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Matching Supply and Demand of Electricity Network-Supportive Flexibility: A Case Study with Three Comprehensible Matching Algorithms

Matching supply and demand of electricity network-supportive flexibility: A case study with three comprehensible matching algorithms

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Abstract

Due to an ongoing energy transition, electricity networks are increasingly challenged by situations where local electrical power demands are high but local generation is low and vice versa. This finally leads to a growing number of technical problems. To solve these problems in the short-term, the electrical power of load and generation must be adjusted as available flexibility. In zonal electricity systems, one often discussed concept to utilize flexibility is local flexibility markets. Based on auction theory, we provide a comprehensible framework for the use of network-supportive flexibility in general. In this context, we discuss the problem of matching supply and demand. We introduce three matching approaches that can be applied and adapted for different network situations. In addition to a qualitative description of the three approaches, we present a case study of an exemplary distribution network and explore different scenarios to demonstrate the utility of the algorithms. We compare the three approaches on a qualitative level with quantitative inputs from the case study. The comparison considers the specific cost, flexible energy, ensured demand coverage, data minimization, computational effort and the transferability of the three approaches.

Keywords: local flexibility markets, matching, multi-dimensional winner determination, electricity network operation
JEL classification: D44, L94, Q41

1. Introduction

Due to an ongoing energy transition, electricity networks are increasingly challenged by a growing number of renewable energy plants as well as load technologies such as heat pumps and electric vehicles. Situations where local electrical power demands are high but local generation is low and vice versa can cause technical problems, such as congestion of lines and transformers as well as over- or under-voltage. Such problems can be solved preventively, through grid investments, or reactively, with different techniques of the network operation. Measures of network operation can be divided into (i) adjustments of network assets and (ii) adjustments of load and generation power; the latter adjustments are referred to as network-supportive flexibility. There is an active debate on network-supportive flexibility, especially concerning the European energy system. This debate addresses whether the use of flexibility can sustainably replace network investments (e.g., Spiliotis et al., 2016) and which mechanisms should be used to give network operators access to flexible assets.

The local flexibility markets (LFM) approach is one of these mechanisms (Jin et al., 2020). On a conceptual level, LFM involve a marketplace where the network operator represents a demander for network-supportive flexibility supplied by the flexible assets within the concerned network. The design of such markets contains some challenging aspects, especially the definition of appropriate market processes and flexibility products (see Heilmann et al., 2020). In this context, the concept of matching supply and demand must be defined. Due to the high complexity of technical issues in the electric network, the question of how to match supply and demand of network-supportive flexibility leads to a multidimensional optimization problem that is also influenced by the possibility of complex bidding. The matching is of outstanding importance because it ensures the efficient use of the required flexibility that is central to a market approach in general.

The paper at hand discusses this problem and contributes to the current debate. Using a comprehensible auction model to facilitate network-supportive flexibility, we provide three different matching approaches that can be applied and adapted for different network situations and flexibility products.[1] In addition to a qualitative description of the three approaches, we present a case study of an exemplary distribution network and explore different scenarios to demonstrate the utility of the algorithms. We compare the three approaches on a qualitative level with quantitative inputs from the case study. The comparison considers the following aspects of the matching outcomes: specific cost, flexible energy, ensured demand coverage, data minimization, computational effort and the transferability of the algorithms with respect to network issues and different flexibility mechanisms.

The remainder of this paper is organized as follows. Section 2 contains an overview of the literature on network-supportive flexibility and auction design basics. In Section 3, a model for the network-supportive use of flexibility that is based on auction design is introduced. Section 4 contains a conceptual discussion of the three matching approaches. Section5 describes the design of the case study. The results from this study are presented and discussed in Section 6. The paper closes with a conclusion in Section 7.

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[1]Although following an auction approach, the underlying mechanism is not necessarily marketplace, but can also be the legal obligation, e.g. of power plants to provide their network-supportive flexibility.

2. Literature review

In the following section we provide an overview of relevant literature on matching supply and demand for network-supportive flexibility. We first discuss the literature related to network-supportive flexibility, especially in distribution networks. We then briefly introduce some aspects of auction design that are the basis for our understanding of matching supply and demand.

2.1. network-supportive flexibility

In last few years, there has been an active discussion on the use of flexibility for the future energy system in general and for network-supportive measures specifically. Different reviews and conceptual works on the topic consequently exist. Villar et al. (2018) provide a conceptual overview of flexibility products and markets for different use cases, including congestion management and power quality control for distribution system operators (DSOs) and transmission system operators (TSOs). Khajeh et al. (2019) review recent research related to flexible resources and potential trading structures at the TSO, DSO and customer level in smart grids. Huang et al. (2014) differentiate congestion management techniques into direct and indirect control mechanisms. The latter comprise different market-based mechanisms such as dynamic tariffs and flexibility service markets. Ramos et al. (2016) define LFMs as "long- or short-term trading actions for flexibility in a specific geographical location, voltage level, and system operator (DSO and TSO), given by network conditions or balancing needs, where participants in a relevant market can be aggregated to provide flexibility services". We focus on such LFM approaches, as they are a major aspect of the current academic discussion. Jin et al. (2020) provide a broad review of LFM literature and compare different congestion management methods, model formulations and solution approaches. Schittekatte and Meeus (2020) and Radecke et al. (2019) review and compare different pioneering approaches to LFM in Europe. Heilmann et al. (2020) provide a framework for the product design of LFM.

In addition to these conceptual works, there are various studies that contain LFM approaches and related simulation studies. We give a chronological overview of some of these works to show the currency of the topic. Kok (2012) presents a flexibility integration theme based on optimized dynamic pricing. Ding et al. (2013) in connection with Heussen et al. (2013) and Zhang et al. (2013) propose an LFM approach for flexibility services based on a clearing house concept. Torbaghan et al. (2016) formulate a complex optimization problem to enable flexibility trading that contains day-ahead as well as intraday elements. Kornrumpf et al. (2016) provide a simulation study of flexibility provision that is also based on two time horizons. Lamparter et al. (2016) provide an agent-based market model that matches supply and demand with a Vickrey-Clakes algorithm. Dauer (2016) discusses the market design of local flexibility markets from a mechanism design point of view. A market design containing uni- and bidirectional optimization approaches (without local considerations) is defined and tested using simulation studies. Olivella-Rosell et al. (2018b) provide a detailed LFM approach including a simulation test case. Esmat et al. (2018) describe the optimization approach of an LFM considering rebound effects of the flexibility suppliers.

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Shen et al. (2019) combine dynamic pricing, network configuration and flexibility products in a complex congestion management approach. Niu et al. (2020) propose an optimization model for coordinating ancillary services based on multi-flexibility measures. Laur et al. (2020) consider and evaluated a concept for DSO overload management using a two-part tariff service market that is modeled as a three-stage stochastic market.

The works listed above mainly contain a brief description of the matching for a specific LFM approach. We abstract this point of view and interpret the problem of matching network-supportive flexibility supply and demand as general tool for network operators' congestion management. Therefore, also other approaches for the utilization of flexibility (e.g. Schermeyer et al., 2018) are plausible. Nevertheless, auction theory provides a reasonable basis for the problem of matching supply and demand. Therefore, in the following section, we give an overview of the most important terms in the context of auction design.

2.2. Auction design basics

The term "auction" describes a wide range of trading mechanisms that determine a price for specific goods based on a competitive bidding process with explicit rules (McAfee and McMillan, 1987). There are four standard auction types (ascending-bid, descending-bid, first-price sealed-bid and second-price sealed-bid auctions) that sell a single good based on the price only (Pham et al., 2015). Since the theory of auction design has been part of the academic literature for more than 30 years, there are various approaches for a more detailed generic description of auctions (e.g. Wurman et al., 2001; Teich et al., 2004; Abrache et al., 2007; Parsons et al., 2011; Pham et al., 2015). At a high level of abstraction, the main auction design elements are the traded products, the organization and rules of the bidding process, the matching [2] and pricing. Each of these design elements contains different aspects that increase potential design varieties in an exponential manner. To handle this quasi-infinite design space, the academic literature has defined some classes of auctions with similar properties. In the following paragraphs, we define the most important terms.

Multi-unit auctions contain more than one item of the traded good. In general, most auctions for scalable commodities are multi-unit auctions. Cumpston and Khezr (2020) provide a survey of related literature.

Reverse or procurement auctions entail a trading process in which one or more buyer can ask for a specific good. Unlike in selling auctions, the auctioneer's aim in reverse auctions is to procure the lowest price. As a hybrid-form, two-sided auctions combine procurement and selling auctions: their aim is to achieve the highest possible trading volume.

Combinatorial auctions contain all type of auctions where a complex bidding is possible (Abrache et al., 2007). Complex bids can, for example be connected block bids (AND-bids), optional OR-bids or exclusive optional XOR-bids. Such bid formats allow the supply side to express preferences in complex bundle bids and allow the demand side to consider different side conditions (Sandholm and Suri, 2006; Bichler et al., 2009). Combinatorial auctions

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[2]In the academic literature of auction theory, the terms "winner determination" or "scoring rule" are synonymous with matching supply and demand.

increase the complexity of the matching problem (Sandholm, 2002) and the related pricing (Xia et al., 2004).

MMultidimensional or multi-attribute auctions consider further product attributes for matching in addition to the price of a good. Such attributes may include quality properties of the traded good that would not be considered in a one-dimensional auction (Chetan et al., 2019; Pham et al., 2015). Multidimensional attributes are often used for procurement auctions in the public sector (de Smet, 2007). The consideration of multiple attributes leads to highly complex matching (Branco, 1997). Different approaches to reduce the complexity of the matching problem without losing the advantages of the additional attributes have been discussed in the literature. These include scoring approaches (e.g., Asker and Cantillon, 2008), techniques of multi-criteria decision making (e.g., Cheng, 2008) and the approach of pricing out the additional attributes (e.g., Thiel, 1988; Teich et al., 2006).

3. Techno-economic problem description – an auction perspective

As shown in Section 2.1 , network-supportive flexibility is often discussed in the context of LFM. In the following section, we introduce a high-level auction model for the network-supportive use of flexibility that is consistent with this market-based approach. In keeping with basic auction principles, this model contains the components "bidding process," "matching" and "pricing". The aim of the model is to provide a framework for solving a technical problem within electricity networks by using the flexibility of suitable assets in the network. Figure 1 summarizes the auction model. We discuss the individual components in the sections 3.1 – 3.3.

3.1. Participants

We first briefly describe the relevant participants within the auction model. These participants must be subdivided into supply and demand sides. A detailed discussion of the technical aspects of both sides of the market has been provided by Heilmann et al. (2020).

On the demand side, there is at least one network operator that faces technical network problems. These problems may include congestion of lines and transformers and over- or under-voltages. The network operator's task is to solve these problems at the lowest possible cost. If more than one interconnected network area is involved, the implicated network operators can be interpreted as one demander. To ensure secure operation of the whole network, a coordination of network operators can deemed mandatory (e.g., Gerard et al., 2016).

