the validity of the design. This is also supposed to investigate the importance of the auction format on truth-revealing behavior in this context. Field tests can further validate these findings and enable the investigation of practical issues. Finally, it would also be interesting to examine some other parameters than those chosen alongside the possibility of market entry and mechanisms to prevent collusion.

Acknowledgments

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Appendix

Part A - Literature overview

Table 2.2: Overview of literature with related auction mechanisms

Reference	Method	Type of auction	Major finding	Comments
Ausubel and Cramton (2002)	Mathematical proofs	Multi-unit auction with discriminatory and uniform pricing	Bidders have an incentive to understate demand in uniform price auctions with private values	-
Back and Zender (1993)	Theoretical model/ mathematical proofs	Divisible good auction; sealed-bid uniform pricing vs. discriminatory pricing	Sellers' revenue is lower in uniform-price auctions because of self-enforcing collusive strategies (very steep demand curves)	-
Bernard et al. (1998)	Laboratory experiments	Uniform-price auction with last-accepted offer and first-rejected offer pricing	Group size has a much greater impact on prices and efficiency than auction type	Single buyer; two, four or six sellers; reservation price
Burke and Auslander (2009)	Theoretical/ mathematical proofs	Divisible good auction with uniform pricing	Pricing mechanism for automatic real-time electricity pricing	Residential electricity auction
Chao and Wilson (2002)	Mathematical proofs	Uniform price multi-unit auction	Incentive compatible mechanism by using capacity bids only for reserving capacity and using the marginal energy price for energy called (i.e. the last unit of energy actually needed determines the energy price for all energy called)	Procurement auction for reserve energy
Engelbrecht-Wiggans and Kahn (1998)	Theoretical model/ mathematical proofs	Multi-unit auction with uniform pricing	Equilibria in uniform price auctions	-
Haghighat et al. (2008)	Mathematical model/proofs and simulations	Discriminatory and uniform pricing multi-unit auction	Theoretically, no difference between both designs concerning profits, market clearing price and bidding strategies; with transmission constraints, profits are influenced by the pricing mechanism	-

Continued on next page

Table 2.2 – continued from previous page

Reference	**Method**	**Type of auction**	**Major finding**	**Comments**
Hao (2000)	Mathematical model and numerical examples	Multi-unit auction with fixed MWh blocks and one-part price bids	No true cost bidding under uniform pricing	Electricity auction
Hudson (2000)	Comprehensive market simulation of energy and ancillary services markets	Multi- unit auction with uniform and discriminatory pricing	Discriminatory pricing limits market power in periods of high demand through higher price visibility	Energy and ancillary services markets
Rassenti et al. (2003)	Laboratory experiment	Multi-unit procurement auction with uniform and discriminatory pricing	Discriminatory pricing raises prices and bidders submit higher offer curves; price variance is lower; discriminatory pricing leads to "tacit collusion", bidders coordinate on the highest observed offers of the previous round	Electricity trading with simulation of typical trading days
Swider and Weber (2007)	Theoretical model and empirical application in MATLAB	Multi-unit auction with discriminatory pricing	Estimation of the profit-maximizing bid in a discriminatory auction by deriving the probability of acceptance	Procurement auction for power systems reserve
Wang and Zender (2007)	Theoretical model/ mathematical proofs	Divisible good auction (uniform and discriminatory pricing, symmetric and asymmetric information, risk-neutral and risk-averse bidders)	There is a continuum of equilibria, but with a reserve price of zero, it can be reduced to only one; For risk-averse symmetric bidders, the auctioneer's revenue in a discriminatory auction is strictly greater than in a uniform-price auction; only risk-neutral bidders submit completely flat bid schedules; in divisible good auctions there is almost always some degree of demand reduction; auctioneer's revenue is strictly increasing in the precision of public information	-

Part B - MATLAB code for the pricing function when detailed information is available:

```
function bid_price = flatAndConstProfit(BID, transferred_q)

    % Function bid_price
    % Determines the price of a bid in case full information is provided
    % Parameters:   BID: Instance of Bidder Class
    %               transferred_q: argument of pricing function
    % Author: Christiane Rosen
    % Date: 05.07.2012
    % Revision: 10.08.2012

theoretical_Profit =
   BID.stored_Target_Bid(1,1) - BID.cost_Function(1,BID.costfactor_a0,
   BID.costfactor_a1,BID.costfactor_a2,BID.costfactor_b,
   BID.stored_Target_Bid(1,2));
theoretical_Profit =
   BID.discount_Factor * theoretical_Profit * BID.stored_Target_Bid(1,2);

if (transferred_q < BID.stored_Target_Bid(1,2))
   bid_price = BID.discount_Factor * BID.stored_Target_Bid(1,1);
else
   bid_price =
   theoretical_Profit ./ (transferred_q) + BID.cost_Function(1,
 BID.costfactor_a0,BID.costfactor_a1,BID.costfactor_a2,BID.costfactor_b,
 transferred_q);
end
if (bid_price > BID.reserve_price)
    bid_price = BID.reserve_price;
end
if (bid_price <
   BID.cost_Function(1,BID.costfactor_a0,BID.costfactor_a1,
 BID.costfactor_a2,BID.costfactor_b,transferred_q))
   bid_price =
   BID.cost_Function(1,BID.costfactor_a0,BID.costfactor_a1,
 BID.costfactor_a2,BID.costfactor_b,transferred_q);
end
end
```

Chapter 3

The Role of Information Feedback in Local Reserve Energy Auction Markets

Abstract

In any auction market, the amount of information provided to its participants is one of the most important design choices. It is the basis for decisions and supports the learning process. While there is little research available on learning in multi-unit or divisible good auctions, some important theories have been developed in the context of first-price auctions. These approaches also have been validated experimentally in single-unit auctions (e.g. Dufwenberg and Gneezy, 2002). While single-unit first-price auctions have the advantage of being mathematically tractable, their practical use is limited to certain domains (e.g. on-site art auctions). Multi-unit or divisible good auctions, on the other hand, are employed in a number of important practical applications, such as Treasury bond, energy, (radio) spectrum auctions and other public tenders. A natural and necessary extension to the current literature is, therefore, to examine the effect of price feedback in divisible good auctions. We contribute to this field of research by conducting such a laboratory experiment with an energy market framing. Two treatment variables are investigated in a two by two design: the strength of competition and, more importantly, the amount of information provided.

3.1 Introduction

One of the key topics in economic research is analyzing and understanding markets. A number of today's markets rely on auction mechanisms in addition to or instead of individual bargaining and trading. Some of very important examples of such applications are Treasury bond auctions, radio spectrum auctions, and energy markets, whereof the latter have recently gained increasing scientific attention. Although they are public tenders from very different fields, these markets share a common property, namely there are either multiple, identical goods or the good is perfectly divisible, resulting in almost the same theoretical properties. Research in this area has made some considerable progress in recent years with notable theoretical and empirical findings emerging. Some issues, however, have still not been studied in detail. One of these is learning and the impact of feedback in divisible good or multi-unit auctions. Feedback, i.e. information on the results of individual behavior, is the crucial factor that enables learning and fosters convergence to the theoretically predicted (equilibrium) behavior. In a market environment, this means that determining the amount of information provision is an important design variable. To date, research on feedback has mainly focused on general learning theories and theories applied to first-price auctions. However, many real-world markets, especially those mentioned in the beginning, are not set up as first-price auctions, but as multi-unit or divisible good auctions. In order to be able to use theoretical and experimental results from existing approaches on learning behavior in these important markets, it is essential to verify their applicability to the relevant auction types.

Experiments offer a structured way of investigating individual behavior. By manipulating relevant variables, they help to identify dynamics resulting from processes taking place internally within a subject, and externally as interaction with other players. Along the same lines, markets are highly influenced by scenarios that are driven by the cognition and the explicit or implicit communication (such as signaling) of its participants. In order to answer the question of how feedback impacts divisible good markets, we conduct an experiment with an energy market framing.

In the context of energy markets, there are recurring concerns about transparency and collusion. As will be discussed further below, the amount of information provided within (and possibly outside) the market can support or hinder such undesired market phenomena. We have shown in an agent-based simulation study (Rosen and Madlener, 2013a), that this can also have long-term effects on the market outcome. Building upon these results, and in order to further evaluate them, in this paper we examine the reserve energy market, i.e. a divisible good auction, experimentally. In a computerized laboratory, human bidders can interact with each other and thereby experience market dynamics. The goal of the current research is to find out how feedback information impacts this process. To this end, we analyze four treatments differing in the amount of information provided and the competitive strength of the market, i.e. the number of market participants.

To our knowledge, information has so far not been studied as a treatment variable in divisible good auctions. In the context of electricity auctions, its role in policy decisions has been established theoretically by Ray and Cashman (1999). With this study we contribute to the literature on divisible good auctions and procurement auctions, while examining a topic of practical relevance for the transformation of the energy system.

We proceed as follows: Section 3.2 gives an overview of relevant related research. Section 3.3 introduces the experimental market, derives some theoretical benchmarks, and explains the experimental procedure. Section 3.4 presents the results obtained and provides some in-depth discussion, especially of the findings concerning the learning direction theory. Section 3.5 concludes.

3.2 Related work

As already mentioned, in previous research we have analyzed the short and long-term influences of information in several degrees or aggregation types in an agent-based simulation (Rosen and Madlener, 2013a). The result is that with very detailed information, the equilibrium market price is lowest and reached very early. When no information on the behavior of other bidders is provided, but only feedback on the individual success, the convergence process takes more than twice the time and the equilibrium market price remains on a higher level indefinitely. We will later see whether this holds in an experimental setting with human bidders as well.

Starting with the general role information has played in experiments, let us turn to Nikiforakis (2010), who evaluates the effect of framing of information. For this purpose, he conducts an experiment in the context of public goods. In each treatment, he provides the same information in a different format. First, he only shows the contributions of each individual, then the earnings of each individual (with equal endowments being the endowment less the contribution plus the share of the public good) and then both the contributions and the earnings. He finds that the information format has an influence on the behavior of individuals. When earnings are displayed, participants tend to punish peers more harshly.

Danz et al. (2012) examine a two-player game under varying extents of information provision. In the baseline treatment they give full information, whereas in the other two treatments information is withheld either on previous performance or on the opponent's payoff. They find that a lack of already one of the two types of information leads to less strategic behavior. Furthermore, performance-related feedback is essential for learning during the course of the experiment and also enhances strategic behavior over time.

Weber (2003) challenges common learning theories and claims that learning also takes place when no feedback is provided. He proves this idea in an experiment of a repeated game with and without priming. Primes are meant to induce participants to think about strategic aspects of the game. Convergence to equilibrium outcomes can be observed in all treatments, which means that learning takes place in all cases. It is, of course, most distinctive in the control treatment with feedback, but shows the same direction in all other treatments. Priming did not have an unambiguous effect in the sense that stronger priming would lead to faster learning.

The main relevance of feedback is explained by its impact on learning processes that can ultimately drive individual behavior in a specific direction. In addition to, or as a result from, experiments, several theories have been developed that try to explain the behavioral pattern both qualitatively and quantitatively. Learning processes in auctions and other games have been analyzed theoretically and experimentally. For auctions, the main research subject has been single-unit first-price auctions. For this specific type of auction, Ockenfels and Selten (2005) develop the impulse balance theory. It states that bids are a reaction to impulses experienced from feedback after an auction round, given that more rounds are to follow. In an experiment, they can confirm this with a repeated sealed-bid first-price auction, where bids are lower when feedback on losing bids is given compared to situations where it is not provided. The extent of these bid movements can be explained by their theory. The bidding patterns are a result of the different weights attached to downward and upward impulses.

Dufwenberg and Gneezy (2002) explain the observed bid movements with signaling between the bidders. They conduct an experiment on competition in first-price procurement auctions, which is repeated 10 times and offers a different amount of information for each treatment. The authors implement a full information feedback, a semi-full information feedback, and a no information feedback treatment. In the first treatment, bidders are informed about all bids that have been submitted, in the second only about the winning bids, and in the third only about their own payoff. They find that when all (winning and losing) bids are announced, bids remain on a much higher level than is predicted by theory. In the other two treatments, bids converged to the theoretical prediction. The authors explain this with signaling, which only makes sense when it can be observed by other bidders. This kind of transparency is exclusively guaranteed in the full information treatment. In comparison to an earlier publication (Dufwenberg and Gneezy, 2000), the authors further find that with three and four competitors, bids always approach the Nash equilibrium.

Isaac and Walker (1985) consider a discriminative sealed-bid auction where bidders have unit demand. They implement a full information and a limited information treatment, where the full information treatment displays all submitted bids including the identification number of the bidder. In the limited information feedback case, bidders only obtain the winning bid with the identification number. Prices in the limited information treatment are greater than those in the full information treatment, but efficiency is not affected. Also, all prices are higher than predicted in equilibrium for risk-neutral bidders.

Engelbrecht-Wiggans and Katok (2008) interpret bid movements as attempts to evade regret. To this end, they differentiate between two types of regret that can be observed in a first-price sealed-bid auction. When a bidder wins an auction and learns that the second-highest bid was substantially lower, he can suffer from "money-left-on-the-table" regret, because he has paid too much for the item. On the other hand, if he does not win, but learns that the highest bid was still smaller than his valuation, he can suffer from "missed-opportunity-to-win" regret. They show that in the case of the first type of regret, bids decrease when the second highest bids are displayed. For the second type of regret, bids increase when winning bids are displayed.

Neugebauer and Selten (2006) investigate both the learning direction theory and the impulse balance theory experimentally. The goal is to study the effect of information in a first-price sealed-bid auction with single demand. They find that information feedback in the form of achieved prices leads to overbidding in first-price auctions. Results could be correctly predicted by the learning direction theory in qualitative terms and by the impulse balance theory in quantitative terms.

Neugebauer and Perote (2008) extend these findings and find evidence for anchoring on the side of the bidders. In addition to the treatments with information, they also introduce a treatment where absolutely no feedback is provided. They find that this results in average bids below the risk-neutral Nash equilibrium, while feedback leads to overbidding. They explain this with anchoring of the bidders on the published market prices.

When talking about feedback (information) in the context of auctions, one should keep in mind that depending on the auction format, different degrees of information are per se provided to the bidders. Comparing two standard formats, the English (open cry) and the Dutch (descending clock) auction, it becomes obvious that in the former type all bidders hear all bids, whereas in the latter only the final price is called out. This means that although there is a lack of experimental studies examining the effect of feedback in multi-unit and divisible good auctions, existing studies which investigate different auction formats can offer some limited insights into the learning pattern when multiple items are bought or sold at the same time.

One of the first studies of this kind is Plott and Smith (1978), who implicitly examine two kinds of information treatment due to the choice of auction design. In their open-cry auction they inform bidders only about the highest and the lowest bid of the previous round and total quantity available. In contrast, in their posted-bid market all bids from the previous (but not the current) round are known. However, the authors assume this informational difference to be minor. They establish that the open-cry design leads to overbidding, whereas the posted-offer design leads to underbidding. One should also note that bidders in their multi-unit auction have single-unit demand, whereas in the posted-offer market several units are traded at the same time.

Cox et al. (1984) study the impact of information in a discriminatory-price sealed-bid auction, where bidders each demand a single unit. They compare the auction outcome when the highest rejected bid and the highest accepted bid are displayed to the auction outcome when this information is not displayed. In both cases, they observe underbidding relative to the risk-neutral Nash equilibrium. Underbidding was enhanced when information was blocked, which resulted in 60% of the bidders bidding too low, whereas when the relevant information was available, only 48% bid too low.

Kagel and Levin (2001) explore the effect of feedback in a multi-unit auction. They use computer bidders with single demand that follow the dominant strategy (i.e. bid their value). They restrict human bidders to bidding the same or lower on the second unit and examine (among others) a clock auction with and without feedback, i.e. the clock pauses as soon as one of the computer rivals drops out in the feedback treatment. They find significant behavioral differences when feedback is missing, as bidders have better chances to adjust their behavior when information flows continuously. The clock auction without feedback, therefore, has very similar outcomes to the sealed bid auction, where intermediate information gathering is hindered.

In addition to their earlier publication, Kagel and Levin (2005) examine the behavior of bidders in multi-unit auctions with a sealed-bid and an ascending-bid (open-cry) design. Here, they used the same information feedback throughout the entire experiment, namely all bids, ranked according to price, highlighting the winning bids. As in their earlier experiment, they let computers with single-demand compete against individual human bidders with demand for multiple units. They find that bidders are closer to the predicted behavior in the open-cry design, confirming the finding of Ockenfels and Selten (2005) that feedback reduces overbidding.

