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Putting renewable energy auctions into action – An agent-based model of onshore wind power auctions in Germany

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ABSTRACT

The following analysis looks into auctions for renewable energy, specifically onshore wind power in Germany. Following an agent-based modeling approach, the two most commonly applied auction pricing rules are compared (uniform and pay-as-bid) and first conclusions on outcomes are drawn for future policy design. The auctions are modeled to closely represent the auction design foreseen in the German Renewable Energy Sources Act (EEG, 2017) and replicate their parameters.

The analysis draws on auction theory. For both pricing schemes, individually rational agents with independent valuation are assumed. As support for renewable electricity through auctions is to be established permanently and auction rounds will be held multi-annually, a further focus lies on agents learning over time by adapting their behavior to new information.

The model results show that pay-as-bid exhibits lower prices and thus support costs than uniform pricing, whereas allocative efficiency suffers under pay-as-bid. Over time, one can observe a decline in the strike price, which is due to learning effects, whereas agents' profits increase in the course of the auctions. Furthermore, smaller actors will experience difficulties and agent diversity is likely to suffer in the long term, if this is not accounted for in other ways.

1. Introduction

The Renewable Energy Sources Act 2017 (EEG, 2017) was introduced in Germany in 2016. Under this act, auctions will determine the future sliding feed-in premiums for the support of renewable energies according to the directive 2009/28/EC on the promotion of the use of energy from renewable sources (European Parliament and Council Directive, 2009) and to the "Guidelines on state aid for environmental protection and energy 2014–2020″ (No. 2014/C 200/01) by the European Commission (2014). Starting in 2015, the first (pilot) rounds were already executed for solar PV and in 2017, onshore wind will become subject to tendering as well.

Onshore wind power in Germany has seen a substantial expansion during the past decade, due to ambitious goals for climate protection and successful support strategies implemented by the German government and specifically the Ministry for Economic Affairs and Energy (Bundesministerium für Wirtschaft und Energie (BMWi)). So far, a price-based mechanism, namely a sliding feed-in premium with an administratively set, fixed strike price was used to subsidize all wind power plants in Germany equally (only adjusted by a certain locational correction factor – the so-called "Korrekturfaktor der Standortgüte" (EEG, 2017)). From this year on, the expansion will start being subsidized by an auction-based support scheme, in which different projects compete for support. A certain amount of electric capacity will be tendered, corresponding to the EU's goals for deployment of electricity from renewable energy sources (RES) for each member state. This amount is to be generated by RES according to the Renewable Energy Sources Act (EEG, 2014; EEG, 2017).

Under the pay-as-bid (PAB) pricing rule, which has been implemented in the first German wind onshore auctions, the agents holding a winning bid receive exactly their submitted bid as support for their fed-in electricity for the following 20 years. An exemption is made for citizens' energy companies, which will be awarded under a uniform pricing rule and enjoy several other advantages. Prequalification

Abbreviations: EEG, Renewable Energy Sources Act; BMWi, Ministry for Economic Affairs and Energy; RES, renewable energy sources; BImSchG, Federal Immission Control Act; PAB, pay-as-bid; ABM, agent-based modeling; LCOE, levelized cost of electricity; CDF, cumulative distribution function

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criteria that are required by the BMWi are a valid permit according to the Federal Immission Control Act (Bundesimmissionsschutz-Gesetz (BImSchG, 2017)) for the participating project and bid bonds of 30 €/kW. For citizens' energy companies, the bid bond amounts to 15 €/kW, followed by a second bid bond of 15 €/kW in case of being successful in the auction (EEG, 2017).

This paper presents insights into whether pay-as-bid pricing induces a more cost efficient outcome than the uniform pricing rule, the most prominent alternative. Under uniform pricing, the lowest not accepted bid or highest accepted bid determines the support level of all the successful agents in the auction. The comparison usually depends on the conditions and the environment of the auction (Fabra et al., 2006) and has thus far not been examined for renewable energy auctions to our knowledge.

Specifically, the question is examined in the context of the recently introduced German onshore wind power auctions by modeling the German auction design as precisely as possible. We then draw lessons learned for policy makers from our results, concerning prices, efficiency, as well as impacts on actor diversity.

2. Theoretical background and literature review

To find out whether a PAB pricing scheme is indeed more support cost efficient than uniform pricing in the upcoming German onshore wind power auctions, we applied an agent-based modeling approach in which the agents and the setting are modeled according to auction theory. By support cost efficiency, we mean minimizing the costs for consumers to support the renewables deployment and thus expansion. In our definition, we only account for direct payments to generators for fed-in electricity and no indirect costs occurring e.g. for the necessary grid expansion or the integration of RES. Our methodology thus builds on the foundations of economic theory, while making use of an effective way to model decision making (Dam et al., 2013). The focus hereby lies on agent behavior and long-term optimization strategies in the two auction schemes.

The next section provides a short outline of the most important auction theoretic elements that found their way into the design of our model and the agents participating in the auctions. Auctions are one form of market-based allocation mechanisms, which provide a support cost efficient[1] approach whenever information asymmetry between an agent and a principal exists (McAfee and McMillan, 1987). In the market for RES there is a basic knowledge of the cost distribution (Wallasch and Luers, 2013). Nevertheless, an auction mechanism could increase support cost efficiency by improving the allocation of overall subsidies (Klessmann et al., 2015). The present paper focuses on PAB and uniform pricing auctions[2] as these are the most widely used "in situations in which the marginal values are declining – that is, the value of an additional unit decreases with the number of units already obtained" (Krishna, 2010). This is also true for renewable energy auctions, where multiple goods are auctioned.[3]

Onshore wind power auctions are multi-unit auctions. Precisely, a certain capacity of wind power is tendered. In each round, different bidders enter with their projects of different scopes and sizes. Since the auctioneer procures a specific amount of power, the good can be defined as homogeneous from an auctioneer's point of view according to the theory of Myerson (1981). Nevertheless, as locations differ in their RES potential, i.e. more or less ideal wind conditions or solar irradiation, and thus capacity factors, the so-called correction factor (Korrekturfaktor) under the framework of the reference yield model (Referenzertragsmodell) – which accounts for the locational quality (EEG, 2017) – ensures a level playing field for all bidders. Nevertheless, one can argue, that the correction factor actually decreases allocative efficiency, on the terms that it makes the sites with the lowest locational quality the cheapest in terms of corrected costs. On the other hand, one could say that the overall economic costs decrease through correcting, because they allow for a more balanced expansion of renewable energy generation and therefore lower system costs (grid expansion, integration etc.). For more insights see e.g. Klessmann et al. (2015) or Bade et al. (2015). These estimations are however beyond the scope of our paper.

