

The importance of penalties and pre-qualifications

A model-based assessment of the UK renewables auction scheme

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Abstract

This paper assesses the technology neutral auctioning of Contracts for Difference (CfDs) in the UK, with a special focus on how pre-qualifications and penalties affect bidders' behaviour, risk aversion and bidding strategies and thus the auction outcomes in terms of prices and realisation probability. The auctions are modeled to closely represent the auction design foreseen by the implementing agency, the Department of Energy and Climate Change (DECC).

Two alternative designs are presented: In the first one, bidders bid their true costs as a drop-out after being awarded would be penalized. The second one does not include a penalty. In that case, bidders are modelled with a cost function that includes a higher level of uncertainty. The model results show that low pre-qualifications and low or no penalties lead to an increased drop-out of agents after being awarded. For the policy-maker this means a lower realisation rate for the auctions. Furthermore, the no-penalty case does not yield lower prices compared to a case with a stricter penalty/pre-qualification system in place.

Keywords: Auction, Simulation, Agent-based modelling, Renewable Policy

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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 number 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 in case of non-realisation have a large influence on the realisation rate 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 is depicted in the model. Then I model the auction 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 as well as the auction-theoretic background necessary for understanding 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, the year the CfD auction took place, 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 (Terrawatt hours)) 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.

¹UK 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.²

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 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 a bit challenging.

²The first of these auction rounds 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

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. It can be differentiated between descending and the ascending clock auctions

has been auctioned in this second round, such that the results will only be partly of interest for the

(dynamic) and the uniform and pay-as-bid (PAB) auctions. These formats or combinations and variations of them have already been applied in RES auctions in different countries worldwide. Single-unit auctions are used when a certain project is tendered, commonly applied for e.g. offshore wind power auctions.³ 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.⁴ 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, I look at symmetric, risk-neutral and single-project bidders. As explained beforehand, the product auctioned is a homogeneous good. The following overview⁵ of the design elements of the standard multi-unit auction format will be limited to the properties I assess in this paper. Bidder's valuations in this specific format are modelled as independent values (IPV approach), as each bidder draws independently from a given cost range. However, one could say that due to the fact that cost decreases take place simultaneously and equally for all bidders, a certain common value component also exists.

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 fi-

following analysis.

³In that case, participants usually bid for the permit and support payments to realise a specific, pre-developed offshore wind project.

⁴Since 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).

⁵The concepts presented in the following are based on the overview in (Haufe and Ehrhart, 2016;

nancial 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-qualification processes or penalization of delay/non-delivery) 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). This is due to the fact, that the bidder's insecurity of actually being able to finance a project is reduced by the administratively predetermined financial security. **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). Outbidding means that bidders could submit several bids although planning to realize only one of the submitted projects. This way, they can influence the price and also hinder competitors. 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, which makes them more risk averse and more desirable for loans, as bankruptcy (Chillemi and Mezzetti, 2009) is not a straightforward option (which could be the case for smaller, recently founded entities). 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), meaning that bidders are willing to incur a certain loss in order to regain their pre-qualification.

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 proactiveness.

Del Río, 2015)

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 ISI's 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 (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), Bunn and Oliveira (2001), or Li and Shi (2012) and forthcoming work by Anatolitis and Welisch (2017) 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 highest awarded bid in this particular case. 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. 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 approximate the outcomes of the simulation, the mean of 100 simulation rounds per scheme 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 answer the 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 translate the annually capped budget into a certain amount of capacity auctioned for each budget year. As agents in the UK renewables auctions themselves calculate as to which amount of tendered capacity is 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:⁶

$$\begin{aligned}
 \text{Budget impact}_{s,yr,p} &= (\text{Strike Price}_{cy,t} - \text{Reference Price}_{yr}) \\
 &\times \text{Load Factor}_{t,yr} \times \text{YR1F}_{s,c,p} \times \text{Capacity}_{s,p} \times (\text{Days}_{yr} \times 24) \\
 &\times (1 - \text{TLM}_{yr}) \times \text{RMQ}_t \times \text{CHPQM}_s
 \end{aligned} \tag{2}$$

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

⁶The 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 included into the equation 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 $\text{YR1F}_{s,c,p}$ is applied to account for phased projects and equals 1

of onshore wind and PV:⁷ 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:⁸

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

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. Furthermore, as seen in the outcome of the CfD auction that took place in 2014, only onshore wind and solar PV were awarded in the pot 1 for mature technologies. This shows that the modelled simplification actually matches the empirical evidence. 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,

otherwise. For simplification purposes, I leave it at 1, assuming that all projects participate for the full year. The year 2015/16 has 365 days.