Table 3.1: Overview of studies on multi-unit and divisible good auctions

Study	**Auction format**	**Treatment**
Cox et al. (1984)	sealed-bid auction with and without information on rejected bids	discriminatory pricing
Cummings et al. (2004)	sealed-bid auction with revision rounds	discriminatory pricing (uniform pricing only in 2 initial rounds)
Engelmann and Grimm (2009)	open and sealed bid	uniform pricing, discriminatory pricing, Vickrey, Ausubel
Kagel and Levin (2001)	ascending-bid clock auction with and without feedback, sealed-bid auction	uniform pricing and dynamic Vickrey auction
Kagel and Levin (2005)	ascending-bid clock auction vs. sealed-bid auction	uniform pricing
Plott and Smith (1978)	oral and sealed-bid (posted-offer)	discriminatory pricing

Note: all studies used independent private values

Engelmann and Grimm (2009) also look into different pricing rules and auction design in the field of multi-unit auctions. They conduct an experiment with two units and two bidders, where bidders can either observe drop-out prices or bids, depending on whether the auction format is open or sealed-bid. The pricing rules are based on uniform and discriminatory pricing as well as the Ausubel and the Vickrey auction. Auctioneer's revenue is then less dependent on the pricing rule, but more on whether it is open or sealed-bid, hinting again at a behavioral impact of the implicit information provision.

Cummings et al. (2004) find some evidence for the learning direction theory in the context of multi-unit auctions. They examine several types of auctions to determine the design best suited for the Georgia irrigation reduction auction. The most important similarity is that it is also a procurement auction, as farmers sell their permits. A very significant difference, however, is that the buyer (auctioneer) does not buy a prespecified amount or number of permits, but has a fixed budget. Valuation has a common and a private element and their market is much larger than ours (9 to 42 participants). To our knowledge, they are the only ones that applied an information treatment to an experiment on multi-unit auctions. However, the authors do not implement repeated bidding, but allow bidders to revise their offers upon knowledge of the competing bids. This continues until no one wants to change his offer any more or until the auctioneer chooses to terminate the auction. Cummings et al. observe that after participants receive a provisional acceptance, they often increase prices. On the other hand, when not being accepted in a round, they decrease prices again. In a couple of additional sessions with a smaller number of bidders, the experiment was repeated while not announcing the cut-off price, but only the ID numbers of accepted permits. However, as each bidder holds three different permits, they are able to deduce the approximate cut-off price nonetheless and game with their offers. It is important to note that when revision rounds are announced before the start of the auction, incentives are quite different to those in repeated bidding auctions. This means that the results from Cummings et al. (2004) cannot fully be transferred to our case either way.

Table 3.1 summarizes the existing studies in the field of multi-unit and divisible good auctions. An in-depth analysis of the role of information in divisible good auctions is still missing in the literature. Therefore, we want to fill this gap with our study, while creating a very reliable, and at the same time very innovative market design in the context of reserve energy.

3.3 Methodological approach

In this section, the experimental market is introduced, theoretical predictions for the outcome of the experiments are derived, and the experimental procedure is defined. Here, we present a local solution for trading. It is meant to enable private households with generation equipment to sell their self-produced energy "in the neighborhood". An alternative to such an auction market would be a decentralized market with bilateral trading. Moreno and Wooders (2002), however, show that such an organization can lead to inefficient market dynamics and produce delays in trading. This becomes even more severe in a small market, where the number of bidders has a significant impact on the matching process, which is the necessary starting point for a trade (Wooders, 1998).

3.3.1 The experimental market

The market under consideration consists of several bidders who try to sell their goods to a single buyer, the auctioneer. Production costs follow a step-function, i.e. there are quantity chunks that cause different and increasing types of costs. The bidder can choose to sell his entire capacity or only part of it. His bid consists of the quantity he offers and the price he asks per unit. The auction is repeated for several identical rounds. This repetition influences the bidding behavior over time. We do not only wish to analyze its development, but also how price information can alter it. To this end, we conduct an experiment with two feedback conditions. Feedback on the success of one's own bid is always given, i.e. bidders always know whether their bid got accepted or not. In addition, for the treatment with more extensive feedback, prices of all accepted bids are displayed. This information can foster the learning process, but might also trigger other effects like anchoring or signaling, which are discussed in the results section (3.4.3).

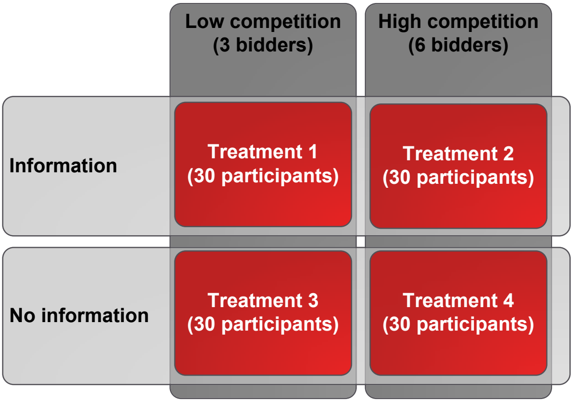

FIGURE 3.1: Overview of experimental treatments

It is also a way to test the observation put forward by Ray and Cashman (1999) that a lower degree of information can help to foster competition in an imperfect market that might otherwise give rise to market power. The central idea hereby is that scarce information hampers collusion, such that high prices cannot be sustained. This might be especially important with low levels of competition. To further examine this, we introduce a second treatment variable, namely competition. By manipulating the number of direct competitors, it allows us to estimate the relative size of the impact of competition and information. An overview of the resulting treatment combinations can be seen in Figure 3.1.

For the experiment, participants were asked to imagine they lived in a household with typical decentralized, small-scale energy generation and storage equipment, for example photovoltaics, micro-combined heat and power, or storage batteries. Having different technical properties, the resulting differences in cost structures are obvious. Available capacities were presented as a portfolio of three quantities at different (production) costs (see Table 3.2). Each first, second, and third price and quantity pair were drawn from the same distribution. For reasons of fairness, the portfolios were then constructed in a way that ensured the most similar total amount of available capacity for each bidder.

Participants could determine the amount of capacity (in kW) they wanted to offer and the price (per kW) they wanted to receive in each auction round. The amount could be freely chosen as long as it was not larger than the sum of their capacities. For any smaller amount, the function determining the profit assumed that the amount produced by the technology with the lowest costs was sold first, thereby maximizing the individual's profit. The average costs of the quantity offered were at the same time the minimum price limiting the possible bids from below. This procedure prevented losses on the side of the participants during the entire session. There was also a maximum, or reservation, price for the bids, which was set at 100 ECU (experimental currency units). Above this price, bids were not accepted by the system, i.e. participants faced an error message asking them to observe the reservation price. For the auction process, this upper limit was non-binding. If a bidder decided not to participate in an auction round, he or she could simply enter an amount of 0. The bidding groups, i.e. the competitive field, as well as individual price and quantity schedules remained fixed during the auction rounds. Bidders had no knowledge of the portfolio of their competitors, except that it was "similar".

The auctioneer was a single buyer with fixed demand, which was not made public. In each auction round, bids were ranked according to price and accepted until the auctioneer's demand was at least fulfilled. Marginal bids were completely accepted without rationing. The reason for this is that the technical equipment in households cannot freely set their operating point, such that they could not react to a rationed quantity. Being framed as a reserve energy market[1], this procedure also ensures some safety margins. Furthermore, market participants are assumed to be small (household) producers with a generation capacity of up to 50 kW. With this lack of market power, they would, therefore, not be able to abuse the situation in a real-world setting. Details of the auction mechanism can be found in the Appendix to this chapter.

The information provided to the participants was always direct feedback on their bids, i.e. whether their bid had won, and the resulting profit for the current round. In the information treatment prices of all accepted bids, ranked from lowest to highest, were additionally displayed. The no information treatment did not offer such a display. Bidders were not made aware of their informational status. Nevertheless, when asked what kind of feedback to expect, participants got the true answer corresponding to the treatment they took part in.

3.3.2 Theoretical benchmark and expected results

In each experimental auction market, there are n bidders and each bidder i disposes of a total quantity $K_i = \sum_j \kappa_{i,j}$ with $\sum_i K_i = \frac{Q}{\alpha}$. Hereby, α is the ratio of demand to

[1]Reserve energy is used to counter fluctuations in the energy grid, i.e. to balance stochastic demand and supply. Generators to fulfill this task are determined on the reserve energy market and remain on stand-by until needed. Without sufficient reserve energy, the energy grid could collapse, resulting in a blackout.

supply. Bidder i's total cost are described by the following function:

$$C_i(\kappa_i) \quad = \sum_j \kappa_{i,j} \cdot c_{i,j} \quad \text{with} \quad c_{i,j} < c_{i,j+1} \tag{3.1}$$

with $c_{i,j}$ being the marginal cost of each quantity chunk j for bidder i (with $1 \leq j \leq 3, j \in \mathbb{N}$). For the concrete form this takes in the experiment, please refer to Table 3.2.

Due to the chosen allocation rule without rationing, it is always optimal to offer the entire quantity that can be produced at costs that are at or below the stated (bid) price. In the presented auction market, neither profit nor the allocation probability can be positively influenced by offering only part of a chunk. A bid should be optimally be constructed in such a way that it entails one, two, or all three parts of the quantity portfolio, as long as these chunks are entirely offered and not partially. *Ceteris paribus*, the latter would inevitably lead to reduced profits on some of the units. And again, a change in allocation probabilities cannot be reached by such behavior, at least not when assuming symmetric behavior of all bidders.

To create a competitive setting, we would usually set demand at 50% of supply. Due to our chosen allocation rule, where marginal bids are fully accepted, we here chose to set demand at 40% of supply. Note that this does not impact the (theoretical) equilibrium price. For analyzing possible bidding behavior, we assume $\kappa_{i,1} = \kappa_{i,2} = \kappa_{i,3} = \frac{1}{3}K_i$ with associated unit costs of $c_{i,1} < c_{i,2} < c_{i,3}$. The costs that are actually incurred by the bidder result from the units accepted during the auction $\tilde{\kappa}$, multiplied with the costs of the affected quantity chunk, leading to $C_i(\tilde{\kappa}) = \tilde{\kappa}_{i,1} \cdot c_{i,1} + \tilde{\kappa}_{i,2} \cdot c_{i,2} + \tilde{\kappa}_{i,3} \cdot c_{i,3}$.

While a quantity bid of $q_i = \kappa_{i,1} + \kappa_{i,2} + \kappa_{i,3}$ with a price bid of $p_i \geq c_{i,3}$ is optimal, there exist several other sensible bidding possibilities:

$$\begin{aligned} & q_i = \kappa_{i,1} \\ & \text{with} \quad p_i \geq c_{i,1} \\ \text{or} & \\ & q_i = \kappa_{i,1} + \kappa_{i,2} \\ & \text{with} \quad p_i \geq c_{i,2} \end{aligned} \tag{3.2}$$

Assuming all bidders behave symmetrically, the lower bound for the expected profit when offering the entire quantity is:

$$\pi_i \geq \frac{2}{n}(\kappa_{i,1} + \kappa_{i,2} + \kappa_{i,3}) \cdot c_{i,3}. \tag{3.3}$$

$\frac{2}{n}$ is the probability for symmetric bidders of being allocated.

Although the optimal bid is straightforward and a rational bidder should not deviate from it, competitive pressure might lead price decreases. Once the price drops below $c_{i,3}$, bidders cannot afford to offer their entire capacity anymore and need to move on to bidding only $q_i = \kappa_{i,1} + \kappa_{i,2}$ at a price of $p_i \geq c_{i,2}$. Such strong competition is more likely to emerge when price information is displayed and when more bidders compete against each other, i.e. in the high competition scenario. Assuming symmetric behavior again, demand is still fulfilled and the allocation probability remains the same. The welfare advantage of this is that more expensive units are not offered anymore, which makes the result more efficient than when the entire quantity portfolio is sold. The predictions are, thus:

- **P1: With price information displayed, more bidders will offer a lower quantity ($q_i = \kappa_{i,1} + \kappa_{i,2}$) to remain profitable.**
- **P2: With higher competition, more bidders will offer a lower quantity ($q_i = \kappa_{i,1} + \kappa_{i,2}$) to remain profitable.**

From the literature, we can form some further expectations. The learning direction theory (Selten and Stoecker, 1986) suggests that bidders react to the success or non-success of their actions by increasing or decreasing their bidding price. Even though they can manipulate a second variable, namely the quantity, in a divisible good auction, the principle of price adjustments should still hold. However, we expect it to be distorted by additional information about the prices of their competitors, which can be used as anchors (Neugebauer and Perote, 2008). Resulting from these considerations, the predictions for the presented experiment are, in short:

- **P3: Over the rounds, price movements will be according to the learning direction theory.**
  - P3a: This is more pronounced when no price information is displayed.
- **P4: When price information is displayed, bidders will use them as anchors.**

3.3.3 Experimental design and procedure

The experiment was conducted in four sessions with 120 participants in total, meaning 30 in the four treatments and sessions. The low competition sessions accommodated ten bidding groups of three bidders each, and the high competition sessions five bidding groups of six bidders. Bidding groups describe the competitors in one market, i.e. they comprise all sellers that bid competitively to one auctioneer. Both competition scenarios were constructed with and without feedback (hereafter: information and no information treatment). Most participants were students with either an engineering or a business economics background, or both. Each subject could only participate once, which was checked by with the help of the recruitment system ORSEE (Online Recruitment System for Economic Experiments), developed by Greiner (2003).

Upon arrival, participants were asked to draw their seating number from a randomized stack. This ensured random seating, especially preventing people knowing each other - who can be assumed to have higher incentives for and lower barriers to collaboration - from cheating. They were seated at terminals that are protected by dividers on three sides. In addition to random participant seating, the distribution of the group IDs on the terminals was also randomized, such that bidding group members would not sit close to each other. At no point in time did participants know their competitive situation or who was part of their bidding group. Print-outs of the instructions were handed out and read aloud giving ample time for questions. To ensure that everyone really understood the auction mechanism and the resulting bidding possibilities, the first four screens consisted of test questions that had to be answered individually. Only when every participant had answered all questions correctly did the experiment start. To prevent any anchoring effect, prices and quantities for the quiz differed from the prices and quantities in the experiment with a factor of at least 20.

Participants received 10 Euros as a base pay and an additional variable pay, which was equal to their total profit, summed over all 20 auction rounds, divided by 1000, and rounded to the nearest Euro. Final payouts ranged from 15 to 22 Euros. The experiment took about 90 minutes and has been programmed in z-Tree (Fischbacher, 2007), a common toolbox for laboratory experiments.

Table 3.2 shows the capacity portfolio of the bidders. For the high competition scenario, each bidder type was assigned to two participants.

TABLE 3.2: Cost and quantity portfolios per bidder

Bidder 1		**Bidder 2**		**Bidder 3**	
Quantity	**Cost**	**Quantity**	**Cost**	**Quantity**	**Cost**
10	6	12	6	14	7
16	10	14	12	16	12
23	15	18	15	17	15

3.4 Results

In this section we first look at the development of quantity bids, auctioneer's expenditures, price bids, and bidders' profits. Thereafter, we test whether the predictions of the learning direction theory hold or whether alternative bidding patterns can be observed. In the end, we discuss the results obtained. The data analysis is done with the help of the software MATLAB. Specifically, we conduct Kruskal-Wallis tests and regression analyses. The latter are done both non-parametrically with a Mann-Kendall test and parametrically with a linear regression. The Mann-Kendall test reports a qualitative result for the general trend, which can be quantified with a linear regression, also because the measurement points can be regarded as being equidistant, i.e. there occurs the same amount of learning for every round.

3.4.1 Data analysis

In the experiment, results show that, with no information, capacity withholding decreases. This is irrespective of the accepted capacity, or, from the point of view of the seller, the amount sold, but only takes into account the sum of the bid quantities.

Capacities offered in the market slightly increased over time, especially in the low competition treatment without information (see Figure 3.2). The Mann-Kendall test and the linear regression support this with p = $3.26e^{-18}$ and a coefficient of 0.52 in the no information treatment. The trend is a little less strong, but still highly significant in the information treatment with p = $3.44e^{-6}$ and a coefficient of 0.31. In the high

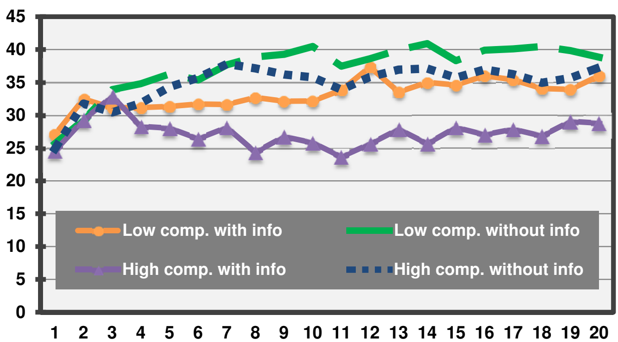

FIGURE 3.2: Development of mean capacities (comp. = competition; info = information)

TABLE 3.3: Capacities: Descriptive statistics (upper part) and Kruskal-Wallis ANOVA (lower part)

	Treatment	**Mean**	**St.dev.**	**Range**
Low comp.	Info	33.2 kW	11.7	2 to 49 kW
	No Info	37.3 kW	10.6	4 to 49 kW
High comp.	Info	27.3 kW	10.3	1 to 49 kW
	No Info	34.8 kW	13.0	0 to 49 kW

	Source	**SS**	**df**	**MS**	**Chi-sq**	**Prob>Chi-sq**
Low comp.	Columns	$4.03e^{6}$	1	$4.03e^{6}$	34.01	$5.48e^{-9}$
	Error	$1.38e^{8}$	1,198	$1.15e^{5}$		
	Total	$1.42e^{8}$	1,199			
High comp.	Columns	$1.43e^{7}$	1	$1.43e^{7}$	121.36	$3.19e^{-28}$
	Error	$1.27e^{8}$	1,198	$1.06e^{6}$		
	Total	$1.41e^{8}$	1,199			

competition scenario, neither test can reveal a statistically significant trend for the information treatment. The no information treatment, on the other hand, shows a similar trend as in the low competition scenario with p = $2.69e^{-9}$ and a coefficient of 0.34. As suggested by P1, capacity bids were generally on a higher level when no feedback was provided. Mean, standard deviation, and range of the obtained values can be seen in Table 3.3. The very low values of 1 or 2 in the range column might have been entered by mistake, because they are clearly outliers. The 0-bid, on the other hand, results from non-participation. The differences between the information and the no information treatment were statistically significant at the 1% level (see Table 3.3). If higher quantities can be translated as higher levels of competition (with less capacity withholding), then less information does indeed support the competitive situation as suggested by Ray and Cashman (1999). In contrast, we argue that the higher capacity bids observed in the no information treatments hint at reduced competition when price information is not available. With competitive pressure, higher-cost generators are driven out of the market, which reduces the total capacity offered (see also P2). What appears to be increased capacity withholding is, therefore, actually increased efficiency. This effect can be observed when comparing the information with the no information treatments, but also when comparing the low and the high competition scenarios.