On the supply side, any potential flexibility-providing asset can be integrated. Such assets include controllable energy plants, storage batteries or demand-side management approaches. Flexibility suppliers can have one of two motivations. The first option is a legal obligation that engages the supplier to provide flexibility in a regulated framework.[3] The second option that is more consistent with the auction model is the marketing of flexibility

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[3]Such a framework exists, for example, in the European electricity transmission system. This framework is embedded in the national legislation of European countries.
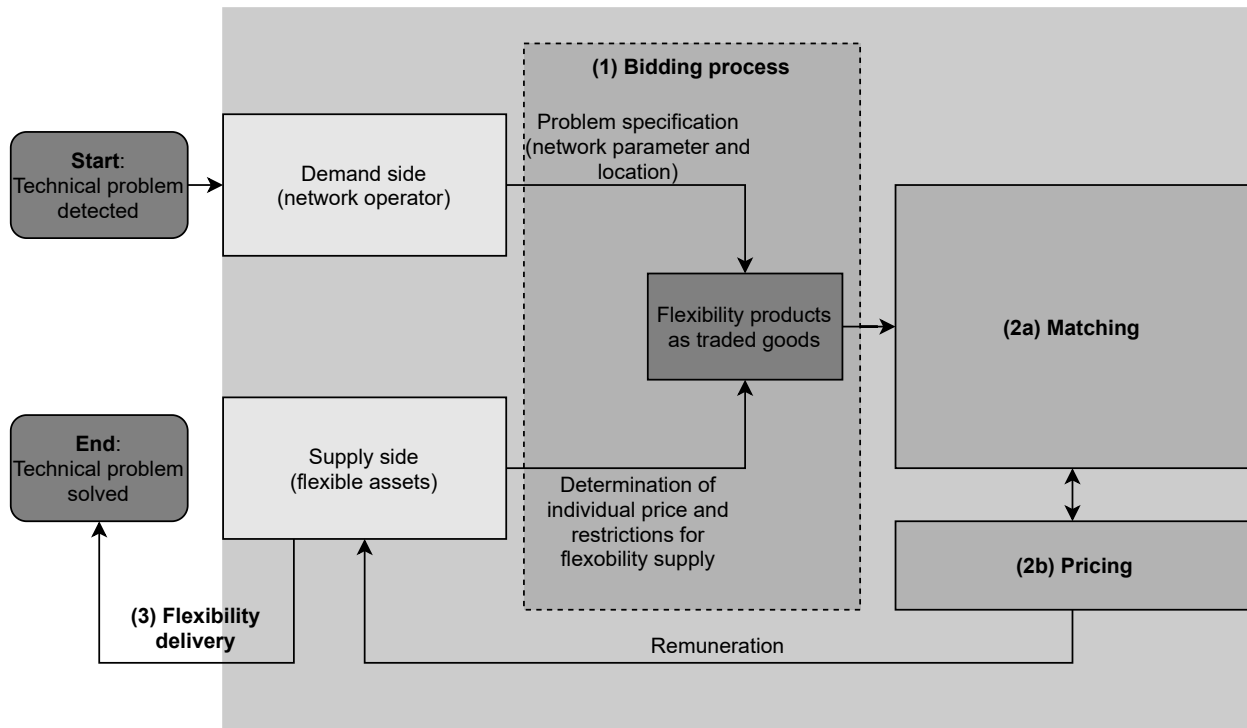
Figure 1: Generalized auction model for network-supportive use of flexibility

to pursue economic goals. This option implies voluntary participation. In this case, the supplier must balance monetary interests and comfort requirements, especially for small demand-side units (Petersen et al., 2012). In this context, aggregating the flexibility po-
160   tential of different units is important (Kouzelis et al., 2015). Aggregation provides different advantages, such as improvement of the forecast quality and availability of the provided flexibility (Eurelectric, 2015). Olivella-Rosell et al. (2018a) discuss the optimization problem from an aggregator's point of view and provide a simulation study. However, the appropriate aggregation level is dependent on the number of available units. Highly aggregated
165   flexibility is thus not an option for local problems at low voltage levels. Müller et al. (2019) analyzed the sensitivity of different pooling formation options. Potential aggregation levels can be based on grid topology (at local transformers and defined grid topology points) or on a dynamic effectiveness evaluation. Further consumer requirements must be considered when aggregating flexibility from distributed energy resources. According to Tušar et al.
170   (2012), these requirements can be quantified by control parameters to reach an optimum demand response to market and grid conditions.

3.2. Product design and bidding

The auction model starts with a bidding process (see Figure 1, Step 1) that allows both sides of the auction to express their individual preferences. On the demand side, this entails
175   a detailed description of the technical problem, including technical requirements for the solution. These requirements contain information about a technical measure, the location

within the network and the time . The supply side may have technical restrictions or other preferences and can specify the offer price[4] of the provided flexibility (see Section 3.1). There are two ways to address these demand-side and supply-side preferences. The first possibility is to design suitable flexibility products. We follow the framework provided by Heilmann et al. (2020): a flexibility product must contain a local attribute in order to evaluate the flexibility in relation to a specific technical problem. The incorporation of technical requirements and restrictions is optional within the product design. The second possibility is the implementation of a complex bidding language, for example, with AND-, OR- or XOR-bids (Abrache et al., 2007; Bichler et al., 2009). The resulting combinatorial bids can replace the technical rules or constraints of a flexibility product.

3.3. Matching and pricing

Based on the flexibility bids, the matching problem (see Figure 1, Step 2a) can be solved. At a high level of abstraction, the problem involves the selection of flexibility bids that are both suitable for the solution of all problems and at the lowest possible cost. The resulting problem is a multidimensional optimization problem. In contrast to other multi-attribute auctions that contain products with quality attributes, the location of an individual flexible asset cannot be changed. Therefore, the concerned network structure must captured with nonlinear side conditions. Because the cost of flexibility is considered, the matching is also connected to the chosen pricing scheme (see Figure 1, Step 2b). Different pricing schemes and complex flexibility products or a complex bidding language lead to different detailed matching problem formulations (Xia et al., 2004; Abrache et al., 2007). After the matching, the auction model ends with the provision of the procured flexibility for the determined time (see Figure 1, Step 3).

3.4. Advantages of the auction model

TThe application of the auction model provides some advantages compared to a purely technical discussion of network-supportive flexibility. First, the model contains a comprehensive description of the congestion management process, starting with the technical problem identification and ending with the problem solution. Second, the steps of the process can be considered separate design elements with interdependence. The complexity of the matching approach, which is the core optimization problem of the auction model, is strongly dependent on the chosen product design, the complexity of the bidding language and the selected pricing scheme. Nevertheless, although the flexibility products determine the matching problem, one does not need to consider whether the flexibility bids are based on a market process or if they can be traced back to legal obligations of individual flexibility suppliers. Therefore, the introduced auction model can be interpreted as a framework for allocating and using flexibility for congestion management and not necessarily as a trading mechanism.

The auction model can be classified as multi-unit, multi-attribute (price and network location) procurement auction with a high probability of combinatorial elements (based on

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[4]If the price is not regulated due to legal provisions

supply-side technical restrictions). Therefore, the resulting matching problem is a technoeconomic optimization problem of high complexity. Due to its complexity and nonlinearity, this optimization problem is comparable to the optimization of topological network operation (e.g., Granelli et al., 2006) as well as network planning (e.g., Scheidler et al., 2018). A decentralized optimization at the level of individual network operators is a reasonable approach for optimizing the global network (Wang et al., 2017).

4. Selected matching approaches

Matching is at the core of the generalized auction model. The model's goal is to determine the most efficient dispatch of flexibility. A comprehensive discussion of the optimal design of the matching approach is beyond the scope of this paper. Examples of different optimization approaches can be found in the literature highlighted Section 2.1. For example, Jin et al. (2020) provide a review of solution approaches based on the underlying model formulation. In the following section, we introduce three selected matching approaches that are applicable to different network situations but are also adjustable to different flexibility product designs and bidding rules.

4.1. Merit order

The first optimization approach contains a heuristic algorithm that uses a merit order list (MOL). The MOL contains all bids in the related network area sorted in ascending order by the cost of their application. This heuristic uses power flow calculations to determine the status of the concerned network and how it is impacted by individual bids. A problem measure[5] summarizes all congestion problems to be solved.

The algorithm has two main steps. In the first step (see Figure 2), a list of potential solutions (a subset of the MOL) is selected using a hill-climbing approach. The lowest-cost bid on the MOL is used as an input for a power flow calculation of a temporarily adjusted network. If the problem measure of the temporary network is lower than that of the current network, the bid is accepted as potential solution. The temporary network and its problem measure are then stored as the current network. If the problem measure of the temporary network is higher or equal to that of the current network, the bid and the temporary network status are rejected and the next bid from the MOL is used. This step is reiterated until the problem measure is zero or until every bid of the MOL has been used without reaching a problem measure of zero. In the latter case, the list of bids has not lead to a solution that solves all problems. If the problem measure is zero, the algorithm continues to the second step.

After selecting a list of bids that solve all problems, the algorithm tries to reduce the list of bids by searching for redundancy[6] (see Figure 3). Each bid from the list of potential solutions

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[5]The problem measure is generally a vector of all relevant network problems such as line congestion or voltage problems. If the problem measure is equal to zero, all problems are solved.

