The importance of penalties and pre-qualifications

A model-based assessment of the UK renewables auction scheme

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1 Introduction

Support for renewable energy (RES) in the EU has been subject to change in the last decade. We have seen it become more market-oriented, as e.g. the sliding feed-in premium in Germany or contracts for difference in the UK which are oriented towards the market price, rather than previous fixed feed-in tariffs or other static support systems. Aside of introducing feed in premiums instead of feed in tariffs, the European Commission's guidelines on state aid for environmental protection and energy 2014-2020 foresee a gradual implementation of "competitive bidding processes" for allocating public support.

Different member states have already complied with these guidelines and started implementing auction schemes and pilot rounds with different designs and also aiming for different goals, ranging from least cost support (e.g. the Netherlands) to fostering or maintaining actor diversity (e.g. Germany). A variety of design elements exists, to create a tailor-made auction scheme, fit to a country's policy goals as well as its electricity market. Tweaking these design elements has crucial impacts on the auction outcome and therefore, in the long term also on renewables deployment in the respective country.

An interesting question when it comes to auction design is **how penalties and pre-qualifications affect bidding behaviour** and how the realisation rate is affected by setting these penalties and pre-qualification criteria. The United Kingdom's (UK) market is a particularly fit setting to assess this kind of question, due to the specific properties of its auction design. The bidding process is rather complex and there is not a clearly visible time-line of auction rounds foreseen. Furthermore, bidding takes place into different commissioning years - increasing insecurity of bidders in two respects: First of all, as the competition for the respective years is quite difficult to appraise beforehand, winners curse from bidding into a year with a low amount of participants can occur. Secondly, no effective non-delivery penalty was in place for the first auction round.

According to Kreiss et al. (2017) cost insecurities and potential negative consequences of non-realisation have a large influence on the actual realisation of projects awarded in an auction. Thus, both factors mentioned beforehand give participants in the UK renewable energy (RES) auctions an incentive to factor non-realisation into their bidding strategy: as the possibility of winners curse is not unlikely and as dropping out of the auction in the case they do not break even with their submitted bid will not be penalized.

The following paper will firstly give insights into the UK's RES support system and electricity market and then describe the auction design and how it found it's way into the model. Then I will model the auction system and look into different bidding strategies and potential outcomes - by taking into account how potential changes in the design of penalties and pre-qualifications could influence lower bidders' insecurities and impact non-realisation rates.

2 Background

This section shortly outlines the UK's electricity market and auction scheme, the auction-theoretic background necessary for the understanding of the analysis. Furthermore, agent-based modelling is explained and its suitability to assess the research question as well as potential limitations of the approach are shown.

2.1 UK electricity market and CfD scheme

The UK has a population of around 65 million people and in 2014 its final energy consumption was 143 Mtoe (million tonnes oil equivalent) electricity that made up 18.5% of the UK's final energy consumption (26 Mtoe/339 TWh) according to the Office for

National Statistics. Under the EU Directive 2009/28/EC, the UK is bound to meet 15% of energy consumption across all sectors from renewable sources by 2020 which translates to approximately 30% in the electricity sector. This is due to its favourable conditions for generating electricity from renewable sources (RES-E), especially from wind power according to the Department of Energy and Climate Change (DECC, 2009). In 2014, the RES share of electricity generation was almost 20%, and overall renewable electricity supplied 7.8% of final energy consumption (DECC, 2015). The UK's target for the electricity sector is likely to be reached, whereas the country falls short in respect to the heating and transport targets.[1]

Interconnection currently exists with France, the Republic of Ireland, Northern Ireland and the Netherlands, amounting to a total capacity of 4 gigawatt (GW). More are planned in the future, possibly to Belgium, Norway, France and Denmark, meaning that the UK could become increasingly integrated into the wider European electricity network (Fitch-Roy and Woodman, 2016). As the Brexit is currently being rolled out, however, the future of this integration remains to be seen. Electricity generation and retail markets are liberalised. However, despite some recent trends towards independent electricity supply, electricity generation and supply in the UK remain dominated by six vertically integrated firms often referred to as the Big Six (Fitch-Roy and Woodman, 2016). Together, the Big Six account for more than 90% of domestic electricity supply and own approximately 70% of the UK's generation capacity (Ofgem, 2015).