The development of the auctioneer's expenditure can be seen in Figure 3.3. Table 3.4 shows mean, standard deviation, and range. Although the mean values and the developments of both low competition treatments look very similar, the Kruskal-Wallis test (see Table 3.4) does not confirm this, i.e. treatments produce results that are significantly different. For the range, some extreme values can be observed. It should be noted, however, that these values only occurred during the first rounds; in later rounds, some convergence took place, but full convergence could never be reached.

TABLE 3.4: Auctioneer's expenditure: Descriptive statistics (upper part) and Kruskal-Wallis ANOVA (lower part)

	Treatment	**Mean**	**St.dev.**	**Range**
Low comp.	Info	18.3 ECU/kW	8.7	9.0 to 51.6 ECU/kW
	No Info	18.3 ECU/kW	6.1	9.5 to 52.3 ECU/kW
High comp.	Info	13.7 ECU/kW	3.9	9.6 to 37.3 ECU/kW
	No Info	15.6 ECU/kW	2.5	12.3 to 25.8 ECU/kW

	Source	**SS**	**df**	**MS**	**Chi-sq**	**Prob>Chi-sq**
Low comp.	Columns	$2.28e^5$	1	$2.28e^5$	17.04	$3.67e^{-5}$
	Error	$5.11e^6$	398	$1.28e^4$		
	Total	$5.33e^6$	399			
High comp.	Columns	$2.31e^5$	1	$2.31e^5$	68.93	$1.02e^{-16}$
	Error	$4.36e^5$	198	2,200.6		
	Total	$6.67e^5$	199			

While the general impact of information on auctioneer's expenditure is not clear, the no information treatments do show a lower standard deviation. This could mean that bidders stick to a certain strategy when they do not obtain market information. Whether this strategy is closer to the theoretically predicted behavior is ambiguous. The effect of competition, on the other hand, becomes very obvious: The low competition scenarios resulted in significantly higher (at the 1% level) expenditures per unit than the high competition scenarios. This result is not surprising, but shows that the mechanism works in the anticipated way. Transferred to the scenario analyzed in Rosen and Madlener (2013a), which emphasizes the use of such a mechanism as an incentive scheme for renewable energy, the necessary goal of attracting market participants in an early phase with little competition is accomplished.

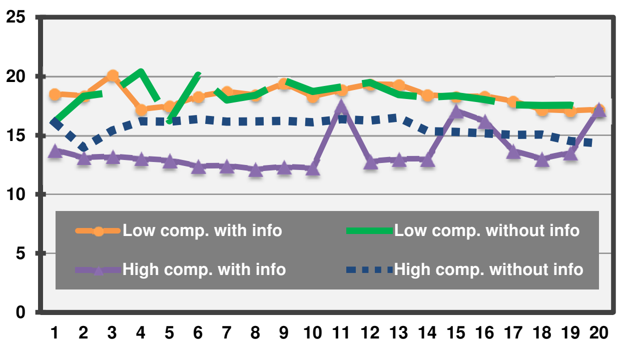

FIGURE 3.3: Development of weighted auctioneer's expenditures (in ECU/kW)

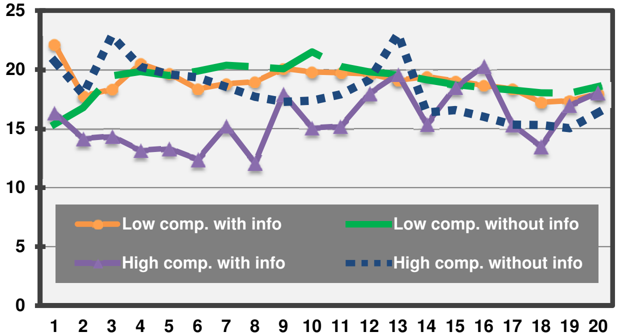

FIGURE 3.4: Development of prices (in ECU)

Prices develop very similar in all treatments except for the high competition information treatment (see Figure 3.4). The no information treatments seem to have a slight tendency to produce higher values than the information treatments, as can be seen in Table 3.5. In the low competition treatments, means are again very close to each other, but the Kruskal-Wallis ANOVA (Table 3.5) shows that they do not come from the same distribution, i.e. the differences between the treatments are significant.

In the high competition case, the mean values change considerably. Here, the samples obviously do not come from the same distribution, as the Kruskal-Wallis test (Table 3.5) confirms. Both treatments in the low competition scenario do not seem to follow any clear trend. The Mann-Kendall test is non-significant with p = 0.9804 for the information treatment and p = 0.5157 for the no information treatment. This means that sellers seem to have submitted on average the same prices in every round. Quite

TABLE 3.5: Prices: Descriptive statistics (upper part) and Kruskal-Wallis ANOVA (lower part)

	Treatment	**Mean**	**St.dev.**	**Range**		
Low comp.	Info	19.0 ECU/kW	11.5	7 to 100 ECU/kW		
	No Info	19.1 ECU/kW	10.4	7 to 100 ECU/kW		
High comp.	Info	15.7 ECU/kW	13.4	6 to 100 ECU/kW		
	No Info	18.1 ECU/kW	11.6	7 to 100 ECU/kW		
	Source	**SS**	**df**	**MS**	**Chi-sq**	**Prob>Chi-sq**
Low comp.	Columns	$3.41e^{6}$	1	$3.41e^{6}$	28.56	$9.10e^{8}$
	Error	$1.40e^{8}$	1,198	$1.17e^{5}$		
	Total	$1.43e^{8}$	1,199			
High comp.	Columns	$3.22e^{7}$	1	$3.22e^{7}$	272.85	$2.71e^{-61}$
	Error	$1.09e^{8}$	1,198	$0.91e^{5}$		
	Total	$1.41e^{8}$	1,199			

to the contrary, the high competition information treatment exhibits a rather strong positive trend with the Mann-Kendall p = 0.0064 and a regression coefficient of 0.20, while the high competition no information treatment follows a negative trend with the Mann-Kendall p = -8.36e^{-6} and a regression coefficient of -0.27.

Over the rounds, the development of bidders' profits mirrors that of prices to some extent. The difference between low competition and high competition scenarios, however, is more pronounced. The values are summarized in Table 3.6. For better comparability, we also calculated the capacity-weighted profits (Table 3.7). Mean values here are relatively low, because we do not discriminate between bidders that won an auction but did not make any profit, and bidders that did not win an auction and therefore made no profit by definition. It becomes apparent that the differences between the competitive scenarios are larger than those between the information treatments. When implementing such a mechanism in a real-world setting, it is, thus, more important to attract participants than to give thought about the information to be provided. The three peaks that can be observed for the high competition information treatment in rounds 11, 15, and 20 (Figure 3.5) are outliers that result from three individual bidders who were lucky or able to game the system with bidding prices close to or at the reservation price, while offering their entire capacity.

In the low competition information treatment, (capacity-weighted) profits follow a negative trend with a coefficient of -0.11 (significant at the 10% level, but not in the Mann-Kendall test: p = 0.8940). The slightly negative trend in the low competition no information treatment is not significant in either test (Mann-Kendall: p = 0.1250). The high competition information treatment shows the opposite trend, i.e. a positive development with p = 6.00e^{-5} (Mann-Kendall) and a coefficient of 0.09. The high competition

TABLE 3.6: Profits: Descriptive statistics (upper part) and Kruskal-Wallis ANOVA (lower part)

	Treatment	**Mean**	**St.dev.**	**Range**
Low comp.	Info	210.9 ECU	356.9	0 to 3450 ECU
	No Info	209.8 ECU	365.8	0 to 4155 ECU
High comp.	Info	92.4 ECU	241.0	0 to 3890 ECU
	No Info	111.7 ECU	135.1	0 to 1744 ECU

	Source	**SS**	**df**	**MS**	**Chi-sq**	**Prob>Chi-sq**
Low comp.	Columns	8.54e^5	1	8.54e^5	7.22	0.0072
	Error	1.41e^8	1,198	1.18e^5		
	Total	1.42e^8	1,199			
High comp.	Columns	1.15e^6	1	1.15e^6	9.77	0.0018
	Error	1.40e^8	1,198	1.17e^5		
	Total	1.41e^8	1,199			

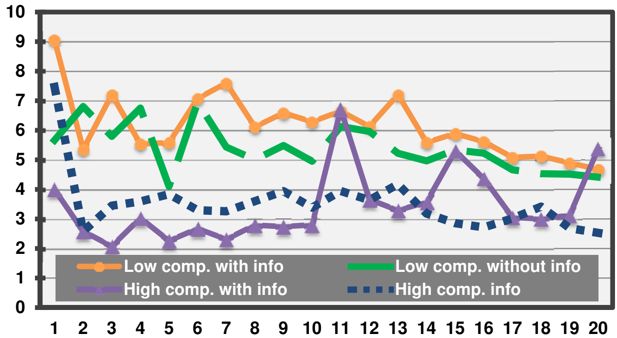

FIGURE 3.5: Development of capacity-weighted profits (in ECU/kW)

TABLE 3.7: Capacity-weighted profits: Descriptive statistics

	Treatment	Mean	St.dev.	Range
Low comp.	Info	6.2 ECU/kW	9.2	0 to 78.4 ECU/kW
	No Info	5.4 ECU/kW	8.0	0 to 88.4 ECU/kW
High comp.	Info	3.4 ECU/kW	5.7	0 to 88.4 ECU/kW
	No Info	3.5 ECU/kW	5.2	0 to 91.8 ECU/kW

no information treatment, however, exhibits again a negative, but non-significant trend with p = -0.5254 and a coefficient of -0.09.

In all variables examined here, differences are significant between the two informational treatments. We have seen that without information feedback, capacities withholding decreases, i.e. more generators enter the market. However, this also means that efficiency suffers because more expensive units are offered. At the same time, and as a result of the inclusion of higher-cost generators, prices increase, and therefore also the auctioneer's expenditures. Profits, however, are not necessarily positively influenced by a lack of information, only by decreasing intensity in the competitive situation.

3.4.2 Testing for the learning direction theory

After receiving feedback from a round, a bidder can be in two different states: He can either be successful with his last bid or unsuccessful. In the following round, he has the opportunity to react to this state by manipulating his bid price. It can be increased, kept equal, or decreased. The learning direction theory Selten and Stoecker (1986) suggests that bidders will decrease their bid price when their bid has not been accepted, whereas they increase their bid price when their bid has been accepted.

We evaluated this for all our treatments. In addition to the two states defined by the learning direction theory ("Strategy 1"), we also consider all other possible combinations for completeness. These can be clustered into doing nothing, i.e. remaining with the same bid ("Strategy 2") and bidding contrary to the predictions of the learning direction theory ("Strategy 3"). Some of these combinations result from sensible behavior in the market. One of these is keeping the bid price equal although the preceding bid has been successful. Such behavior makes sense when bidders are aware that the competitive situation does not allow an increase in the price or when the market approaches its steady-state (which is again a result of competitive forces). Another one is the counter-intuitive behavior when the bid price is lowered although the bidder has been successful. This would again be a result of competitive forces when bidders perceive their bid price as being the marginal bid price, which might not be allocated again in the following round. Obviously, such behavior only makes sense when the average market price is known, i.e. in the information treatment. We, thus, have the following six possible types of behavior:

- Strategy 1: Following the learning direction theory
  - 1a: no success, bid lowered
  - 1b: success, bid increased
- Strategy 2: Remain with the previous bid
  - 2a: success, bid equal
  - 2b: no success, bid equal
- Strategy 3: Bid contrary to the learning direction theory
  - 3a: no success, bid increased
  - 3b: success, bid lowered

Table 3.8 summarizes the bid movements observed over all rounds and treatments. One can see that most moves in bidding behavior conform to the learning direction theory in all four treatments. Nevertheless, some important differences can be observed when comparing the results in more detail. First of all, while increasing the bid price after a successful bid is the behavior most often observed in all cases, it occurs much more often in the low competition scenario. This means that higher competition affects not only the level of bid prices, but also directly impacts the bid movements. Secondly, the learning direction theory does not suggest that bidders lower their bids after a successful round. However, this behavior occurs in substantial numbers when information on competing

TABLE 3.8: Results for bid movements (in %)

	Low comp. info	**Low comp. no info**	**High comp. info**	**High comp. no info**
Strategy 1a	19.6	24.4	15.6	30.0
Strategy 1b	35.1	38.4	28.8	34.4
Strategy 2a	29.1	30.7	37.2	27.4
Strategy 2b	1.8	1.2	3.7	2.1
Strategy 3a	1.2	0.2	0.2	2.3
Strategy 3b	13.2	5.1	14.6	3.9

prices is provided. This supports the notion of Neugebauer and Perote (2008) that bidders anchor on published bid prices. More generally, the numbers reveal that bid prices are indeed kept equal, and increasingly so in the later rounds. It is unclear whether this constitutes a steady-state of the market, because logic would dictate unsuccessful bid prices to be kept equal as well. This, however, cannot be observed, indicating that bidders are still profitable enough to have options and prices have not reached marginal cost. It might, therefore, be inspired by a feeling of "never change a winning horse", rather than rational reasoning.

3.4.3 Discussion

The results can be explained by two diverging trends: On the one hand, competitive forces move prices downward over time. On the other hand, bidders tried to gradually approach higher prices wherever possible. In the information treatment, they used the published prices and oriented their own bids towards the upper end. In the no information treatment, they concluded the market prices from their own accepted or rejected bids. Furthermore, they seem to have applied different strategies in the two treatments. When prices were displayed, two thirds of the participants reported to have included this information in their decision process to react with their own price bid appropriately. This is evidence for the anchoring effect observed by Neugebauer and Perote (2008), and explains why no clear trend can be observed in the data. Although more bidders anchored on the higher accepted bids (20% - 30%), some anchored on the lower accepted bids (7% - 17%), suggesting a continuous replication of the preceding prices. While in the no information treatment prices are also an important decision variable, quantity-driven considerations are relatively more important than in the information treatment. The high competition information treatment was the only one where bidders became very competitive. Some stated that they tried to drive others out of the market, or were bidding in a specific way just to hinder others from gaining higher profits, even if their own profits were suffering. Others tried to bring down prices until their competitors were not able to offer sufficient supply at the prevailing price level. At this point, they would step in and offer a large amount at very high prices to maximize their own profits (this behavior can explain the peaks observed in Figure 3.5). This means that the successful gaming described in the last section is not a result of collusion, but of individual bidders who patiently drove down market prices (and thereby quantities) over a couple of rounds until demand was not fulfilled anymore to be able to enter the market with their entire capacity at a very high price. Since their competitors offered too little, this high bid had to be accepted, rewarding them with exorbitant profits.

Even though several bidders strictly oriented their bidding prices towards the upper end of the accepted price scale, explicit attempts at collusion were unsuccessful. The bidders do not seem to have understood the signals their competitors were trying to send to the market (a few participants were very frustrated by this and complained after the experiment that their colleagues were "too stupid"). As we do not display losing bids, this result is in line with Dufwenberg and Gneezy (2002), who found that signaling only happens when all submitted bids are displayed. It should be noted that, in general, bidders in the high competition information treatment understood very quickly that they had to reduce their quantity offers to stay profitable.

In Section 3.3, we theoretically derived that price information as well as higher competition lead to lower quantities being offered (P1 and P2). Both predictions are equally supported. When combined, the effect is amplified, i.e. the lowest quantity offers can be found for the high competition information treatment.

From the learning direction theory, we also predicted the price movements and established that they should follow the learning direction theory even more, when no information is displayed (P3 and P3a). This information can lead to distortions, because the bidders might use them as anchors (P4). We find support for all predictions. As mentioned above, P3 and P3a only mirror the results to some extent, because about one third up to one half of the bid movements cannot be explained by the learning direction theory. As put forward in P4, this is especially true for the information treatments, where bidders indeed use published prices as anchors.

3.5 Conclusion

We examined the impact of information on a divisible good auction market experimentally and compared the results to the theoretical predictions derived from the assumption of symmetric bidding behavior and the learning direction theory. For this purpose, we defined an information treatment, where bidders could observe all winning bids after each auction round, and a no information treatment, where such feedback was not available.