[6]Redundancies in the list of potential solutions can occur if the last bid leads to a significant over-fulfilment. In this case, the over-fulfilment can be reduced by removing smaller bids.
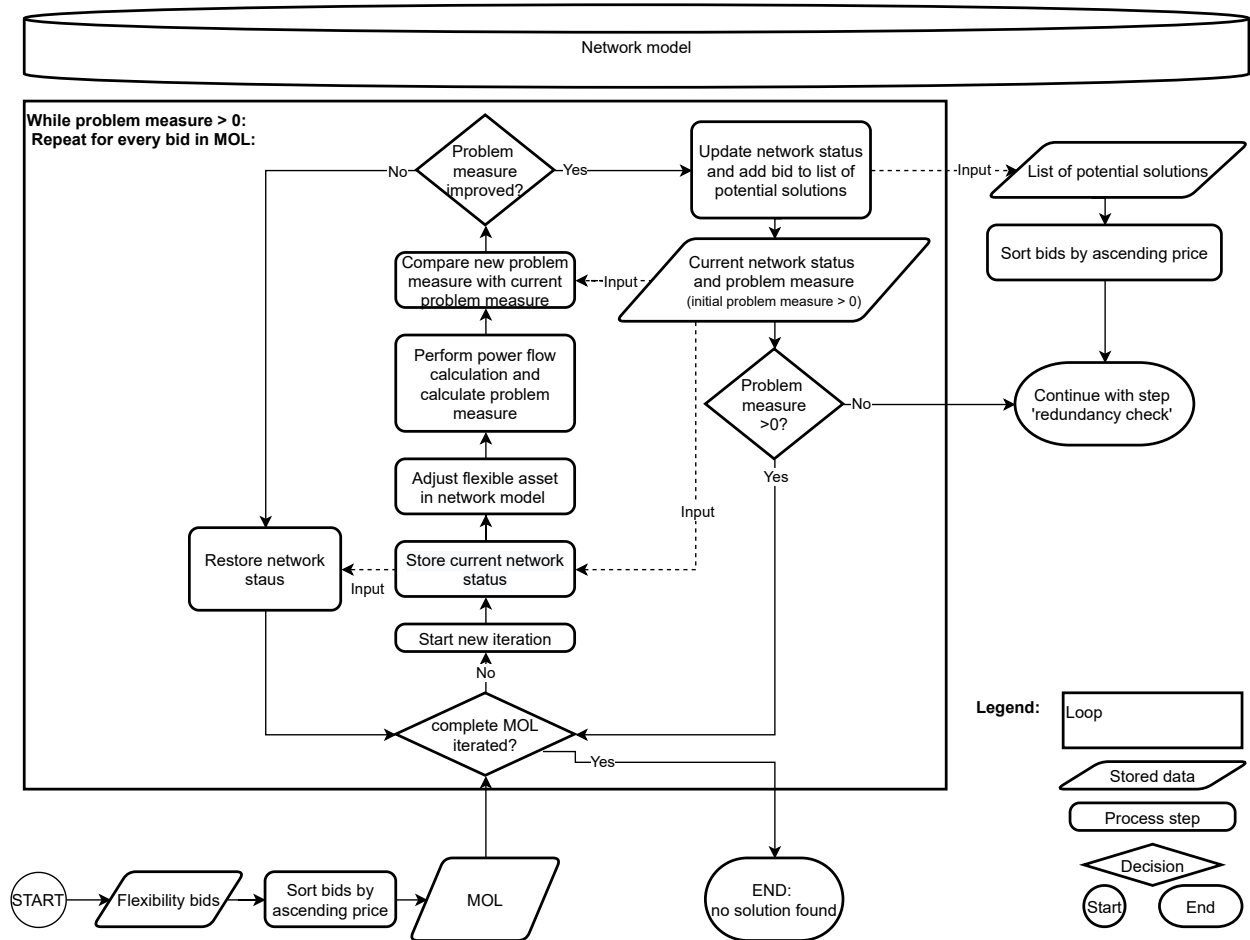
Figure 2: MOL algorithm Step 1: find potential solutions with the MOL
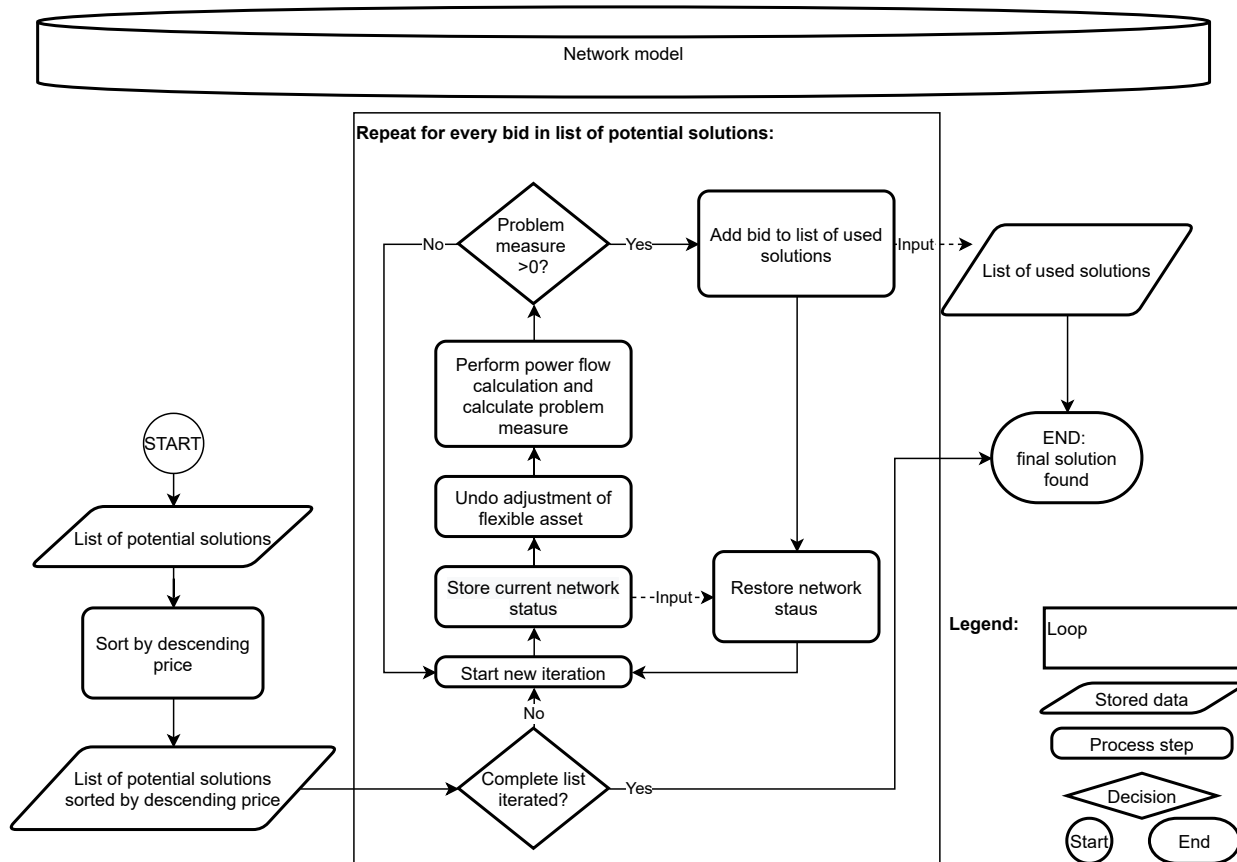
Figure 3: MOL algorithm Step 2 (wMOL algorithm step 3): redundancy check

sorted in descending order by the cost is used as an input for a power flow calculation of a temporarily adjusted network. If the problem measure is still zero, the bid is obviously not necessary and is therefore removed. If the measure changes, the bid is kept as part of the final solution list.

The output of the algorithm is the list of solutions for one specific network situation. It can be repeated for every relevant time step. In this basic representation, the algorithm does not consider combinatorial bid elements but can be extended to include them (see Section 5.1.2).

4.2. Weighted merit order

The second optimization approach is an alternative version of the first approach. It also uses power flow calculations and a problem measure of the concerned network to find a list of bids that solves all problems. Unlike the first approach, the algorithm does not use the MOL but instead preprocesses all bids to generate a weighted merit order list (wMOL). The preprocessing step weights the cost of every bid with the technical effect and therefore decreases the weight of bids that have only a small effect on the problem.

In this preprocessing step (see Figure 4) every single bid is used as an input for a power flow calculation of a temporarily adjusted network. If an individual bid improves the prob-
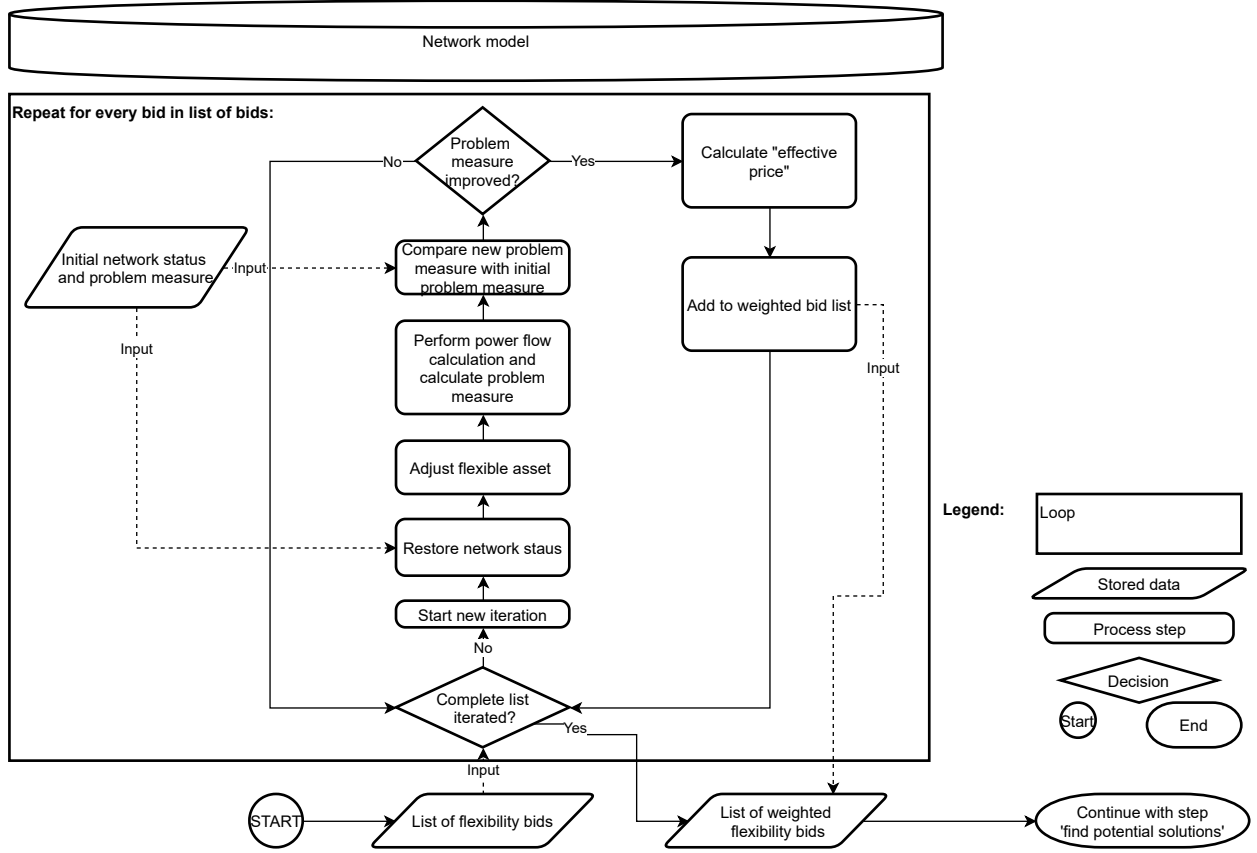
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Figure 4: wMOL algorithm Step 1: preprocessing the wMOL

lem measure of the network, "effective cost" can be calculated as the relation between the problem measure improvement and the cost of the bid's use.

$$Effective\ cost = \frac{Cost\ of\ the\ bid}{Problem\ measure\ without\ bid - Problem\ measure\ with\ bid} \quad (1)$$

Bids that do not have a positive impact on the problem measure are not processed
270 further. The wMOL is formed by sorting the list of evaluated bids in ascending order by their effective cost.