⁷Pot 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.

⁸Taking 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: 5,028 MW of PV were installed according to

2017/18, 2018/19, 2019/20, 2020/21) before being inflated. For simplification purposes, I take these capacities as an approximation, without factoring in an inflation rate.

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 take the 2014 capacity shares for solar PV and onshore wind bidders as calculated beforehand to estimate the share of bidders on average: 21.5 % for solar PV and 78.5 % for wind onshore in 2014. In terms of the number of bidders, there was no information available, so I had to make an estimate on the wind and PV sector in the UK using the official statistics by DECC). As the bidding volume was not reached in any of the bidding years, I assume participation to be rather low in the auctions, with 1,025 MW participating for the first bidding year and a slight increase in each upcoming year⁹. To approximate the size of participating projects, I resort to the auction results as shown in the Appendix 5. All of the assumptions on the bidders are shown in Table 1.

Next, to introduce variation and show a realistic range of participants, I model four types of bidders, i.e. a strong and a weak type for each technology who differ in their cost

UK government statistics (DECC) and 8,536 MW of onshore wind, also according to DECC. Deducting the small-scale installations below 5 MW which receive a FiT (2,802 MW for solar PV and 433 MW for onshore wind), this yields 8,130 MW for onshore wind and 2,226 MW for solar PV. Assuming that the two technologies make up 100 % of all auction participants for the mature technology pot, we thus have a share of around 78.5 % onshore wind bidders and 21.5 % solar PV bidders.

⁹This increase is due to two facts. Firstly, the budget in the first year is lower. Secondly, later

distribution. Long-term bidding behaviour cannot be differentiated, as we are looking at a one-shot auction. Table 1 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
Average number of bidders first delivery year	10	10	15	15
New random draw of bidders per delivery year	0-2	0-2	0-2	0-2
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
Cost digression	1.95% per year		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 implemented as four bidding rounds with a different cost digression for onshore wind and solar PV but without learning from previous auction rounds. Finally, the revealed costs (which can lie below the true costs), that agent’s draw their bid from in the non-penalty auction case are assumed to be drawn from a larger range of insecurity as explained in the following.

bidding years potentially attract more participants, as especially for wind power, longer lead times for

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 (KPMG, 2015). 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 ($b_i = c_i$). 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 (Ausubel, 2008). 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 underbidding due to lack of penalties or pre-qualification criteria 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 simplification purposes, in the ongoing parts, I mention mostly just penalties, whereas from a theoretical point of view, these impacts can also be expected for the loss of pre-qualifications (see e.g. Waehrer (1995)).

As explained 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 lost), 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 are modelled with a different bidding function: the function in the system with a functioning penalty/pre-qualification has lower insecurity than the one without. Specifically, this means that the bidder receives her signal and can willingly choose to bid from the lower range of her cost signal distribution, i.e. acting more risk-loving than a bidder for whom defaulting comes at a cost. If the auction outcome is not favourable for the bidder (i.e. negative profit), she does not accept the bid.

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. In this auction, agents bid their true costs according to their signal. Then I model a no-penalty case. In this case, the bidder's cost range contains more insecurity

ity, increasing the likelihood that they submit a bid that is below their true costs. If the final strike price however lies above their actual costs, the bidders default without consequence. So the bidder receives a signal x with an uncertainty factor δ :

$$y = x + \delta \text{ where } \delta \in [-\epsilon, \epsilon] \quad (4)$$

The bidding function resulting is:

$$b^2(x) = x - \delta \quad (5)$$

Due to the fact, that the bidder is able to default¹⁰, she is able to submit a bid in the lower bound of the range of her signal, even though it might result in a loss. These equations are adaptations of Board (2007). The distribution of the uncertainty factor is assumed to be common knowledge (see e.g. Parlane (2003)).

