Load Balancing in the Smart Grid: A Package Auction and Compact Bidding Language

Research-in-Progress

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Abstract

Distribution system operators (DSOs) are faced with new challenges from the continuous integration of fluctuating renewable energy resources and new dynamic customer loads such as electric vehicles, into the power grid. To ensure continuous balancing of supply and demand, we propose procurement package auctions to allocate load flexibility from aggregators and customers. The contributions of this research are an incentive-compatible load flexibility auction along with a compact bidding language. It allows bidders to express minimum and maximum amounts of flexibility along with unit prices in single bids for varying time periods. We perform a simulation-based evaluation and assess costs and benefits for DSOs and balancing suppliers given scenarios of varying complexity as well as computational aspects of the auction. Our initial findings provide evidence that load flexibility auctions can reduce DSO costs substantially and that procurement package auctions are well-suited to address the grid load balancing problem.

Keywords: Smart Grid, Auctions, Sustainability

Introduction

With the current energy strategy of the European Union, the vision of a sustainable, low-carbon and climate-friendly economy has been established. Moreover, energy security, sustainability and competitiveness have been identified as important dimensions of future energy markets (EC 2015). To this end, new electricity market designs that promote the sustainable integration of renewable energy sources as well as customers through demand response programs are required (EC 2015a). As a result, distribution system operators (DSOs) in particular are faced with new challenges, also given the growth of fluctuating wind and solar generation in their daily operations (EC 2009; He et al. 2013). Traditionally, power generation is adapted to non-controllable demand by means of non-volatile and flexible power plants such as pumped storage. Given the increased share of renewable generation within the grid and policy requirements that demand these sources to be integrated into the generation mix, this task is becoming much harder as demand and supply must always be in balance. To avoid critical grid situations where demand and supply are out of balance, DSOs can currently invoke direct load control (DLC) contracts on customers or fall back to the operating reserve, which represents costly emergency generation solution that is currently accessed to stabilize the grid in case of near-failures. Given that DLC mostly applies to large customers and using the operating reserve is an expensive mechanism, recent literature focuses on integrating the demand side on a local level by means of demand side management and demand response (Albadi and El-Saadany 2008; Palensky and Dietrich 2011). DSOs could avoid high balancing costs by leveraging new local markets of electrical load flexibility on the demand side to substitute the operating reserve.

We propose the application of package (combinatorial) auctions to allocate balancing potential of customers to DSOs. The combinatorial nature allows auction participants to express electricity usage patterns that emerge from technical or economic rationales. The contributions of this research are an incentive-compatible load flexibility auction for the smart grid along with a compact bidding language. It allows bidders to express minimum and maximum amounts of electric flexibility (production or consumption) along with unit prices in single bids for time periods of different size. In addition, the winner determination considers the operating reserve as a fixed price outside option in the procurement auctions. To the best of our knowledge, this combination has not been addressed in existing literature. This is required, however, to facilitate utilization of the full electric flexibility potential to address the grid load balancing problem with feasible numbers of bids.

We evaluate our proposal by simulation experiments based on a combination of real-world and synthetic data and assess costs and benefits for the DSOs in scenarios of varying complexity as well as computational aspects of the auction. Our findings provide evidence that load flexibility auctions can reduce DSO costs substantially and that procurement package auctions are well-suited to address the grid load balancing problem.

The remainder of this paper is organized as follows. We first present provide an overview of related work. Then, we discuss our research method and present the proposed bidding language and auction. This is followed by a description of our experiments and initial results before concluding the paper.

Literature Review

Smart grids facilitate monitoring and control of power systems on a granular local level in real time (DOE 2003). This introduces capabilities already present in today's high voltage grids to the distribution grid where supervision was so far impossible (Varaiya et al. 2011). Hence, distribution grid control can evolve from a “blind” manual operation mode into a more sophisticated dynamic task in a complex granular system (Ipakchi and Albuyeh 2009). This enables operators to improve efficiency by achieving a better balance of supply and demand over space and time. The historic rule that supply follows demand changes into a system where both sides play an active role (Strbac 2008). Integrating the demand side has been focus of recent research and policy makers (SG-CG 2012; EC 2014; He et al. 2013; Sioshansi 2011).