In the next step (see Figure5), the wMOL can be used to find a list of potential solutions. This procedure is similar to the hill climbing method of the MOL-algorithm, but the wMOL only uses bids that have a positive impact on the problem and therefore accepts all bids
275 until the problem measure is zero. If all bids are used without achieving a problem measure of zero, the wMOl has failed to solve all problems. The final redundancy check is the same as that of the MOL-algorithm (see Figure 3).

Like the MOL algorithm, the wMOL algorithm's output is the list of solutions for one specific problem situation. The algorithm can be repeated for every relevant time step. Again,
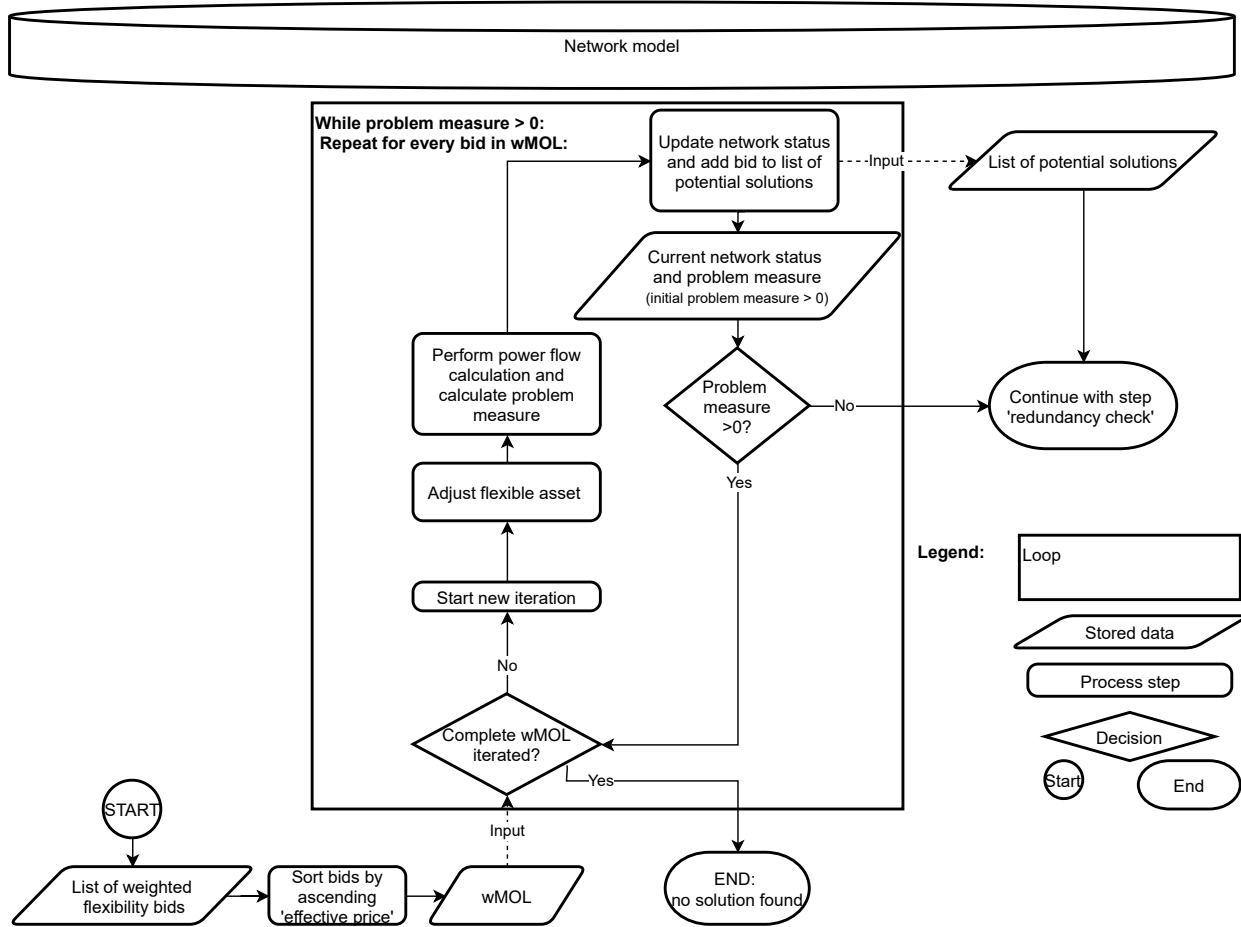280 in this basic representation the algorithm does not consider combinatorial bid elements but

Figure 5: wMOL algorithm Step 2: find potential solutions using the wMOL

can be extended to consider them (see Section 5.1.2).

4.3. Constrained optimization under consideration of effectiveness

The third approach is based on an integrated constrained optimization (Zeiselmair and Köppl, 2021). To reach an optimized solution, effectiveness-weighted supply bids are allocated to demand bids over the whole considered time period. Therefore, cost is minimized with simultaneous penalization of non-fulfillment. Unlike in both preceding approaches, the power flow calculation is not an integral part of the constrained optimization itself (Zeiselmair et al., 2019; Köppl et al., 2019). Instead, the impact of flexible power adjustment to potential demands at all network connection points is evaluated in advance. The results of this initial sensitivity evaluation are then used as input data for the optimization itself in the form of linearized effectiveness functions, as described by Estermann et al. (2018).

Similar approaches have been proposed by Vanet et al. (2015) that use a sensitivity matrix for voltage control issues in low voltage networks. To find a global optimum of the results, deterministic linear optimization is used, as described by the following objective function.

$$\min_{P_{ij}^+, P_{ij}^-} \sum_{j=1}^{96} \sum_{i=1}^{n} \left(C_{ij}^+ \cdot P_{ij}^+ + C_{ij}^- \cdot P_{ij}^- \right) + \sum_{l=1}^{o} G_{lj} \left(d_{jl}^+ + d_{jl}^- \right) \tag{2}$$

with

$C_{ij}^+ \geq 0$	Costs for positive offer bid i at time period j
$C_{ij}^- \geq 0$	Costs for negative offer bid i at time period j
$P_{ij}^+ \geq 0$	Contracted positive offer bid i at time period j
$P_{ij}^- \geq 0$	Contracted negative offer bid i at time period j
$G_{lj} \geq 0$	Penalty costs for non-fulfilment of demand l
$d_{jl}^+, d_{jl}^- \in \mathbb{R}^+$	Auxiliary variable for the absolute value of non-fulfillment of demand l at time period j

The effectiveness factors are part of the auxiliary variables d_{jl}^+ and d_{jl}^-. A detailed description of the incorporation of these factors are presented in Zeiselmair and Köppl (2021). In addition to sensitivity, the algorithm is capable of considering additional constraints[7] on both the supply and demand sides. Therefore, different forms of combinatorial bidding can be implemented. Mathematically, these constraints are represented using additional boundary conditions that are not discussed in this paper, but can be found in Zeiselmair and Köppl (2021). Figure 6 describes the optimization process, including all relevant input data.

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[7]These include the divisibility of bids, power restriction (i.e., maximum or minimum requested power) as well as time restrictions (e.g., minimum and maximum request duration, minimum time between two calls, the total call duration during a day or the total number of calls per day).
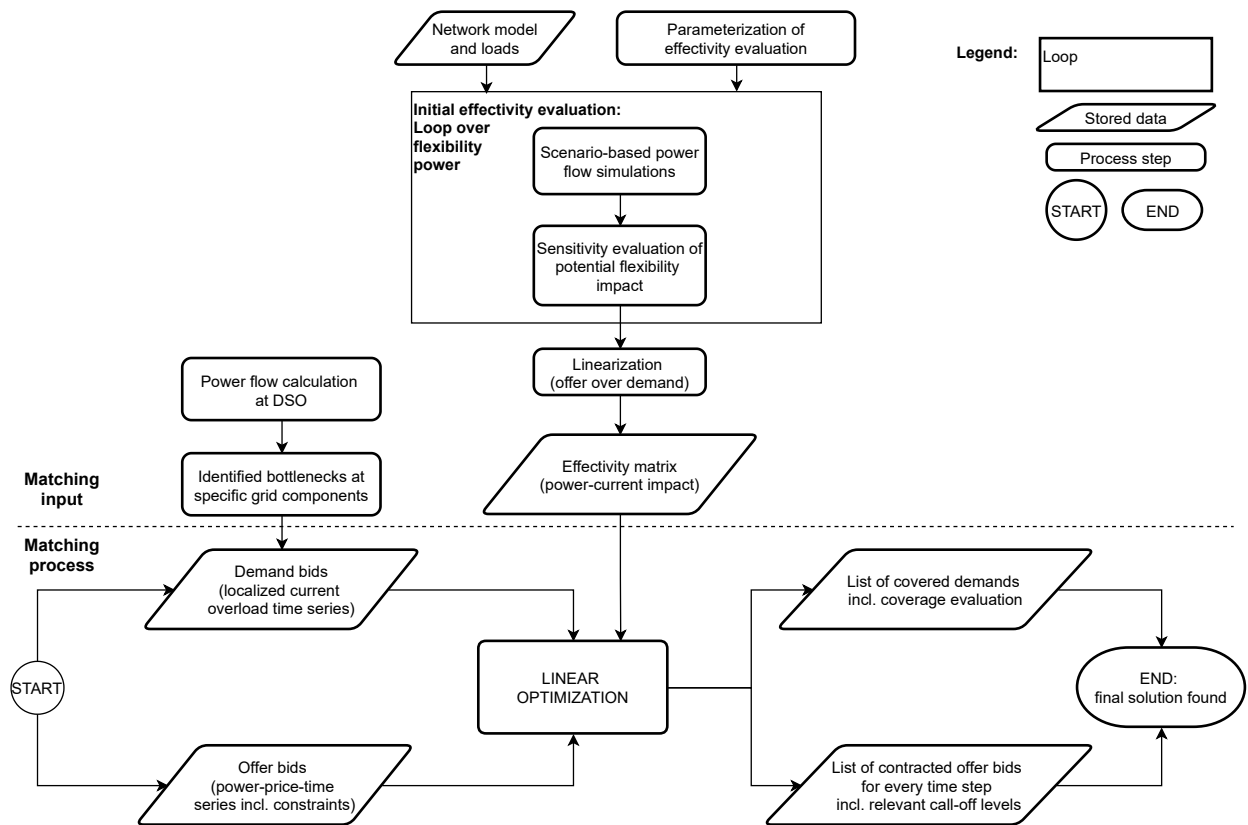
Figure 6: Process description, including relevant input data of the "constrained optimization under consideration of effectiveness" approach
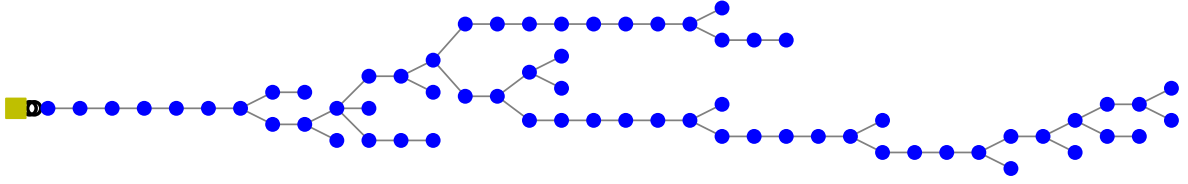
Figure 7: Exemplary network

The integrated optimization approach is quite different from the first two approaches, so its results may also differ (e.g., under-fulfillment is potentially possible). Further optimization is not assessed step-wise for every time step but instead over the entire considered time period. The following case study aims to evaluate the proposed approaches using realistic conditions in order to compare them and to identify divergences.