Both treatments were tested in a high and a low competition scenario, which differed in the number of competitors. In both competition scenarios, quantities submitted were larger in the no information treatment. The same is true for the auctioneer's expenditure, which is higher for no information. This effect is enhanced for a lower level of competition, which means that holding back information seems to hinder competition, as anticipated. Although there was no large absolute difference for prices in the low competition case, it was still statistically significant. In the high competition case, the no information treatment produced much higher prices. However, these prices follow a negative trend, i.e. they decrease again over the rounds. In the high competition information treatment, the opposite can be observed, meaning they increase over the rounds. The results for profits are contradictory in the sense that the two competitive settings produce different outcomes. In the low competition scenario, profits were lower for the no information treatment, while they were higher in the high competition no information scenario.

Overall, our predictions can be confirmed. Price information leads to more competition, such that bidders need to reduce their quantity bids to remain profitable. The same effect is reached by a higher level of competition. When combined, the effects enhance one another, which results in even smaller quantity and price bids.

The predictions of the learning direction theory hold for most moves in the bids. However, we also observed bids which cannot be explained by the learning direction theory, but seem to result from habitual behavior. Furthermore, there is evidence for anchoring on published prices, which might be a counteracting force for the bid movements. Although there were also attempts at signaling and collusion, these have never been successful.

Further research should validate the current findings with respect to their robustness. This concerns the pricing and the rationing rule as well as the auction format.

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Appendix

Auction mechanism

There is a set I of n potential bidders, with $n \in \left\{ 3;\ 6 \right\}$, depending on the treatment. Each bidder $i \in I$ can submit one bid $b_i(p)$, which is composed of a price p_i and a quantity q_i. These bids are ranked according to price, with $b_{i;1}$ being the lowest offer and $b_{i;k_{max}}$ being the highest offer, k_{max} being either 3 or 6. Each bidder knows his costs as a function of quantity, $c_i(q)$. Costs follow a discrete step function and are drawn from a common distribution, as are available quantities.

In the following, we ignore the source of the bid, i.e. neglect the i. Let p be the vector of prices that the auctioneer faces due to the submitted sets of offers $p = \left(p_1;\ p_2;\ ...;\ p_{kmax} \right)$. Further, let $q = \left(q(p_1);\ q(p_2);\ ...;\ q(p_{kmax}) \right)$ be the corresponding quantity vector, as emerging from the bids $b_{i;k}$ ranked according to price. Considering the reservation price p_R enforced in the auction, total expenditure of the auctioneer becomes:

$$\begin{aligned}
&\min_p \sum_i x_i q_i p_i \\
\text{s.t.}\quad &\sum_i q_i \geq Qs \\
\text{with}\quad &s = \begin{cases} 0 \text{ if } \sum_i q_i < Q \\ 1 \text{ otherwise} \end{cases} \\
&x_i \in \{0,1\} \text{ with } x_i = \begin{cases} 0 \text{ if bid } i \text{ is accepted} \\ 1 \text{ otherwise} \end{cases} \\
&p_R \geq p_i
\end{aligned} \tag{A.1}$$

Chapter 4

Multiple vs. Single Bids in Reserve Energy Auctions: An Experimental Analysis

Abstract

In this paper we report on an experimental examination of the comparison between multiple and single bids in a discriminatory-price procurement auction of divisible goods. Having been inspired by reserve energy trading, sellers with a portfolio comprising several cost-quantity pairs bid into a market with a single buyer. Depending on the treatment, they are allowed to submit either one or two bids constructed from their endowments. The allocation rule has no rationing, i.e. marginal bids are completely accepted, which is sensible for a reserve energy market. We specify both a low and a high competition scenario to evaluate the effects of competitive forces on both bidding regimes. We find that multiple bids have a calming effect on the market, reducing volatility substantially. However, this comes at the cost of lower profits for bidders, whereas auctioneer's revenue is maximized. At the same time, supply reduction, which is equivalent to demand reduction in demand auctions, is less pronounced in the multiple-bid setting, but increases over time and with competition.

4.1 Introduction

Markets are the enabling components of economies: With a diversity of different functions and designs they facilitate trading, and some designs are known to be very efficient. In particular, this applies to the field of auctions, whereof multi-unit and divisible good auctions have proven especially useful in public tenders, such as radio spectrum, Treasury bond, or energy auctions. In these types of auctions, an important design feature is the number of bids that can be submitted. While demand as well as supply is often associated with continuous cost or valuation functions, real-world bidding systems usually impose constraints on the number of bids that can be entered. The transformation of continuous cost curves into discrete bids can lead to the obvious problem of not being able to map the underlying preferences or information exactly, and engaging in price/quantity trade-offs that might not be optimal. One can expect that the problem becomes more severe as fewer bids can be submitted. Eventually, inefficiencies and market failures can emerge. An example for this transformation problem can be found in the context of the Treasury bond auctions of the European Central Bank. The number of possible bids (price-quantity pairs) is limited to ten (European Central Bank, 2006, p.26) in the variable-rate tender, but most bidders submit no more than one to three bids (Nyborg et al., 2009). In reserve energy auctions, the number of bids is limited by the amount of prequalified capacity divided by the minimum quantity required for each bid. Despite its practical salience, the majority of studies in the field of divisible good auctions focuses on single bids or continuous bid schedules. The theoretical and practical complexity of these auctions lies in the reciprocal effects of price and quantity, i.e. price and quantity bids need to be traded off against each other, while real-world auction rules, such as the ones just presented, require certain minimum quantities for administrative or other reasons. Tenorio (1997, 1999) and Kremer and Nyborg (2004) have analyzed the impact of discrete bids theoretically, but so far its practical validity has not been examined experimentally for a divisible good auction. In empirical studies, supply reduction has been observed. It can be described as "intra-subject collusion" with the goal of achieving higher prices (Back and Zender, 1993).

In markets with non-professional bidders such as private households, the problem becomes even more severe as these bidders lack the experience and often also the capabilities of determining an appropriate bid. Anecdotal evidence for this can be found with one of the most popular online auction websites, eBay, which offered the possibility of a multi-unit auction for several years. When launching the website it was introduced under the name "Power Auction", being renamed "Multi-Auction" in July 2005, with adjusted rules that were closer to the single-unit auctions, and that allowed bidders to enter one bid consisting of the number of items they wanted to purchase and the price they were willing to pay for each item. As, even in its revised form, the auction seems to have caused confusion among bidders and led to undesired outcomes, it is no longer available (cf. eBay archives).

In this paper, we present an experiment on the effect of the number of permissible bids on bidding behavior (in terms of price and quantity), efficiency, and revenue. It is framed in an energy market context, but results are very broad and can be transferred to any other auction with similar properties. A relevant field hereby is, for instance, the financial sector with Treasury bond auctions, foreign currency auctions, or cloud financing. In our case, however, we focus on procurement auctions where bidders are sellers into a market with a single buyer. Due to technical reasons, we employ a non-rationing rule. A bid hereby consists of the quantity the bidder wants to sell and the price he wants to receive per unit sold. We find that when multiple bids can be submitted, individual profits fluctuate much less than in the single-bid case, while auctioneer's revenue is maximized.

We proceed as follows: Section 4.2 gives an overview of the relevant literature, focusing essentially on experimental and theoretical research on divisible good, single- and multi-bid auctions. Section 4.3 uses this input to provide some theoretical predictions of the experimental results. Section 4.4 explains the experimental procedure, while section 4.5 presents the results obtained. Section 4.6 concludes our findings and their implications.

4.2 Related research

In previous research, mainly three types of bidding regimes are used (Table 4.1). In theoretical studies, continuously differentiable bid functions are the most popular ones, but they are not used exclusively. Elmaghraby (2005) and Alvarez and Mazon (2007) both deliberately decide to use discrete bids in their models, because they better reflect the current auctioning practice in the field of electricity and Treasury bond auctions. In empirical studies, bid schedules in several variations are very common for the same reason. Bidding rules in divisible good auctions often allow for multiple bids to be submitted, and models need to take this into account to be applicable to the available data. Two notable exceptions are Tenorio (1997, 1999) and Kremer and Nyborg (2004), who study the effect of discreteness on the auction outcome. In experimental studies, usually a discrete number of bids is allowed, constituting either a single bid or a bid schedule. To our knowledge, their respective effect on the auction outcome, however, has not been studied yet.

The issue with bids in multi-unit or divisible good auctions is that price and quantity influence each other as well as the auction outcome. One of the first to analyze this reciprocal relationship was Smith (1966). He points to the possibility that upon availability of these decision variables, bidders will reduce them both in a demand auction to increase their profit (i.e. in case of a procurement auction they will reduce the quantity and increase the price). The problem of differences in multiple bids versus single bids was only addressed much later by Scott and Wolf (1979). In their setting, multiple price-bids increase bidders' expected utility gained from the auction and thereby dominate single price-bids.

Previous research in divisible good auctions has either focused on bids for discrete units or on continuous bid schedules. Theoretically, this has been examined by Back and Zender (1993), for example. Experimental research on this topic, but with discrete prices and quantities, has been published in 2013 by Morales-Camargo et al. (for further examples see Table 4.1). The latter find that the mean number of distinct bids submitted was 3.76, which is substantially less than the maximum number of bids, with more bids submitted in the uniform-price auctions than in the discriminatory-price auctions. Bids could be submitted in the form of quantity indications in a predetermined price schedule. Also, they found that most bidders bid in sum for not less than the entire quantity available.

A very similar approach is taken by Sade et al. (2006), who also examine an auction market inspired by Treasury bond auctions with uniform and discriminatory pricing. In their experiment, bidders were allowed to submit four bids, each being a quantity at a predefined price. The sum of the bids was not allowed to exceed the total quantity available. While the theory they applied predicts flat bids in discriminatory auctions, the authors find that 36% of the bidders submit several different price/quantity pairs. They also find a much smaller standard deviation in the demand schedules in the discriminatory-price auction than in the standard uniform-price auction. However, the standard deviation and the skewness are higher than predicted by theory, because bidders did not submit completely flat demands.

In an energy context, Rassenti et al. (1994) conduct an experiment for gas pipeline networks, where bidders are allowed to submit two price-quantity pairs as bids. They, however, do not report how these bids may be constructed or what variance can be observed over several auction rounds.

In an empirical study with data from the Norwegian Treasury bond auction, Bjonnes (2001) finds that the smaller the quantity demanded by the bidder, the fewer bids he submits. Bjonnes divides all bidders into three categories, the first being large (institutional) bidders, the second medium-sized bidders and the last small bidders. He finds

TABLE 4.1: Review of bidding regimes in the literature

Study	Bidding regimes	Type of study
Alvarez and Mazon (2007)	Discrete bids	Theoretical/simulation
Ausubel and Cramton (2002)	Continuous bid function	Theoretical
Back and Zender (1993)	Continuous bid function	Theoretical
Back and Zender (2001)	Continuous bid function	Theoretical
Bourjade (2009)	Continuous bid function	Theoretical
Burke and Auslander (2009)	One bid with soft budget constraint	Theoretical
Denton et al. (2001)	Bid schedule	Experimental
Elmaghraby (2005)	Discrete bids	Theoretical
Federico and Rahman (2003)	Continuous bid function	Theoretical
Hortacsu and McAdams (2010)	Bid schedule (step function)	Empirical
Kang and Puller (2008)	Price grid / discrete and continuous bid functions	Empirical
Kastl (2011)	Bid schedule (step function)	Empirical
Rassenti et al. (1994)	2 discrete bids allowed	Experimental
Rassenti et al. (2003)	Bid schedule (step function)	Experimental
Rosen and Madlener (2013a)	Continuous bid function	Theoretical
Rostek et al. (2010)	Continuous bid function	Theoretical
Sade et al. (2006)	4 discrete bids allowed	Experimental
Scott and Wolf (1979)	Discrete bids (single vs. multiple)	Empirical
Sefton and Zhang (2009)	Multiple discrete bids allowed	Experimental
Smith (1966)	One bid	Theoretical
Tenorio (1997)	Discrete bids	Theoretical
Tenorio (1999)	Discrete bids	Theoretical
Wang and Zender (2007)	Bid schedule (piece-wise differentiable)	Theoretical

that the latter only submit 2.2 bids on average, whereas larger bidders submit up to 7.5 bids on average.

On the theoretical side, Kremer and Nyborg (2004) relax the common assumption of continuous demand functions and introduce discrete bids into a model to analyze underpricing. They conclude that due to an increased price competition on marginal units, underpricing vanishes when supply is either uncertain or larger than individual demand. It can be assumed that non-rationing has a similar effect, because it eases competition on marginal units.

Kastl (2011) has a similar approach and starts his analysis with a standard uniform-pricing model for a divisible good auction. He then introduces a model for step functions, which he applies to the Czech Treasury bond auction. He also establishes a close link between divisible good auctions with discrete bids and multi-unit auctions. His findings suggest that it makes a difference whether one assumes a model with discrete or continuous bidding for analyzing data, but that bidder's profits are not necessarily improved with continuous bidding.

Tenorio (1999) shows that for divisible good auctions with "lumpy bids", i.e. bids that do not follow a continuous bid function, expected revenue is higher the bigger the chunks (in terms of quantity) are that need to be bid for. Lumpiness hereby refers to the discreteness of several units, or alternatively "pieces" of the good demanded at the same price, which is often required by the auction rules through the enforcement of minimum quantities. This implies that when only one bid for the entire quantity can be placed, expected auctioneer's revenue reaches its maximum. An explanation for this would be the perceived risk by bidders of experiencing rationing, which is obviated by more aggressive price bidding. Equivalently, when bidders bid for shares of an object rather than for the whole object, their expected payoffs are larger.

Tenorio (1997) also shows that the above-mentioned phenomena are even more severe in uniform-price auctions than in discriminatory-price auctions, supporting our choice of design. The negative effects on efficiency caused by an altered distribution of units are evident.

Grimm et al. (2008) examine divisible good auctions experimentally, but their focus is very different from that of the aforementioned studies: They evaluate the impact of rationing on bidder behavior. The results, however, cannot be compared to ours in any way, as Grimm et al. use a mechanism where the seller announces a price and bidders can only react with a quantity bid without being able to actually influence the price. This means that the quantity is not necessarily sold completely, resulting in an inefficient market outcome. They do, however, find that a mechanism without rationing is incentive-compatible.

Another experiment on divisible good auctions was performed by Sefton and Zhang (2009). They use uniform pricing, and focus on the impact of communication, i.e. cheap talk. In their set-up, bidders could submit as many price-quantity pairs as they wished until the sum of the quantity bids hit the pre-announced boundary. They find that for the standard allocation rule with rationing, bidders most easily coordinated their actions when communication was allowed.

A direct comparison of single and multiple bids has so far been missing in the literature. We would like to add to the literature by analyzing the respective effects on bidding prices and quantities. In the following, we introduce the auction mechanism with the non-rationing rule and its application in our experiment.

4.3 Market structure and theoretical benchmarks

The auction rules are directly linked to the investigated market framework, but can occur in very similar forms in other markets like cloud financing, and even in fresh fish and timber markets. We consider a local market for reserve energy, where households can offer the energy they produce with their own equipment (e.g. photovoltaics, micro-combined heat and power generators, micro-wind turbines, or batteries). This means that real-world bidders are small relative to market size and, therefore, cannot significantly impact the market. Additionally, the size and the technical properties of their generating equipment do not allow for arbitrary adjustments in the amounts to be produced. This is why we cannot implement a rationing rule, but accept bids completely. Constituting a safety mechanism in the electricity grid, the single buyer is obliged to procure a minimum quantity. By accepting entire bids without rationing, he can, thus, also enlarge his safety margin. The market is meant to complement the existing centralized reserve energy market by helping to better integrate decentralized units, such as those installed in private homes.[1] The price level of the centralized market also gives an implicit reservation price.

Otherwise, prices in the market should emerge from the underlying costs. This means that although the local reserve energy market offers a great opportunity to gain some money on the side, investments into generation equipment should not happen with the sole purpose of participating in it. The operating hours in combination with the dispatch probabilities are unlikely to cover costs. Equipment should therefore serve as supply for own consumption as a primary task. This also means that at times, there is some amount of spare capacity that a household is happy to sell, while any exceeding amount decreases its level of comfort. A household might still be willing to sell this amount, but needs to ask a higher price for this additional quantity to balance its total utility. Furthermore, there might be several different technologies installed, which have different production costs. We represent this increasing cost function with a portfolio with three different quantities and costs. As we allow bidders to submit up to two bids in the multi-bid

[1]This is not only necessary to ensure a safe grid operation, but also security of supply in the light of recent efforts for the energy turnaround. With decreasing levels of acceptance of nuclear power and limited capacities in coal- and gas-fired power plants, the renewable and decentralized generation is required to sustain previous levels of comfort and reliability in electricity supply. However, so far the existing market is not meant to be replaced, but remains as a perfect substitute for decentralized procurement. Further information on the underlying market framework and its functioning can be found in Rosen and Madlener (2013a).

case, the three chunks are necessary to avoid a trivial mapping from the given prices and quantities to the respective bids. Any higher number that can be evenly divided by the number of possible bids would suffer the same drawback, while any other uneven number higher than three would complicate the transformation process needlessly.