In the information systems (IS) area, smart grids are a prime subject of recent research (Goebel et al. 2014; Watson et al. 2010). Here, the research focus is on novel system design and business models that facilitate sustainable and cost-efficient future power system. For example, Strueker and Dinther (2012) emphasize the need to manage demand response. Recent work focusing on IS for electric vehicles have been suggested by Fridgen et al. 2014a and Koroleva et al. 2014 as well as by Wagner et al. 2015. Another stream of research focuses on wholesale electricity prices for end consumers (e.g., Bodenbenner and Feuerriegel 2014; Fridgen et al. 2014b; LeMay et al. 2008). Kranz et al. 2015 give a recent overview of the state of energy informatics and green IS. Smart electricity markets based on combinatorial auctions as envisioned by McCabe et al. (1991) have seen only few adaptors. More generally, combinatorial auctions (Cramton et al. 2006) have emerged as a popular market mechanism in recent years. They have also increasingly been applied to real-world problems in various domains such as logistics (Sheffi 2004; Caplice 2007), telecommunications (Cramton 2013), industrial procurement (Bichler et al. 2006) or cloud computing (Zaman and Grosu 2013). Combinatorial auctions aim for an efficient resource allocation while considering complex bidder preferences for multiple items (bundles). Fukuta and Ito (2012) consider the allocation of electricity based on production plans from factories on a daily basis. We revisit this idea and consider the special case of distribution grid balancing requirements, where allocations are required intra-day and different generation as well as production capabilities are taken into account. To facilitate the utilization of the full electric flexibility potential with feasible number of bids, a compact bidding language that allows bidders to express minimum and maximum amounts of their flexibility (production or consumption) along with unit prices in single bids for time periods of different length is required. In addition, the winner determination has to consider the operating reserve as a fixed price outside option. To the best of our knowledge, this combination has not been proposed in existing literature.

Mechanism design and auction theory provide mature and rigorous methods to build and analyze market designs. An auction mechanism consists of an allocation rule and pricing rule. The former allocates the items among the bidders based on their reported types (or bids). The latter determines the prices the bidders have to pay (or receive in a procurement auction). The Vickrey–Clarke–Groves (VCG) mechanisms with Clarke pivot rule (Clarke 1971; Groves 1973; Vickrey 1961) constitutes the only strategy-proof mechanism that maximizes social welfare when payments from (to) losing bidders are zero. To implement a package auction, the representation of bids (i.e., valuations of bidders) must be encoded in a bidding language to be send to the auctioneer. In combinatorial auctions with m items there are $2^m - 1$ non-empty subsets. Therefore, succinct representations of valuations are often required for practical applications. The design of a bidding language is essentially a trade-off between expressiveness and simplicity (Nisan et al. 2007). Goossens et al. (2007) and Bichler et al. (2011) propose bidding languages which allow specifying bidder cost functions in markets with economies of scale and scope. In our current approach, bidders need to specify discounts with explicit bids for different amounts, though we will investigate the integration of bidders' cost functions in future research. Boutilier and Hoos (2001) propose a generalized language where bids are given by propositional formulae whose subformulae can be annotated with prices. However, for larger markets with many items like the one discussed in our research, even logical bidding languages with full expressiveness may require many bids to be submitted. In this case, domain-specific languages can provide the required expressiveness more succinctly and in a way that is common in the respective domain. For example, Goetzendorff et al. (2015) propose a domain-specific bidding language for the TV ads market where bidders can specify XOR-combined tuples of minimum expected viewership along with prices. Our bidding language is similar in the sense that it also allows to specify limits of the bids' validity. In contrast to existing work, however, it allows to bid on both energy production and consumption along with unit prices in single bids for time periods of different size.

Research Method

We follow the DSR approach proposed by Hevner et al. (2004). The method, model, and instantiation artifacts proposed in this research are: 1. A smart grid auction that constitutes an approach for allocating load flexibility from customers to address the local grid load balancing problem; 2. a compact bidding language that allows bidders to express minimum and maximum amounts of electric flexibility (production or consumption) along with unit prices in single bids for time periods of different size; and 3. the prototype implementation. We apply simulation experiments based partially on real-world data to demonstrate the utility, quality, and efficacy of a design artifact and provide evidence that load flexibility auctions can reduce DSO costs and that procurement package auctions are well-suited to address the grid load balancing problem. Table 1 summarizes the mapping of our approach against the DSR guidelines.