5. Case study

To demonstrate and compare the three different matching approaches, we implemented a case study based on a real medium-voltage network with different load and generation scenarios. Overall, 12 sub-cases of supply and demand combinations were used to compare the matching outcome of the three approaches. In the following section, we provide a brief overview over the network settings by applying the generalized auction model introduced in Section 3. We then describe the implemented experiment.

5.1. Auction model

5.1.1. Participants

The need for flexibility is based on the network conditions of a real medium-voltage network. Figure 7 shows the medium-voltage network under investigation. It is a radial line, 30 % of which consists of cables. The line represents a rural grid (long extensions) with high photovoltaic (PV) generation and low consumption density (Estermann et al., 2020).

The topology and penetration of the network are based on the on-site conditions. Therefore, the network can be described as follows.

- The network contains 66 nodes. Thirty of these nodes represent residential subnetworks, seven nodes are connected to industrial facilities, four nodes are connected to larger PV plants and one node with a biomass combined heat and power (CHP) plant. The remaining 24 nodes represent topological points without generation or load.

- There are 494 smaller PV plants with a total of 7,830 kW electrical power allocated in the residential subnetworks. Each PV plant has a nominal power between 2 and 30 kW.

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- There are 265 residential heat pumps (HP) with a total of 940 kW of electrical power allocated in the residential subnetworks. Each HP has a nominal power between 2 and 6 kW.

- The nominal power of the four larger PV plants totals 1,100 kW. The nominal power of the CHP is 400 kW.

- The nominal maximum load of the industrial loads is between 100 and 400 kW.

The flexibility supply is provided by the assets connected to the network. We make the following assumptions to quantify the available flexibility:

- PV plants can reduce their current generation.

- The CHP can adjust generation either by reducing current generation or by increasing generation until the nominal power is reached.

- HP loads can either reduce their current load or increase their load until their nominal power is reached.

- • Industrial loads can either reduce or increase their load by up to 25 % of their current load. An increase in load is only possible if the maximum load has not been exceeded.

Each mentioned asset can provide flexibility that depends on the current operation status.

5.1.2. Product design and bidding process

We consider the flexibility demand of one day separated into 96 quarter hours. One flexibility bid[8] contains an amount of flexible power in one direction and related cost[9] for the provided flexible energy in a specific quarter hour.

We assume that each asset can bid and provide its individual flexibility at each time and that there are no catch-up effects within a day. In general, the provided flexibility can be divided into smaller sub-bids. The different algorithms handle the divisibility of bids in a different manner. The linear optimization can process each bid as continuously divisible. The heuristic approaches require the definition of sub-bids that are connected via an XOR relationship.[10] The allocation of these sub-bids is defined depending on the type of flexible asset. The consideration of dividable bids is a basic form of combinatorial bidding. Other

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[8]Note that the underlying flexibility product is not specified here (i.e., short-term products for every quarter hour but also long-term products that are transformed into quarter-hour bids are conceivable; see Heilmann et al., 2020).

[9]We assume that the costs are not negative because the flexibility is interpreted as a service for the network operator. Real world bids could contain negative cost (e.g., if an increased load pays for its consumed energy).

[10]Only one sub bid of a flexible asset can be accepted at the same time.
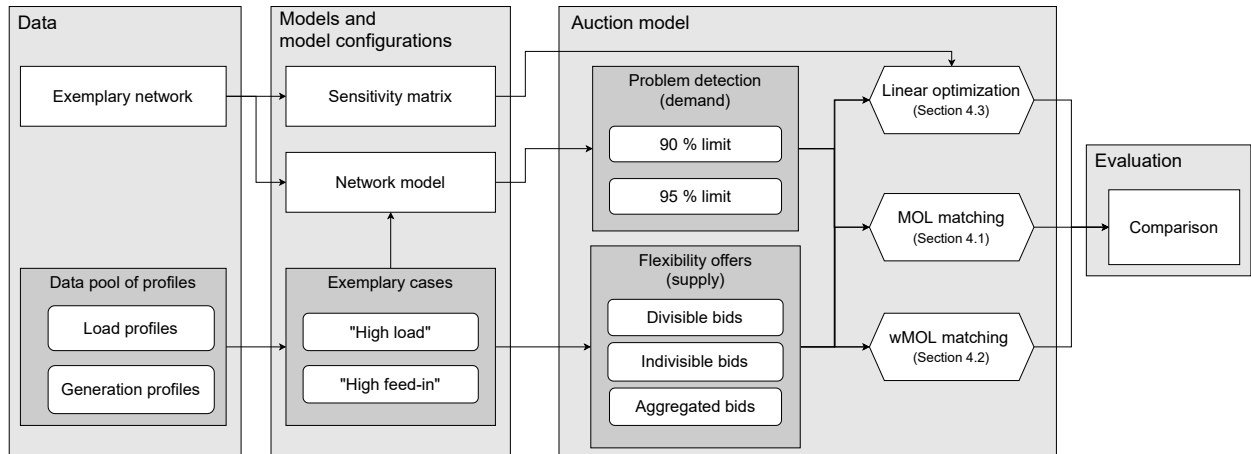
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Figure 8: Experiment design

combinatorial bid options that consider the bidders' preferences[11] are not implemented in this case study.

Optional to the individual, divisible bids, aggregated bids are considered. We assume that the flexibility of every node can be aggregated separately for loads and generations. Aggregated flexibility bids contain the summed flexible power and the weighted average of the flexibility price.

5.1.3. Matching and pricing

We define the pricing scheme of the auction model as the pay-as-bid cost of energy. Every accepted bid is remunerated for the provided flexible energy with the exact defined cost of the bid.

5.2. Experiment description

We transformed the described auction model into a simulation experiment that compares the three different matching approaches. Figure 8 summarizes the setup of this experiment, starting with the input data and ending with the evaluation of the results. In the following subsections, we provide an overview over the used data and models as well as the model specifications for the different cases. The results are discussed in Section 6.

5.2.1. Input data

The core of data used describe the network topology and penetration, as outlined in Section 5.1.1. These data are complemented by load and generation profiles at quarter-hour resolution. The load data are normalized standard load profiles for households and small companies based on BDEW (2017) and normalized exemplary industrial load profiles from the data set by Huber et al. (2019). Fifty normalized PV generation profiles for a sunny

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[11]For example, by defining technical restriction, such as maximal amount of flexibility requests per day, maximal time of flexibility requests, et cetera.

day have been generated that refer to solar panel alignment based on selected real-world solar prediction data from the project region. Three-hundred exemplary, normalized HP profiles are extracted from simulation data that capture several factors, such as the number of persons per household or size, location and age of the building (see Müller et al., 2019 based on Fünfgeld and Fiebig, 2002).

5.2.2. Models and model configurations

We modeled the described network with the Python module "pandapower" (see Thurner et al., 2018) that provides power flow calculations and network analysis tools. Each flexibility provider is modeled as a separate asset in the network that can be adjusted individually. We distinguish two main network situations, namely the "high load" and the "high feed-in" scenarios. These two scenarios are exemplary situations of extreme network states. In the high load scenario, generation in the network is assumed to be zero and the loads are assumed to follow high demand profiles.[12] In the high feed-in scenario, there is high generation from PVs and also from the CHP in the network, and load is low.[13] Both scenarios differ in the direction of the power flow: in the high load scenario, the network receives energy from the upper network levels, and in the high feed-in scenario, energy gets fed back into the upper network levels.

An effectiveness evaluation for the network is performed in advance for the matching approach, "Constrained optimization under consideration of effectiveness." This evaluation considers the effect of flexibility on every node for each network asset.

5.2.3. Variation of supply and demand

The flexibility supply and demand can be determined based on the two network scenarios. Because neither the high load nor the high feed-in scenario results in critical network situations, the flexibility demand is generated by adapting the limit values of the lines' capacity[14]. We implemented two limit values for each network case by taking 95 % and 90 % of the maximum utilization of all lines. On the supply side the available flexibility potential depends on the current operation status of each individual flexible asset (see Section 5.1.1).

Based on the flexibility potential, we implemented three different variants of flexibility bids[15]:

- The first variant is individual flexibility bids that are divisible depending on the providing technology.

- The second variant are individual, indivisible flexibility bids.

- The third variant are bids of flexibility aggregated at a node level and separated into load and generation flexibility.

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[12]This scenario can be interpreted as a cold and cloudy working day.

[13]This scenario can be interpreted as warm and sunny weekend day.

[14]As a simplification; we only considered capacity problems and noT voltage problems.

[15]To determine complete flexibility bids, we assumed randomized flexibility cost for every flexible asset between 1 and 250 € per MWh.

Combining the two network scenarios with the two demand calculations and the three different supply variants, 12 different cases for the case study can be defined. Table 5.2.3 provides an overview of the 12 cases and their corresponding network scenarios, the demand limit values and the supply structures.

Case	Network scenario	Demand	Supply
"HL_90_div"	"high load"	90 percent limit	divisible bids
"HL_90_indiv"	"high load"	90 percent limit	indivisible bids
"HL_90_agg"	"high load"	90 percent limit	aggregated bids
"HL_95_div"	"high load"	95 percent limit	divisible bids
"HL_95_indiv"	"high load"	95 percent limit	indivisible bids
"HL_95_agg"	"high load"	95 percent limit	aggregated bids
"HG_90_div"	"high generation"	90 percent limit	divisible bids
"HG_90_indiv"	"high generation"	90 percent limit	indivisible bids
"HG_90_agg"	"high generation"	90 percent limit	aggregated bids
"HG_95_div"	"high generation"	95 percent limit	divisible bids
"HG_95_indiv"	"high generation"	95 percent limit	indivisible bids
"HG_95_agg"	"high generation"	95 percent limit	aggregated bids

Table 1: Case study variations

For each of the cases, the three proposed approaches match supply and demand. The evaluation of the results is presented in the next section.

6. Results and discussion

6.1. Quantitative results

To compare the three matching approaches, we evaluated the sum of the used flexible energy (Figure 9) and the mean energy cost (Figure 10). These values can be combined to determine the total cost of the flexibility supply (Figure 11).

