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Simulating offshore wind contract for difference auctions to prepare bid strategies

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ABSTRACT

This paper presents a novel agent-based, stochastic model, which uses game-theoretic principles to simulate Contract for Difference (CfD) auctions. The framework has use cases and implications for policymakers and renewable generators alike, and can be used by developers to prepare bidding strategy and for policymakers to empirically test auction design. The model is demonstrated through replication of the offshore wind CfD Allocation Round 3 (AR3) pot, and utilises high-level cost modelling distribution data to estimate bid prices for the competing projects. The model produces a distribution of most likely results which better categorises uncertainty, and through comparison of AR3 and simulation results, demonstrates how outcomes can be predicted with reasonable confidence by developers. Analysis show that the transmission network and grid connection charges are a significant barrier for projects in some geographical regions to be awarded a CfD contract, potentially hindering renewable deployment in those areas. Moreover, this paper demonstrates how players can use probability theory to select an optimum bidding strategy which maximises expected profit while factoring the uncertainty inherent in CfD auctions. Results show that a 1200 MW wind farm development can increase potential profits by £135 million over the CfD contract length in exchange for a 25 p.p. chance reduction in being awarded a subsidy.

1. Introduction

For countries worldwide to meet their energy targets, such as the UK aiming to cut carbon emissions by 68% by 2030 [1] and achieving net-zero by 2050 [2], governments are encouraging the adoption of renewable energy technologies. To achieve this, governments have implemented policies to expand the market penetration of renewable electricity and promote its deployment [3]. Such approaches enable governments to achieve ambitious renewable energy targets and thus reduce their carbon emissions. The UK government's primary subsidy support mechanism for supporting the deployment of new low-carbon electricity generation is through the Contracts for Difference (CfD) subsidy scheme [4]. CfD subsidies are awarded in increasingly competitive auction processes. The contract guarantees developers a fixed price (£/MWh) for the electricity they generate. From a developer's perspective, being awarded a CfD protects them from volatile market electricity prices and provides revenue certainty. Revenue certainty reduces project risk and so decreases the cost of project financing. For many developers of renewable energy technologies, the award of a CfD contract is the most viable route to market.

To maintain competition and ensure value for money for electricity consumers, CfD auctions have a limited subsidy budget. Therefore, many developers bidding for a subsidy at auction are unsuccessful [5]. Developers who fail to win a contract will likely incur project delays as they wait for the next allocation round. On the contrary, a contract-winning developer who does not quantify its costs properly may experience the winner's curse. Developers can experience the winners' curse in CfD auctions because of bidding too low for the capacity on offer and so regret the award of a contract at the resultant price obtained. This can potentially lead to the non-realisation of projects or reduce the profitability of developments [6]. For these reasons, it is crucial that developers properly consider the uncertainty while developing their bidding strategy.

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For developers to formulate an optimum bidding strategy, generators must perform financial and strategic analyses. Financial analysis is related to all known factors (e.g. leasing costs). Strategic analysis is associated with assessing uncertainties (e.g. level of competition, competition costs, forecast wholesale electricity market prices). This strategic element is crucial and is considered non-negligible [7]. In existing auction-theoretic literature, when the auction concerns several homogeneous items, the dominant strategy of players is not to bid at cost, as players may be incentivised to engage in different forms of strategic bidding [8]. Therefore, to determine an optimal bid, bidders must understand the auction dynamics to identify the best bidding strategy. One way of achieving this is through auction simulation. Auction simulation allows testing of dominant strategies in varying bidder configurations, valuations and uncertainty [9].

This paper introduces a novel numerical framework for studying CfD auctions. To the best of our knowledge, there are a number of novel elements associated with the model which do not feature in the few studies conducted on Renewable Energy Subsidy (RES) auctions or in adjacent auction modelling literature. The closest model present in existing literature can be seen in work produced by Anatolitis et al. [10]. However, this work differs from the presented model for two key reasons. Firstly, this model is stochastic, which allows for better categorisation of the uncertainty experienced by auction participants. For example, the model samples from stochastic input data to generate stochastic auction bid prices from an empirical distribution of cost data and forecast future revenue streams. Generated bid prices are then used to obtain a stochastic output made up of many thousand auction simulations, which estimates the most likely auction outcomes. Secondly, it incorporates elements of game theory and probability theory to allow auction participants to test various bidding strategies. For example, the model can determine a bid price for auction participants, which maximises the expected profit for players.