Table 1. Mapping Against Design Science Research Guidelines

Guideline (Hevner et al. 2004)	**Contribution**
Design as an artifact	Our research outcomes 1. smart grid auction, 2. bidding language, and 3. prototype implementation constitute method, model, and instantiation artifacts.
Problem relevance	The addressed research problem responds to the grand challenge of grid load balancing with the growth of fluctuating wind and solar generation.
Design evaluation	We demonstrate utility, quality, and efficacy of our design outcomes in an experimental simulation study.
Research contributions	The design artifacts and design construction knowledge extend and improve the knowledge of electricity market design.
Research rigor	We use auction theory for artifact construction and for design evaluation.

Design as a search process	The discovery of an effective solution in the form of the proposed smart grid auction and iterative improvements and extensions in future work constitute our search process in electricity market design.
Communication of the research	The formal models and technical details inform technology-oriented audiences, implications and opportunities inform management-oriented audiences.

The rationale for selection of game theory to inform the construction of the artifact is as follows. The problem of balancing demand and supply by the DSOs is in fact a problem that is naturally addressed by a market. While the demand side is currently rather inflexible (i.e., there are hardly any truly dynamic pricing schemes for customers), the supply side has been subject to energy exchanges for over a decade. However, these exchanges consider large amounts of energy to balance supply and demand on an abstract level. In contrast, the DSOs have to balance rather small amounts, though the timely balance is not only a matter of economics, but also of grid stability. Mechanism design and auction theory provide mature and rigorous methods to build and analyze market designs (Nisan et al. 2007).

The evaluation of the proposed artifact is informed by the literature on simulation analysis. The simulation of technical and economic systems is a well-established method to evaluate complex artifacts and can be used to numerically analyze the artifact to estimate the true systems characteristics (Law and Kelton 1999). We evaluate the artifact with respect to both the estimated implications for smart grid coordination as well as the computational complexity of different instantiations.

Artifact Description

We describe the load flexibility auction by first introducing the proposed bidding language. Subsequently, we formulate the winner determination problem and the payment rule.

Bidding Language

We consider a set of agents $\mathrm{i} \in \mathrm{I} = \{0, 1, \dots, \mathcal{I}\}$ with an auctioneer (buyer) 0 and bidders (sellers) $1, \dots, \mathcal{I}$. The buyer requests balancing power whereas a seller acts as balancing supplier. The bidders place bids e_j, where the set of bid indices $J = \{1, 2, \dots, \mathcal{J}\}$ is partitioned into subsets of bid indices of the bidders i such that $\forall i \in I\ \exists!\, J_i\ with\ \cup_{i \in I} J_i = J$ and $\cap_{i \in I} J_i = \emptyset$. The bids e_j can contain different energy amounts and directions for each time slot $t \in T = \{1, 2, \dots, \mathcal{T}\}$. The k-th delivery start time of bid j is denoted by $s_{ik} \in T$, the k-th delivery direction of bid j by $\phi_{jk} \in \{-1, 1\}$. $\phi_{jk} = -1$ denotes energy consumption (negative balancing capability) by the bidder and $\phi_{jk} = 1$ production (positive balancing capability) of energy by the bidder. The minimum and maximum delivery amounts of the k-th start time/subbid in bid j are specified by $\underline{a}_{jk} \in \mathbb{R} \geq 0$ and $\overline{a}_{jk} \in \mathbb{R} \geq 0$. The monetary bid (minimum price) per energy unit (production or consumption) of the k-th start time/subbid in bid j is given by $b_{jk} \in \mathbb{R} \geq 0$. The bidders $i \in I \setminus \{0\}$ submit zero or more (XORed) bids e_j with

$$e_j := \Big((s_{j1}, \phi_{j1}, \underline{a}_{j1}, \overline{a}_{j1} b_{j1}), \dots, (s_{jn}, \phi_{jn}, \underline{a}_{jn}, \overline{a}_{jn} b_{jn}) \Big).$$