The different scenarios result in different levels of flexible energy. These differences can be explained by assumptions made in the different scenarios. When the different matching algorithms are considered, the cases "HG_90_div ", "HG_90_indiv " and "HG_90_agg" leads to a substantial discrepancy between the linear optimization approach and the MOL and wMOL approaches. A detailed evaluation of the results indicates that the flexibility demand was not covered in the "HG_90_" cases by the linear optimization approach. This shortcoming was a consequence of the combination of a high number of small demands and a limited number of high demands in the considered time period. The optimizer thus attempted to minimize penalty costs and selected the (permitted) under-fulfillment as the mathematically optimal option (see Section 6.2.2).

In addition to the used flexible energy, the specific price per energy is the second component used to calculate the overall flexibility cost. The aggregated bids generally lead to higher specific cost of flexible energy, because the aggregated bids contain a high number of individual bids that can contain high individual cost. The comparison between divisible
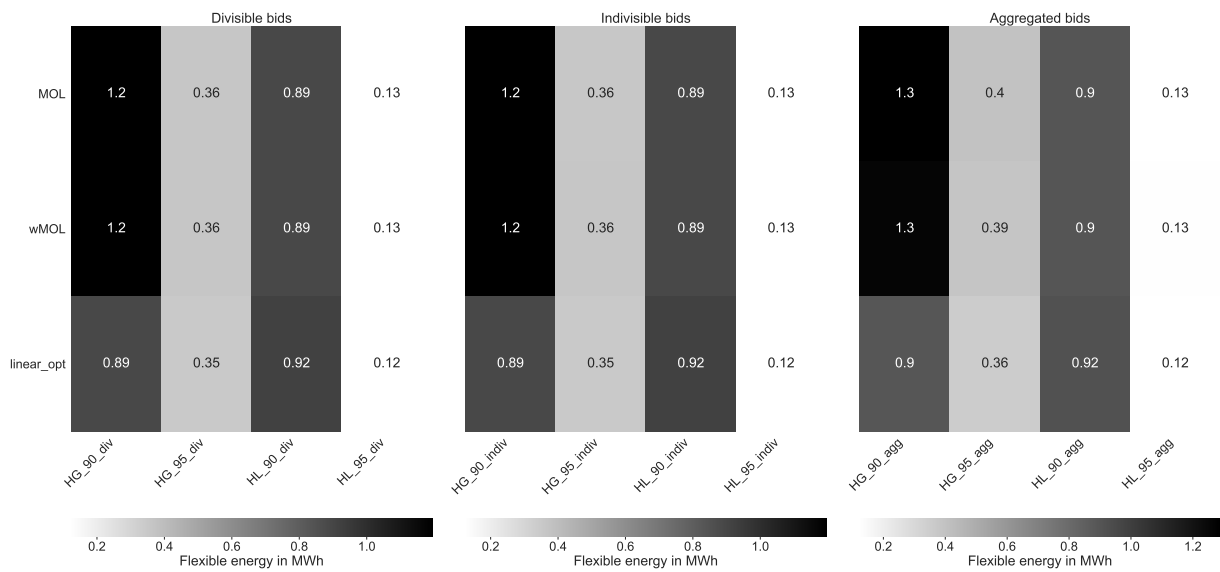
19

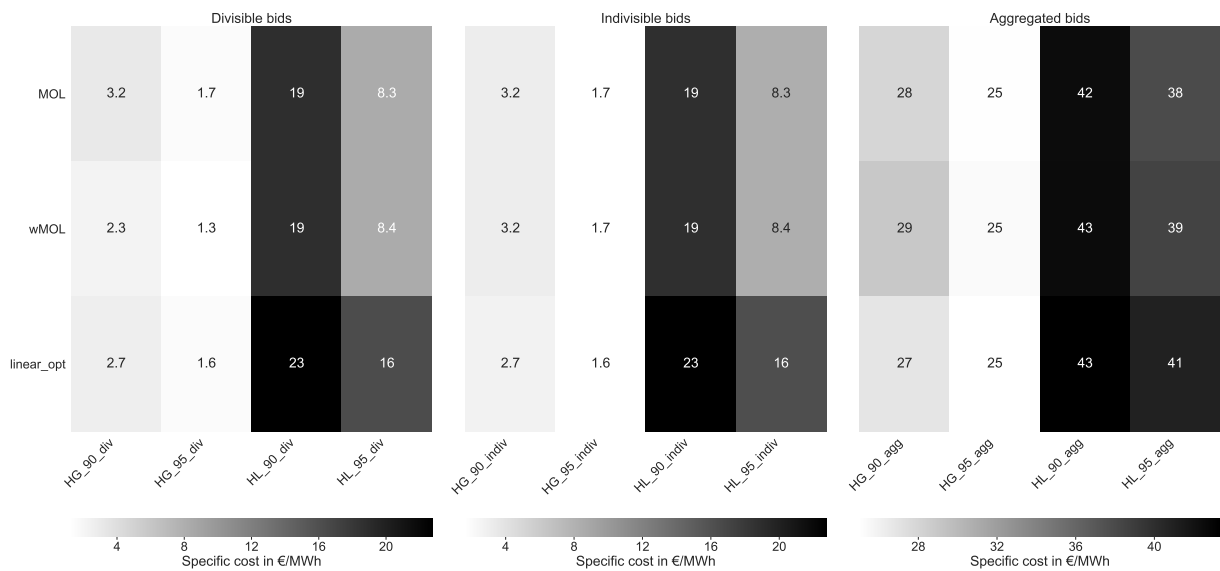Figure 9: Contracted flexible energy in MWh in the case study

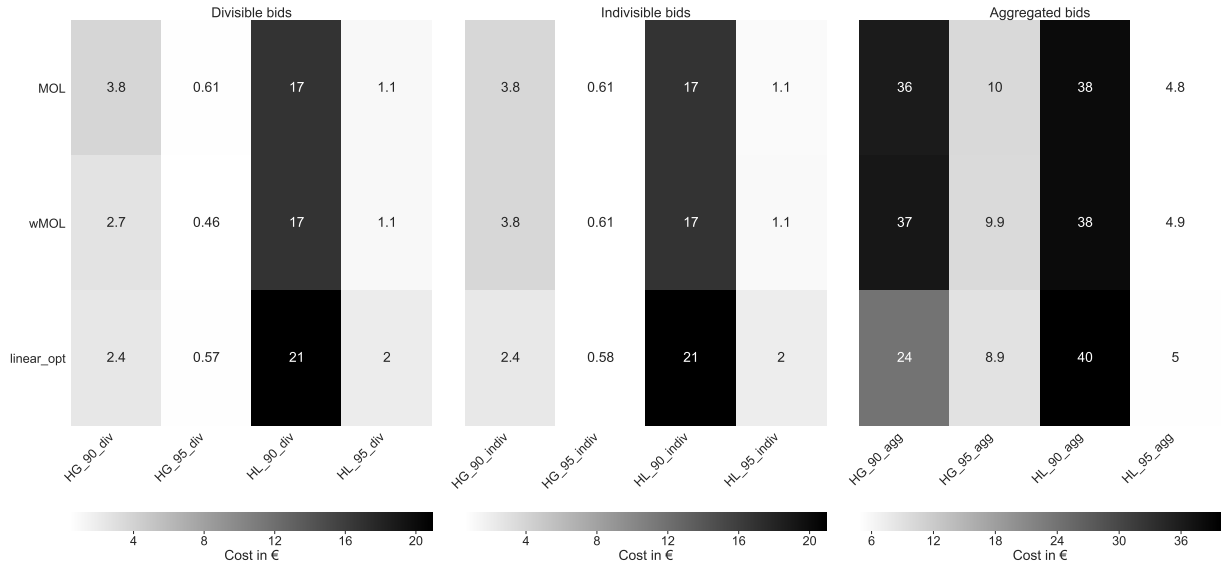Figure 10: Mean cost per energy in €/MWh in the case study

Figure 11: Flexibility cost in € in the case study

and indivisible bids shows that divisible bids can improve the mean energy cost in specific situations.

As a combination of used flexible energy and specific cost, the flexibility cost is the target quantity that should be minimized by every approach. For the "HG_90_" cases the cost of the linear optimization is substantially lower due to the under-fulfillment of the requested flexible energy. For the other scenarios, the linear optimization does not generally outperform the heuristic approaches. The direct comparison between the MOL and the wMOL approach indicates that the latter can improve the cost slightly.

6.2. Qualitative discussion and outlook

The results of the case study demonstrate that each of the provided optimization approaches is in principle suitable for the matching of network-supportive flexibility. Nonetheless, the used algorithms represent basic implementations with the potential for expansion and improvement. A concluding quantitative evaluation of the approaches is consequently unreasonable. In the following subsections, we compare the approaches in a qualitative manner by considering the following topics: specific cost, flexible energy, ensured demand coverage, data minimization, computational effort and the transferability of the algorithms regarding network issues and different flexibility mechanisms. Table 6.2 summarizes the qualitative comparison, rating the algorithms in the mentioned categories with the following measure: "+" = advantages, "-" = disadvantages and "0" = neutral.

6.2.1. Specific cost and flexible energy

As indicated by the quantitative results, no single algorithm tends to perform better or worse than the others. Still, because they use the least expensive bids first, the heuristic

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	Specific cost	Flexible energy	Ensured demand coverage	Data minimization	Computational effort	Transferability (network)	Transferability (mechanism)
MOL	+	0	+	-	0	0	+
wMOL	+	0	+	-	-	0	+
Linear optimization	0	+	-	+	+	0	+

Table 2: Qualitative comparison of matching approaches

approaches MOL and wMOL obtain lower specific costs than the linear optimization. The linear optimization approach can counterbalance this by providing a smaller amount of flexible energy.

6.2.2. Ensured demand coverage

Unlike the other two approaches, the linear optimization approach allows a deficit in the demand of flexibility. Optimization includes all congestion within the considered time period.[16]. Even if a penalty term in the optimization equation forces contracting close to demand, a deficit may occur under certain circumstances. In this case, the level of demand varies among the grid components. Since bids affect several congestion, there are sometimes high excess demands in individual grid components, which in turn are subject to the penalty term. Thus, cost-optimal solutions can occur that do not completely cover all congestion. Including a penalty term for the deficit but not for the excess coverage could be a remedy.

6.2.3. Data minimization

The wMOL and MOL approaches include the repeated execution of load flow calculations, so a complete network model must be available. Depending on the responsible for the matching of network-supportive flexibility, these partly sensitive network data may be not available. The linear optimization approach also requires load flow calculations to create the effective values; thus, this method also requires a complete network model. However, this step is carried out initially (see Figure 6) and can therefore be transferred to a third party.