The methodology described can aid decision-making for policymakers and renewable developers looking to bid in the CfD auction. The model can test for optimum bid strategies, conduct sensitivity analysis on key inputs, make predictions for future auctions, analyse past auctions, or explore auction rule design changes for policy recommendations. The model is demonstrated by re-creating and analysing AR3. A previously validated proprietary stochastic cost modelling tool generates cost data for each participating wind farm project. The results from the simulation are compared to the actual results of AR3 to test auction allocation efficiency and assess how accurately developers can predict auction outcomes prior to the auction. To the best of our knowledge, there is no published literature which has used auction simulation to analyse a past CfD auction result. Simulating past auctions is useful for both developers and policymakers; it allows to test whether the auction was efficient at allocating resources and will enable developers to test hypotheses which can be used to inform future bidding strategies.

The remainder of this paper is structured as follows: Section 2 discusses the CfD auction design and allocation process. Section 3 reviews the theoretical background and the state-of-the-art of renewable energy subsidy auction simulation techniques. Section 4 details the approach and methodology of the present work. Section 5 outlines the AR3 case study and discusses the modelling assumptions. Section 6 then discusses the results before concluding.

2. CfD auction design and allocation process

2.1. CfD background

In the UK, a CfD is a 15-year contract between developers of renewable projects and the Low Carbon Contracts Company (LCCC), a government-owned company. Generators with a CfD agreement are paid the difference between a strike price agreed at auction and a reference price. The generator sells electricity under a Power Purchase Agreement (PPA) to a supplier or trader into the energy market at a live reference price. If this reference price is below the strike price, the generator receives a top-up from the LCCC. On the contrary, if the strike price is above the reference price, then generators pay back the difference to the LCCC [4]. This means that the generator is guaranteed to sell the electricity at the fixed strike price [11]. CfD's provide long-term stabilisation of electricity prices generated by low-carbon sources, protecting consumers from high electricity prices which can occur on energy markets.

Table 1
Budgets are available for each delivery year as set out by the Secretary of State for Energy in a budget notice [15–17]. The results shown are for offshore wind only. Only delivery years which procured offshore wind are shown. The yearly budgets shown in the above Table are for total spending for all successful projects for that allocation round rather than for spending on projects which start generating in a particular delivery year.

	AR 1 (2015)		AR 2 (2017)		AR 3 (2017)	
Delivery year	17/18	18/19	21/22	22/23	23/24	24/25
Budget available (M£)	260	260	290	290	65	65
Volumes procured (MW)	714	448	860	2336	2600	2854

The CfD auction scheme was introduced to the UK in 2014 as part of the Electricity Market Reform. Since its inception, over 25 GW of renewable generation has been subsided [12]. It is one of the UK's primary subsidy support mechanisms for supporting low-carbon energy generation and an essential tool for reaching net zero. Since 2014 there has been a dramatic decrease in the strike price awarded at CfD for offshore wind, shown in Fig. 1.

The monetary budget for supporting renewable generation is announced before the auction. This budget issued by the UK government is divided into different technology pots. The government uses the pot classification to support its policy decisions. For example, from the end of 2015 until 2021, the government excluded onshore and solar as eligible technologies, halting their deployment for several years in the UK. The pots for the latest CfD round, AR4 are Pot 1 — Onshore wind and solar, Pot 2 — "Less established" such as floating wind and remote island wind, and Pot 3 — Offshore wind projects. Capacity minima and maxima caps, in addition to the pot definitions, control the type of different renewable generation technologies connecting to the electricity grid. If the capacity cap is not the limiting factor in determining volumes procured, then the monetary budget will determine the quantity procured.