Aside of the pricing scheme, a variety of other design elements can be included in auctions. These elements help derive efficient outcomes and adapt the auction to the needs of the auctioneer and the market environment. In the following, a (non-exhaustive) overview on the most important design elements used in RES auctions is presented.

Ceiling prices are an important auction design feature that is regularly applied in renewables auctions. How to set this price is a crucial issue since it affects the level of competition and technological diversity in technology neutral auctions (Del Río, 2015).

In the German electricity market, limit prices were set for onshore wind power. According to the EEG (2017), a ceiling price of 7 €ct/kWh[4] will be introduced in the first three rounds. Beginning in the 4th round (01.02.2018), the ceiling price will adapt to the overall price level dynamically (EEG, 2017).

A further important criterion for RES auctions is whether to implement price-only or multi-criteria auctions. An example for multi-criteria auctions would be to award additional points to bidders who achieve more job creation with their projects, as is the case for instance in South Africa (Eberhard, 2013). Prequalification criteria are another way to influence the structure of bidders. In order to achieve a high realization rate and to ensure the support cost efficiency of the auction scheme (Maurer and Barroso, 2011), two prequalification criteria were implemented in Germany. Before the potential bidders can participate in the auction, they need to obtain a valid immission control permit for their specific project and a bid bond in form of a guarantee of 30 € for every kW of their wind project's generation capacity.[5]

The EEG (2017) also contains a so-called "de minimis clause", which states that projects with a capacity of less than 750 kW don't participate in the auctions but fall under a feed-in tariff scheme in order to include small actors and thus maintain actor diversity. Other than that, the German scheme is price-only (EEG, 2017). There are many other features from auction design that can be made use of in auctions for renewable energy, but as this analysis focuses on the difference between the two pricing rules, only this short outline is presented. For further auction theoretic analyses of renewable energy auctions, see e.g.: Ehrhart et al. (2015) or Kreiss et al. (2017).

The second important strand of literature for the present analysis is on agent-based modeling (ABM). According to Bonabeau (2002), agent-based models have certain benefits over other modeling techniques:

[1] We also discuss allocative efficiency of the two different auction schemes later on. The concept of allocative efficiency refers to the actual costs of the supported projects – i.e. as to how the resources are distributed. Allocative efficiency by definition is given when the price function, in our case the bid, intersects with the marginal cost curve, i.e. social surplus is maximized and no distortions in the form of deadweight loss occur (Markovits, 2008).

[2] We distinguish between static auctions, which include the two assessed formats (pay-as-bid and uniform pricing) and dynamic auction formats consisting of several consecutive bidding rounds. Dynamic auction formats allow agents to react on their competitors' bidding behavior during the course of an auction, whereas static auctions are so-called "one shot" auctions, meaning that each agent submits a bid and these bids are then ranked in order of their respective price.

[3] Single unit auctions, on the other hand, are usually applied when only one good with uncertain valuation to the auctioneer is sold (Krishna, 2010). In RES auctions, this is the case when a certain project is auctioned for realization, e.g. the offshore wind power auctions in Germany or in Denmark, in which the participants bid for the right of implementing one specific offshore wind farm, for which the plans have been already outlined.

[4] From here on, we will refer to €ct simply as ct.

[5] In contrast, citizens' energy companies only have to provide an advance guarantee of 15 €/kW and have to provide the other 15 €/kW only if they have bid successfully (EEG, 2017). The immission control permit only has to be obtained, if they were successful in the auction and is thus not a prerequisite for participation. Citizens' energy companies also benefit from a prolonged realization period compared to the other bidders.

being able to capture emergent phenomena, providing a natural description of a system, and being flexible in regard to changes. Moreover, Axtell (1999) highlights that ABM has the property of establishing sufficiency theorems. As the main idea behind ABM consists of simulating the interactions between individual agents over time (Masad and Kazil, 2015), it is important to understand what exactly defines an agent. Wooldridge (2006) describes agents as software-based computer systems located in some environment, who aim to reach their design objectives by autonomously taking actions. Furthermore, Wooldridge and Jennings (1995) define four major properties of agents: autonomy, social ability, reactivity, and pro-activeness.

The following overview shows past applications of ABM in energy research. Several studies applying the ABM approach were published in energy research, whereas they often model an electricity (spot) market with a vast amount of agents in frequently occurring auctions, as e.g. power market simulations in PowerACE (Genoese and Fichtner, 2012) or the EMLab Generation Model by TU Delft (Chappin, 2013). Furthermore, a substantial amount of literature exists where ABM has been used to display and model complex interactions on the broader electricity market, i.e. modeling different agents' (TSOs, generators, regulatory institutions, consumers) behavior and their respective interactions and sometimes contradictory objective functions and constraints, see e.g. Kiose and Voudouris (2015) and Widergren et al. (2006). ABM has also been used to assess different market design elements and policies for renewable subsidies, as shown in currently published research by Iychettiria (2017). Auctions for renewable energy have, to our knowledge, not yet been analyzed using an ABM design. Among the studies on agent-based electricity market models, comparing PAB and uniform pricing has been a popular research question in the past (Weidlich and Veit, 2008). Further scientific energy-related auction literature applying an ABM approach comprises e.g. Kiose and Voudouris (2015), Veit et al. (2009), Bunn and Oliveira (2001), or Li and Shi (2012) among others.

Adaptation is also an important feature of agent-based modeling (Dam et al., 2013). As this paper focuses on the procurement auctions of renewable energies with a very clear time horizon and only a limited amount of rounds, the possibility of learning effects for the agents is limited. Nevertheless, a certain amount of learning is implemented as shown in the following section.