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[16]in the case study, one day

6.2.4. Computational effort

The main factors that determine computational effort are the necessity and quantity of network calculations. While the linear optimization technique only uses network calculations initially, the MOL and wMOL algorithms calculate the network status several times per optimization. The wMOL in particular runs one network calculation for every flexibility provider as a pre-processing step before conducting the optimization itself. Therefore, the operation of the heuristic approaches has a high computational effort that grows with added flexibility suppliers and more complex networks. owever, the complexity of the linear optimization also depends on these factors.

Another aspect of the computational effort is which bidding structure leads to the lowest computing time. Due to a substantially lower number of bids, the matching of aggregated bids is significantly faster[17] than that of individual bids. Nevertheless, the overall cost of flexibility also increases significantly.

6.2.5. Transferability (network)

The case study applies the three approaches to a medium-voltage line in different network situations (see Table 5.2.3). Systematic obstacles to applying these approaches to other grid areas, grid types or voltage levels cannot be identified. When scaling these approaches to larger areas with a high number of problems and solution options, dividing the network into self-contained electrical areas should be considered to save resources. However, any conclusive statement on the proposed approaches' compatibility with other networks requires further investigations.

6.2.6. Transferability (mechanism)

The case study considers one specific flexibility bid setting (see Section 5.1.2). This format is compatible with day-ahead network operation processes and can be adjusted to arbitrary time slots. Moreover, the possibility of divisible bids was considered in the case study. Still, the used bidding format does not include more complex combinatorial bidding options, such as block bids or restrictions of use. All the introduced matching approaches can generally be adjusted for such combinatorial elements. In addition to the bid structure, the pricing scheme was defined as pay as bid for only positive prices. Other pricing schemes could also be implemented,[18] but would also need further adjustments.

7. Conclusion

The present paper contributes to the current discussion on network supporting flexibility by explicitly discussing the aspect of matching supply and demand. Although different

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[17]An evaluation of the calculation time shows that matching individual bids needs up to 30 times more time than the relevant aggregated matching.

[18]Note that negative prices under the premise of minimized cost could lead to a significantly higher amount of flexible energy (than under the restriction of only positive cost) due to the local balancing of positive and negative flexibility (as long as the overall cost decreases). We state that this should not be the target of network-supportive flexibility.

⁵¹⁵ underlying mechanisms for the utilization of network supporting flexibility are plausible, the use of flexibility can be modeled based on basic auction theory. This auction model can be classified as a multi-unit, multi-attribute (price and network location) procurement auction with a high probability of combinatorial elements. In general, the related matching problem is a complex optimization problem that aims to solve all technical problems at the
⁵²⁰ lowest possible cost.

We introduced three different matching approaches, addressing transparency and reproducibility of these algorithms. Two of the approaches are heuristic algorithms that use either a merit order list or a weighted merit order list in combination with a hill climbing approach to solve all problems by calculating the network status at different settings of flexibility
⁵²⁵ dispatch. The third approach transfers the technical problem into a linear optimization. The network information is thus part of the optimization itself, and no additional network calculation needs to be executed.

We presented a case study to demonstrate the utility of the three approaches and compared them qualitatively with quantitative inputs. The comparison demonstrates that the
⁵³⁰ algorithms are generally suitable for the described problem. Individual differences between the three approaches can be identified especially in the fields of ensured demand coverage, data minimization and computational effort. Nevertheless, all three algorithms may be improved, for example, with respect to their reliability and calculation effort. Future work could apply the algorithms to other network situations or flexibility bidding formats.

Data Availability

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Datasets related to this article can be found at http://dx.doi.org/10.17632/3rgw59mmp5.1, an open-source online data repository hosted at Mendeley Data (Heilmann, 2021). We provide the code of the heuristic matching approaches (MOL and wMOL) and a synthetic adjustable network model. The detailed description including an exemplary application
⁵⁴⁰ of the approach using constrained optimization under consideration of effectiveness can be found in Zeiselmair and Köppl (2021). Note, that the real-word network can not be provided due to data protection issues.

Acknowledgments

References

Abrache, J., Crainic, T.G., Gendreau, M., Rekik, M., 2007. Combinatorial auctions. Annals of Operations Research 153, 131–164. doi:10.1007/s10479-007-0179-z.

Asker, J., Cantillon, E., 2008. Properties of Scoring Auctions. The RAND Journal of Economics 39, 69–85.
⁵⁵⁰ BDEW, 2017. Standard load profilesfor electricity. URL: https://www.bdew.de/energie/standardlastprofile-strom/.

Bichler, M., Pikovsky, A., Setzer, T., 2009. An Analysis of Design Problems in Combinatorial Procurement Auctions. Business & Information Systems Engineering 1, 111–117. doi:10.1007/s12599-008-0014-3.

Branco, F., 1997. The Design of Multidimensional Auctions. The RAND Journal of Economics 28, 63. doi:10.2307/2555940.

Cheng, C.B., 2008. Solving a sealed-bid reverse auction problem by multiple-criterion decision-making methods. Computers & Mathematics with Applications 56, 3261–3274. doi:10.1016/j.camwa.2008.09.011.

Chetan, T.G., Jenamani, M., Sarmah, S.P., 2019. Two-Stage Multi-attribute Auction Mechanism for Price Discovery and Winner Determination. IEEE Transactions on Engineering Management 66, 112–126. doi:10.1109/TEM.2018.2810510.

Cumpston, A., Khezr, P., 2020. Multi-Unit Auctions: A Survey of Theoretical Literature: MPRA Paper No. 101336. URL: https://mpra.ub.uni-muenchen.de/101336/.

Dauer, D., 2016. Market-based Allocation of Local Flexibility in Smart Grids: A Mechanism Design Approach. Dissertation. Karlsruher Institut für Technologie. Karlsruhe.

Ding, Y., Hansen, L.H., Cajar, P.D., Brath, P., Bindner, H.W., Zhang, C., Nordentoft, N.C., 2013. Development of a DSO-Market on flexibility services.

Esmat, A., Usaola, J., Moreno, M., 2018. Distribution-Level Flexibility Market for Congestion Management. Energies 11, 1056. doi:10.3390/en11051056.

Estermann, T., Köppl, S., Mader, N., 2020. Development of a fitting for simulation parameters to apply and derive a cluster analysis regarding grid bottlenecks.

Estermann, T., Müller, M., Köppl, S., Weiß, A., 2018. Approach to determine the effect of local flexibility options within the framework of a smart market platform.

Eurelectric, 2015. Flexibility and aggregation - requirements for their interaction in the market. Ieee Transactions on Power Systems .

Fünfgeld, C., Fiebig, C., 2002. Bestimmung von Lastprofilen für unterbrechbare Verbrauchseinrichtungen.

Gerard, H., Rivero, E., Six, D., 2016. Smartnet.

Granelli, G., Montagna, M., Zanellini, F., Bresesti, P., Vailati, R., Innorta, M., 2006. Optimal network reconfiguration for congestion management by deterministic and genetic algorithms. Electric Power Systems Research 76, 549–556. doi:10.1016/j.epsr.2005.09.014.

Heilmann, E., 2021. Matching network-supportive flexibility supply and demand", mendeley data, v1. doi:10.17632/3rgw59mmp5.1.

Heilmann, E., Klempp, N., Wetzel, H., 2020. Design of regional flexibility markets for electricity: A product classification framework for and application to German pilot projects. Utilities Policy 67, 101133. doi:10.1016/j.jup.2020.101133.

Heussen, K., Bondy, D.E.M., Hu, J., Gehrke, O., Hansen, L.H., 2013. A clearinghouse concept for distribution-level flexibility services, in: 2013 4th PES innovative smart grid technologies Europe (ISGT Europe 2013), pp. 1–5.

Huang, S., Wu, Q., Liu, Z., Nielsen, A.H., 2014. Review of congestion management methods for distribution networks with high penetration of distributed energy resources, in: IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), 2014, IEEE, Piscataway, NJ. pp. 1–6. doi:10.1109/ISGTEurope.2014.7028811.

Huber, J., Klempp, N., Becker, J., Weinhardt, C., 2019. Electricity consumption of 28 German companies in 15-min resolution. Karlsruhe. doi:10.5445/IR/1000098027.

Jin, X., Wu, Q., Jia, H., 2020. Local flexibility markets: Literature review on concepts, models and clearing methods. Applied Energy 261, 114387. doi:10.1016/j.apenergy.2019.114387.

Khajeh, H., Laaksonen, H., Gazafroud, A.S., Shafie-Khah, M., 2019. Towards flexibility trading at TSO-DSO-customer levels: A review. doi:10.3390/en13010165.

Kok, K., 2012. Dynamic pricing by scalable energy management systems Field experiences and simulation results using PowerMatcher. doi:10.1109/PESGM.2012.6345058.

Köppl, S., Lang, C., Bogensperger, A., Estermann, T., Zeiselmair, A., 2019. Altdorfer flexmarkt – decentral flexibility for distribution networks. Internationaler ETG-Kongress .

Kornrumpf, T., Meese, J., Zdrallek, M., Neusel-Lange, N., Roch, M., 2016. Economic dispatch of flexibility options for Grid services on distribution level, in: 19th Power Systems Computation Conference, pp. 1–7.

25

Kouzelis, K., Bak-Jensen, B., Pillai, J.R., 2015. The geographical aspect of flexibility in distribution grids, in: 2015 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), IEEE, Piscataway, NJ. pp. 1–5. doi:10.1109/ISGT.2015.7131888.

Lamparter, S., Becher, S., Fischer, J.G., 2016. An Agent-based Market Plattform for Smart Grids, in: 19th Power Systems Computation Conference, pp. 1689–1696.

Laur, A., Nieto-Martin, J., Bunn, D.W., Vicente-Pastor, A., 2020. Optimal procurement of flexibility services within electricity distribution networks. European Journal of Operational Research doi:10.1016/j.ejor.2018.11.031.

McAfee, R.P., McMillan, J., 1987. Auctions an Bidding. Journal of Economic Literature , 699–738.

Müller, M., Zeiselmair, A., Pedraza Gómez, J., 2019. Tapping flexibility potential of decentralized controllable loads for smart markets through aggregation.

Niu, J., Tian, Z., Zhu, J., Yue, L., 2020. Implementation of a price-driven demand response in a distributed energy system with multi-energy flexibility measures. Energy Conversion and Management doi:10.1016/j.enconman.2020.112575.

Olivella-Rosell, P., Bullich-Massagué, E., Aragüés-Peñalba, M., Sumper, A., Ottesen, S.Ø., Vidal-Clos, J.A., Villafáfila-Robles, R., 2018a. Optimization problem for meeting distribution system operator requests in local flexibility markets with distributed energy resources. Applied Energy 210, 881–895. doi:10.1016/j.apenergy.2017.08.136.

Olivella-Rosell, P., Lloret-Gallego, P., Munné-Collado, Í., Villafafila-Robles, R., Sumper, A., Ottessen, S., Rajasekharan, J., Bremdal, B., 2018b. Local Flexibility Market Design for Aggregators Providing Multiple Flexibility Services at Distribution Network Level. Energies 11, 822. doi:10.3390/en11040822.