Budgets are capped annually, meaning that the winning bid's total cost must fit within that delivery year's budget cap. Delivery years give a choice to the renewable generator as to which year they expect their renewable asset to generate electricity. For offshore wind, there are typically two delivery years available to generators, as shown in Table 1, which also illustrates the budget available and the amount of offshore wind procured for each past auction. The budget impact of a project is calculated based on the submitted capacity, the annual load factor, the strike price agreed at auction, and the reference electricity price set by BEIS [14]. The volume of capacity procured is determined by a monetary budget, which signals to developers how much capacity is tendered. Developers then convert this monetary budget into an estimated amount of capacity auctioned, using the same budget impact equation and an estimated strike price.

2.2. CfD allocation methodology

The allocation process for CfD contracts is as follows: the process begins with National Grid ESO inviting eligible applicants to bid for the available budget in each pot. Bidders must first satisfy several pre-qualification criteria to compete in the allocation process. They must have obtained all the necessary consents for their site, including a grid connection agreement. Furthermore, if the site's total capacity exceeds 300 MW, then a *supply chain plan* must be submitted. The plan must

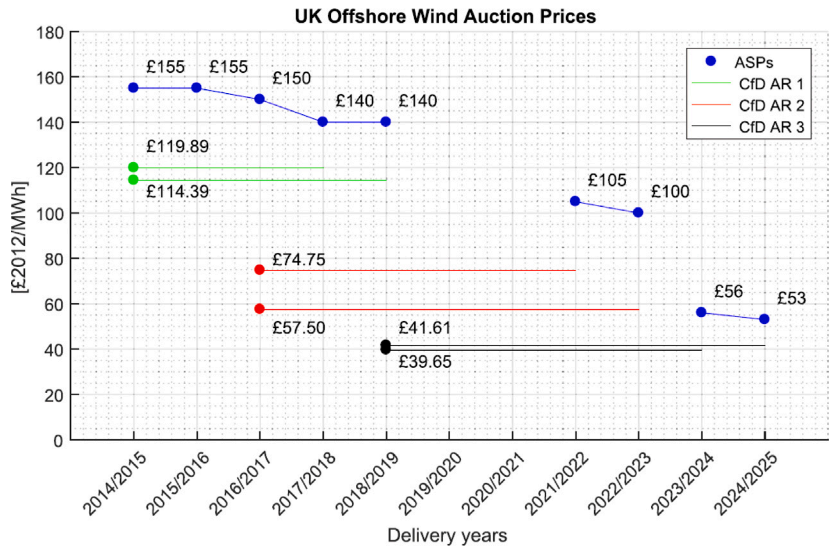


Fig. 1. UK contract for difference allocation round results for offshore wind [13].

outline how the project will promote competition, innovation, and skills in the supply chain.

Developers submit bids that include the technology type, the price, capacity, and the delivery year of the project. A total of four varying *flexible* bids can be submitted to the auction by applicants. These are sealed bids with differing capacities and Target Commissioning Dates, of which no more than two bids may have a Target Commissioning date in the same Delivery Year [18]. National Grid ESO then ranks all the submitted projects in the same pot based on their bid price, regardless of the delivery year. A project's flexible bids are considered if its costs exceed the budget cap when added to the cost of already awarded projects. If the flexible bids of this project also result in a budget breach, then the delivery year is closed, and no other bids are considered for that delivery year. Allocation can continue to the other delivery year until a second breach of budget. As a result, a clearing price is set for each delivery year breach. This is the basis for allocating the budget for AR3, which the case study in this paper is based upon. However, the auction methodology can differ between allocation rounds. For example, in AR4, a budget breach in any delivery year results in the whole auction closing. As a result, only one clearing price is set across the auction [19].

If the total applications do not result in a budget breach, then all applicants will be offered a CfD, non-competitively, at the ASP (Administrative Strike Price). The auctioneer sets the ASP, the maximum possible price awarded to a technology. Further information on the UK implementation of CfDs for renewable energy can be found on the government website. It also provides information on how the ASP is set [20].

3. Theoretical background and literature review

It is important to consider the relevant auction theory to understand the UK CfD auction and its dynamics. The auctions have a multi-unit, sealed-bid, uniform price (pay-as-cleared) format. A multi-unit auction is where several homogeneous items are sold [21]. A uniform price format means that all successful bidders of the same delivery year receive the same remuneration, determined by the highest successful bid. In the CfD auction, this bid sets the strike price as it determines the remuneration bidders receive for each unit (£/MWh) of electricity generated. In uniform pricing auctions, such as the CfD, players can either receive the highest accepted bid (which may be their own) or 0.