3. Modeling framework

To obtain an accurate model of the German onshore wind power auctions, we implemented its basic design in an agent-based modeling framework. Specifically, the program was written in Python using the agent-based modeling infrastructure mesa.[6]

3.1. Auction design

The auctioning procedure takes place as follows: The agents submit their (sealed) bid in each round consisting of a price in ct/kWh and a corresponding capacity of their individual projects to the auctioneer, who sorts the bids from the lowest price to the highest. If two agents bid an equal price, the one with the lower capacity will be preferred. This approach holds for both pricing schemes. Bids are chosen as long as the cumulative amount of capacity is less than the demand. Immediately after the procured quantity is reached or surpassed for the first time, the auction round is closed. This procedure has been directly reproduced by our model.

In the auctions held by the German government, the auctioneer publishes the successful power quantities in detail, as well as the lowest and highest accepted bids together with the weighted average winning bid. The actual bid prices remain private information of the auctioneer. The agents in this simulation learn the weighted average overall bid (see Fig. 1).

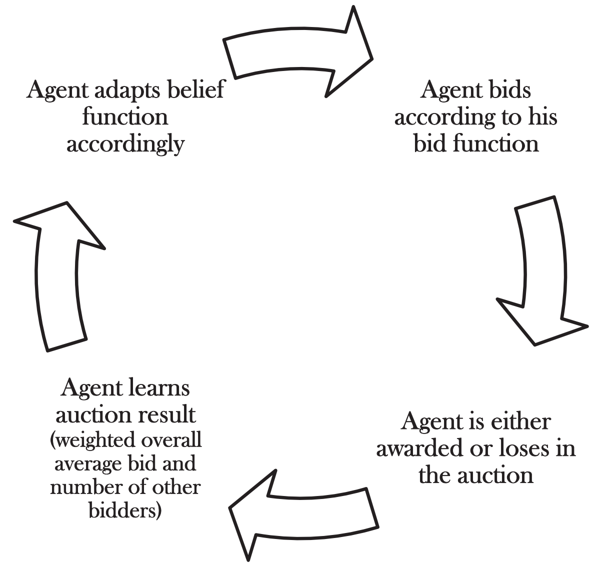

Fig. 1. Simplified learning algorithm of agents in wind power auctions.

According to the EEG (2017), a ceiling price of 7 ct/kWh will be introduced in the first three rounds. Beginning in the 4th round (01.02.2018), the ceiling price will adapt to the overall price level dynamically. The new ceiling price will consist of the highest still accepted bids' average from the three previous rounds increased by 8% (EEG, 2017). This regulation has been fully implemented in our simulation of wind power auctions. The EEG (2017) clearly states the amount in MW, which will be auctioned in each round until the year 2020 and beyond. The German government plans to have auctioned a total amount of 11.3 GW (EEG, 2017) by the end of 2020 and thus an average amount of 807.14 MW will be procured in each auction round. To simplify our simulation, the auctioned quantity per round will equal 800 MW. Due to constraints in the transmission network capacities and the probability of congestion, Germany has been divided in two geographic zones for onshore wind power in the EEG (2017). The so-called "grid-expansion area" will have a limited yearly auction volume which amounts to 58% of the yearly average of the installed capacity from 2013 to 2015 in the specific area (EEG, 2017). This concept will not be taken into account in the simulation, since the EEG (2017) doesn't specify how the two zones will be implemented. Furthermore, this paper analyses the differences between the two static auction formats, such that the regional split is not crucial for the comparative analysis of our model.

A further simplification is that we do not model the citizens' energy companies' exemption clause that enables them to bid into a uniform pricing scheme. In fact, citizens' energy companies receive the highest awarded bid as their remuneration level. Although this will certainly influence the bidding behavior under PAB, this study focuses on the difference between the two pricing schemes in a more generic approach, and thus our results would be diluted by implementing the exemptions.

3.2. Characterization of the agents

When simulating the onshore wind power auctions in Germany, it is crucial to model the agents appropriately. An agent is assumed to behave rationally, i.e. tries to maximize her possibility of winning (over time). Furthermore, the agent is characterized by her attributes, namely the size of her wind power project, and her bidding behavior – the bid function and the implemented learning algorithm.

[6] For further information on mesa, please refer to https://github.com/projectmesa/mesa.

Table 1
Costs for wind onshore in Germany accounting for the correction factor[a].

Locational wind quality	Actual average costs (Wallasch and Luers, 2013)	Correction factor (EEG, 2017)	Corrected costs in the auction
70%	8.6	1.29	6.66
80%	7.8	1.16	6.72
100%	6.7	1	6.7

[a] This table shows the costs for wind onshore in Germany before and after accounting for the correction factor according to the locational wind quality (*Standortgütefaktor*). Specifically, after accounting for the correction factor, the corrected costs in the auction differ only slightly for all locations.

The agents' costs stem from a recent study on onshore wind costs in Germany (Wallasch and Luers, 2013). Since the largest part of the potential locations have a quality factor of less than 100%, which is defined by a reference wind turbine under certain assumptions on the location and wind speed, (BMWi, 2015) we limit the range of projects to a factor of 70–100%. These levelized costs of electricity (LCOE) had to be adjusted with a correction factor to be "translated" into a project corresponding to a 100% quality factor. By adjusting the project costs, allocative efficiency could however be lowered: specifically, the 70% quality region, which initially exhibits the highest costs, becomes the cheapest after the adjustment (see e.g. Klessmann et al., 2015 for further elaborations on this). Since all of the costs amount to an average of roughly 6.7 ct/kWh (see Table 1), we assume a cost range of 6.4–7.0 ct/kWh.

Taking into account a certain degree of learning effects due to multiple realized projects and overall learning effects in the industry, an option for cost digression was added to the model. Whenever an agent lands a successful bid in an auction – always assuming her project is implemented successfully – her cost in ct/kWh decreases by a certain factor. According to Wallasch and Luers (2013) the LCOE for onshore wind power in Germany decreased by 12% on average between 2012/13 and 2016/17. In this period of four years, the average cost decrease amounts to around 2.9% p.a.[7] Since the auction rounds take place every three months (in general), we therefore approximate a cost decrease of around 0.725% (0.029/4 = 0.00725) between two auctions. To account for the randomness of the process, the final factor for each agent is drawn independently from a uniform distribution with bounds 0 and 0.015 – thus 0.725% being the mean value – which leads to factors in the range between 0.985 and 1.