Renewable electricity has been supported since 1990. The first scheme was the so-called Non Fossil Fuel Obligation(auction), which ran from 1990 to 1998. This was replaced by a quota, named the Renewables Obligation (RO) in 2002. Large scale solar (>5 MW) has been excluded from the RO in April 2015 and onshore wind in April 2016.

[1] UK Parliament, September 2016

The RO will expire for all other technologies in 2017. Its replacement - the Contracts for Difference (CfD) scheme - is an auction mechanism, and the first round of bidding took place in late 2014 (Fitch-Roy and Woodman, 2016). In March 2016, the Government announced further auctions for contract allocation, with up to £730 M available for offshore wind and other less established technologies. The first of these auctions will be worth £290M. This round has been carried out and results are supposed to be published in the upcoming week. However, only support for non-mature technologies has been auctioned in this second round, such that the results will only be partly of interest for the following analysis.

The Contracts for Difference (CfDs) are part of a wider Electricity Market Reform package started by the UK Government in 2009. The aims of the reform were ensuring security of supply and decarbonisation of the electricity system at least cost to consumers (Fitch-Roy and Woodman, 2016). The original policy objective of the CfD auctions was to increase competition within technology groups to bring down support costs and limit producer surplus. Technology neutrality is envisaged in the future (unspecified date) (DECC, 2011).

The CfD auctions are multi-unit, sealed-bid, uniform price auctions. Technology-specific ceiling prices known as "administrative strike prices" are intended to represent similar investor returns to the previous support mechanism, the Renewables Obligation (DECC, 2013). The auction scheme furthermore allows for technology capacity minima and maxima to be set. Auctioned volumes are determined by strict budgetary constraints. Budgets are capped year-by-year and thus not considering the total support period of the awarded projects. A winning bid has to thus lie below the highest awarded bid and must furthermore be comprised in the budget cap for any of the years in which a cap has been set (Fitch-Roy and Woodman, 2016). In terms of modelling auctions, this provides rather challenging. As I focus on strategic behaviour and the effects of penalties and pre-qualifications in the UK auctions, there has to be some simplification applied, such that the year-by-year budget cap considerations are ruled out of the bidder's strategies. The respective annual budget is instead broken down to a reasonable approximation of the tendered capacity resulting from each annual pot and then implemented as a tendered amount that the bidder would calculate with for her bidding strategy.

Budgets for the first auction were divided into two "pots", one for established and the other for less established technologies. This actually created two simultaneous auction processes (Fitch-Roy and Woodman, 2016). The first pot, for established technologies, included onshore wind and solar, energy from waste with CHP, hydro (5 to 50 MW), landfill gas and sewage gas. It consisted of £50M (€64M) for projects commissioning from 2015/16, and an additional £15M (€19M) (i.e.£65M (€83M) in total) for projects commissioning from 2016/17 onwards. In the following, modelling will be focused on this pot. It has to be mentioned, however that larger amounts were set aside for the less established technologies (i.e. £260M in total), including offshore wind, biomass CHP, wave, tidal stream, advanced conversion technologies, anaerobic digestion and geothermal. In theory, a third pot for biomass conversion exists. However, no budget was allocated to this for the first auction (Fitch-Roy and Woodman, 2016). This specific distribution of funds shows that a policy objective of DECC seems to be spurring innovation and achieving or maintaining technological diversity in the renewables sector.

2.2 Auction Theory

Although a great variety of different auction designs and hybrid formats exists (Dutra and Menezes, 2002), three basic principles should be met in every auction in order to guarantee a transparent procedure and thus a high acceptance among investors and the public as well(Ausubel et al., 2014; Haufe and Ehrhart, 2016): Bids should be binding, the best bids will be awarded and the winning bidders receive at least their bid price.