The pay-off for player i, represented by π_i, for a particular bidding strategy for a uniform price auction can be represented by Eq. (1). Let $\mathbf{B} \equiv (b_i, b_j)$ denote a bid profile of submitted bids into the auction from two players i, j. Let q_i indicate the quantity of capacity units from player i, which is subsided by the auctioneer. C is the total capacity demanded, c_i is the marginal cost of player i producing a unit of electricity. The remuneration received by player i is interdependent with the bid prices submitted by other players. For more theoretical analysis on multi-unit, uniform price auctions see, for example, Ausubel et al. [8].

$$\pi_i = \begin{cases} [b_j - c_i] \cdot q_i(C; \mathbf{B}), & \text{if } b_i \le b_j \\ [b_i - c_i] \cdot q_i(C; \mathbf{B}), & \text{otherwise} \end{cases} \tag{1}$$

Bidders face significant uncertainty whilst preparing their project bids. The CfD contract only covers a wind farm for the first 15 years. As a wind farm's operational lifetime can be more than 25 years, developers are faced with years of exposure to wholesale electricity market prices. Bidders, therefore, are presented with two significant elements of uncertainty. First, they must predict their project lifetime costs for a project that starts generating in 4–5 years and has a lifespan up to 30 years, and also future electricity market prices; only then can they calculate a CfD bid which optimises profit over the lifetime of the project. As all projects are participating in the same market, they are subject to the same future wholesale electricity market prices and similar cost components (e.g. turbines, cables, foundations) [22]. As players have these two significant common value components, players' costs are interdependent, meaning that estimating competitors' private value for the auctioned goods is possible [23]. Any variations in valuation between players can largely be attributed to different site characteristics, technology differences, risk appetites, and strategic partnerships with OEMs (original equipment manufacturers).

There are also implications for policymakers and consumers due to the uncertainty that bidders face at the CfD auction. During the auction, there is a potential economic risk of auction inefficiency [5]. This is where projects that are awarded contracts do not have the lowest generation costs when compared to unsuccessful projects. For example, this could occur when awarding a contract to a project with intrinsically poor site characteristics but with very high optimistic assumptions regarding future wholesale electricity market prices. Optimistic assumptions mean that when calculating future revenues and optimising a CfD bid price, the developer underestimates the CfD bid price it requires. As a result, developers with more economically viable projects but a more conservative outlook on future prices do not get subsidised [22].

Game theory is an important strand of literature to consider for the present analysis; it studies mathematical models of strategic interaction among rational decision-makers. For example, the CfD auction is a game, as the auction outcome depends on the actions of two or more decision-makers (players). Each player must consider their strategy in the auction to maximise their pay-off. Game theory has been previously applied extensively in energy economics, particularly in grid management or electricity markets. A review of such work has been produced by Bajo-Buenestado [24]. For example, Wu et al. [25] proposed a static game model to utilise car batteries to help integrate wind power into a smart grid. Further work by the same author has used game theory to optimise demand-side management for consumers wishing to reduce their electricity bills. This study creates a game between rational consumers as each player is attempting to optimise usage at the same time [26]. Mei et al. [27] use game theory to devise an algorithm to help identify incentives for coalitional operation and help microgrids in a network trade with one another to meet their power requirements while achieving higher expected utility. Lin et al. [28] utilise game theory to test the effect different bidding strategies have on the P2P solar transactive energy markets. Finally, Liu et al. [29] use signalling game theory to study the main bidding mechanisms in electricity auction markets.

Game theory is often used alongside auction theory to explain auction dynamics. Wilson et al. [30] were the first to formalise the multi-unit auction. They noted that an offer is made according to a private value and was one of the first to write about bid-shading in strategic bidding. Ausbel & Cramton [8] found that the optimal/dominant strategy is not simply to bid one's own cost in a multi-unit auction. Instead, larger bidders have an incentive to bid-shade. Bid-shading is where one player bids higher than their valuation to increase their pay-off. The incentive to bid shade depends on the number of units demanded.