According to BWE (2015) project developers make up the main share of actors in the German onshore wind power market during the implementation phase from 2012 until the first half of 2014. Project developers usually implement a certain project and afterwards sell it to other market participants. Moreover, the residual share of the installed capacity during the implementation phase – in a decreasing order – consists of citizens' energy companies,[8] financial investors, local and regional utilities, big utility companies, international investors and industrial companies (BWE, 2015). In order to design the model efficiently, the three largest types of participants were chosen as agent types: project developers, citizens' energy companies and financial investors.

Introducing the correct share of each agent type participating in the auctions is crucial for a realistic auction simulation. In Germany, project developers account for roughly 64%, citizens' energy companies for 16% and financial investors for about 10% of the installed wind onshore capacity from 2012 until the first half of 2014 (BWE, 2015). Altogether, the aggregated share of the three agent types equals around 90%. Assuming, for simplification reasons, the whole market consisted of the three aforementioned agent types, their shares would be 71%, 18% and 11% respectively.

[7] $\sqrt[4]{1.12} - 1 = 0.029$ (p.a.).

[8] The EEG (2017) defines a "citizens' energy company" for the first time (see EEG, 2017).

Table 2
Agents' distribution[a].

Parameter	Project developers	Citizens' energy companies	Financial investors
Number of each type	100	60	14
Cost distribution range [ct/kWh]		6.4–7	
Range of capacity bid [MW]	10–40	3–18	15–40
Average cumulative capacity bid per round [MW]	2500	630	385
Discount factor	0.95	0.6	0.9
New agents in each round	0–2	3–6	0–2
Time span	t = 0,1,…,13 (equals 14 auction rounds)		

[a] This table shows all agents' model input parameters. Most factors are drawn randomly from distributions. The discount factor is chosen by the authors to reflect differences in agents' long-term optimization. The results of the analysis also hold when these factors are varied (the interested reader can request sensitivity results directly from the authors).

From 2013–2015, the average installed capacity amounted to roughly 3500 MW in each year (Deutsche Windguard GmbH, 2016). Applying each agent type's share, the annually installed capacity of each agent type amounts to 2485 MW, 630 MW and 385 MW respectively. Dividing these figures by the corresponding average capacity of each agent's project, the following numbers were derived (see Table 2).

Furthermore, after each round a number of new agents are drawn to participate in the next auction. Their numbers are drawn from a discrete uniform distribution with the minimum and maximum values depicted in Table 2 to provide a realistic approximation. More new agents enter in the citizens' energy company category. This is necessary to uphold the balance between the different agent categories.

The corresponding quantity offered by each agent is also drawn from a discrete uniform distribution. To model the difference in the ability of realizing certain sizes of projects, each type is assigned a different distribution. Derived from BWE (2015) on the wind onshore market in Germany, the authors concluded the ranges depicted in Table 2.

Agents' bidding behavior over multiple rounds also differs: as citizens' energy companies generally have a limited amount of resources and focus on wind power projects in close range to their community (Nestle, 2014) it is assumed in the simulation that those agents don't participate in the following round once they've landed a successful bid (Grashof et al., 2015), which is as well prohibited by the EEG (2017), foreseeing a one year waiting period. The time until re-entry into the auction is modeled as a uniformly distributed, discrete random variable that lies between one and two years (i.e. four to eight rounds). In contrast, project developers and financial investors have the ability to participate immediately in the following round after having won a bid (Grashof et al., 2015). Due to model simplification reasons, we do not have bidders enter multiple projects in one round. Successful project developers and financial investors therefore immediately participate in the next round with a new power capacity that is again drawn randomly from the distributions depicted in Table 2.

Although the EEG (2017) foresees a minimum bid quantity of 750 kW ("de minimis clause"), our simulation does not explicitly contain this design element in form of a minimum quantity for participating in the auction. Since onshore wind power turbines with a capacity of at least 3 MW make up the largest share of the recently installed wind turbines (BWE, 2015), the "de minimis clause" is indirectly taken into account by making 3 MW the smallest potential project size to be drawn from.

It is moreover assumed that larger agents can bear higher risks since they can better diversify their portfolio and command the resources for long-term optimization. Citizens' energy companies – as the smaller auction participants – can bear the least risk (Klessmann et al., 2015). We therefore assume that winning a bid in a future round is less preferable for them compared to larger participants who have more options for bidding strategically and diversifying (see e.g. Del Río and Linares, 2014). They thus discount future revenues more heavily, as shown in Table 2 beforehand.

3.3. Bid functions

In auction theory, the bid function maps an agent's cost for realizing the project (or valuation of a good) to a bid price. Agents can receive b (their bid) under PAB, the highest accepted or lowest not awarded bid in uniform pricing, or 0 depending on the auction's outcome, and try to maximize their profit (Krishna, 2010).

3.3.1. Uniform pricing

Uniform pricing signifies that all successful bidders receive the same remuneration, which in our model is determined by the lowest rejected bid. The bid function is derived from auction theory. Several studies have shown, that bidding one's own cost in a multi-unit auction with uniform pricing (when the agent only places a bid for one unit) or in a second price auction – the single unit equivalent – is a weakly dominant strategy (Milgrom, 2004).

$$b_t = c_t$$

In our simulation, agents therefore bid truthfully (their exact costs c_t) in every round. According to theory, the outcome of a functioning uniform pricing regime is incentive compatible[9] (Klemperer, 2004). Uniform pricing serves as a benchmark case in the analysis, as the bidding strategy is not influenced by parameters other than the agent's cost.