Bidding Language Example

Suppose the bidder i wants to submit two bids with $J_i = \{1,2\}$. In the first bid e_1, he offers supply of 9 to 10 EU (energy units) for 20 MU/EU (monetary units per energy unit) over 6 TU (time units), i.e., $s_{11} = 1, \phi_{11} = 1, \underline{a}_{11} = 9, \overline{a}_{11} = 10\,, b_{11} = 20$. Furthermore, he offers a supply of 12 EU for 23MU/EU beginning at $s_{12} = 7$. Alternatively, in e_2, bidder i offers a constant supply of 8 EU for 19MU/EU ($s_{21} = 1, \phi_{21} = 1, \underline{a}_{21} = 8, \overline{a}_{21} = 8\,, b_{21} = 19$). Then, the submitted bids are specified as follows, also depicted in Figure 1.

$$\begin{array}{ccc} e_1 & \oplus & e_2 \\ \Big((s_{11}, \phi_{11}, \underline{a}_{11}, \overline{a}_{11} b_{11}), (s_{12}, \phi_{12}, \underline{a}_{12}, \overline{a}_{12} b_{12}) \Big) & \oplus & \Big((s_{21}, \phi_{21}, \underline{a}_{21}, \overline{a}_{21} b_{21}) \Big) \\ \big((1,1,9,10,20), (7,1,12,12,23) \big) & \oplus & \big((1,1,8,8,19) \big) \end{array}$$

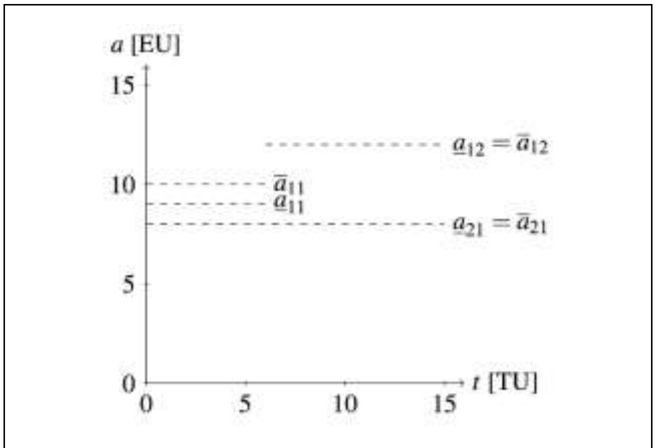


Figure 1. Delivery Amounts of Example Bids.

Winner Determination Problem

Let ϕ_j^t, $\underline{a}_j^t$, $\overline{a}_j^t$, and b_j^t be the direction, minimum/maximum amount, and monetary bid submitted in the jth bid that are valid in t $\left(\phi_j^t, \underline{a}_j^t, \overline{a}_j^t, b_j^t : (s_{jn}, \phi_{jn}, \underline{a}_{jn}, \overline{a}_{jn} b_{jn}) \in e_j \wedge s_{jn} = \max(\{s_{jn} : s_{jn} < t\})\right)$. Within bid e_j, a subbid with start time s_{jn} thus implicitly remains active until superseded by another subbid with start time $s_{jn+1} > s_{jn}$. a_0^t specifies the amount requested by the auctioneer. The accepted positive and negative delivery amounts of bid j in t are denoted by a_{j+}^t and $a_{j-}^t \in \mathbb{R} \geq 0$ $\left(a_{j+}^t \cdot a_{j-}^t = 0\right)$. f_+^t and f_-^t denote the positive and negative amount of electricity (additional production or consumption) purchased using an outside option at prices o_+^t and o_-^t. Since the valuation of the buyer is assumed to be fixed and the costs are subtracted, the winner determination problem (i.e., maximization of social welfare, which is given by the difference of the valuation of the buyer and the costs by the sellers, $v_0(X) - c(X)$, for an allocation X, buyer valuation $v_0(X)$, and seller costs $c(X)$), can be formulated as the following minimization problem.