There is uncertainty that occurs for bidders trying to estimate the competition and price level for several budget years, i.e. due to the one-shot auction format. However, according to theory, the expected revenue is on average the same for sequential or one-shot auctions, or at least its effect cannot be determined (see e.g. Hausch (1986) among others). I therefore, take into account price predictions for RES technologies and expectations on competition levels. In the appendix (5), the auction results are shown and a further explanation is given, why these results offer too little insight to actually “reverse engineer” bidder’s expectations on competition in different bidding years, based solely on these results. Mezzetti et al. (2008) find that whether or not revenue for the seller is higher (i.e. in our case lower support costs for the auctioning body) in sequential or one-shot auctions, depends on whether the informational effect of executing several

construction are preferential.

¹⁰According to Parlane (2003) in a second-price auction, which is the single unit equivalent to the

rounds outweighs the so called “low-balling” effect, which yields lower prices (in our case higher support costs) in the first round.

In summary, this leads to two cases that were simulated: a one-shot, no penalty auction, a one-shot auction with a penalty. In the non-penalty case, the bidder can bid in the lower area of her received signal and thus increases the probability of incurring a loss and defaulting.

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. 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.

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. As we model bidders to bid their true costs, according to theory, this factor will not be taken into account. It could, however, in reality, increase the risk of defaulting even further.

The following graphs show how the strike price changes in the auction scheme with

uniform pricing auction, when bidders face limited liability (reduced or no loss) for defaulting, there is

and without penalty. The expected default rate in the non-penalty case is furthermore shown in Figure 2.

a strictly positive probability to do so. According to Waehrer (1995) a model of limited liability can be interpreted equivalently to a model of a lost deposit, making this applicable to the UK CfD auction model.

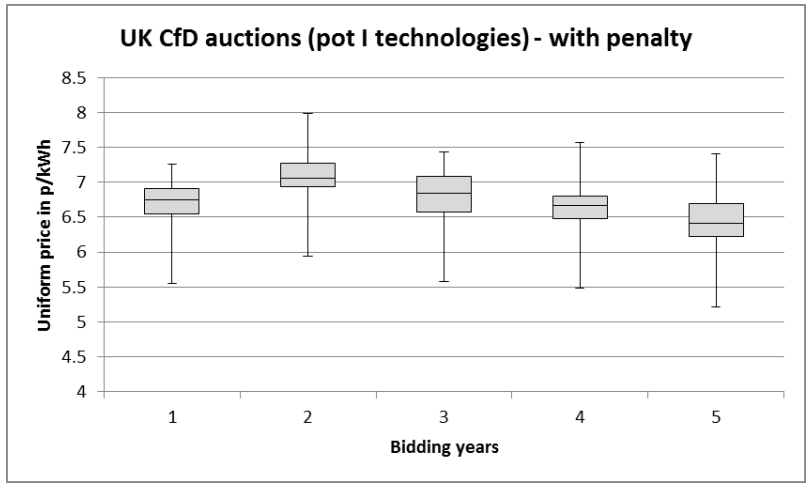
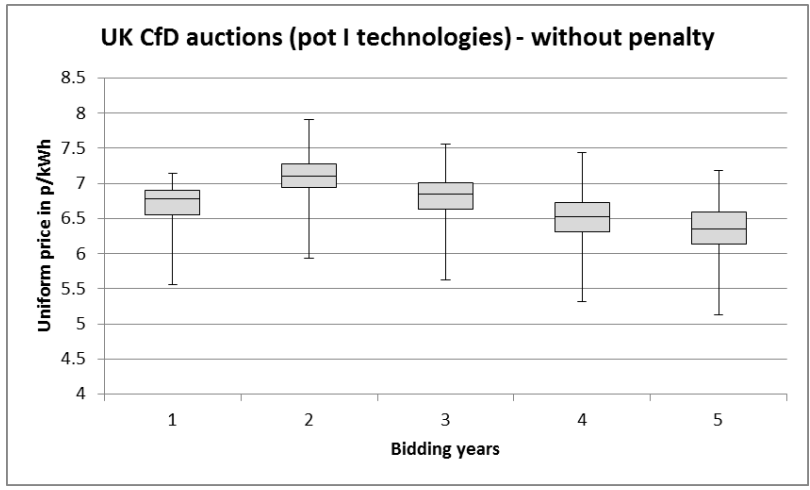


Figure 1: Modelling results

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'

course 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.