In terms of single-unit auctions, the four most common formats are: the English auction, the Dutch auction the first-price and the second-price sealed-bid auction (Milgrom and Weber, 1982). For multi-unit auctions, the distinction can be derived from these formats. We there differentiate between the descending and the ascending clock auctions (dynamic) and the uniform and pay-as-bid (PAB) auctions. All these formats have already been applied in RES auctions all over the globe. Single-unit auctions are used when a certain project is tendered, as in the Danish offshore wind power auctions. In that particular case, participants bid for the permit and support payments to realise a specific offshore wind farm. (Onshore) wind power auctions as well as auctions for large-scale solar PV are currently being implemented in several European member states. These auctions fall into the category of multi-unit auctions.[2] Since in the case of (onshore) wind farms and large-scale solar PV auctions, the auctioneer procures a specific electric capacity, the procured good is defined as homogeneous from the auctioneer's point of view.

In the auction simulations modelled in this paper, we will look at symmetric, risk-neutral and single-project bidders. As explained before, the product auctioned is a homogeneous good. The following overview[3] of the design elements of the standard multi-unit auction format will be limited to the properties I assess in this thesis. Bidder's valuations in this specific format are thus modelled as independent values (IPV approach).

[2]Since countries generally buy power in RES auctions, the overview will be based on the properties of procurement auctions. In this case, the auctioneer is the buyer, and the bidders are the suppliers. In contrast, "classical" auction theory studies auctions to sell with the auctioneer being the seller and the bidders as buyers. Nevertheless, the outcomes in both auction types are analogous (Klemperer, 1999).

[3]The concepts presented in the following are based on the overview in (Haufe and Ehrhart, 2016; Del Río, 2015)

According to Kreiss et al. (2017), one of the main reasons for non-realization in auctions, are bidders' uncertainties concerning their project costs. The non-realization risk can be reduced by taking various measures. The most common measures are financial and physical pre-qualifications and penalties (Kreiss et al., 2017). While these measures are very commonly used in practice, not a lot of theoretical literature on what happens before and after the auction (i.e. pre-qualifications or penalties) exists (Wan and Beil, 2009).

Implementing pre-qualification requirements can have ambiguous consequences. If pre-qualification costs are sunk costs, this may discourage the participation of actors (especially the smaller ones) by increasing the costs of participation (Del Río, 2015) and thus reduce competition in the auction. **Financial pre-qualifications** are very common in RES auctions, as e.g. in Germany, Denmark or Brazil. They help ensure that bidders are able to realize the project in case they are awarded (Held et al., 2014). **Physical pre-qualifications** are e.g. a construction permit or further country specific permits (Kreiss et al., 2017). These requirements are supposed to ensure serious bids and planning security (Del Río and Linares, 2014). They are also employed to avoid strategic bidding, i.e. outbidding to block others from realizing their projects (Del Río, 2015). In general, pre-qualifications like securities prove to be effective for achieving higher realisation rates as shown e.g. by Calveras et al. (2004).

A **penalty** is a necessary condition, meaning that the bidder has to pay if she is awarded and does not comply with the expectations afterwards (Kreiss et al., 2017). It is crucial, when setting penalties, to choose an appropriate level, as also shown e.g. for capacity markets (Mastropietro et al., 2016). A penalty set too high will discourage participation, whereas low levels or no penalties would lead to ineffectiveness in the realization process (Del Río, 2015). In terms of practical implementation it is crucial to see whether the project developer is actually responsible for a delay or non-delivery or if it occurred due to external causes (Held et al., 2014).

Larger bidders are in general more able to pay a penalty, making them less risk averse. They are also more able to pre-qualify. Without a penalty or pre-qualification in place, bidders bid more aggressively: with a penalty system or a bid bond, the limit for losses changes to the maximum of security and assets or penalty (Kreiss et al., 2017).

2.3 Agent-based modelling

In this section, I explain agent-based modelling (ABM) and outline the benefits of this methodology for the present analysis. According to Bonabeau (2002), agent-based models have certain benefits over other modelling techniques: 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 and Jennings (1995) describe agents as software-based computer systems located in some environment, who aim to reach their design objectives by autonomously taking actions. Furthermore, they define four major properties of agents: autonomy, social ability, reactivity, and pro-activeness.