The final strand of literature concerns similar work where models have been used to simulate RES auctions. Anatolitis et al. [10] used an ABM (agent-based model) to simulate onshore wind power auctions in Germany and compare the efficiency of pay-as-bid and uniform pricing auctions. Welisch et al. [31] used an adapted version of this model to model the UK CfD auction and assess the impact that penalties issued for the non-realisation of projects would have on bidders' behaviours and prices. Welisch et al. produced another paper using ABM to analyse bidding behaviour in the German PV pilot auction [32].

To the best of our knowledge, there is currently no published academic literature that simulates CfD auction dynamics to select optimum strategies. The literature survey suggests that there have been some recent attempts to simulate renewable energy auctions to understand auction dynamics better and ensure the efficient design of auctions to meet governmental policy. Several features and phenomena of a real-life auction are not considered by existing literature on this subject. Firstly, there has been no attempt to enhance agents' utility functions by assigning agents to real and non-theoretical projects. Secondly, no published literature has re-created and analysed previous auctions using accurate cost data for each project. Thirdly, no model has incorporated game-theoretic phenomena to optimise bidding strategy.

4. Model methodology

The numerical framework recreates the CfD allocation mechanism as outlined in Section 2, through the utilisation of the Python framework for agent-based modelling (ABM), Mesa [33]. ABM is useful to model the intended problem as it simulates the actions and interactions of autonomous agents acting in the same space while quantifying the effect on the environment. Therefore, this modelling approach is well suited to a CfD auction as non-cooperative developers act in the same auction space, and their actions directly affect the outcome of the others. Additionally, ABM allows agents with different levels of intelligence to be modelled, which introduces additional dynamics and allows for game-theoretic phenomena to be studied.

To properly model the CfD allocation framework, the model allows for up to four flexible bids to be submitted per project and can model two delivery years in one auction run. Bids for each player are determined by analysing the costs and revenue streams of an individual project over its lifetime. The present framework considers stochastic inputs for one simulation; therefore, each complete simulation typically contains over 20,000 auction runs. One auction run contains two main stages: *Bid preparation* and *Allocation mechanism*, illustrated in Fig. 2. The methodology behind these two stages is described in this Section. In Fig. 2, there are two types of players shown in the model: *smart* and *other*. The smart player has added capabilities, which allow it to optimise a bid price (explained in Section 4.2.4).

4.1. Model set up

The ceiling strike price and the total capacity of electricity to be procured are specified in order to initiate the auction. Setting a capacity budget reduces the complexity of the auction procedure without sacrificing too much detail of the auction design. This is because a maxima technology cap was set for Offshore Wind in AR3, and it was this cap which was the limiting factor in determining the amount of capacity procured [18]. Although a monetary budget was issued by BEIS, the reference used meant that each accepted project had a limited budget impact, resulting in the capacity cap acting as the limiting factor [18]. Regardless, BEIS issues a monetary, annually capped budget for each pot of the allocation round. For a player to understand what proportion of the budget their project is represented by, auction participants are required to estimate the total amount of capacity available from the monetary annually capped budget. This calculation allows for agents to scale the monetary budget to what they expect for the amount of capacity tendered. Then they can assess how much competition they have for the budget. The same procedure is already performed for each agent in the model, as this monetary budget is transformed into an available amount of MW in each delivery year. Scaling uses the official valuation formula found in the 2014 allocation framework [14]. This slight simplification of CfD simulation models is in line with previous literature produced by Welisch et al. [6]. This is appropriate for the case study demonstrated due to the maxima cap being the limiting factor in determining the volume of capacity procurement, as explained previously.

4.2. Bid preparation

The bid preparation stage converts input project data into a CfD bid price, b_i, for a player i. The bid function $b_i(c_i, r_i)$ is a function of one's total discounted costs c_i and also the total expected discounted revenue r_i generated by a project. Costs and revenue streams are discounted to determine a b_i which gives discounted equity return (further explained in Section 4.2.2). Calculating cash flows of renewable generating projects in order to determine a bid price is consistent with previous analysis on this topic [34].