Keeping this in mind, the market mechanism can be described as a procurement auction with a discriminatory pricing mechanism. This means that bidders receive exactly the price that they bid in case they are allocated. Costs are private information and increase discretely for the quantity chunks. Each bid consists of a price and a quantity, which can be chosen as integer numbers within the given limits. The highest price that can be achieved is the reservation price, p_R, which is set in advance and is commonly known. In total, one or two bids may be submitted, but do not have to be submitted, i.e. the quantity in either bid can always be set to zero. With regular repetition it is a repeated game, which might set an incentive to collude, especially in the first rounds. Marginal bids are accepted completely, i.e. without rationing.

In mathematical terms, this means there is a set of potential bidders I consisting of n bidders. Each bidder $i \in I$ can submit up to two bids $b_{i,j}$, which are composed of a price $p_{i,j}$ and a quantity $q_{i,j}$. Each bidder knows his costs as a function of quantity $c_i(q)$. Costs follow a discrete step function and are drawn from a common distribution, as are available quantities. Let $\mathbf{p_i}$ be the vector of prices that bidder i submits, and let $\mathbf{q_i}$ be the corresponding quantity vector. From there we obtain the set of all possible bids $\mathbf{b_i}$.

$$\mathbf{p_i} = \begin{pmatrix} p_{i,1} \\ p_{i,2} \end{pmatrix} \text{ with } \; p_{i,j} \geq 0, \quad \mathbf{q_i} = \begin{pmatrix} q_{i,1} \\ q_{i,2} \end{pmatrix} \text{ with } \; q_{i,j} \geq 0 \tag{4.1}$$

$$\mathbf{b_i} = \begin{pmatrix} \{p_{i,1}, q_{i,1}\} \\ \{p_{i,2}, q_{i,2}\} \end{pmatrix} = \begin{pmatrix} b_{i,1} \\ b_{i,2} \end{pmatrix} \tag{4.2}$$

A bid can either be accepted or rejected. Both bids can be accepted at the same time, and are, thus, not mutually exclusive. Acceptance is a binary variable described by

$$\mathbf{x_i} = \begin{pmatrix} x_{i,1} \\ x_{i,2} \end{pmatrix} \tag{4.3}$$

with $x_{i,1}, x_{i,2} \in \{0,1\}$. Bidder i's revenue in one round is, therefore determined by (we leave out the "i" for simplicity):

$$\sum x_j p_j q_j = x_1 p_1 q_1 + x_2 p_2 q_2 \tag{4.4}$$

The auctioneer needs to procure a fixed, predetermined quantity Q and tries to do so at the lowest possible costs. This leads us to the minimization problem, where the binary variable s indicates whether the total demand can be satisfied by all offers.

$$
\begin{aligned}
&\min_{x_{i,j}} \left\{ \sum_i \sum_j x_{i,j} p_{i,j} q_{i,j} \right\} \\
\text{s.t.}& \\
&x_{i,j} \geq 1 - s \ \forall \ i,j \\
&\sum_i \sum_j x_{i,j} q_{i,j} \geq Qs \\
\text{with}& \\
&s = \begin{cases} 0 \text{ if } \sum_i \sum_j q_{i,j} < Q \\ 1 \text{ otherwise.} \end{cases}
\end{aligned}
\tag{4.5}
$$

Note, that in case $s = 0$ due to the first constraint, all bids are accepted and the objective function is constant in $x_{i,j}$ with value $\sum_{i,j} p_{i,j} q_{i,j}$.

4.3.1 Implementation in the experiment

As a result from the non-rationing rule, the above-mentioned formulation of the optimization problem could lead to a situation where a bidder's offer is rejected even though his price is lower than the accepted price of an opponent. In that case, a bidder could believe that his demanded price was too high, even if it was clearly not, and falsely adjust the price downwards during the following auction round. To avoid sending such false signals to the participants of the experiment, we altered the optimization process in such a way that those rejected bids at lower prices are additionally accepted. Alternatively, one can imagine the bids to be ranked according to price, with $(b_{i,j})_1$ being the lowest offer and $(b_{i,j})_m$ representing the highest offer. Index k with $k \in \{1, 2, ..., m\}$ hereby denotes the rank of an individual bid among all submitted bids with m being the number of all submitted bids. This means that in order not to provoke undesired behavior and false signals, bids are strictly accepted according to their rank. As bidders are relatively small, this does not impose any problems or exorbitant deviations in the experiment. In a real-world market, this issue should be even less pronounced as bidders are much smaller in comparison to the market size.

While non-rationing has been shown to lead to truthful bidding (Grimm et al., 2008), we believe that our implementation further enhances this effect as misleading feedback is undermined. However, it is also possible that bidders feel less pressure to bid "aggressively", i.e. competitively, which would result in higher market prices. An opposing effect emerges from the fact that the non-rationing rule absorbs some of the prevalence of the price-quantity interdependence. Thereby, the focus is shifted to more price-oriented competition, which again supports lower market prices.

4.3.2 Predictions: The cost-quantity rule

Solution concepts for equilibria in multi-unit auctions are quite complex and rely on heavy assumptions. Especially in the context of electricity markets, the methods of supply function equilibria (e.g. Genc and Reynolds, 2011) and bid function equilibria (Crawford et al., 2007) have emerged. While the supply function approach requires continuous functions, the bid function approach allows for discreteness in bids and units, thereby accounting for important properties of the real-world electricity market, namely discrete generators. There exists an extension to discriminatory pricing for the supply function approach to accommodate reserve energy markets (Holmberg, 2009), but the bid function approach is restricted to uniform pricing, making it difficult to apply it to our chosen scenario. The major obstacle lies in the identification of a "price-setter" and a "non-price-setter" (cf. Crawford et al., 2007), because in a discriminatory auction, every bidder is his own price-setter.

In our scenario, we have n bidders and each bidder i disposes of total capacity $K_i = \sum_j \kappa_{i,j}$ with $\sum_i K_i = \frac{Q}{\alpha}$. Hereby, α is the percentage of demand to supply. Bidder i faces a total cost function of

$$C_i(\kappa_i) \quad = \sum_j \kappa_{i,j} \cdot c_{i,j} \quad \text{with} \quad c_{i,j} < c_{i,j+1} \tag{4.6}$$

with $c_{i,j}$ being the marginal cost of each generator j for bidder i. Due to the chosen allocation rule without rationing, in the single-bid treatment it is obviously always optimal to offer the entire quantity that can be produced at costs that are at or below the stated (bid) price. In the presented auction market, neither profit nor the allocation probability can be positively influenced by offering only part of a chunk. In the multi-bid treatment, this cost-quantity rule can in principle be applied in the same way, but bids can be truncated such that each represents one, two, or all three parts of the quantity portfolio. Another option would be to construct a safe bid that is close to the presumed market price and has a very high chance of being allocated, and a "gambling" bid with a very high price and a lower chance of being allocated. This bid is then used for an occasional profit boost, but also to gather information about the possible set of prices which are still allocated. This kind of information cannot be obtained otherwise,

TABLE 4.2: Possible distributions of capacity over bids

Single bid	Multi bid	
	Bid one	Bid two
1st chunk	1st chunk	2nd (& 3rd) chunk
1st & 2nd chunk	1st & 2nd chunk	3rd chunk
entire capacity	entire capacity	

because prices are not published during the auction process. When constructing such bids, the "rule" of using entire lumps should, however, still be observed. Any other way of distributing the quantities over the bids leads, *ceteris paribus*, to reduced profits on some of the units. And again, a change in allocation probabilities cannot be reached by such behavior, at least not when assuming symmetric behavior of all bidders. Table 4.2 shows the possible distributions of bidder i's capacity over bids in case of three generators, which is the endowment of each bidder in all experimental treatments.

For predicting the bidding behavior, let us assume $\kappa_{i,1} = \kappa_{i,2} = \kappa_{i,3} = \frac{1}{3}K_i$ and respective unit costs $c_{i,1} < c_{i,2} < c_{i,3}$. His actual production costs are determined by the units accepted in the auction process $\tilde{\kappa}$, multiplied with the costs of the respective generator, resulting in $C_i(\tilde{\kappa}) = \tilde{\kappa}_{i,1} \cdot c_{i,1} + \tilde{\kappa}_{i,2} \cdot c_{i,2} + \tilde{\kappa}_{i,3} \cdot c_{i,3}$. To create a competitive setting, we would usually set demand at 50% of supply. As marginal bids are not partially accepted, but completely, we here chose to set demand at 40% of supply. This does not change the theoretical market price ($c_{i,2}$), but spices up the competition, especially for the numerical implementation.

From the cost-quantity rule, we know that in the single-bid case, $q_i = \kappa_{i,1}+\kappa_{i,2}+\kappa_{i,3}$ and $p_i \geq c_{i,3}$ (also see Rosen and Madlener, 2013c). In the multi-bid case, several additional options are possible:

$$\begin{aligned}
& q_{i,1} = \kappa_{i,1} && \text{and} \quad q_{i,2} = \kappa_{i,2} \ (+\kappa_{i,3}) \\
\text{with} \quad & c_{i,1} < p_{i,1} < c_{i,2} && \text{and} \quad p_{i,2} \geq c_{i,2} \quad (\text{or} \quad c_{i,3}) \\
& \text{or} && \\
& q_{i,1} = \kappa_{i,1} + \kappa_{i,2} && \text{and} \quad q_{i,2} = \kappa_{i,3} \\
\text{with} \quad & c_{i,2} < p_{i,1} < c_{i,3} && \text{and} \quad p_{i,2} \geq c_{i,3}
\end{aligned} \tag{4.7}$$

From here, assuming symmetric behavior of all bidders, we can determine the expected profits for the multi-bid case. The probabilities result from the chances of allocation in each case, and prices are estimated to equal the costs of the adjacent, more expensive chunk or the highest costs of the portfolio.

$$\begin{aligned} \pi_{m,1} &\approx \kappa_1 \cdot c_2 + \frac{1}{n}\kappa_2 \cdot c_3 \\ \text{or} & \\ \pi_{m,2} &\approx \frac{2}{n}(\kappa_1 + \kappa_2) \cdot c_3 \end{aligned} \tag{4.8}$$

While for the single-bid case or when a bidder decides to submit only one bid in the multi-bid case, the expected profit can be approximated by

$$\pi_s \geq \frac{2}{n}(\kappa_1 + \kappa_2 + \kappa_3) \cdot c_3. \tag{4.9}$$

Although these are quite some simplifications, it is easy to see that the expected profit is higher when only a single bid that includes all units is placed. Comparing this profit to the expected profits in the more price-oriented scenarios with lower quantities, it is strictly larger, giving preference to quantity- over price-strategies. The bids resulting in $\pi_{m,1}$ should never be placed, because they have the lowest payoff. Theoretically, only the bid resulting in the highest profits (π_s) should be submitted. Note that the resulting allocation is not efficient anymore, because more costly units would also be allocated.

Using these considerations and calculations, we can form some expectations for the experiment. The different treatments exercise different amounts of competitive pressure which lead to higher or lower levels of market prices. In the multi-bid environment, bidders can react to this pressure by reducing the quantity in their first bid, and are thereby able to offer lower prices as well, while maintaining their profit margin. Their remaining (high-cost) capacity can still be offered at higher prices in the second bid, which means it does not remain unused. In the single-bid environment, such an adaptation to the market is not possible. As bidders will nonetheless want to use their entire capacity, they cannot reduce their prices in a similar way. Therefore, we expect that:

- **P1: For the multi-bid case, bidders will reduce their price for the first bid, such that they cannot offer more than κ_1 and κ_2.**
- **P2: For the single-bid case, bidders will remain with the optimal bid and offer their entire capacity ($\kappa_1 + \kappa_2 + \kappa_3$).**

Without knowing the market or being able to calculate an obvious bidding strategy, there is a high chance that bidders behave arbitrarily at the beginning of the experiment. Once they learn which bids get accepted and which bids do not, they can adjust their offers accordingly. Market pressure develops as prices decrease slowly in the course of the auction rounds, while bidders compete for being allocated. Furthermore, participants need experience to understand, discover, and eventually apply the optimal bidding strategies. The predictions for each treatment can, therefore, be expected to develop and fortify over the auction rounds:

- **P3: Due to learning over time, the tendencies will further materialize over the auction rounds, such that total quantities will decrease in the multi-bid treatment, but increase in the single-bid treatment.**
- **P4: The development of quantities is mirrored in the development of prices.**

The issue of learning and other effects of repetition are also further discussed and analyzed in Rosen and Madlener (2013c). As mentioned above, we evaluate a low and a high competition scenario. In the high competition scenario, we double the number of bidders, but also the demand, such that the competitive situation is theoretically identical. Nevertheless, we expect the above-mentioned tendencies to be even more articulated.

When following (Tenorio, 1999), we would expect the single-bid treatment to result in higher competition, i.e. lower prices and smaller quantities and, therefore, lower auctioneer's expenditures. In principle, in the multi-bid treatment, bidders can partition their available quantity and reduce their offer in any way they like, resulting in numerous possible outcomes (see Li and Tesfatsion 2012 for a discussion of different modes of supply reduction in an energy context). In contrast, in the single-bid treatment, they can only determine the amount from their total supply, but this induces many possibilities as well.

4.4 Experimental procedure

In the experiment realized, 126 test subjects participated in four different treatments (high competition multi-bid, high competition single-bid, low competition multi-bid, and low competition single-bid). The experiment was programmed using z-Tree (Fischbacher, 2007), and was conducted in the AIXperiment Lab at the School of Business and Economics, RWTH Aachen University. Participants were recruited using the web-based online recruitment tool ORSEE (Online Recruitment System for Economic Experiments) developed by Greiner (2003). Most participants were students and had either an engineering or a business studies background, or both. It was only possible for them to participate in the experiment once.

Table 4.3: Cost and quantity pairs of the three bidders considered

Bidder 1		Bidder 2		Bidder 3	
Quantity	Cost	Quantity	Cost	Quantity	Cost
10	6	12	6	14	7
16	10	14	12	16	12
23	15	18	15	17	15

When all participants had arrived at the laboratory, they were randomly allocated to seats. Instructions were handed out and read aloud. Afterwards, there was ample time for questions. To foster the understanding of the auction mechanism, a quiz containing questions and calculation exercises had to be taken and only when all participants had completed it successfully, the actual experiment began. To prevent any anchoring effect, prices and quantities for the quiz differed from the prices and quantities of the experiment by at least a factor of 20.

For each session, there were either ten fixed bidding groups consisting of three bidders, or five groups consisting of six bidders. Bidders were seated in the same room in booths that were protected on three sides by screens. In order to prevent collusion, they were neither aware of how many competitors they had nor of who was in their group. Additionally, group IDs were randomly distributed, meaning that any two participants seated close to each other were unlikely to be competitors.

One session was composed of 20 identical one-shot auctions, which were called "rounds" during the experiment. Settings did not change from round to round, so that quantities and costs always remained the same. The individual supply capacity was in the form of a portfolio of three quantities at three different prices. Table 4.3 indicates the available quantities and costs to bidders in the three-person (low) competition case. For the six-person (high) competition case, each portfolio is assigned to two bidders. Participants were told that they could imagine these to be different generation technologies with specific operating properties in an energy context. Using these endowments, bidders could construct one or two bids (depending on the treatment), which could be the sum of these three quantity chunks at a maximum, i.e. the maximum amount they can produce in total. When they chose to sell less, and in the two-bid treatment, the system automatically assumed that they would sell the lowest-cost quantities first, thus maximizing their profit. The costs were calculated accordingly, beginning with the lowest costs and subsequently adding further costs proportionally. The average costs of one quantity-bid also determined the minimum price that could be offered, i.e. the price could not be lower than the costs for the chosen quantity in the quantity bid. If participants tried to bid below their costs, they faced an error message, but this hardly occurred after the test questions were successfully answered. This way, they could not make a loss during the entire session. The profit was calculated in the same way, i.e. such that the accepted bid - irrespective of it being the first or the second bid entered - was assumed to have the lowest costs. In the case of two bids, the lower bid was assumed to have the lower costs. The maximum price that could be entered was limited by a reservation price of 100 ECU, which was common knowledge. For offers that were accepted, however, this reservation price was non-binding. Payouts consisted of a show-up fee of 10 € and the sum of all profits in all rounds divided by 1000.

Treatments differed in the number of bids that could be submitted. The goal is to examine whether and how bidders behave strategically in terms of price and quantity. In the first treatment, participants are only allowed to submit one single bid, whereas they may submit up to two bids in the second treatment. The sum of these two bids may not be more than the sum of the supply portfolio. This way, participants were given the possibility to "fine-tune" their offers, in the sense that they could better adjust their bids to their cost structure. Both treatments were conducted in a low (three bidders) and in a high (six bidders) competition scenario, which allow us to disentangle the competitive effects.

4.5 Results

4.5.1 Total quantity bids

In general, the total amount offered was significantly higher in the multi-bid treatment than in the single-bid treatment (Figure 4.1), in both competitive situations. In the low competition scenario, quantities ranged from 15 to 49, with a mean of 43.7 (approximately 94 % of individual total supply) and a standard deviation of 6.9 for the multi-bid treatment, whereas the single-bid treatment only led to quantities from 4 to 49, with a mean of 37.3 (approximately 80 % of individual total supply) and a standard deviation of 10.6. In the high competition scenario, quantities ranged from 12 to 49, with a mean of 38.7 (84 %) and a standard deviation of 9.4 for the multi-bid treatment, whereas the single-bid treatment only led to quantities from 0 to 49, with a mean of 34.8 (74.5 %) and a standard deviation of 13.0. In each case there was excess supply at all times.