$$WD(I) = min \sum_{t \in T} \sum_{j \in J} \left(b_j^t a_{j+}^t + b_j^t a_{j-}^t\right) + f_+^t o_+^t + f_-^t o_-^t$$

subject to

$$\sum_{j \in J} \left(a_{j+}^t - a_{j-}^t\right) + f_+^t - f_-^t = \phi_0^t a_0^t \quad \forall t \in T \qquad (1)$$

$$a_{j+}^t \geq \underline{a}_j^t x_j \phi_j^t \quad \forall j \in J, t \in T \qquad (2)$$

$$a_{j-}^t \geq -\underline{a}_j^t x_j \phi_j^t \quad \forall j \in J, t \in T \qquad (3)$$

$$a_{j+}^t \phi_j^t \leq \overline{a}_j^t x_j \quad \forall j \in J, t \in T \qquad (4)$$

$$-a_{j-}^t \phi_j^t \leq \overline{a}_j^t x_j \quad \forall j \in J, t \in T \qquad (5)$$

$$a_{j+}^t \phi_j^t \geq 0 \quad \forall j \in J, t \in T \qquad (6)$$

$$-a_{j-}^t \phi_j^t \geq 0 \quad \forall j \in J, t \in T \qquad (7)$$

$$f_+^t, f_-^t \geq 0 \quad \forall t \in T \qquad (8)$$

$$\sum_{j \in J_i} x_j \leq 1 \quad \forall i \in I \qquad (9)$$

$$x_j \in \{0,1\} \quad \forall j \in J \qquad \textbf{(10)}$$

Since the load flexibility auction is a procurement auction, the objective is to minimize the cost of accepted bids in WD. We extend the general WD by minimum and maximum amounts, unit prices, a combination of energy production and consumption potential, and a fixed price outside option. Constraint (1) ensures that the DSO's requested balancing amount is fulfilled in every time slot. Moreover, constraints (2)-(5) limit the accepted amounts to the minimum and maximum amounts in the bids, in accordance with the offered delivery direction. Constraints (6) and (7) restrict the purchases to the offered direction. Constraint (8) ensures positive outside option amounts. Finally, constraint (9) models the XOR relation of the single bids and ensures that at most one bid can be accepted per bidder.

Payment Rule

We apply the Vickrey–Clarke–Groves (VCG) mechanism with Clarke pivot rule (Clarke 1971; Groves 1973; Vickrey 1961) to determine agent payments in an incentive-compatible manner. Let b_i^{t*} and a_i^{t*} denote the winning bids and amounts of winning bidder i from the set of winners $W \subseteq I$ and let $WD^*(\cdot)$ denote the optimal solution to WD. The payment that bidder $i \in I \setminus \{0\}$ receives is calculated as $p_i = \sum_{t \in T} b_i^{t*} a_i^{t*} - \left(WD^*(I) - WD^*(I \setminus \{i\})\right)$. That is, prices reflect the externality imposed on other players by a given agent. Note that the winning bid is empty and the $WD^*(\cdot)$ terms cancel for non-winning bidders and are therefore zero. The buyer pays $p_0 = -\sum_{i \in I \setminus \{0\}} p_i - \sum_{t \in T}(f_+^t o_+^t + f_-^t o_-^t)$, i.e., VCG payments are only applied for the bidder side. Naturally, payments are bounded by the outside option prices as these are available for all $t \in T$. Therefore, every bidder can at most receive a payment of $\sum_{t \in T} o_{max}^t a_i^{t*}$ where $o_{max}^t = \max(\{o_+^t, o_-^t\})$. This follows from the observation that the product of winning bids and amounts cannot exceed the optimal value of WD, i.e., $\sum_{t \in T} b_i^{t*} a_i^{t*} \leq WD^*(I) \;\; \forall\, I \setminus \{0\}$, since they are part of a sum that gives the resulting value. Then, we have $p_i \leq WD^*(I) - \left(WD^*(I) - WD^*(I \setminus \{i\})\right) = WD^*(I \setminus \{i\})$. With $WD^*(\cdot) \leq \sum_{t \in T} o_{max}^t a_i^{t*}$ this yields $p_i \leq \sum_{t \in T} o_{max}^t a_i^{t*}$.