As described in Section 1, bidders are faced with significant uncertainty while bidding at auction. The uncertainty associated to their b_i is captured by the uncertainty associated to the cost component $c_i(s_c^i)$ and the revenue component $r_i(s_r^i)$. Where s_c^i and s_r^i differ for each player and are empirical distributions on an interval $[-\overline{s}, \overline{s}]$. The realisation of s_c^i and s_r^i are unknown prior to the auction, but it can be assumed that the distribution for each variable reduces over time as developers certify procurement contracts and confidence in wind farm power outputs is increased. Therefore, the bid function of participants when uncertainty is considered can be represented by $b_i(c_i, s_c^i, r_i, s_r^i)$. This function represents the bid price which needs to be achieved at auction for their project to meet the set investment criteria. Let P denote the strike price achieved at auction, q_i represent the quantity

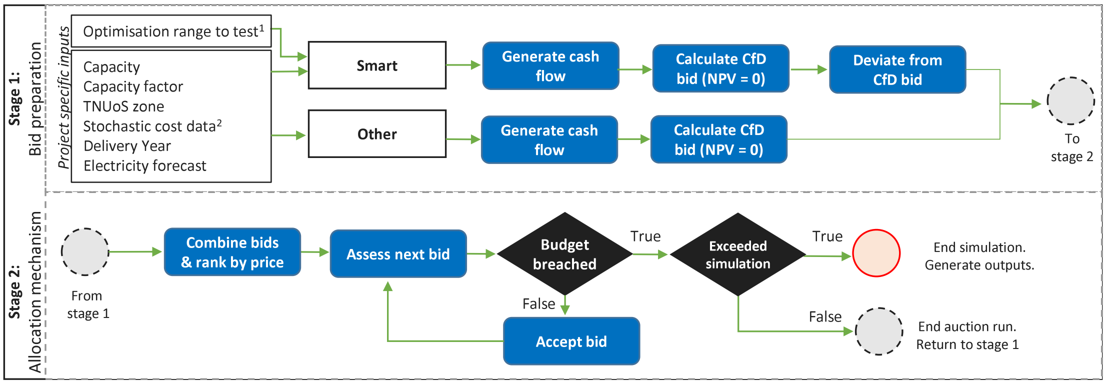


Fig. 2. High-level flow diagram illustrating one auction run process.[1] Highlights the optimum bid price range to test, which is user input and gives the *smart* agent added flexibility to deviate from the calculated CfD bid price. The range provided allows the *smart* player to test the success of a range of bids given the competition it expects.[2] Stochastic cost data includes the DEVEX, CAPEX, OPEX and DECEX.

of capacity procured by the auctioneer from player i, then the pay-off for a winning player i, who bids truthfully into the auction is shown in Eq. (2).

$$\pi_i(c_i, s_c^i, r_i, s_r^i) = q_i \cdot (P - b_i) \tag{2}$$

The pay-off for the player is dependent on the uncertainty components s_c^i and s_r^i, which reduce over time. Therefore, the winning bidder's profit might become negative, i.e., the bidder incurs a loss if realising the project. For this reason, there is value in categorising these uncertainty components s_c^i and s_r^i. Therefore, the model has inbuilt stochasticity, which makes uncertainty explicit, allowing ranges and likely outcomes to be quantitatively analysed. The advantage for strategy teams is that they can determine an estimated success rate of a selected bidding strategy and quantify the downside risk associated to the uncertainty parameters s_c^i and s_r^i.

As the inputs to the model are stochastic, for every single auction run, each project will have a different CfD bid calculated for it. Therefore, every auction run involves calculating a new bid price via the bid preparation stage. A complete simulation comprises 15,000 auction runs to average over stochastic values. The bid preparation stage consists of four main components, which are outlined in Fig. 2 and described in this subsection: (a) Project cost data assigned to each player (b) Cash flow generated (c) CfD bid price calculated and mapped to each agent (d) Game-theoretic deviation from CfD bid price.