3.3.2. Pay-as-bid

Under discriminatory pricing rules (first-price sealed-bid and PAB), successful agents are paid exactly their bid b_t. Due to this fact, bidders will at least bid their individual cost, usually with a certain margin on top. In auction theory, this behavior is known as "bid-shading" (Menezes and Monteiro, 2005). Under the PAB pricing mechanism, the agent maximizes her expected profit π over her chance of winning and the amount received in case of being successful by adjusting her bids accordingly and taking into account the possibility to win in the following rounds. In general, the higher her bid is, the lower her probability to win in the auction but the higher the profit in case of winning (e.g. Samuelson, 1986, McAfee and McMillan, 1987). Since the German onshore wind power auctions are designed as sequential multi-unit auctions, the bid vector b contains all the bids from the current round t until the last round in T. The discount factor is $0 < \delta < 1$, since winning in a future round is less favorable (Sugianto and Liao, 2014), and c_t is the agents' specific cost in round t. Assuming that the agents participate with only a single project in each round, they can only take part in the following rounds with their specific project if their current bid is unsuccessful. Consequently, the expected profit in one of the following rounds has to be adjusted by the probability of losing in the past auctions. Thus, the current bid not only influences the current expected profit, but also the future ones, as the profit of the specific project is maximized taking into account a specific period of time and the expected probability of winning over all auction rounds. Adjusting the discount factor δ^t enables to account for the specific risk aversion of each agent type. The expected utility is calculated in each round, with T being the final round.

for t=0, 1, 2,…,T

$$E(\pi(\boldsymbol{b})) = \sum_{i=t}^{T} \delta^{i-t} \cdot (b_i - c_t) \cdot Pr(\text{"successful bid in round } i\text{"}) \prod_{x=1}^{i-t} Pr(\text{"unsuccessful bid in round } i-x\text{"}))$$

As agents include the level of competition into their expected profit, the concept of order statistics (Ahsanullah et al., 2013) has been implemented. In order to determine the probability of submitting a successful bid, the agent assumes $n - 1$ participants (without her) with n_s (successful) bidders being able to win in the auction round. Therefore, at least the n_s^{th} lowest out of the $n - 1$ other participants' bids has to be higher than her own one b_t. The agents assume the competition and the number of winners to be the same as in the preceding auction round. Due to a lack of information in the first round, they assume the number of competitors to be 150 and the number of possible winners to be 50. We further introduce a cumulative distribution function (CDF). This function $F(\cdot)$ captures an agent's belief on the other participants' bid distribution and specifically, the probability that another bid b_j is lower, hence Pr $(b_j < b_i)$. Consequently, $1-F(b_i)$ depicts the probability of the agent's own bid being lower than her opponent's. Based on the approach in Ahsanullah et al. (2013), we can calculate the probabilities in the following way:

$$E(\pi(b)) = \sum_{i=t}^{T} \delta^{i-t}(b_i - c_i) \sum_{j=0}^{n_{t-1,s}-1} \left(\binom{n_{t-1}-1}{j} F(b_i)^j (1-F(b_i))^{n_{t-1}-1-j} \right) \prod_{x=1}^{i-t} \sum_{k=n_{t-1,s}}^{n_{t-1}-1} \left(\binom{n_{t-1}-1}{k} F(b_{i-x})^i (1-F(b_{i-x}))^{n_{t-1}-1-k} \right)$$

Although the above equation is based on the auction-theoretic concept of first-price sealed bid auctions (McAfee and McMillan, 1987), we won't derive a bid function taking into account the other bidders' behavior. In this simulation, the above equation will be solved using maximization algorithms. Citizens' energy companies use this bidding strategy under the PAB scheme in the simulation as well, although their remuneration according to the EEG (2017) is based on the highest awarded bid (i.e. uniform pricing). Our approach can be justified, since these companies will conduct some sort of bid-shading from an auction theoretical point of view either way. Bidding their own cost would be a weakly dominant strategy if their remuneration was based on the highest awarded bid by a *non*-citizens' energy company. Since this is not the case, their own bid might be the highest one awarded and thus they will put a mark-up on their cost to earn a profit.

3.4. Learning algorithms

Agents, as autonomous entities, should be able to adapt their behavior to changes in the system to simulate a realistic environment and learn from past occurrences. Information provided by the auctioneer flows into the learning algorithm implemented in the simulation for the PAB pricing rule. Each agent optimizes her expected payoff over the entire time horizon. As shown previously, the expected profit depends on the CDF's parameters. The CDF is modeled as a normal distribution, similar to modeling the distribution of the market clearing price in electricity markets (Azadeh et al., 2012; Bhattacharya, 2000; Rahimiyan and Rajabi Mashhadi, 2008, 2007).

Therefore, the mean value (μ) can be seen as a central configuration parameter besides the standard deviation. The agents' learning algorithm consists of adapting μ to new information generated throughout the course of the auctions. In the first round, the assumptions on μ of $F(\cdot)$ are based on each agent's own signal (their individual cost) which is the best approximation regarding the other agents' bids (Krishna, 2010). In the course of the auctions, new information becomes available, which is incorporated by the agents: they adjust the CDF, by updating μ with the last round's overall mean bid. This definition of

[9] Incentive compatibility is given when a mechanism induces bidders to reveal their true preferences in order to achieve the best possible outcome (Krishna, 2010).