Parsons, S., Rodriguez-Aguilar, J.A., Klein, M., 2011. Auctions and bidding. ACM Computing Surveys 43, 1–59. doi:10.1145/1883612.1883617.

Petersen, M., Hansen, L.H., Mølbak, T., 2012. Exploring the value of flexibility. IFAC Proceedings Volumes 45, 43–48. doi:10.3182/20120902-4-FR-2032.00010.

Pham, L., Teich, J., Wallenius, H., Wallenius, J., 2015. Multi-attribute online reverse auctions: Recent research trends. European Journal of Operational Research 242, 1–9. doi:{0.1016/j.ejor.2014.08.043},.

Radecke, J., Hefele, J., Hirth, L., 2019. Markets for Local Flexibility in Distribution Networks. URL: http://hdl.handle.net/10419/204559.

Ramos, A., de Jonghe, C., Gómez, V., Belmans, R., 2016. Realizing the smart grid's potential: Defining local markets for flexibility. Utilities Policy 40, 26–35.

Sandholm, T., 2002. Algorithm for optimal winner determination in combinatorial auctions. Artificial Intelligence 135, 1–54. doi:10.1016/S0004-3702(01)00159-X.

Sandholm, T., Suri, S., 2006. Side constraints and non-price attributes in markets. Games and Economic Behavior 55, 321–330. doi:10.1016/j.geb.2005.06.001.

Scheidler, A., Thurner, L., Braun, M., 2018. Heuristic optimisation for automated distribution system planning in network integration studies. IET Renewable Power Generation 12, 530–538. doi:10.1049/iet-rpg.2017.0394.

Schermeyer, H., Vergara, C., Fichtner, W., 2018. Renewable energy curtailment: A case study on today's and tomorrow's congestion management. Energy Policy 112, 427–436.

Schittekatte, T., Meeus, L., 2020. Flexibility markets: Q&A with project pioneers. Utilities Policy 63.

Shen, S., Huang, S., Wu, Q., Repo, S., Xu, Y., Østergaard, J., 2019. Comprehensive Congestion Management for Distribution Networks Based on Dynamic Tariff, Reconfiguration, and Re-Profiling Product. IEEE Transactions on Smart Grid 10, 4795–4805. doi:10.1109/TSG.2018.2868755.

de Smet, Y., 2007. Multi-criteria auctions without full comparability of bids. European Journal of Operational Research 177, 1433–1452. doi:10.1016/j.ejor.2005.04.014.

Spiliotis, K., Ramos Gutierrez, A.I., Belmans, R., 2016. Demand flexibility versus physical network expansions in distribution grids. Applied Energy 182, 613–624. doi:10.1016/j.apenergy.2016.08.145.

Teich, J.E., Wallenius, H., Wallenius, J., Koppius, O.R., 2004. Emerging multiple issue e-auctions. European Journal of Operational Research 159, 1–16. doi:10.1016/j.ejor.2003.05.001.

Teich, J.E., Wallenius, H., Wallenius, J., Zaitsev, A., 2006. A multi-attribute e-auction mechanism for procurement: Theoretical foundations. European Journal of Operational Research 175, 90–100. doi:10.1016/j.ejor.2005.04.023.

Thiel, S.E., 1988. Multidimensional auctions. Economics Letters 28, 37–40. doi:10.1016/0165-1765(88)90068-7.

Thurner, L., Scheidler, A., Schafer, F., Menke, J.H., Dollichon, J., Meier, F., Meinecke, S., Braun, M., 2018. Pandapower—an open-source python tool for convenient modeling, analysis, and optimization of electric power systems. IEEE Transactions on Power Systems 33, 6510–6521. doi:10.1109/TPWRS.2018.2829021.

Torbaghan, S.S., Blaauwbroek, N., Nguyen, P., Gibescu, M., 2016. Local market framework for exploiting flexibility from the end users, in: 13th International Conference on the European Energy Market (EEM), pp. 1–6.

Tušar, T., Šikšnys, L., Pedersen, T.B., Dovgan, E., Filipič, B., 2012. Using aggregation to improve the scheduling of flexible energy offers, in: Proceedings of the 5th International Conference on Bioinspired Optimization Methods and their Applications, BIOMA 2012, pp. 347–358.

Vanet, E., Toure, S., Kechagia, N., Caire, R., HadjSaid, N., 2015. Sensitivity analysis of local flexibilities for voltage regulation in unbalanced LV distribution system, in: 2015 IEEE Eindhoven PowerTech, Institute of Electrical and Electronics Engineers, Piscataway, New Jersey. pp. 1–6. doi:10.1109/PTC.2015.7232627.

Villar, J., Bessa, R., Matos, M., 2018. Flexibility products and markets: Literature review. Electric Power Systems Research 154, 329–340.

Wang, Y., Wang, S., Wu, L., 2017. Distributed optimization approaches for emerging power systems operation: A review. Electric Power Systems Research 144, 127–135. doi:10.1016/j.epsr.2016.11.025.

Wurman, P.R., Wellman, M.P., Walsh, W.E., 2001. A Parametrization of the Auction Design Space. Games and Economic Behavior 35, 304–338.

Xia, M., Koehler, G.J., Whinston, A.B., 2004. Pricing combinatorial auctions. European Journal of Operational Research 154, 251–270. doi:10.1016/S0377-2217(02)00678-1.

Zeiselmair, A., Köppl, S., 2021. Constrained optimization as allocation method in local flexibility markets. energies Special Issue "Innovation, Policy, and Regulation in Electricity Markets" (in Review) .

Zeiselmair, A., Köppl, S., Estermann, T., Lehmann, N., Kraft, E., Klempp, N., 2019. Netzdienlicher handel als element des zellulären energiesystems am beispiel des altdorfer flexmarkts (alf). 11. Internationale Energiewirtschaftstagung (IEWT) .

Zhang, C., Ding, Y., Ostergaard, J., Bindner, H.W., Nordentoft, N.C., Hansen, L.H., Brath, P., Cajar, P.D., 2013. A flex-market design for flexibility services through DERs, in: 2013 4th PES innovative smart grid technologies Europe (ISGT Europe 2013), pp. 1–5.
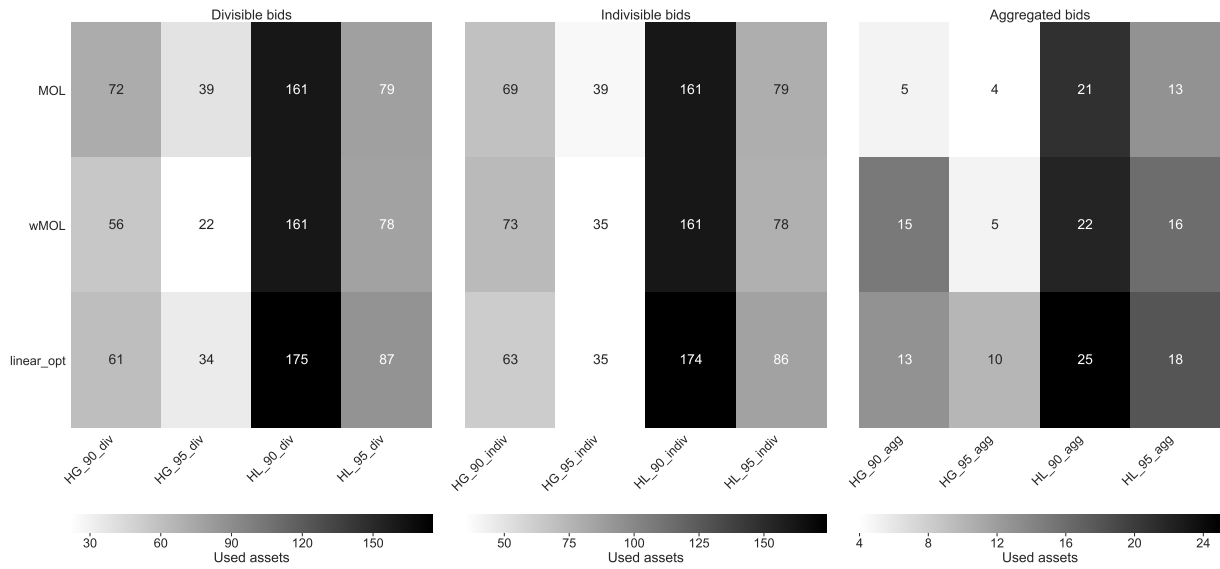
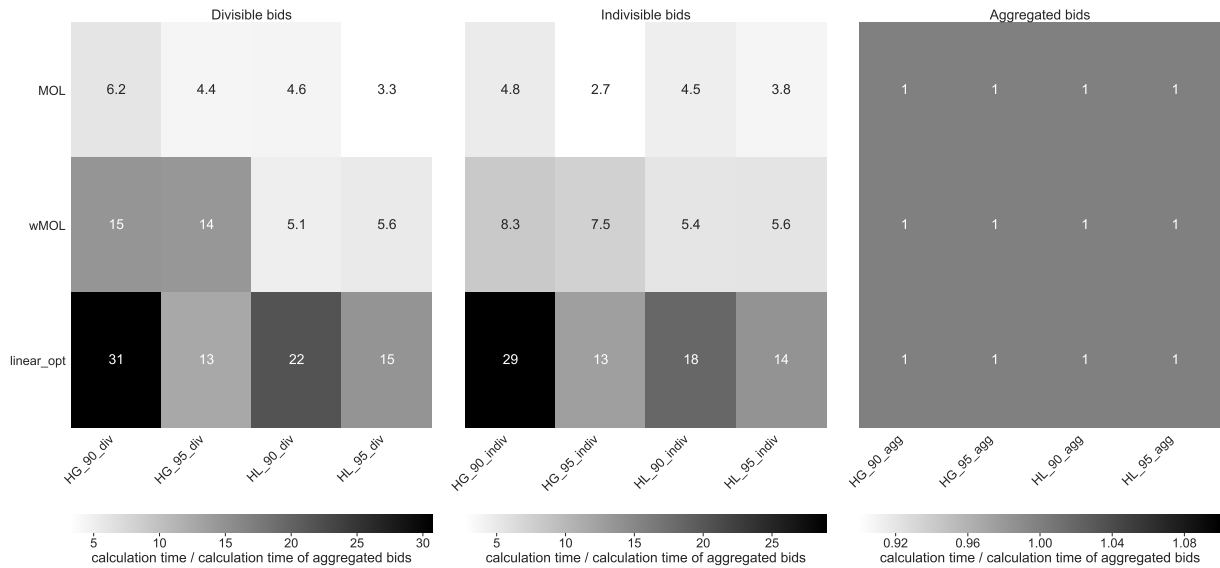# Appendix A - supplementary figures

Figure A1: Used flexible assets

Figure A2: Relative calculation time (normalized on cases "_agg")