4.2.1. Project cost data is assigned to each agent

Example inputs for one participating agent in the model are illustrated in Table 2. A previously validated proprietary stochastic cost modelling tool generates cost data for each wind farm. The cost model has been developed by Mora et al. [13]. The model uses the publicly available site and project-specific data (such as mean wind speed, foundation type and water depth) to generate project cost estimates rapidly. The costs generated from this costing model have been validated to an accuracy of ± 15%. It produces stochastic outputs based on uncertainties associated with the individual cost parameters. Stochastic values drawn from this model are used to derive an empirical distribution of costs rather than assuming a specific distribution shape. Fig. 7, shown in Section 5, illustrates the empirical distribution of costs and capacity factor generated by the cost modelling tool.

The distributions created by stochastic cost modelling represent the uncertainty experienced by players, where the true value lies somewhere on this distribution. The bid function can be represented by $b_i(c_i, s_c^i, r_i, s_r^i)$, which includes the cost and revenue streams and their associated uncertainty. Monte Carlo sampling from the distributions for the cost and revenue stream components (discussed in Section 4.2.2), which together make up the uncertainty represented by s_c^i and s_r^i, allows multiple estimates of b_i to be calculated. This produces an empirical distribution of b_i values for each player, spread over $[-\overline{S}, \overline{S}]$. Therefore, the following relationship depicted in Eq. (3) highlights the basis for Monte Carlo sampling from cost and revenue component distributions to characterise the inherent uncertainty.

Table 2
Illustrative inputs for one participating agent and the stochastic inputs in the model. The stochastic cost data generated by the cost model is empirical, meaning that the data does not fit a specific family of distributions. Importantly, the cost data inputs are interdependent. For example, for each CapEx value selected by the model, there is a corresponding capacity factor and OpEx value selected.

Input	Example data	SD of stochastic inputs
Project name	Alpha	
Capacity (MW)	1000	–
Capacity Factor	0.55%	0.025%
DevEx (£m)	100	–
CapEx (£m)	1000	23
OpEx (£m /year)	15	0.175
DexEx (£m)	75	–
Discount Rate	8%	–
Electricity forecast	Curve 3	–
Delivery Year	1	–
Location	Zone 7	–

$$b_i(S_b^i) = b_i(c_i, s_c^i, r_i, s_r^i) \tag{3}$$

As there is a trade-off between the number of auction runs and computational time, only the project costs that significantly affect the final cash flow value have been made stochastic. Therefore, the model only changes the inputs on each auction run for the capacity factor, capital expenditure (CapEx) and operational expenditure (OpEx). The development expenditure (DevEx) is not stochastic, as this total cost is small compared to the other project costs. The same applies to the decommissioning expenditure (DecEx); which has a small nominal value and is incurred at the end of a project lifetime and therefore is heavily discounted. Therefore, DecEx has a negligible impact on the cash flow. This is a simplification, as in reality, DecEx and DevEx are stochastic values. Project capacities are not assumed to be stochastic; this is because the costs generated by the cost model are reliant on a deterministic capacity value.

As the model assumes a 15-year period of exposure to market electricity prices, agents are required to forecast future wholesale market electricity beyond the CfD contract period. Forecasting allows agents to consider revenues across the lifetime of a project to optimise a minimum CfD bid. Due to difficulties in predicting future electricity prices, the model has three different scenarios ranging from optimistic outlooks (high future prices), central outlooks and pessimistic outlooks (low future prices), see Fig. 3. Typically, different electricity price curves are derived by modelling different scenarios. Factors such as

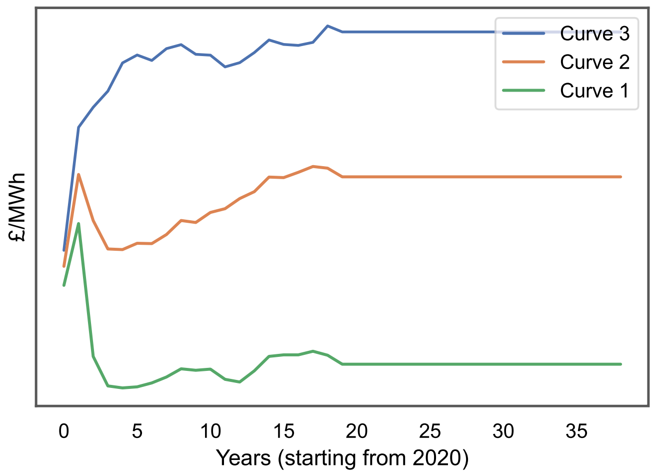


Fig. 3. Illustration of the three wholesale electricity market price curves used in the model. The curves are proprietary, so some information has been redacted.