The aim of this paper is to provide an understanding of auctions for RES and how design of penalties and pre-qualifications changes auction outcomes. Therefore, the choice of methodology needed to be one that allows deeper insights into the specific settings. While econometric analysis would also be a very interesting complementary tool to assess the nexus in auctions for renewable energy, there is currently a lack of empirical data to allow us the usage of this methodology. Theoretical analysis, from an auction or game theoretical perspective is a further interesting choice of methodology which allows very interesting insights. The theoretical analysis however usually requires to limit the assessment by many factors, which then lowers its empirical applicability and the direct derivation of policy implications. As shown in the following, ABM has its limitations and results found by modelling country modelling cases will not necessarily be mirrored in actual auctions. However, for the given research question and aiming to provide policy relevant results rather than adding to theoretical expansions of auction theory, the approach proves to be the most suitable for this thesis.

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 Fraunhofer ISIs model 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. modelling different agent's (TSOs, generators, regulatory institutions, consumers) behaviour and their respective interacting 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 Iychettira et al. (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 is e.g. Kiose and Voudouris (2015), Veit et al. (2009) Veit et al. (2009), Bunn and Oliveira (2001), or Li and Shi (2012) among others.

Adaptation is also an important feature of agent-based modelling van Dam et al. (2013). As this paper focuses on the procurement auctions of renewable energies with a very clear time horizon, the possibility of learning effects for the agents is limited. Nevertheless, a certain amount of learning is still implemented through assumptions on cost digression for the participating technologies.

3 Model-based Analysis

The model-based analysis presented in the following chapters has its foundations in auction theory. To answer specific questions of relevance to policy makers, auction theoretic concepts have been implemented in an agent-based model, using all available data to model the respective market and its participants very close to reality. After introducing my methodology, its application will be shown and results discussed.

3.1 The Modelling framework

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) in 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).

In the UK CfD auctions, pay-as-clear (i.e uniform pricing) is implemented as a pricing mechanism. Uniform pricing means, that all successful bidders receive the same remuneration, which is determined by the lowest rejected bid in our model. 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).

$$b_i = c_t \tag{1}$$

In the 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 (Klemperer, 2004). However, a different strategy is modelled for the case in which agents have an incentive to bid strategically instead of revealing their true costs.

The auctions in the UK are not held sequentially, but instead one auction is held and participants can decide in which year they want do bid into. This requires participants to make an estimate on competition in that year and calculate their strategic bid at that point in time. The assumptions taken are outlined in the following sections. To stochastically optimize the outcome of the simulation, the mean of various simulation rounds is used as a final result.

To closely represent the UK auction scheme and its participants, I had to make several decisions on reducing complexity to get at the actual research question, without sacrificing too much detail of the auction design. In this section, I describe the model design and the features of the agents and explain the specific choices: The **auction design** has been simplified in terms that agents do not take into account an annually capped budget but rather a certain amount of capacity auctioned annually. As agents in the UK renewables auctions themselves do some form of calculation as to which amount of tendered capacity is more or less represented by the annual budget, I did the same and thereby approximated how the monetary budget cap can be translated into an amount of MW by using the official valuation formula depicted in the 2014 allocation framework[4]

$$\begin{aligned} Budget\,impact_{s,yr,p} &= (Strike\,Price_{cy,t} - Reference\,Price_{yr}) \\ \times Load\,Factor_{t,yr} &\times YR1F_{s,c,p} \times Capacity_{s,p} \times (Days_{yr} \times 24) \\ &\times (1 - TLM_{yr}) \times RMQ_t \times CHPQM_s \end{aligned} \tag{2}$$

Specifically, the following procedure was applied, taking into account market shares

[4] The official reference price assumed for the year 2015/16 is 51.06. The administratively set strike price for onshore wind was 95 and for solar PV it was 120 in 2015/16. The capacity represents the capacity of the plant up to two decimal points. Load factors for onshore wind are 26.7% and for solar PV 11.1%. For the same year, the transmission loss multiplier (TLM_{yr}) is 0.0085 and the renewable qualifying multiplier (RMQ_t) is 1 for both technologies as is the CHP qualifying multiplier ($CHPQM_s$). The factor

of onshore wind and PV:[5] The amount of budget has to be divided by the approximate annual amount of subsidy received for one MW of RES. As costs and load factor differ for solar PV and onshore wind, they will be included as to their respective market share into the calculation. This market share, will be scaled up as if the market for mature RES technologies would only consist of onshore wind and solar PV - thus ignoring the other participating technologies to facilitate the assessment of the auction outcomes:[6]

$$Capacity = \frac{Budget}{BI\,PV_{s,yr,p} \times 0.38 + BI\,onshore_{s,yr,p} \times 0.62} \tag{3}$$