Evaluation

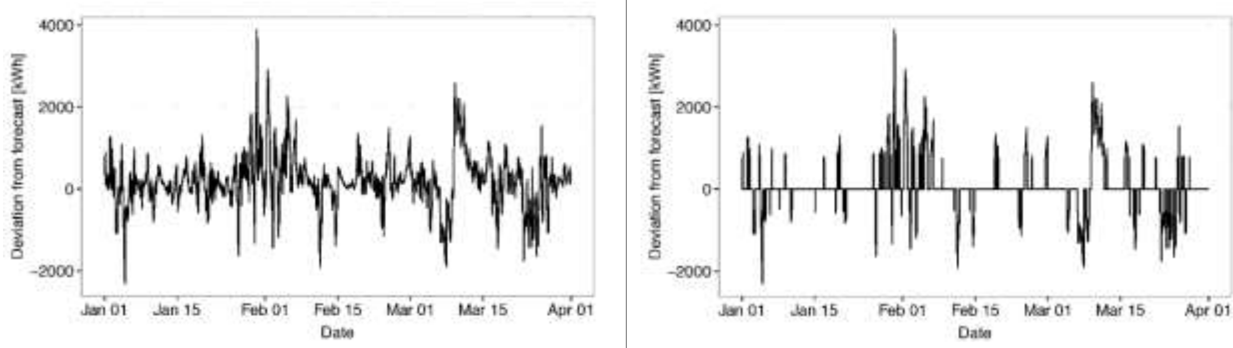
We evaluate the proposed artifact from an economic and computational perspective in simulation experiments. Next, we present our assumptions as well as the underlying input data. Subsequently, we assess the utility, efficacy, and efficiency of the auction for different parameters.

Simulation setup

DSOs have to balance electrical load and generation within their local distribution grids. We assume that local supply is constituted by fluctuating generation from a wind farm. Time is discretized in time slots $t \in T = \{1,2,\dots,\mathcal{T}\}$. Additional (conventional) generation and consumption (load shedding) can be purchased from the transmission system operator (TSO) for outside option prices o_+^t and o_-^t, which are assumed to be higher than the costs from wind farm generation. When demand deviations from predicted generation occurs, load difference curves (LDCs) are calculated, which contain positive or negative load changes per time slot for a given period. With the LDCs, the auctions are initiated to procure the required balancing amounts.

Following Feuerriegel et al. (2014), we model balancing requirements using real-world wind generation data provided by the EEX transparency platform (EEX 2013) for the year 2013. We use the expected and realized wind feed-in time series data to model the discrepancies between forecast and realized renewable generation. We use the Tennet transmission system as a reference scenario for balancing requests. For each simulation run we randomly select a week and retrieve the expected and realized wind feed-in for a 15-minute time span. We denote the difference between realized and forecast wind feed-in as Δ_t. Assuming that the DSO runs flexibility auctions for larger deviations only, we filter $\Delta_t$to determine the balancing demand time $D_t$series: $D_t = \Delta_t 1\left(|\Delta_t| \geq \underline{\Delta}\right)$.

To illustrate, Figure 2a shows the difference between forecast and realized generation for Q1/2013. This data is filtered by $\underline{\Delta}$ which is assumed to be the 10% quantile (Fig. 2b). Finally, a time window from the filtered data is chosen for the auction. We use outside option prices based on balancing power prices from the Tennet TSO which are in the range of $[-2{,}498.4, 1{,}608.2]$ EUR/kWh for the year 2013.



(a) (b)

Figure 2. Balancing request data: (a) Raw and (b) filtered wind power deviations in Q1/2013.