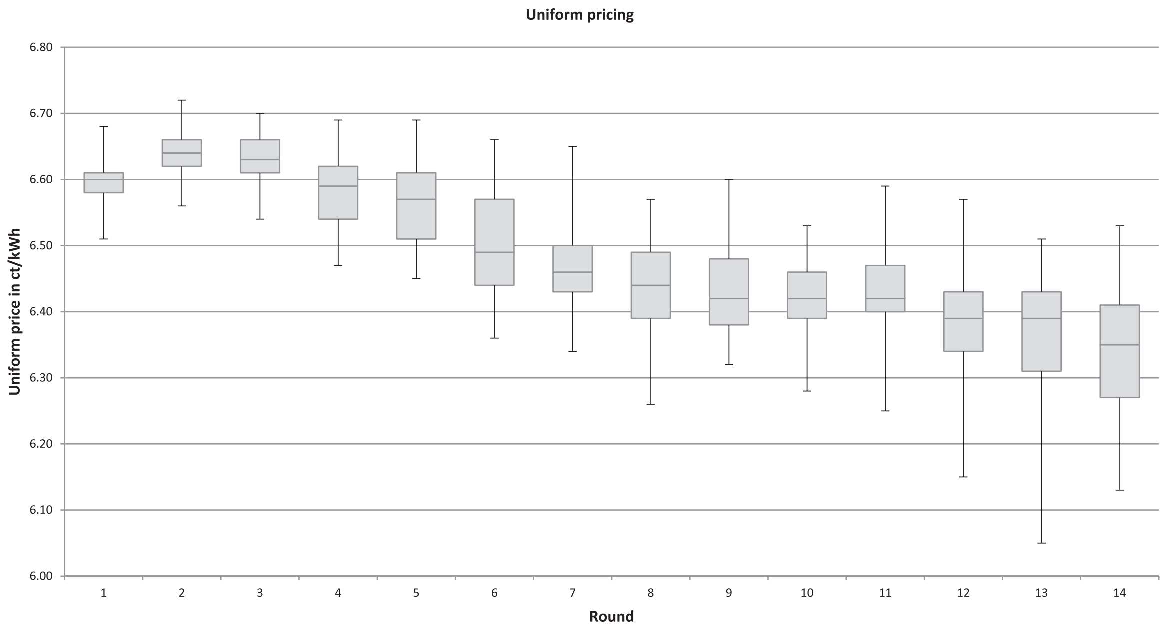

Fig. 2. Development of prices in uniform pricing scheme over time (14 rounds).

learning is one of the main properties of ABM (Wooldridge and Jennings, 1995): the environment – in our particular case the overall mean bid and the number of (successful and overall) participants – influences the agents' behavior and in return the agents' individual bids have an impact on the overall average bid.

3.5. Simulation rounds

In order to derive an accurate answer to the research question, both pricing rules were simulated in 50 iterations. Each iteration consists of 14 auction rounds with 800 MW of power demand auctioned respectively, which corresponds to the average auctioned amount until the end of 2020 (EEG, 2017). Each agent's bid vector is calculated before the auction round takes place by using the "SLSQP"[10] algorithm (Kraft, 1988). Using this specific algorithm has the advantage of defining boundaries for the optimization and thus not obtaining extreme values, which would be a possible result from applying a standard normal distribution. We employ the agents' own cost as an initial guess for the maximization algorithm. In all simulations executed, algorithm and model generate realistic values: within each bid vector, the corresponding bids decrease over all rounds, i.e. the later an auction takes place, the more aggressive the agents' bids become. This also leads each round's current bid (b_t) – which determines the specific auction's outcome – to decrease (c.p.) over time.

4. Results and discussion of the outcome of the two pricing schemes

In this section, the results of both pricing schemes are presented and analyzed in detail, followed by a comparison of the pricing rules.

4.1. Uniform pricing

Looking at the boxplots in Fig. 2, it becomes clear that the median price under the uniform scheme falls over time.

Running a regression to prove the hypothesis statistically, we receive highly significant coefficients, i.e. the further the model advances, the lower the final price becomes. This finding is in accordance with the experience of onshore wind power auctions in Brazil, where prices fell during the course of auction rounds from 2009 to 13 by about 40% (Förster and Amazo, 2016). It could also be largely observed in several European auctions for other renewable technologies (see e.g. IRENA, 2017, Tiedemann, 2015 or Fitch-Roy and Woodman, 2016).

In contrast, the weighted average profit per round increases. The average profit is calculated as the difference between the agents' received remuneration and their individual cost weighted by their bid volume. It can be interpreted as the average mark-up on the successful bidders' cost. Since the cost reduction applies only to successful bidders, the new entrants face relatively higher costs. Due to the fact that the price under the uniform mechanism is determined by the lowest not accepted bid, which in most cases is submitted by a new or recently entered participant, the decrease in prices does not outweigh the cost reduction. Therefore, although prices are falling, the successful bidders' profit rises throughout the auctions.

Another aspect that should be examined is how the number of successful bidders evolves over time. The number of project developers and financial investors stays approximately on the same level with a mean value of around 23 and 6 per round respectively. Citizens' energy companies have their maximum number of successful bids in the first round, but due to the restriction of being able to realize only one project in every one to two years, their number falls during the course of the auctions. These restrictions to participation are firstly due to the aforementioned regulations (EEG, 2017) but also due to specific characteristics of smaller agents, i.e. limited financial resources or less ability for risk diversification and long-term planning (Grashof et al., 2015). Their overall mean value amounts to roughly 5 per round.

4.2. Pay-as-bid pricing

In the following, we examine the effects under PAB pricing. As in the uniform format, we can observe falling prices under the PAB pricing rule (see Fig. 3).

Falling prices over the rounds is contradictory to Weber (1983) who showed that in two sequential auction rounds, the expected (average) price of the first and second round are identical in the case of continuous bidders. Jeitschko (1998) who examined the behavior in a microeconomic (selling) auction, modeled two rounds and three

[10] Sequential Least Squares Programming.