Quantities offered in the market slightly increased over time, especially in the single-bid treatments, but quantities were generally on a higher level when the format allowed multiple bids. As can also be seen in Section 4.5.5, this results from the strategy of constructing a safe bid and using the remaining units for a gambling bid. In contrast, the high competition scenario did not lead to larger amounts offered in the market. This

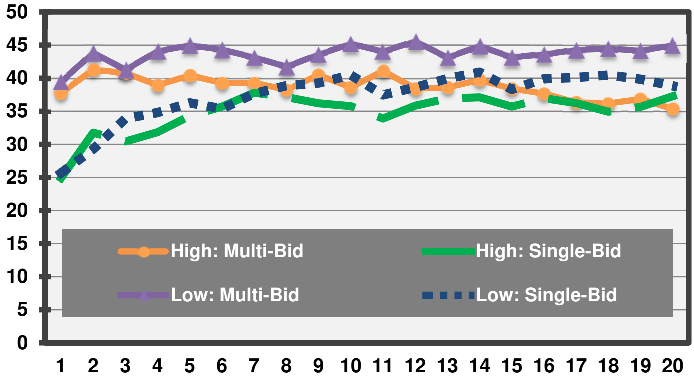

FIGURE 4.1: Development of quantities in all treatments

means that stronger competition eventually leads to supply reduction. This should not be confused with collusive behavior (along the lines of Back and Zender, 1993), but can be explained with an increased efficiency in the market, meaning that high-cost supply is displaced by lower-cost supply. As it stands, both effects are favorable: It is always good to have all units thrown into the market as seen in the multi-bid format, but for the sake of efficiency supply reduction is acceptable under the pressure of high competition.

The chosen experimental setting with 20 repetitions calls for important learning effects. We test this statically by comparing the first ten rounds with the last ten rounds and dynamically by determining the trend in the data. This can be done non-parametrically using the Mann-Kendall test and, because the measurement points can be interpreted as being equidistant, additionally with a simple linear regression analysis, which also provides the magnitude of the trend.

Starting with the static analysis, the Wilcoxon signed rank test shows that in the multi-bid high competition scenario, the bids in the first ten rounds and the bids in the last ten rounds do not come from the same distribution (hypothesis rejected at the 1%-level of significance in a two-sided test, p = 0.001). The same is true for the single-bid high competition scenario with p = 0.0021. The Mann-Kendall test supports the visual impression of a positive trend this with p = $1.34e^{-9}$ in a one-sided test. The regression analysis quantifies the trend with a coefficient of 0.34, which means that the offered quantities indeed rose over the rounds. In the multi-bid treatment, the Mann-Kendall test reveals a negative trend with p = -$5.38e^{-4}$ in a one-sided test. The regression analysis supports this with a coefficient of -0.20, indicating a reduction in quantity offers.

In the low competition scenario, the bids in the multi-bid treatment do seem to come from the same distribution in both parts of the experiment, at least when tested at the 5%- significance level (though not at the 1%- level), with a p-value of 0.0354. The Mann-Kendall test also weakly rejects the hypothesis of a trend with p = 0.1001 in a two-sided test, while the regression analysis reveals a coefficient close to zero. In the single-bid treatment, the first ten auction rounds and the last ten auction rounds do not come from the distribution, the hypothesis is rejected at the 1%- level with a very small p-value of $2.22e^{-9}$. The Mann-Kendall test shows that this is due to a positive trend with p = $1.63e^{-18}$ in a one-sided test. Again, in the regression analysis we find a coefficient of 0.52, pointing to a relatively strong positive trend in the data. From this, we can conclude that with low competition, quantity bids increase only in the single-bid treatment, whereas they decrease or do not significantly develop in either direction in the multi-bid treatment. This is in line with our predictions in Section 4.3.2. As argued in that section, a reason for this might be that bidders learn over time that they achieve the highest expected profits by bidding their entire quantity in the single-bid treatment. In the multi-bid treatment, the probability of having the most expensive quantity allocated is very low, which might discourage bidders from offering that quantity. The test results are further supported by a Kruskal-Wallis-ANOVA (Table 4.4), which shows that the differences between multi- and single-bid treatments are significant in both competition scenarios.

When comparing the results with the predictions of Tenorio (1999), we find that they hold qualitatively and that quantities offered are indeed smaller in the single-bid treatment. This also means that supply-withholding is more pronounced in the single-bid treatments, but decreases over time.

Table 4.4: Quantities in multi- vs. single-bid treatments - Kruskal-Wallis ANOVA table

Competition	Source	SS	df	MS	χ^2	Prob > χ^2
High	Columns	$2.55 \cdot e^6$	1	2552557.5	21.67	$3.24 \cdot e^{-6}$
	Error	$1.39 \cdot e^8$	1198	115752.9		
	Total	$1.41 \cdot e^8$	1199			
Low	Columns	$1.43 \cdot e^7$	1	14308257.6	122.99	$1.40 \cdot e^{-28}$
	Error	$1.25 \cdot e^8$	1198	104485.7		
	Total	$1.39 \cdot e^8$	1199			

Note: SS = sum of squares; df = degrees of freedom; MS = mean square

4.5.2 Price bids

Several distinct features influence the price development process. In a procurement auction, bidders may be uncertain as to how much they can ask, especially when just entering the market and being confronted with discriminatory pricing. This means that they first get to know their environment and learn possible price regions in the first couple of rounds. At the same time, competitive forces are at work that move prices down, depending on their strength. As a last issue, in a divisible good auction there is also interplay between quantity and price. In order to be able to interpret the results, we thus need to consider all three simultaneously.

When analyzing the price development it is important to keep in mind that we are looking at the prices entered into the bidding mask. The successful prices, i.e. those that were accepted, might differ from these, and are captured in the profits (cf. Section 4.5.4), which is why we focus our attention on the entire set of price bids.

Figure 4.2 suggests that prices in the low competition single-bid treatment were much higher than prices in the low competition multi-bid treatments. This graphical impression is also supported by a Kruskal-Wallis test (Table 4.5, part 2). The lowest prices are, of course, those from the first bids in the multi-bid treatment. In the high competition scenario, however, the second-bid price declines very rapidly, too, and comes close to the first-bid price. Nevertheless, the prices in the single-bid treatment are not much higher, such that the difference between the single-bid and the multi-bid treatments is not statistically significant (Table 4.5, part 1).

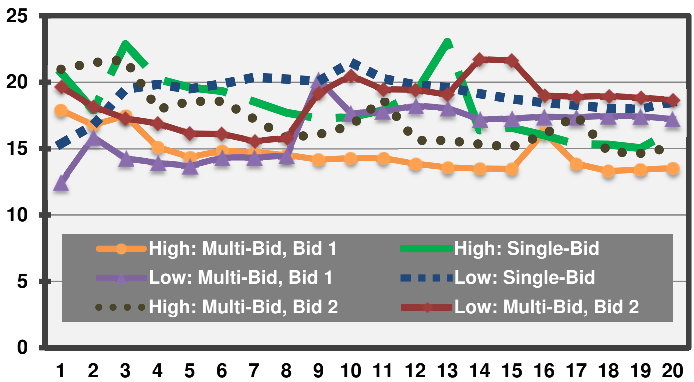

FIGURE 4.2: Development of prices (in ECU) in all treatments

TABLE 4.5: Second price in multi- vs. price in single-bid treatments - Kruskal-Wallis ANOVA table

Competition	Source	SS	df	MS	χ^2	Prob > χ^2
High	Columns	0.96	1	1	$8.15{\cdot}e^{-6}$	0.9977
	Error	$1.42{\cdot}e^{8}$	1198	118257.4		
	Total	$1.42{\cdot}e^{8}$	1199			
Low	Columns	$1.20{\cdot}e^{6}$	1	1204283.5	10.28	0.0013
	Error	$1.39{\cdot}e^{8}$	1198	116263.3		
	Total	$1.40{\cdot}e^{8}$	1199			

Note: SS = sum of squares; df = degrees of freedom; MS = mean square

Speaking in numbers, prices ranged from 6 to 100 ECU in the first bids, with a mean of 14.7 ECU and a standard deviation of 7.5 ECU for the high competition scenario, while the mean was 16.3 ECU and the standard deviation 12.9 ECU for the low competition scenario. The second bids ranged from 10 to 100 ECU in the high competition scenario (mean: 17.2 ECU, standard deviation of 8.7 ECU), while they ranged from 9 to 100 ECU in the low competition scenario (mean: 18.6 ECU, standard deviation of 13.0 ECU). In contrast, they spanned from 7 to 100 ECU in the single-bid treatment in the high competition scenario, with a mean of 18.1 ECU and a standard deviation of 11.6 ECU. In the low competition scenario, prices have the same range, but a mean of 19.1 ECU and a standard deviation of 10.4 ECU.

In the low competition case, the Mann-Kendall test does not identify any trend in the single-bid treatment with p = 0.5157, and also the regression analysis quantifies the coefficient as close to zero. For the first bids in the multi-bid treatment a positive trend with p = $1.26e^{-8}$ can be found (all tests two-sided in this paragraph). The regression analysis supports this with a coefficient of 0.23. For the second bids in the multi-bid treatment, the Mann-Kendall test finds a slightly negative trend with p = -0.0293. The regression analysis, however, finds a slightly positive trend in the data with a coefficient of 0.14. One should note that the p-value for this coefficient is 0.13, indicating that it is not very reliable. As the p-value is also comparatively large in the Mann-Kendall test, we can conclude that there is no obvious trend for the second bids in the multi-bid treatment.

In the high competition case, there seems to be a negative trend for both treatments and in the multi-bid treatment for both bids, with a stronger trend in the second bid. The Mann-Kendall test confirms this with p = $-8.36e^{-6}$ in the single-bid treatment, p = $-6.88e^{-4}$ for the first bids and p = $-6.21e^{-43}$ for the second bids in the multi-bid treatment. The coefficients from the regression analysis are -0.27 in the single-bid treatment, -0.17 for the first bids, and -0.31 for the second bids in the multi-bid treatment.

Unlike our theoretically implied prediction in Section 4.3.2, in the high competition case, bids do not only decrease in the multi-bid treatment, but also in the single-bid treatment. In the low competition case, the predicted trend can only be confirmed for the second bid. The reason for this is that the first bids already provide a reasonable solution (cf. Section 4.5.5), whereas the second bids are used for "gambling" with low chances of winning. In the resulting absence of success, bidders are inclined to reduce their prices to increase their chances. This means that bidders followed a simple algorithm, such as the learning-direction theory would propose (Erev and Roth, 1998), at least to some extent. Another interesting observation is that although bidders increase their quantities in the single-bid treatments in both scenarios, they lower their prices (or at least they do not raise their prices), despite increasing marginal costs. This means that while following the optimal strategy of offering the entire capacity, there are strong competitive forces that impact the prices and profit margins. In the multi-bid treatments, the developments are not that clear, but profit margins are already lower in the beginning. While both quantities and prices decrease in the high competition scenario, prices increase in the low competition case, but quantities remain constant. This means that profits increase. Although they still remain within range (cf. Section 4.5.4), this can be interpreted as a first sign of collusive behavior. It is not surprising that such behavior can only be observed in the low competition multi-bid treatment, because bidders are much better informed about the market than in any other treatment. Using their two bids, they can gather quite accurate information about the market price and carefully increase their bids. One should remember, though, that open signaling is not possible, which hinders explicit collusion.

4.5.3 Auctioneer's expenditure

The auctioneer has the goal of minimizing his expenditure. To this end, the multi-bid format is preferable compared to a format where only one bid may be submitted irrespective of the competitive situation. In particular, in the single-bid treatment (Figure 4.3) the quantity-weighted expenditures ranged from 9.5 to 52.3 ECU, with a mean of 18.3 ECU per unit and a standard deviation of 6.1 ECU in the low competition scenario. In the high competition scenario, the expenditures ranged from 12.3 to 25.8 ECU, with a mean of 15.6 ECU per unit and a standard deviation of 2.5 ECU. The lower variation in the high competition scenario is simply a result of the greater number of bidders in one group, i.e. the higher amount that needs to be procured, which averages out some of the more extreme values. It should be noted, however, that the extreme values could only be observed during the first rounds; in later rounds, some convergence took place, but full convergence could not be reached. In the multi-bid treatment (Figure

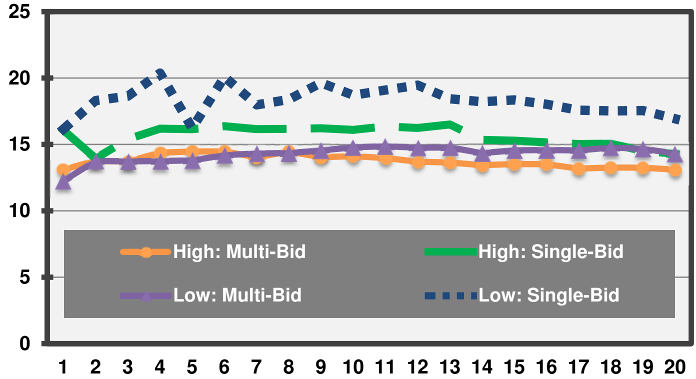

FIGURE 4.3: Average expenditures (in ECU) per unit of the auctioneer in all treatments

4.3), the weighted expenditures ranged from 10.9 to 19.1 ECU for the low competition scenario, with a mean of 14.3 ECU per unit and a standard deviation of 1.5 ECU. In the high competition scenario, the multi-bid treatment produced values between 11.3 and 19.5 ECU, with a mean of 13.9 ECU and a standard deviation of 1.7 ECU. This means that the multi-bid treatments exhibit considerably less variation in the results than the single-bid treatments, which might be an important criterion for companies engaged in the market. The stabilizing effect of multiple bids can also be observed in the bidders' profits (which will be discussed in the next section), supporting the notion of a reliable market environment.

Single-bid settings seem to be less advantageous for the auctioneer in terms of expenditures in our procurement auction. Expenditures are more than 20% higher in both (high and low competition) single-bid treatments and show more variation over time. A Kruskal-Wallis test shows that the differences in the treatments are highly significant (Table 4.6). Nevertheless, the absolute impact on average expenditures is the highest for the single-bid treatment in the low competition case. Put differently, the effect of the multi-bid format in absolute terms, though still significant, is less pronounced under high competition.

4.5.4 Bidders' profit

A more comprehensive variable for analysis might be the profits generated by bidders, because they can be more easily compared across treatments than prices and quantities.

TABLE 4.6: Auctioneer's revenue in multi- vs. single- bid treatments - Kruskal-Wallis ANOVA table

	Source	SS	df	MS	χ^2	Prob > χ^2
High competition	Columns	168432.1	1	168432.1	50.28	$1.33 \cdot e^{-12}$
	Error	498217.9	198	2516.3		
	Total	666650	199			
Low competition	Columns	$1.54 \cdot e^{6}$	1	1540329.21	115.24	$6.98 \cdot e^{-27}$
	Error	$3.79 \cdot e^{6}$	398	9530.08		
	Total	$5.33 \cdot e^{6}$	399			

Note: SS = sum of squares; df = degrees of freedom; MS = mean square

From Figure 4.4 we can already see that the single-bid treatments lead to higher profits for bidders. The difference is large in the low competition case and significant at the 1%-level (Table 4.7, part 2). For the high competition case it is somewhat smaller, but still significant at the 10%-level (Table 4.7, part 1). Similar to auctioneer's expenditure, the absolute effect of the single-bid treatment with low competition is most salient. This means that for profits the competitive situation has again a higher impact than the number of bids.