To harness the synergies between heterogeneous generation assets and flexible loads, the concepts of virtual power plant (VPP) (Pudjianto et al. 2007) and microgrid (Lasseter and Paigi 2004) have been introduced. While VPPs focus on generation, microgrids also include consumption properties, e.g., storage systems or electric vehicles. Asmus (2010) provides a detailed comparison of these concepts. We abstract from these concepts by focusing on the coordination properties of the auction; the investigation of organizational properties are beyond the scope of this research. With respect to the balancing suppliers, we make the following assumptions. A balancing supplier is either a single customer or a pool of customers in form of an aggregator. Aggregators therefore act as intermediaries between the market and customers that bundle flexible loads into portfolios. These entities are distinguished by the quantity of flexible loads they bring to the market. Furthermore, a balancing supplier communicates his collective flexibility potentials for the given time span T to the market. These potentials are unidirectional and hence each participant will either offer positive *or* negative balancing capability for each $t \in T$, but never both. Available flexibility potentials are subject to constraints reflecting technical or economic rationales. For example, a small factory may have ramping cost that require it to run for a certain time to ensure economic viability. Similar considerations can be applied for storage systems or electric vehicle batteries due to deterioration considerations. For this reason, bids resulting from the available flexibility are subject to a minimum runtime constraint m_i that limits changes from positive to negative balancing activity or vice versa. Here, we assume that each balancing supplier submits exactly $\left\lceil \frac{T}{m_i} \right\rceil + 1$ bids as opposed to the theoretical maximum of $2^T - 1$ bids. This is in accordance with his minimum runtime m_i and reflects that notion that the supplier is initially prepared to offer his complete profile or only exclusive parts of it. In addition, bid sizes of the different customers are heterogeneous in order to capture current electricity market structures with few large and many small utilities with a direct link to customers. To this end, we leverage Zipf's law to instantiate an empirically valid yet parsimonious model for modeling (firm) size heterogeneity (Axtell 2001). Bid size heterogeneity is parameterized with a heterogeneity level h. Given the total trading volume parameter D, which is determined after all bids have been submitted, the k-th largest of n firms assumes a bid size of $D \cdot (\frac{1}{k^h} / \sum_{j=1}^{n} \frac{1}{j^h})$. Note that for $h = 0$ bid sizes are uniformly distributed, whereas for $h \rightarrow \infty$ the largest bidder assumes all quantity. Aggregators or large individual customers are reflected by large bids whereas smaller bids reflect market participant of smaller relative size.

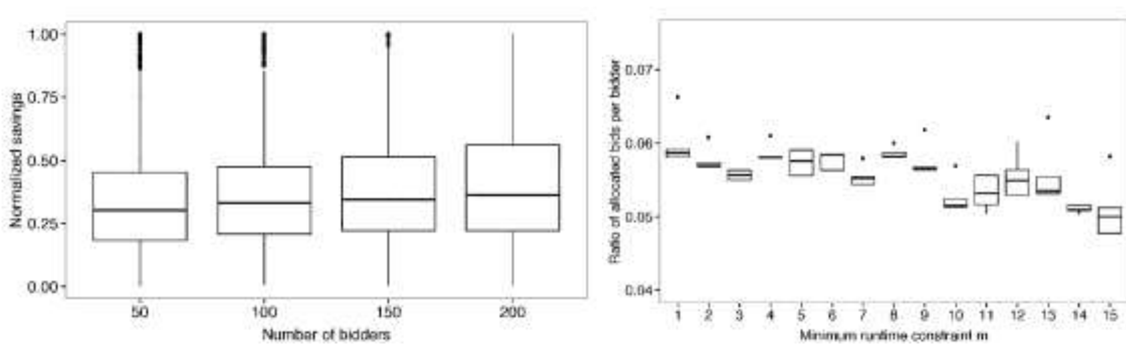
The simulation is parameterized as follows. With $n \in \{50,100,150,200\}$ bidders representing small to medium local areas available to aggregate and bidder heterogeneity h set to completely homogeneous to very heterogeneous ($\{0,0.4,0.8,1.2\}$) amongst all bidders, bid prices are uniformly distributed in $[1,20]$ and bid minimum runtime is uniformly distributed over T. The simulation time horizon is set to 15 time slots. We further repeat every simulation 100 times. There are 16 parameter combinations, for which different simulation experiments are conducted. Each simulation run is initiated with a DSO demand profile that holds for each parameter combinations. In total, we arrive at 1600 simulation runs.

Preliminary Results

This section presents the simulation results of the above described evaluation settings. We consider different evaluation contexts. In particular, we focus on the perspective of the balancing requester (DSO), the balancing suppliers as well as global computational considerations.

First, we investigate the benefits of the auction for the DSO regarding different numbers of participating balancing suppliers. We measure reduced costs from not having to rely on the outside option, i.e. the DSO's savings. As we can see in Figure 3a, average savings increase with supply size. Given a larger supply size, the DSO is able to allocate more flexibility from balancing suppliers. By doing so, the same amount does not have to be procured from the outside option. In more detail, average savings range from 35.38% to 42.20%. However, in settings with more balancing supply (≥ 150 bidders), we only see a marginal improvement in savings. Here, the size of a few larger aggregators, in particular those with no marginal cost, can prevent other intermediaries or small individuals from participating successfully in the market at some point. Given that the DSO's objective is to fully address its balancing demand by employing a flexibility auction, these results suggest that the DSO must address a pool of balancing suppliers that is not too small and at the same time neither too homogeneous nor too heterogeneous. This is a relevant finding for the DSO that can help assessing appropriate regional boundaries for such a market.