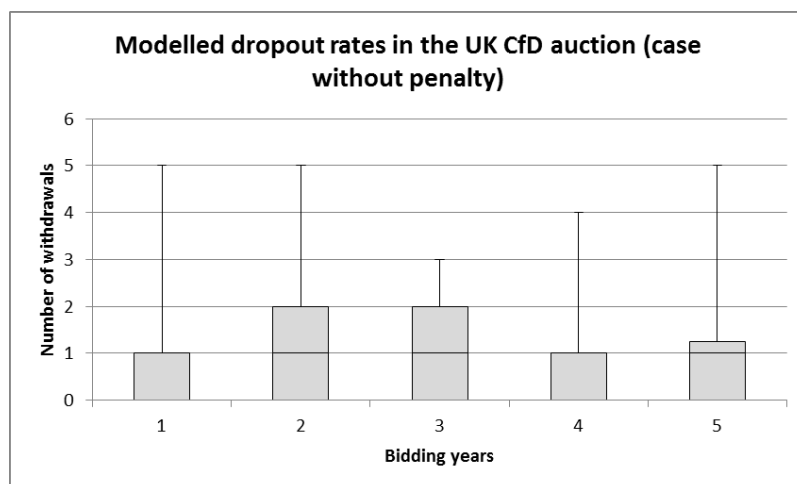


Figure 2: Modelled dropout rate

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 the beginning, but then reaches slightly lower levels than the no-penalty case. Overall, there is no significant difference to be seen. The capacity awarded is comparable for the penalty and the non-penalty case, however with roughly 1 bidder dropping out per bidding year in the non-penalty case, on average 23 MW will not be built per year 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. This difference is however marginal.

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 (Ausubel, 2008). 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 the outcome of the non-penalty case does not show lower prices on average. 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/MWh) 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.

In the empirical outcomes, it could be also observed, that the level of competition was quite fluctuating between the different auction rounds. This shows, 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. From a policy-maker perspective it thus has to be assessed, whether the administrative effort of holding e.g. annual auctions instead, to increase stability actually outweighs the benefits of more balanced participation and of more accurate and potentially lower costs in later auction rounds. A further advantage of such a 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 general learning effects among participants will be observable.

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, ABM has its limitations. However, as this paper aims to provide policy relevant results rather than adding to theoretical expansions of auction theory, the approach proves to be the most suitable for the given research question.

The modelling of auction schemes 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, especially by combining agent based modelling, which allows quite precise depictions of human

behaviour, with an auction theoretic background, we receive insights 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 and has no advantage in terms of lower prices, is quite 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 presents 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 are 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 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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Appendix

Empirical outcomes and elaborations on competition

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.

Looking into possibilities for “reverse engineering” 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), led me to looking into the auction results. 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 (£/MW)	95	95	95	90
Ceiling price solar PV (£/MW)	120	120	115	110
Strike price (£/MW)	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, which is likely due to the fact that these projects are large wind farms which need a long lead time for construction. However, in general competition was low overall. As these results do not allow drawing unambiguous conclusions on bidder's expectations, I instead rely on the auction theory to model bidder's uncertainty in their bidding function.

Complete model results for all bidding years

The following table contrasts the model results of the two cases (average values of 100 simulation rounds).

Table 3: Auction model results (Uniform pricing with penalty)

Bidding year	2015/16	2016/17	2017/18	2018/19	2019/20
Capacity awarded	582.86	748.68	750.99	749.57	749.3
Awarded bidders solar PV	0	1	1	1	1
Awarded bidders on-shore wind	20	25	24	24	25
Strike price (p/kWh)	6.73	7.1	6.83	6.64	6.48
Average profit	0.97	1.19	1.10	1.08	1.05

Table 4: Auction model results (Uniform pricing without penalty)

Bidding year	2015/16	2016/17	2017/18	2018/19	2019/20
Capacity awarded	580.59	747.97	749.55	751.58	751.16
Awarded bidders solar PV	0	1	1	1	0
Awarded bidders on-shore wind	19	24	24	24	24
Strike price (p/kWh)	6.7	7.08	6.82	6.54	6.38
Average profit	0.96	1.21	1.12	1.03	1.0
Drop out	1	1	1	1	1