Profits ranged from 0 to 4155 ECU per person in the single-bid low competition case. The mean was 209.8 ECU and the standard deviation was 365.8 ECU. As bidders could not make a loss, this relatively high standard deviation is mainly a result from high profits above the mean, which can also be seen from the range of obtained profits. This range was much lower in the multi-bid case, with 0 to 340 ECU per person, and also the mean was only 102.9 ECU with a standard deviation of 74.0 ECU. In the high

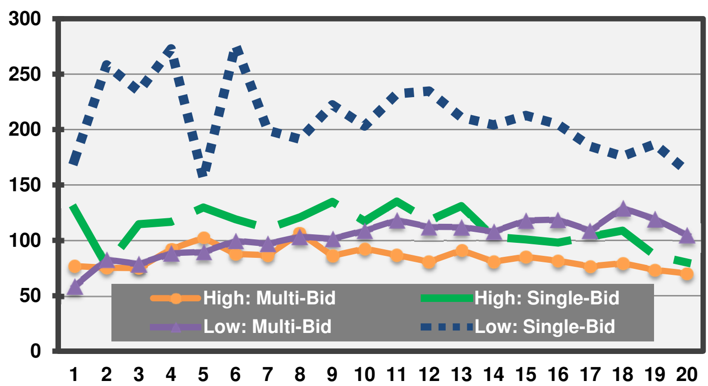

FIGURE 4.4: Mean bidders' profits (in ECU) per round and person in all treatments

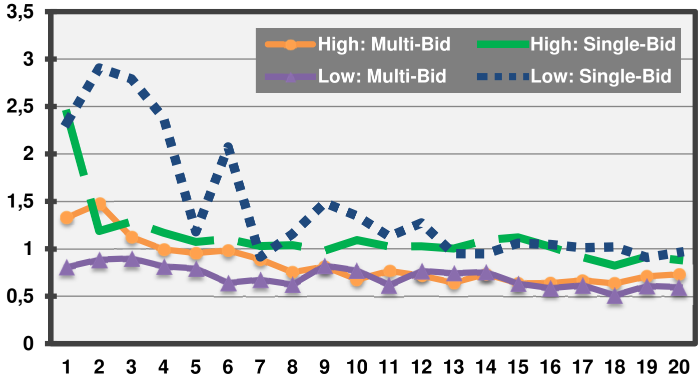

Figure 4.5: Weighted standard deviations of profits in all treatments

competition scenario, the range was also smaller with 0 to 1744 ECU in the single-bid treatment (mean: 111.7 ECU, standard deviation: 135.1 ECU), but larger in the multi-bid treatment with 0 to 590 ECU (mean: 84.3 ECU, standard deviation: 72.6 ECU). This hints again at two forces being present: The high competition scenario reveals a competition effect which only allows low profits, and the multi-bid treatment induces a balancing effect.

To further investigate the latter effect, which is shown to be significant, we decided to look at the standard deviation in each case. Note that the standard deviation needs to be constructed in a way that rules out the leverage effects imposed by the mere size of the profits. The data have therefore first been normalized for each round and only then used for calculations (Figure 4.5).

We find that single-bid treatments exhibit a significantly larger standard deviation with a lot more variance over time than the multi-bid treatments. This means that the possibility of submitting more than one bid levels out the market. This leads to a more reliable market both for bidders and the auctioneer, as both can count on stable prices and plan accordingly. While this might not be important to institutional bidders, it is certainly a favorable attribute for markets with smaller bidders that do not have the opportunity for hedging due to their size.

4.5.5 Optimal quantity bids

As we have shown in section 4.3.2, the optimal bidding behavior resulting from non-rationing is to always bid the entire quantity that can be produced at costs lower than the price bid. This means that bidders should bid the first quantity, the first and the second quantity or their entire available quantity, depending on the price chosen, but never only a part of the respective stack. Taking the inexperience and possible insecurity of the bidders into account, we allow a small deviation from the actually optimal bidding behavior when testing it. In terms of quantity, bids with a reduction of up to 10% of the predicted values are still counted as conforming to the optimal bids, while the price bids for each chunk need to be strictly less than the costs for the following chunk and for the last chunk strictly higher than the costs. It should be noted that the quantity deviation could hardly be observed.

For the analysis, we only consider the last round of each treatment to evaluate the structure resulting from market movements. In the low competition multi-bid treatment, 53% of the bidders bid such that they obtain $\pi_{m,2}$ (equation 4.8, second part), i.e. they bid their first and second stack in the first bid and the rest in the second bid. In the high competition multi-bid treatment, only 40% of the bidders followed that strategy. In both treatments, no other obvious strategy was followed with the two bids in the last round, i.e. no bidder offered the first stack in the first bid and the second or both remaining stacks in the second bid. When only considering the first bids in the multi-bid treatment, we find that 60% of the bidders followed the optimal strategy with their first bid in the low competition treatment, while 13% of the bidders offered their entire quantity (Figure 4.6). Only 3% of the bidders offered only their first stack. In the high competition treatment, 53% of the bidders bid according to the $\pi_{m,2}$-strategy with their first bids, while 3% of the bidders only offered their first stack and no bidder offered the entire quantity available. It is important to note that the percentage of bidders bidding according to the optimal strategy increases dramatically over the rounds, which supports both P1 and P3 (cf. section 4.3.2).

In the low competition case, bidding in the last round of the single-bid treatment results in 53% of the bidders offering their entire quantity, 23% of the bidders offering their first and second stacks, and no bidder offering his first stack (Figure 4.7). In the high

Table 4.7: Profits in multi- vs. single- bid treatments - Kruskal-Wallis ANOVA table

Competition	Source	SS	df	MS	χ^2	Prob > χ^2
	Columns	440603.4	1	440603.4	3.76	0.05
High	Error	$1.40 \cdot e^8$	1198	116873.3		
	Total	$1.40 \cdot e^8$	1199			
	Columns	$4.23 \cdot e^6$	1	4234269.6	35.68	$2.32 \cdot e^{-9}$
Low	Error	$1.38 \cdot e^8$	1198	115225.7		
	Total	$1.42 \cdot e^8$	1199			

Note: SS = sum of squares; df = degrees of freedom; MS = mean square

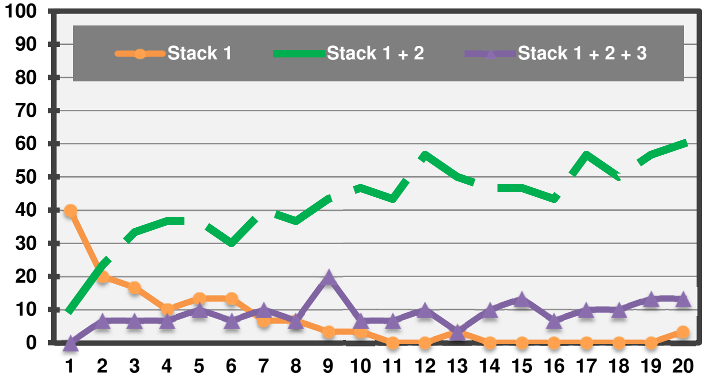

FIGURE 4.6: Strategies applied for the first bids in the multi-bid/low competition treatment (percentage of all bidders)

competition case, a very different picture results with 50% of the bidders following the $\pi_{m,2}$-strategy and 37% of the bidders following the π_s-strategy (equation 4.9). This means that P2 is supported only to some extent, because, as suggested in P4, competition drives down prices and thereby quantities such that bidders cannot sustain the $\pi_{m,2}$-strategy.

Comparing the treatments, it becomes clear that the single-bid treatments are ex-post less efficient than the multi-bid treatments, especially in the low competition case. For the high competition case, the difference is much less obvious. When looking at the equations in section 4.3.2, one sees that the π_s-strategy has strictly higher expected profits. An important characteristic of the π_s-strategy is that bidders offer the entire quantity they are able to produce. In the multi-bid setting it is possible to divide the total quantity into two bids, and as soon as the first bids accumulate sufficient supply, the second bids are not allocated anymore. As the latter include the more expensive units, this means that only the cheaper units are allocated. In the single-bid treatments, such subdivision of supply quantities is not possible. Therefore, when trying to maximize the quantity offered by bidding the total quantity available, less efficient (because more expensive) units are automatically included. However, competition seems to be able to cure this loss in efficiency to a great extent.

4.5.6 Evaluating the predictions

The first prediction (P1, Section 4.3.2) was that in the multi-bid treatment, a decrease in prices will force bidders to offer less in their first bids. More precisely, the decrease will

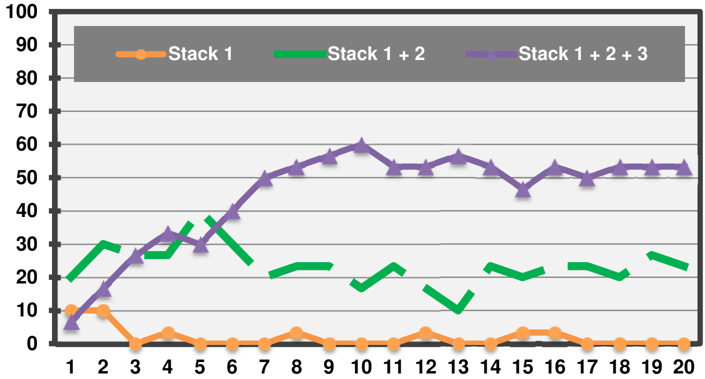

FIGURE 4.7: Strategies applied in the single bid/low competition treatment (percentage of all bidders)

be in such a way that only the first and second quantity chunks enter the first bid. This is confirmed with the majority (53% - 60%) of bidders offering the first and the second quantity stack in the first bid. It should also be noted that the observed supply reduction is not a result of collusion, but of increased efficiency, because high-cost generators are driven out of the market. While the quantity expectations are fulfilled in all cases, the foreseen price development can only be discovered in the high competition scenario. This means that the general intuition holds, but the low competition scenario gives the bidders an opportunity for increasing prices, and thereby profits.

The second prediction (P2, Section 4.3.2) was that in the single-bid treatment, bidders will submit the optimal quantity bid, which includes the entire capacity. The reason for this was that even in case of high competition, bidders would want to offer their entire capacity. When no second bid is available, this can only be done in one bid. This prediction is only supported to some extent. In the low competition scenario, the majority of bidders (53%) does indeed follow this bidding strategy. In the high competition scenario, one can observe a decrease in prices over the rounds. This seems to force a large portion of bidders (50%) to resort to bidding less, i.e. the first and the second chunk.

The third prediction (P3, Section 4.3.2) said that bidders learn over time, and, as a result of this, the tendencies put forward in P1 and P2 accelerate over the course of the rounds. Specifically, we predicted that quantity bids decrease in the multi-bid treatment, but increase in the single-bid treatment. This seems to have come true, both when evaluating the total quantity bids and when observing the development of the optimal quantity bids.

The multi-bid treatments exhibit either a negative or no trend at all, while the single-bid treatments both exhibit a positive treatment. When looking at the optimal bids, which can be described as the micro-level, participants also learn to bid more profitably over the rounds.

The fourth prediction (P4, Section 4.3.2) claimed that the developments of the quantity bids would be mirrored in those of the price bids. This means that for a negative trend in quantities, we would expect the same negative trend in prices, and vice versa. The evidence hereby is mixed. In the high competition scenario, quantity bids decrease in the multi-bid treatment and increase in the single-bid treatment, while price bids decrease in both treatments. In the low competition scenario, the quantity bids remain on the same level in the multi-bid treatment and increase again in the single-bid treatment, while the price bids remain (on average) on the same level. With the exception of the high competition multi-bid treatment, all other cases seem paradoxical, but in fact only show the influence of competition, which reduces overly large profit margins. It can be interpreted as a healthy functioning of the market.

4.6 Conclusion

In this paper we have presented an experiment on the impact of different formats when submitting bids in a divisible good auction. We investigated a multi- and a single-bid treatment in both a high and a low competition scenario.

We expected that bidders reduce prices and quantities in the multi-bid treatment, while they increase quantities in the single-bid treatment. During the experiment, quantities indeed developed as predicted, but prices only decreased in the high competition scenario. In the low competition scenario, they even increased for the multi-bid setting. This can be explained by the amount of information bidders are able to gather relative to market size.

It has been shown that a format where multiple bids may be submitted is, in terms of auctioneer's revenues, much more favorable than a format where only one bid may be submitted. In the multi-bid format higher quantities were offered, which could be evidence for a reduction in the theoretically predicted supply-withholding effect. In our case, however, this was not found to have an impact on prices, as competition seems to be strong enough to compensate possible strategic behavior. Bidders' profits were diminished by competition and by the multi-bid format, although the latter also led to smaller fluctuations and thereby more reliable income streams. Furthermore, in the multi-bid treatments bidders coordinated on a more efficient solution than in the single-bid treatments, at least in the low competition case. In the high competition case, multi- and single-bid treatments show some convergence to the same solution.

Resorting to the most simple way of testing the model of Tenorio (1999), namely comparing a situation with one bid to a situation with two bids, our laboratory experiment is also suitable for validating his finding. However, we can only confirm his results in terms of quantities, not in terms of prices. There might be two reasons for these diverging outcomes: First of all, he assumes rationing, which is not possible in the investigated market due to technical reasons, and, therefore, not in our experiment, while this fact is explicitly communicated to bidders in the instructions. They can therefore not be afraid of being rationed with behavioral consequences. Tenorio interpreted competitive price bidding as a result of the fear of rationing, which cannot be found in our set-up.

Our findings suggest that in divisible good auctions, wherever possible, multiple bids should be preferred to single bids. They support efficiency, a reliable market environment, and auctioneer's revenue. Further research is needed to validate this with different auction formats, especially with uniform pricing, and to further examine the optimal number of bids, which might be more than two. Another aspect is the cost or valuation schedule, which should be altered or resolved to study the robustness of our findings in different settings. Lastly, when considering other markets (such as the Treasury bond auctions), it might be worthwhile to implement different rationing rules and analyze their effect on the outcome.

Acknowledgments

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Chapter 5

Epilogue: Overarching Lessons Learned

Although laboratory experiments are known to produce very reliable and replicable results, they can still be influenced by the human participants and their individual behavior. The research presented in this thesis already surpassed the assumptions of traditional economic theory and the homo oeconomicus by embracing a behavioral economic approach. Some of the most important concepts in this field are the influence of bounded rationality, emotions, social preferences, and limited cognitive resources. In Chapter 2, these ideas can be found in the modeling of bidding agents that use the available information differently and can be "satisfied" or "not satisfied". Even more importantly, the feedback is used for learning, and for adjusting the behavior accordingly. While being an integral of behavioral economic theories, another human aspect becomes apparent when evaluating the experiments in Chapters 3 and 4: Every person is an individual with specific characteristics and abilities, using different approaches and heuristics. This results in a wide spectrum of auction outcomes. It is therefore worthwhile to get to know the participants somewhat better to understand the sources of these differences. This can be done with a questionnaire (see Appendix C), which each participant was asked to fill out after the experiment in addition to answering the usual debriefing questions. The difference hereby is that the debriefing questions were included in z-Tree and only concerned issues that were directly linked to the bidding process. In Chapter 3, Section 3.4.3, the answers to these questions have been used to explain some of the observed strategies as well as anchoring and (unsuccessful) signaling processes. The paper-based questionnaire was meant to assess the chances of success of the introduced local market in a real-world setting, and to provide some further background to the results observed during the experiment. After asking socio-demographic questions, the first block of items concentrated on the auction process and the market idea. The second block investigated the participants' experiences during the experiment and the third block their earlier experiences with online auction markets. The questionnaire uses a 5-point-Likert scale with the extremes "strongly agree" and "strongly disagree". It was pilot-tested and assessed by experts in advance of using it in the experiment. In total, 251 participants filled out the questionnaire. The evaluation is also structured in three parts, which are a general analysis, a gendered analysis, and an analysis with respect to educational background.

5.1 General results

Since most participants were students from RWTH Aachen University, 90 % of the bidders were between 19 and 29 years old. 172 respondents were male, while 79 were female, which means that both groups were large enough to justify the use of a t-test.

The general part reveals that participants enjoyed bidding in the auction (mean: 1.55, standard deviation: 0.81), although most participants stated that they did not engage in any kind of online trading (mean: 2.81, standard deviation: 1.50), particularly not in selling (mean: 3.41, standard deviation: 1.51), in real life. They found the market mechanism transparent (mean: 2.27, standard deviation: 1.00) and easy to understand (mean: 1.76, standard deviation: 0.88). Also the written instructions were found to be easy to understand and complete (mean easy: 1.95, standard deviation: 0.97; mean complete: 1.78, standard deviation: 0.94). In terms of usability, interfaces as well as input and output masks were rated very highly (mean input masks: 1.30, standard deviation: 0.55; mean output masks: 1.64, standard deviation: 0.86). This can also be seen in the boxplots in Figure 5.1 on the left-hand side. These are important factors for the internal validity of the experiment and imply that the results are not random, but are really produced by the market mechanism.

Whether the proposed market will be successful in a real-world setting depends on the acceptance by prospective participants. One of the motivations for conducting the experiments was to evaluate the market functioning with human bidders. For assessing whether participants were satisfied with their own performance, the two items "efficient strategy" and "success in the market" can be combined to form a scale for successful bidding with a mean of 2.34 and a standard deviation of 0.83. Along these lines, 65% of the participants in the experiment evaluated their own bidding as successful. As a second step, a similar procedure can be applied to the items "own participation" and "recommendation to others", which then form a scale for the success of the real-world market. Since the market design tested during the experiments fulfills the criterium of eliciting a satisfactory performance, the introduced market can be seen as fair for all stakeholders. When looking at the 65% who stated that they performed well in the market, the evaluation of the market acceptance reaches a mean of 2.62 with a standard deviation of 1.02. When only including those participants who evaluated their own success as above-average in the entire sample, the assessment of the real-world market becomes even more positive with a mean of 2.46 and a standard deviation of 1.02 (see Figure 5.1, right-hand side). The external validity, therefore, seems to be given by the well-functioning of the market mechanism already. A next step for examining the external validity, especially when it comes to a roll-out of the proposed market, would be to conduct an appropriate survey among prospective real-world participants.