Given that bids from balancing suppliers are subject to a minimum runtime constraint, we now explore the effect of minimum runtime lengths for the supplier. We measure the effect in terms of average number of allocated bids per bidder over all runs. On a general level, this analysis confirms that a shorter minimum runtime increases the chance of being allocated (Figure 3b). In more detail, especially the shortest and therefore most flexible runtime $m = 1$ has the greatest value for an individual balancing supplier. That is because such bids, if allocated, can act as fill-ins for other, more complex bids to be matched in total to current balancing demand. This finding should spur balancing suppliers to improve more technologically, e.g., by adopting advanced battery technology or optimizing fleet charging and usage. In addition, the results suggest that longer runtimes, usually seen in more inflexible and traditional plants, can be of value to bidders and should not be ruled out as a means to participate in the auction. Interestingly, local non-monotonicity reflects the combinatorial nature of the auction. In order to increase allocations of longer runtimes, balancing suppliers must either look into generating accurate and reliable balancing demand forecasts or use pooling effects to be able to internally manage their reported flexibility. Additionally, longer runtimes can also act as fill-ins, as they might be less expensive in total when combined with other bids (in the opposing direction) from other balancing suppliers.



(a) (b)

Figure 3. (a) Savings for the DSO given varying number of bidders and (b) ratio of allocated bids per bidder given different market size

Finally, we consider computational runtimes for different configurations of balancing supply, i.e. the number of bidders. The runtime is defined as the sum of the runtime of the winner determination problem as well as all runtimes required for payment calculations. For $n = 50$ bidders, the average runtime is 4.76s ($\sigma = 3.57$), for $n = 100$ it is 16.99s ($\sigma = 10.46$), for $n = 150$ we measured 36.72s ($\sigma = 21.83$), and for $n = 200$ the runtime amounts to 64.63s ($\sigma = 39.99$). Clearly, the runtimes increases with more auction participants. However, note that as described in the assumptions, bids are limited by supplier i's minimum runtime m_i and a XOR relationship over specific subsets.

Conclusions

The contributions of this research are an electrical load flexibility auction along with a compact bidding language. We extend the general WD and bidding language by minimum and maximum amounts, unit prices, a combination of energy production and consumption potential, and a fixed price outside option in procurement auctions. We have provided an analysis of the potential for cost reduction by DSOs and of the suitability of customer sets with different characteristics. We have evaluated the artifact by means of simulation which is partially based on real-world data. The evaluation has shown the efficacy and usefulness of the artifact in different scenarios, enabling DSOs to balance grid load by procuring generation and consumption of electrical load. Our findings provide evidence that load flexibility auctions can reduce DSOs costs substantially and that procurement package auctions are well-suited to address the grid load balancing problem.

The implications for DSOs are based on the potential for cost reduction. However, DSOs have to carefully analyze the structure of their customers to assess the potential benefits. In particular, the customer population should be comprised of a mix of larger but also smaller customers to maximize synergies by also facilitating balancing between customers.

In future work, we will investigate the application of bidder-Pareto-optimal core payment rules to the problem addressed. Further, we will analyze the suitability of more compact bidding languages and investigate the trade-off between complexity and expressiveness for electrical load flexibility auctions. Although VCG mechanisms are the only efficient and strategy-proof mechanisms, they can result in unacceptably low seller revenues for forward auctions, or high buyer payments in procurement auctions, and low perceived fairness of prices. The application of core-selecting auctions can mitigate these issues. As Day and Raghavan (2007) show, a payment rule that minimizes total payments in the core (for procurement auctions, payments have to be maximized in the core) also minimizes incentives to deviate from truthful bidding. In addition, whenever the VCG outcome is in the core, it is selected by a bidder-Pareto-optimal core mechanism (Ausubel and Milgrom 2002; Day and Milgrom 2008).

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