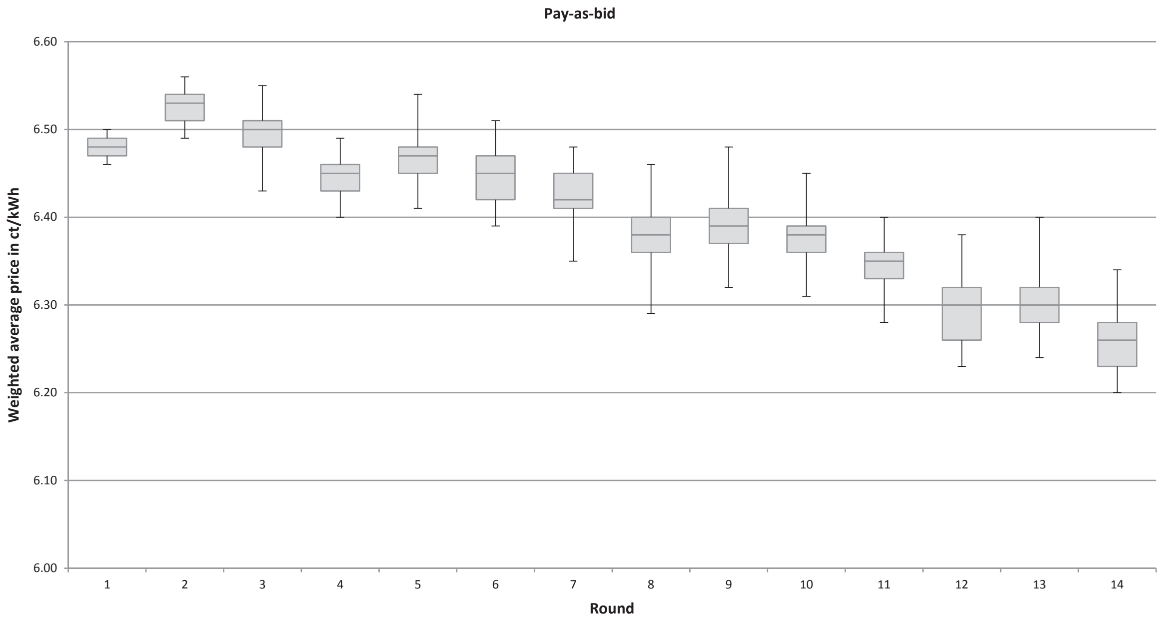

Fig. 3. Development of prices under the PAB pricing scheme (14 rounds).

bidders with a discrete distribution of types (high and low valuation) and put more emphasis on the influence of learning.

Nevertheless, he also predicted the expected winning bid in the first and second auction to be the same, due to three effects: first of all, more bidders participate in the first auction, leading to higher priced bids, whereas in the second one the high valuation type bidder doesn't participate, which leads to less competition and thus a lower average bidding price.

This property does not apply to our simulation, since successful bidders (except for citizens' energy companies) do participate in the following round. Secondly, since it is more likely that the opponent bidders are low value types in the second auction, high value participants bid a low price on average. This fact is similar to our model, since agents include the increasing overall mean bid in their bid function through the CDF and thus are able to place higher bids on average. Finally, Jeitschko (1998) states that with the second round being the final one, high value agents submit higher bids as they need to win this auction as the alternative would be receiving none of the goods. In our simulation we observe the same effect. The agents have a lower possibility of winning in one of the following rounds and thus the individual bids in the bid vector decrease throughout the rounds.

Jeitschko (1998) concluded that the first two effects offset the third one, making the expected price equal in both rounds. In our case, the main reason for falling prices seems to be the third effect, which together with the cost reduction leads to a decrease in prices. Despite lower prices, the average profit is increasing. Due to the cost reduction, successful bidders face decreasing costs for their projects, whereas unsuccessful participants' costs remain the same throughout the auctions. The bidding function takes the average overall mean bid into account, which decreases more slowly than the weighted average successful bid under PAB. Thus, although the successful bidders face lower costs with advancing rounds, they increase their bid-shading since the average overall mean bid consists of successful and unsuccessful bidders, but only winners' costs decrease over time.

The average number of agents per round develops as follows: on average 23 project developers and 6 financial investors submit a successful bid per round. Around 16 citizens' energy companies were successful in the first round, but due to the restriction of being able to realize only one project in every one to two years, their number decreases sharply during the auctions with an overall mean value of roughly 6 winning bids per round. This fact is in accordance with the concern expressed in Nestle (2014), who states that by implementing auctions, many small citizens' energy companies won't be able to participate in the onshore wind power market in the long term.

4.3. PAB leads to a more support cost efficient outcome

To see whether PAB is more support cost efficient than uniform pricing in the German onshore wind power auctions, we examine the outcomes under both pricing rules (see Table 3). In our modeling results, we can observe that PAB generates a statistically significant 1.08% lower average price compared to uniform pricing and a 14.69% lower mark-up on the cost on average. This effect can be attributed to the way the agents maximize their expected profit, taking into account the competition and their opponents' mean bid in the respective auction rounds.

This shows that PAB (under the aforementioned assumptions) generates a slightly more support cost efficient outcome than the uniform pricing rule in the German onshore wind power auctions, which is, nevertheless rather insignificant in economic terms. To approximate overall savings over the 20 year duration of the awarded feed-in premiums for both pricing schemes, we assume 1600 full load hours p.a., an overall installed generation capacity of 11,300 MW and an average electricity price of 35 €/MWh. Without taking into consideration the time value of money (i.e. without discounting to the present value), uniform pricing will lead to support payments of around 10.74 billion €, whereas the payments under PAB amount to around 10.49 billion €. This leads to savings of around 253 million €, or around 2.36%. From a welfare theoretic perspective, uniform pricing leads to 871.5 million € of producer rent (price received less the cost) over the 20 years, whereas PAB leads to a producer rent of 743.4 million € and thus to a 128 million € (14.7%) lower mark-up.

Regarding the allocative efficiency, we examine whether the projects with the lowest costs are successful. Therefore, in each round we calculate the average cost in ct/kWh of the projects with the lowest costs until the auctioned volume is reached and compare them with the average costs of the successful projects. We are able to show that under PAB allocative efficiency is not always reached. This is due to the fact that it is possible that low-cost projects increase their mark-up due to bid-shading up to the point, that bidders with higher costs but a lower

Table 3
Comparison between uniform pricing and PAB[a].

	Uniform	PAB
Average price [ct/kWh]	6.47	6.40 (−1.08%)***
Average profit [ct/kWh]	0.241	0.2056 (−14.69%)***
Average costs of cheapest projects [ct/kWh]	6.2290	6.1944
Average costs of awarded projects [ct/kWh]	6.2290	6.1970 [+0042%]***

Levels of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[a] Relative deviation between the two pricing schemes in parentheses, deviation compared to the cost of the cheapest projects (in the case of PAB) in square brackets.

mark-up are successful. In the case of uniform pricing in our model, allocative efficiency directly results from the assumption of incentive compatibility as the participants always submit their true costs. Consequently, the projects with the lowest costs will always be successful.