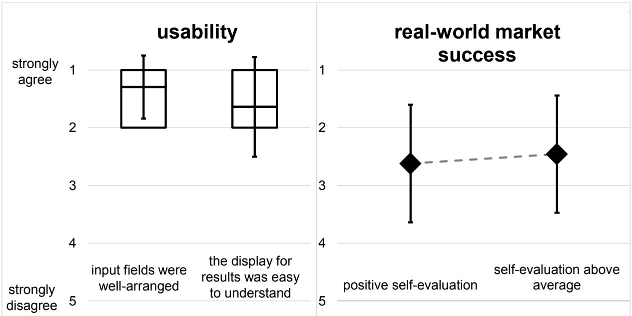

FIGURE 5.1: Evaluation of usability (left) and market acceptance (right)

5.2 Socio-demographic differences in bidding: Gender

Some surprising differences appear when comparing questionnaire results for each sex. While males evaluated bidding in the auction (mean: 1.88, standard deviation: 1.01) and participating in the experiment (mean: 1.75, standard deviation: 0.94) almost equally with $r = 0.77$ and $p \approx 0.00$, females also showed a significant, albeit much weaker correlation between these two items with $r = 0.53$ and $p \approx 0.00$ (mean bidding: 1.91, standard deviation: 0.87; mean participation: 1.85, standard deviation: 0.83). That is, when participants liked bidding in the auction, they liked participating in the experiment even more. Comparing the answers to these two items directly, no significant difference between the sexes can be found in a t-test (p bidding: 0.87, p experiment: 0.30). Another interesting difference in the gendered evaluation is that males liked participating when they found the remuneration scheme motivating, shown by $r = 0.61$ and $p = 0.00$ with means for joy of participation of 1.70 (standard deviation: 0.87) and for money-based motivation of 2.39 (standard deviation: 1.27). For females, this correlation is again significant, but weaker with $r = 0.50$ and $p \approx 0.00$ (mean joy: 1.84, standard deviation:

0.84; mean motivation: 2.38, standard deviation: 1.20). In the context of experience with other auction formats, we find that they use auction platforms like eBay and others when they have fun buying things on those platforms ($r = 0.72$ for females and $r = 0.71$ for males, $p \approx 0.00$ for both).

While the difference between the sexes in joy of buying things on eBay and other auction platforms is significant only at the 10% level ($p = 0.06$), the difference in use of those platforms as sellers is significant at the 5% level with $p = 0.04$ (mean males: 3.17, standard deviation: 1.55; mean females: 3.62, standard deviation: 1.66). This might also result from the higher amount of pleasure males experience from selling (mean males: 2.71, standard deviation: 1.31; mean females: 3.13, standard deviation: 1.42). The difference thereof is highly significant with $p = 0.02$.

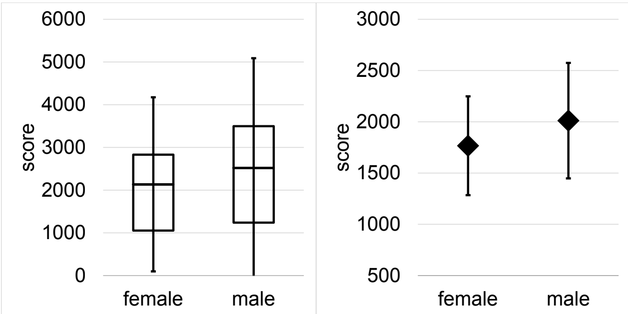

FIGURE 5.2: Boxplot of profits for females and males (left) and the mean and standard deviation for the adjusted sample

In total, males performed better than females in the experimental auction. The boxplot in Figure 5.2 (left-hand side) illustrates this for 75% of each group (upper and lower percentiles are left out). However, the difference is not significant ($p = 0.21$). One reason for the observed tendency might be that males generally found the market mechanism easier to understand, which is significant with $p \approx 0.00$ (mean males: 1.59, standard deviation: 0.76; mean females: 2.10, standard deviation: 1.00). When including the educational background of the largest subgroups in the analysis, the difference between the sexes reduces. When adjusting for outliers though, such that the 12.5% percentiles from below and from above are not included in the analysis, the difference between male and female participants becomes highly significant with $p \approx 0.00$ (see also Figure 5.2, right-hand side). These results might suggest that the two populations could exhibit different variances. This also means that there is further need for research on the influence of socio-demographic factors on bidding behavior. This is especially true since the samples sizes differed largely between the groups, such that a future study should include equal sample sizes not only for the two sexes, but also for different types of educational background.

5.3 Socio-demographic differences in bidding: Education

Altogether, 145 participants, thereof 21 females, had a technical background (i.e. engineering), 85 participants, thereof 41 females, had a background in business administration or economics, and 21 participants had a different background, such as geography, natural sciences, or medicine.

As already mentioned in the preceding section, these educational differences also lead to diverging results in the evaluation of the experiment and of the market itself. Participants with a technical background are much more inclined to participate in such a market in reality than participants with a background in business economics with $p = 0.02$ (mean technical: 2.47, standard deviation: 1.18; mean business economics: 2.87, standard deviation: 1.26). At the same time, they also claimed to have better understood the market mechanism with $p = 0.03$ (mean technical: 1.63, standard deviation: 0.79; mean business economics: 1.88, standard deviation: 0.93) and found the written instructions more comprehensible with $p = 0.04$ (mean technical: 1.82, standard deviation: 0.91; mean business economics: 2.09, standard deviation: 1.04), which might be an explanation for their more positive attitude towards participating in reality. Interestingly, there are some similarities to the tendencies found in the gendered analysis, there mostly at an even higher level of significance. The reason could be that there were relatively more male participants with a technical background, and more female participants with a business economics background. In the educational subgroup of business economics, the sample size was actually balanced.

5.4 Concluding remarks

In this thesis, a market design for local (reserve) energy markets has been developed and analyzed using a simulation and two laboratory experiments. The agent-based simulation already showed that feedback information can have an important short-term as well as long-term impact on the bidding behavior in the market, such that the price convergence takes longer and higher prices are sustained indefinitely. This design variable was further scrutinized in a laboratory experiment with human bidders. The results from the simulation analysis could be confirmed, i.e. participants achieved higher prices when no information was available and when competition was lower. On the other hand, higher competition and information also had a positive effect on efficiency, because high-cost generators were driven out of the market. Furthermore, bidders exhibited behavior that was in line with the learning direction theory in most cases, but there were also attempts at signaling and collusion, which remained unsuccessful. Another important variable on prices and their development has been proven to be the number of bids that can be submitted. In a second laboratory experiment, it could be shown that multiple bids have a calming effect on the market, making revenues more predictable. They also have a positive effect on competition and increase the market efficiency in a similar way to information. These design choices are even more relevant in the initial phase of a local market, when the number of participant might be rather small. A balance needs to be struck to attract more bidders, while keeping the market efficient and the auctioneer's expenditures within affordable limits. The optimal market design for a local reserve energy market should, therefore, provide the bidders with as much feedback information as possible and allow them to submit multiple bids.

While this thesis used a behavioral economic approach, which explains observations diverging from standard economic theory, this chapter aimed at discerning the individual differences observed during the experiments. The questionnaire showed that participants had very specific socio-demographic characteristics, which might have an influence on their bidding behavior. It could further be revealed that the experimental results should have a high internal and external validity. The internal validity is given by the high ratings for the usability items as well as the comprehension of the market mechanism itself. External validity can expected to be reached by the right amount of background information and an appropriate communication strategy towards prospective users. Furthermore, this procedure can enhance a quick and wide diffusion of the described market. This diffusion is necessary for two reasons. On the one hand, with the coming phase-out of the feed-in tariff scheme, new - and preferably market-based - mechanisms are needed to remunerate electricity produced by private households. On the other hand, there is a need for mechanisms that enable the integration of renewable, decentralized electricity generation into the existing infrastructure without jeopardizing a reliable grid operation. With an increasing share of such generation capacities, the introduction of those mechanisms becomes all the more urgent, also with respect to the policy goals for the energy turnaround and against the climate change. The results of this research are meant to be the first pieces of a puzzle for reaching these targets without endangering the security of supply, and thereby enhancing the societal well-being in a sustainable future.

Appendix A

Instructions for Single-Bid Treatments

Welcome to Aixperiments @ FCN – Experiments in energy economics!

Imagine you live in a household with several possibilities of energy generation and storage. Your equipment consists of three different technologies such as solar panels, micro-CHPs (small combustion engines for heat and power) and storage batteries (e.g. for self-produced power).

THE MARKET
You now have the possibility to participate in a market where your own and other households can sell their self-produced energy. This happens in an auction in which there is a single, central buyer with fixed demand, who of course tries to procure as cheaply as possible. This means that starting with the lowest offer, the buyer accepts bids until his demand is fulfilled. In the case where there are several offers with the same price, the winner is determined by lottery. The buyer accepts as many bids as are at least necessary to satisfy his or her demand. If the last (marginal) offer is greater than his or her residual demand, it is nevertheless fully accepted. For that matter, only the price decides about acceptance, not the quantity that is still required. Demand remains constant over all 20 equal auction rounds.
The capacity that is at your disposal also remains constant in each auction round. You can see it on the left-hand side of your screen (cf. the screenshot on the next page). It is composed of three parts that are not meant to be offered separately, but can be combined into a single bid at your will. Every part of the capacity corresponds to one of the three available technologies. All technologies have different underlying costs, which are displayed right next to the quantity as production costs per **kWh**. Costs are only incurred for the amount of an accepted bid.

Available quantity	Costs
A	a
B	b
C	c

BIDDING PROCEDURE

On the right-hand side of the screen, you will find one input field for the quantity and a corresponding input field for the price. Here you can enter your bid. The bid consists, thus, of a price stated **per kWh**, and the quantity which you want to offer. Please note that bids can only be entered as integers.

Your bid is confirmed by clicking the "OK" button.

Please note that you **cannot make offers below your production costs**, and quantity-wise **not more than your total capacity (A+B+C)**. It is assumed that you always want to sell the least-expensive amount first (which is A), then proceed with B, and only in the end offer C. This means that when determining your production costs, the lowest are assumed first, and higher costs are added proportionally. If, for example, quantity A is offered completely with half of B in the first offer, the production costs per kWh amount to: (a*A + b*B/2)/(A+B/2). This weighted average price is the lower limit for the price bid, which is also submitted per kWh. If the bid is too low, an error message pops up. Since there is a reservation price of 100 ECU, above which bids are not accepted, an error message also appears if the bid is too high.

If you decide not to bid, please enter your minimum price in the price field and zero in the quantity field.

Once all market participants have submitted their bids, the screen displays whether your bid has been accepted and how much profit you have made during the current round. It is calculated according to the following formula:

Profit = (Price – Costs)*Quantity

This procedure is repeated in each round.

Your compensation is your total profit in Euro (summed over all rounds) divided by 1000 plus a fixed payment of 10 Euros.

We will now start with a couple of test questions that are meant to improve your understanding. These have completely different values from those that are used in the actual auction. An error message only appears when your answer is wrong. As soon as everyone has answered all questions correctly, the experiment will begin. First, the picture below will appear in order to prepare you for the structure of the input fields. Here you only need to click "OK".

Appendix B

Instructions for Multi-Bid Treatments

Welcome to Aixperiments @ FCN – Experiments in energy economics!

Imagine you live in a household with several possibilities of energy generation and storage. Your equipment consists of three different technologies such as solar panels, micro-CHPs (small combustion engines for heat and power) and storage batteries (e.g. for self-produced power).

THE MARKET
You now have the possibility to participate in a market where your own and other households can sell their self-produced energy. This happens in an auction in which there is a single, central buyer with fixed demand, who, of course, tries to procure as cheaply as possible. This means that starting with the lowest offer, the buyer accepts bids until his demand is fulfilled. In the case where there are several offers with the same price, the winner is determined by lottery. The buyer accepts as many bids as are at least necessary to satisfy his or her demand. If the last (marginal) offer is greater than his or her residual demand, it is nevertheless fully accepted. For that matter, only the price decides about acceptance, not the quantity that is still required. Demand remains constant over all 20 equal auction rounds.
The capacity that is at your disposal also remains constant in each auction round. You can see it on the left-hand side of your screen (cf. the screenshot on the next page). It is composed of three parts that are not meant to be offered separately, but can be distributed over your two bids at your will. Every part of the capacity corresponds to one of the three available technologies. All technologies have different underlying costs, which are displayed right next to the quantity as production costs per **kWh**. Costs are only incurred for the amount of accepted bids.

Available quantity	Costs
A	a
B	b
C	c

BIDDING PROCEDURE
On the right-hand side of the screen, you will find two input fields for the quantity and two corresponding input fields for the price. Here you can enter your bids. The bids consist, thus, of a price stated **per kWh**, and the quantity which you want to offer at that price. Please note that bids can only be entered as integers.
Bids are confirmed by clicking the "OK" button.
Please note that you **cannot make offers below your production costs**, and in total (i.e. as the sum of both bids) **not more than your total capacity (A+B+C)**.
It is assumed that you always want to sell the least-expensive amount first (which is A), then proceed with B, and only in the end offer C. This means that when determining your production costs, the lowest are assumed first, and higher costs are added proportionally. If, for example, quantity A is offered completely with half of B in the first offer, the production costs per kWh amount to: (a*A + b*B/2)/(A+B/2). This weighted average price is the lower limit for the price bid, which is also submitted per kWh. If the bid is too low, an error message pops up. Since there is a reservation price of 100 ECU, above which bids are not accepted, an error message also appears if the bid is too high.
If you decide not to bid, please enter your minimum price in the price field and zero in the quantity field.

Once all market participants have submitted their bids, the screen displays which of your bids have been accepted (maximum of two) and how much profit you have made during the current round. It is calculated according to the following formula:

Profit = (Price – Costs)*Quantity

This procedure is repeated in each round.

Your compensation is your total profit in Euro (summed over all rounds) divided by 1000 plus a fixed payment of 10 Euros.

We will now start with a couple of test questions that are meant to improve your understanding. These have completely different values from those that are used in the actual auction. An error message only appears when your answer is wrong. As soon as everyone has answered all questions correctly, the experiment will begin. First, the picture below will appear in order to prepare you for the structure of the input fields. Here you only need to click "OK".

Appendix C

Questionnaire

THE MARKET	Strongly agree	Agree	No opinion	Disagree	Strongly disagree
Bidding in the auction was fun for me	☐	☐	☐	☐	☐
The auction mechanism was transparent	☐	☐	☐	☐	☐
The bidding procedure was motivating	☐	☐	☐	☐	☐
I tried to maximize my profit during the auction rounds	☐	☐	☐	☐	☐
I could imagine participating in a real electricity market of this kind	☐	☐	☐	☐	☐
I would recommend participation in a real electricity market of this kind to others	☐	☐	☐	☐	☐
I succeeded in applying an efficient bidding strategy	☐	☐	☐	☐	☐
I participated in the market with success	☐	☐	☐	☐	☐
The market mechanism was easy to understand	☐	☐	☐	☐	☐
The market helps to protect the environment	☐	☐	☐	☐	☐
The market supports sustainability	☐	☐	☐	☐	☐

Imagine such an electricity market existed in reality and you already possessed the necessary generation equipment to participate in the market. Would you do it?

☐ yes, because ______________________________

☐ no, because ______________________________

THE EXPERIMENT	**Strongly agree**	**Agree**	**No opinion**	**Disagree**	**Strongly disagree**
Participating in the experiment was fun for me	☐	☐	☐	☐	☐
Written instructions for the bidding procedure were easy to understand	☐	☐	☐	☐	☐
Written instructions for the bidding procedure were complete	☐	☐	☐	☐	☐
Input fields for entering the bids were well-arranged	☐	☐	☐	☐	☐
The payout system was motivating	☐	☐	☐	☐	☐
The display of the results after an auction round was easy to understand	☐	☐	☐	☐	☐
The time consumed by an entire auction round including the display of results was reasonable	☐	☐	☐	☐	☐

AUCTIONS IN GENERAL	**Strongly agree**	**Agree**	**No opinion**	**Disagree**	**Strongly disagree**
I use auction platforms (e.g. eBay, hood.de, centgebote.de) as a private buyer	☐	☐	☐	☐	☐
I use auction platforms (e.g. eBay, hood.de, centgebote.de) as a private seller	☐	☐	☐	☐	☐
I have fun selling something at auctions	☐	☐	☐	☐	☐
I have fun buying something at auctions	☐	☐	☐	☐	☐

How often do you use auction platforms on average?

☐ once a week or more

☐ two to three times a month

☐ once a month

☐ every two months

☐ once a year or less

☐ never

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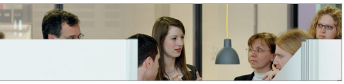 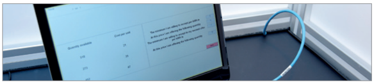 

This thesis proposes and evaluates a local market design for reserve energy in which private households can trade their self-generated energy. The market conceptualization builds upon the idea of a microgrid connecting households with and without power generation equipment. The notion of balance groups can be seen as the current administrative groundwork, with the balance group responsible party acting as an auctioneer. Such a mechanism helps to better integrate distributed generation and acts as an alternative incentive scheme once the fixed feed-in tariffs are abandoned. The market has some definite characteristics that result from the specific technologies and their users. The predominant attribute is the involvement of private households, i.e. retail customers – now in the role of producer-consumers ("prosumers") – without much expertise in the field of energy trading. Hence, trading rules need to be simplistic to create something like an "energy-eBay". While the growing presence of renewables imposes challenges on the current energy system, the local market concept for reserve energy proposed in this thesis can foster the security of supply and a reliable grid operation.

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