BI is the budget impact of the respective technology calculated according to the official valuation formula. As mentioned, this assumption is simplifying, however, agents bidding in the auctions also perform some scaling of the budget to their expectations of capacity tendered and the potential competition. This calculation procedure thus yields an expected capacity that all agents can include into their respective bidding function to maximize their possibility of winning and their profits. As the modelling is performed primarily to find out how behaviour is affected by penalties and pre-qualification criteria, the actually auctioned amount of capacity is not crucial for our research question. Furthermore, as one can see in the outcomes of the auction that took place in 2014, only

$YR1F_{s,c,p}$ is applied to account for phased projects and equals 1 otherwise. For simplification purposes, I leave it at 1, assuming that projects participate for the full year. The year 2015/16 has 365 days.

[5] Pot 1 (mature technologies) has been split among these two technologies and energy from waste with CHP, hydro, landfill gas and sewage gas. As however none of these technologies were awarded in the first auction round and due to simplification purposes, it will be assumed that only onshore wind and solar PV projects bid into the pot 1 technology auction. As in the first auction, no capacity minima or maxima were set for specific technologies in pot 1, both technologies compete for the whole pot in the modelled auction.

[6] Taking the installed capacity shares of onshore wind and solar PV from the October 2014, where the first allocation round took place, this yields the following: 5028 MW of PV were installed according to UK government statistics and 8258 MW of onshore wind according to Renewable UK. Assuming that the two technologies make up 100 % of all auction participants for the mature technology pot, we thus have a share of 62 % onshore wind bidders and 38 % solar PV bidders.

onshore wind and solar PV were awarded in the pot 1 for mature technologies. This shows that the simplification does not diverge too strongly from reality. The estimated capacity according to my calculations amounts to 565 MW in 2015/16 (£50M). For the remaining years the estimated capacity is derived from a budget of £65M per year (inflated by a factor of 1.0195). This translates to 734.5 MW for the following delivery years (2016/17, 2017/18, 2018/19, 2019/20, 2020/21) before being inflated.

The **pricing rule**, as described beforehand, is pay-as-clear (uniform pricing within each year). A separate price can be determined for technologies for which a minimum volume has been set, unless the general clearing price for that year is higher than the clearing price for the protected technology (DECC, 2013). As this however was not the case for mature technologies in the UK auction, I instead assume wind onshore and solar PV agents competing in one auction.

The **distribution of the agents** is as follows. First of all, I assume the initial shares for solar PV and onshore wind bidders as calculated beforehand to estimate how the budget translates into tendered capacity: 38 % for solar PV and 63 % for wind onshore. In terms of the number of bidders, there was no information available, so I had to make an estimate taking into account different sources on the wind and PV sector in the UK (e.g. RenewableUK).

Next, taking into account agent distribution on the UK market for onshore wind and PV, I model four types of bidders: a strong and a weak type for each technology to provide some variety. Basically, the strong and weak types only differ in their cost distribution. Long-term bidding behaviour cannot be differentiated, as we are looking at a one-shot auction. The following table describes the agent's characteristics (data on costs has been taken from BEIS):

Table 1: Agent distribution

Agent type	Wind strong	Wind weak	PV strong	PV weak
Number of bidders per delivery year	10	10	15	15
Range of capacity bid [MW]	5-15	5-15	5-50	5-50
Cost distribution [p/kWh]	4.7-6.2	6.2-7.6	7.1 - 8	8 - 9.4
Revealed cost distribution [p/kWh]	3.76-6.2	4.96-7.6	5.68-8	6.4-9.4
Cost digression	1.95% per year	1.95% per year	piecewise (7.5% first year, then 2.5%)	piecewise (7.5% first year, then 2.5%)