4.4. Discussion

(Pilot) auction rounds that have been executed, e.g. in Spain show questionably low levels of support, leaving doubts whether agents actually bid their true costs (Del Río, 2016) and whether the projects will actually be realized. Looking into RES auctions in Germany (ground-mounted PV pilot), relatively low prices have been observed compared to the previously fixed level of support. These results as well as our simulation outcomes demonstrate that determining the support level for RES via auctions, usually leads to lower feed-in tariffs/premiums. Whether this can be appointed to truthfully revealed costs or rather strategic underbidding remains to be seen in the longer term.

In regard to our model, although agent-based simulations provide an appropriate modeling tool to simulate complex systems and real-word phenomena, its usage entails a distinct disadvantage. Whenever models involve human agents, usually soft factors as irrational behavior and complex psychological features are difficult to quantify. Since these input parameters and the data used in models usually lack accuracy, it might be dangerous to solely base the decision-making on the quantitative outcome of an agent-based model (Bonabeau, 2002). In the case of this simulation, the comparative advantage of PAB should hold under the predefined assumptions.

By examining renewable energy auctions, we made the implicit assumption that auctions are generally suitable for the allocation of renewable energy subsidies and lead to a more support cost and allocative efficient outcome than traditional support mechanisms. Suitability of auctions is however only given, if there is enough competition, i.e. supply is greater than demand. Otherwise strategic bidding and collusion can lead to higher prices, depending on the respective market situation as well as the implemented scheme. This leads to the conclusion, that under certain assumptions, fixed-price schemes might be a better option (Hailu and Schilizzi, 2004).

The pricing rule, which was the main focus of our analysis, plays an important role for both the cost and allocative efficiency of an auction. In the uniform pricing simulation agents always bid their true costs under the assumption of symmetric, single-project, and risk-neutral participants, as this bidding strategy is weakly dominant according to auction theory. This result changes, however, when bidders submit multiple bids in the uniform pricing auction, as it incentivizes them to bid strategically (Ausubel et al., 2014). Thus, by bidding with several projects at different prices, participants might try to determine the strike price with a high bid and at the same time try to secure another project with a substantially lower bid or by demand reduction. Investigating this behavior further is nevertheless beyond the scope of our paper. In contrast, empirical evidence and models in which the assumptions are relaxed, suggest that a certain amount of bid-shading occurs under uniform pricing. The reason might be either irrational behavior or strategic bidding in the form of demand reduction, depending on whether the scheme is lowest rejected or highest awarded bid (de Keijzer et al., 2013; Ausubel et al., 2014). Nevertheless, this agent-based simulation should be considered as a starting point, where uniform pricing is implemented as a benchmark model. Since the assumptions required by auction theory were fully implemented, the incentive compatibility of uniform pricing is given in this case.

Moreover other factors are important as well. While we tried to capture as many of these factors as possible, there are some limitations to our analysis: first of all, the model doesn't account for the influence of realization probability. It would be interesting to perform more sensitivities to see whether the observed falling prices are a result of our assumptions on cost digression.[11] For simplification purposes, multiple projects are absent in the simulation. Maximizing outcomes with multiple projects would yield a different bidding behavior compared to only maximizing expected profit for one project. Further limitations due to simplification are that in the German auction scheme, only the average winning bid is published. In this model, the agents learn the average *overall* bid.

Finally, our model outcomes (prices) depend largely on the assumed price ranges and thus it has to be seen in the future whether these prices occur in reality. Furthermore, actual auction outcomes also depend on a multitude of external factors, e.g. the development of electricity prices or the political and economic situation, which cannot be accounted for in our model. Nevertheless, the developed simulation model can be regarded as a first step in the scientific literature following an agent-based approach to model renewable energy auctions.

5. Conclusions and policy implications

In the present analysis, we use an agent-based modeling approach to assess the future wind onshore auctions in Germany planned for 2017. In general, it can be observed that prices fall in the auctions over time, and that furthermore smaller actors' participation decreases over the 14 implemented rounds. Moreover, we provide insights into the performance of the two most prominent pricing rules and show how pay-as-bid compares to uniform pricing in auctions for onshore wind in the German market. We demonstrate that pay-as-bid has slightly lower prices on average which directly translate into a slightly lower producer rent (lower mark-up by the bidders on their respective bids). This difference is however marginal in economic terms (total support costs), making up 2.36% or 253 million €. Moreover, the structure of successful bidders changes over time: the number of smaller agents (the citizens' energy companies) decreases.

It will be very interesting to compare these simulated outcomes to those of the actual wind power auctions, that the German government will conduct, starting mid-2017.[12] So far, our modeling results are in line with outcomes for the PV auctions that already started in 2015 (i.e. low prices that are decreasing over time) as well as outcomes in other EU and non-EU countries (e.g. Förster and Amazo, 2016).

The following policy relevant findings result from our analysis: While pay-as-bid generates slightly lower prices in the German wind onshore auctions than uniform pricing, in terms of economic (support cost) efficiency, the pricing mechanisms do not differ substantially. It can furthermore be stated that no matter which auction design is implemented,

[11] In sensitivity analyses performed without or with lower cost digression implemented, the prices still exhibited a certain decrease although it was lower than the one shown in our model results. If interested, all sensitivity results can be requested directly from the authors.

[12] Since the initial submission of our study, the first German wind onshore auction took place. The auction resulted in an average awarded price of 5.71 ct/kWh, with the lowest awarded bit amounting to 4.2 ct/kWh and the highest to 5.78 ct/kWh. 807 MW were awarded in this auction round, with 256 bids – amounting to 2137 MW - submitted. Out of the 70 awarded bids, 65 (93%) were submitted by citizens' energy companies, thus amounting to roughly 96% of all awarded capacity (Bundesnetzagentur, 2017).

smaller actors will experience difficulties and agent diversity is likely to suffer in the longer term, if this is not accounted for in other ways. This holds for both uniform as PAB pricing, showing that there are a lot of other auction design elements to consider besides the pricing rule.

Interesting expansions of our model would be to enhance the agents' utility functions by implementing more parameters – e.g. predicted electricity prices or the location and wind speed of a project. It would also be interesting to see the agents’ reaction to disruptive changes in the market environment. Future research could also take into account the outcomes of auction experiments aiming to better approximate human behavior in the tendering process.

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