Aside of their different prerequisites, the two technologies compared also differ in the development of their respective **costs**. As so far only one auction round has been executed in the UK, learning of agents and cost digression over several rounds could not be taken into account. However, assumptions on technology cost digression should have influenced bidder's valuations of future delivery years - as there was a possibility to bid into several financial years. In the model this is depicted as four bidding rounds with a different cost digression for onshore wind and solar PV but without learning from previous auction rounds. As a sensitivity, a comparison has been modelled to show how the auction results would change, if an auction would have been held in every financial year and thus enabling intra-auction learning effects (on competition and competitor's costs). Finally, the revealed costs (which are below the true costs), that agent's draw their bid from in the non-penalty auction case are assumed to be around up to 20% lower than the actual cost.

According to IRENA estimates, costs for onshore wind could drop between 9 and 22% by 2020. Taking the average, this would mean around 1.95 % per delivery year starting 2015/16. For solar PV, a quite steep decrease has been observed in the past year, which is likely to have already been anticipated at the point in time of the auction. However, future expectations for module price developments are rather cautious and do not expect the extreme price decrease to continue, s.t. a piecewise linear digression for solar PV costs is implemented which starts with a stronger decrease but then stays flatter until 2020. In total, DECC (2015) estimates that the decrease in the LCOE will be around 20% from 2015 to 2020 (**?**). Taking into account their calculations, I assume a 7.5% decline between 2015 and 2016 and then a 2.5% decline for the following rounds.

Under the pay-as-clear pricing mechanism, the **bid function** in theory should be the weakly dominant strategy of bidding one's true costs ($b_i = c_t$). However, as the UK auctions' outcome is based on the highest accepted bid, auction participants have the incentive to exaggerate their true costs, due to the fact that their own bid might be the highest accepted one and thus determine the clearing price (**?**). At the same time, insecurity exists about the level of competition in the respective years that participants can bid into. This could also lead to strategic underbidding (depending on the expectations on the clearing price, the number of competitors, their costs and their bidding strategies) which in turn could lead to winner's curse for some bidders. Finally, a bid that does not break even can be rejected easily, because no actual penalty exists. Summarizing, the UK CfD auction has some design features, that incentivize strategic behaviour. The type of strategic behaviour I want to investigate is strategic underbidding due to lack of penalties and its impacts on auction outcomes - prices, realisation rates and agent distribution. As shown by Kreiss et al. (2017) similar considerations hold for the case of pre-qualifications, if they also count as a loss for the bidder in case of non-realisation. Due to the limited scope of the paper, the analysis will be focused on penalties. Whereas similar impacts can be expected for pre-qualifications, results on the pre-qualification sensitivity will be provided in forthcoming research to investigate this in more detail.

As shown in the theoretical section, bidding behaviour changes, depending on whether the bidder factors in a penalty or not. I therefore compare two cases: one where bidders bid their costs and in which a drop-out would be penalized. The second one does not include a penalty (or a financial pre-qualification that could be lose), i.e. if bidders refuse to accept the bid afterwards, i.e. because of winners' curse as they strategically underbid and now cannot cover their costs, because the final strike price is too low, they will not be penalized. In this case, bidders were modelled with two cost functions: true costs and revealed costs. The revealed costs go below the true costs of the bidders, as they assume that they can increase their chances of winning by lowering their bid - without the risk of winners curse. If the auction outcome is not favourable for the bidder (i.e. negative profit), she does not accept the bid. At the same time, agents try to strategically factor in the level of competition (another layer of insecurity) into their bidding strategy. If they expect the competition to be strong, they increase their underbidding (as they are less likely to be price determining or to end up with winners' curse). If they expect a round to have less competition, their bids are higher.

In the model this is implemented as follows. First of all, a default round is executed to show how a pay-as-clear auction with a functioning penalty scheme would have performed. This shows agents bidding their true costs. Then I model a no-penalty case. In this case, bidder's cost range goes below their true costs (i.e. they have a second underlying cost structure - the revealed costs - from which they select their bid). If the final strike price however lies above their actual costs, the bidders default without consequence.

$$b_i = c_{revealed}\,(if\, c_t > c_{revealed}\; and\, strike\, price < c_t,\; bidder\, defaults) \tag{4}$$

Bidders can bid into different years, which is implemented as a sequential auction without learning the previous results but with some assumptions on cost decrease in future financial years. This cost decrease differs by technology. Finally, assumptions on competition have to be made. This is a crucial insecurity for bidders as well as for the auctioneer. As estimating the competition for a future auction round is quite complex, especially when it comes to a one-shot auction for different bidding years, it is difficult to derive and model one particular strategy and assume that all bidders have followed it. Instead, I make use of the actual auction outcomes and try to "reverse engineer" potential assumptions of bidders on the respective competition in the rounds (according to a) the strike price and b) the number of bids submitted in that round). Thereby, an "average" strategy on estimating competition for different bidding years can be implemented, which also impacts bidders' behaviour. The following table shows the auction outcomes for the delivery years:

Table 2: Delivery years

Delivery year	2015/16	2016/17	2017/18	2018/19
Capacity auctioned	565 MW	734.5 MW	734.5 MW	734.5 MW
Ceiling Price Onshore Wind	95	95	95	90
Ceiling Price Solar PV	120	120	115	110
Strike Price	50	79.23	79.99	82.5
Capacity awarded Onshore Wind	0	45	77.5	566.05
Capacity awarded Solar PV	32.88	38.6	0	0

Trying to derive agent's expectations on competition levels from these outcomes is a complex task. The extremely low strike price for the first delivery year indicates winners' curse and the assumption of a higher level of competition than actually occurred. Overall, most bidders bid into the last delivery year 2018/19, but in general, competition was low overall. In the model, slightly more aggressive bidding was implemented in the first year, to approximate for expectations on high competition. The following section shows the modelled final strike prices for one select financial year. These are then compared to a comparable auction scheme with a functioning penalty system and to outcomes of a sequential annual auction scheme. The same comparison is performed for drop-out rates and profits for bidders.

3.2 Modelling results

As explained beforehand, the model is run for a standard uniform pricing scheme to provide results of an auction with a functioning penalty system that enforces bidders' compliance and thus induces them to bid truthfully and not go below their actual costs. The results of this uniform pricing scheme are then contrasted with the outcome of a uniform pricing scheme, where bidders are able to default without penalty after being awarded, given that the strike price is below their true costs. The model results show that not factoring in a penalty can lead bidders to bid too low (the same holds for the lack of pre-qualification criteria). If they experience winners' curse as a result, they default. This leads to an increased drop-out of agents after being awarded. For the policy-maker this means a lower realisation rate from the auctions.

Another factor that increases insecurity for the auctioneer as well as for the bidders, is the estimation of competition levels for several delivery years (Fitch-Roy and Woodman, 2016). Bidders have the possibility, in the UK auction scheme, to bid into several years, however not knowing how many other bidders will be competing with them for each of the budgets. If they bid into a year with low competition and strategically underbid, this increases the likelihood of experiencing winners' curse. Therefore, as a second sensitivity, the scheme is contrasted to an annual auction, where bidders can draw upon experiences from previous rounds and can account for competition levels and prices from the past year. The annual auction scheme is performed for the penalty and the no penalty case. The following table contrasts the default model round and the three sensitivities for one selected year (2017/18). These results are explained in more detail in the following and then discussed and contrasted with the literature in the discussion section.

Table 3: Auction model results (Exemplary year: 2017/18)

Model run	Annual		One shot	
	Uniform Pricing	Uniform (no penalty)	Uniform Pricing	Uniform (no penalty)
Capacity awarded	740.5	743.25	756.25	746.625
Awarded bidders Solar PV	0.5	0.1	1	1.5
Awarded bidders Onshore Wind	55.4	53.2	26	26
Strike Price	6.678	6.807	7.1975	7.285
Average Profit	1.21	1.35	1.10	1.30
Drop Out		1.71		1.7

The most important findings from comparing the different modelling runs are the price differences and the differences in realisation probability. One can interestingly observe, that the strike price is slightly higher in the no penalty case in both the annual as well as the one shot auction. The capacity awarded is comparable for the penalty and the non-penalty case, however with on average 1.7 bidders dropping out in the non-penalty case, on average 46.75 MW will not be built and have to be deducted. Furthermore, comparing the average profit shows that in the non-penalty case bidders achieve a larger profit than in the case where a functioning penalty is in place.

Another interesting however not particularly surprising result is that the average strike price is lower in annual auctions, assuming that bidders have more accurate information on technology costs in the actual auction year, rather than planning several years ahead. From a policy-maker perspective it thus has to be assessed, whether the administrative effort of holding annual auctions actually outweighs the monetary benefits of a more accurate and potentially lower cost in later auction rounds.

Furthermore, it is an interesting finding, that a lower number of bidders in the onshore wind sector was awarded in the annual auction. As we are only comparing one particular year in this analysis, however, it is difficult to draw conclusions from this. In further research however, the agent distribution and their changes will be analysed. For the scope of this paper however, other topics are of more crucial importance.

4 Discussion

As the UK CfD auctions' outcome is based on the highest accepted bid, auction participants have the incentive to bid strategically, due to the fact that their own bid might be the highest accepted one and thus determine the clearing price (**?**). This could be a factor which influences the bidding behaviour, i.e. inducing the agent to bid above her costs. It is interesting to see, that while the model was clearly programmed to allow underbidding, the outcome still shows higher costs for the non-penalty case. Furthermore, a certain amount of participants underbid and then drop out in the model. As there is no information on realisation rates of the UK auction thus far, it remains to be verified whether this will actually be the case. However, extremely low strike prices for the first delivery year (£50) were observed which are unlikely to allow bidders to cover their costs. In general, one can conclude from the theoretical literature, the empirical outcomes and the auction modelling, that the auction outcome is less predictable and capacity expansion goals are more likely to not be achieved when the auction design allows bidders to bid strategically without consequences.

The results also show, that bidder's insecurities rise, when they have little knowledge of the competition that they can expect in a certain delivery year. Learning effects, i.e. technological but also from previous auction rounds are important and should be made use of in designing an auction scheme. Modelling an alternative system with annual auction rounds induces lower prices for bidders as seen in the modelling. A further advantage of this scheme is that it allows the auctioneer to adapt better to technological or market developments, by changing auctioned capacities or adapting the ceiling price. The second auction round in the UK only took place for non-mature (Pot II) technologies, so the empirical results will unfortunately not provide further input data to refine the modelling of the mature technology auctions. However it will be interesting to see, if some learning effects among participants will be observable.

The modelling of auction schemes has its limitations and is of course to a large part dependent on the model's input parameters. As auctions for renewable energy are a relatively new phenomenon especially in Europe and as the energy market as well as technological development are constantly changing in sometimes unforeseen ways, the model results cannot and are not aiming to provide accurate predictions of future auction outcomes. However, they do provide insights, especially by combining agent based modelling, which allows quite accurate depictions of human behaviour and learning with an auction theoretic background, which are valuable for policy makers looking into designing or improving an auction scheme. Specifically the result showing that the no penalty case lead to drop-out as well as slightly higher prices, is quite surprising and useful for application of future policies. Overall, the analysis provides a novel approach of looking into renewables auctions and their specific design features and adds some interesting findings to the existing literature.

5 Conclusions

This paper provides an agent-based modelling approach to assess the impact of penalties and pre-qualifications in the UK CfD auction scheme for renewable energy. An auction theoretic framework is part of the model, as well as specific characteristics of the UK electricity market and the market participants. Policy makers receive important insights from this analysis on how to design their auction policies according to their respective goals. While risking a reduced realisation rate, according to the model results, lower prices cannot be achieved in auctions with little or no pre-qualifications or no penalty for drop-out. If achieving a certain amount of installed capacity is important to the commissioning authority, higher pre-qualifications or an efficient penalty system could ensure this, as drop-out can be decreased and strategic underbidding avoided.

Further research is planned, to assess in more detail how the participant's structure changes in different scenarios with or without pre-qualifications or penalties. It is furthermore planned, to perform a more detailed analysis which differentiates further between penalties and pre-qualifications. It would also be interesting to empirically assess and contrast the first and second round, especially as the auction scheme's design has not been changed, and look into learning effects and their impact on agent behaviour.

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