renewable energy penetration, total demand, technological advances, load factors, and carbon fuel costs make up these different scenarios [35]. For example, a risk-averse player with a negative outlook on future electricity prices would be assigned Curve 1. This would result in a higher calculated CfD bid as the agent would attempt to generate most of the project's revenue in the first 15 years covered by the CfD contract. This would mean that if wholesale market prices at the end of the CfD contract are low, then most of the revenue for the project is already secured. However, having a negative outlook relative to other participants on forecast wholesale electricity market prices will reduce the probability of being awarded a CfD. Past bidding behaviour by specific participants can be used as an indication of risk appetite concerning future electricity price predictions.

The model considers the geographical spread of the agents by considering a wider TNUoS (Transmission Network Use of System) charge. Similarly to predicting forecast wholesale electricity market prices, it is impossible to estimate TNUoS charges for the duration of a project. This is because charges are dependent on the electricity make-up of the grid and the geographical spread between supply and demand [36]. For an electrical system as complicated as the UK, the exact figure cannot be estimated for a 40-year time horizon. National Grid ESO currently only gives forecast prices up to 5 years in advance [37]; therefore, to gain estimates for the entirety of the project, an inflation multiple of 3% (UK's Consumer price index inflation value [38]) is applied each year. Eq. (4) illustrates the equation for calculating the cost of transmitting electricity over the National Grid. Transmission cost is added to the project's total cost, c_i, which is used to calculate a bid price b_i. The equation is found on National Grid ESO's TNUoS documentation [37]. These charges are levied on generators to reflect the transmission cost of connecting at different locations and to recover the total allowed revenues of transmission owners. The cost is calculated per MWh of electricity produced. The equation is derived by taking into account the power produced by the wind farm and transmitted on the electricity grid; this is represented by multiplying the equation by the capacity, C, and the capacity factor, Cf. $YRSE$ represents the Year-Round-Shared Element, the proportion of transmission network costs shared with other zones. $YRNSE$ represents transmission costs specific to particular zones. AE represents the adjustment element, which adds a non-locational charge to the Wider TNUoS tariff to ensure that the correct amount of aggregate revenue is collected from generators as a whole. $YRSE$, $YRNSE$ and AE are location-dependent and are published by the National Grid ESO. Cf and C are known parameters and vary between wind farms.

$$c_{i,TNUoS} = C \times ((YRSE \times Cf) + YRNSE + AE) \tag{4}$$

4.2.2. Generation of cash flow

Each auction simulation round assesses every project's costs and revenue stream. The cost streams include capital, operational, decommissioning, development, rent, interest payments, tax and grid charges. Revenue streams include CfD payments, contracted power, and wholesale revenues. Fig. 4 illustrates the life stages and their respective lengths used to calculate each project's cash flow. The model assumes the same cash flow life cycle for all projects and all bids.

The DevEx cost is spread equally across the Development Period. The CapEx cost is spread equally across the construction phase. The DecEx cost is incurred entirely within the end of life phase. An OpEx (Operational Expenditure) annual estimation which includes wider TNUoS charges, is also included in calculating the cash flow. A discount rate applied to calculate each cash flow is user input and can vary between projects, which estimates a player's WACC (Weighted Average Cost of Capital). The discount rate varies accordingly to the perceived risk appetite of a player. The model includes a 2% [39] charge on revenue as a leasing cost for seabed access applied to developers of offshore wind projects. Additionally, a 19% corporate tax is levied on all revenues [40].

Revenue is calculated using the generation (MWh/year) from the project's capacity, the hours in a year, and the capacity factor. The lifetime of the wind farm T, is assumed to be 42 years for all agents, with no agents considering the possibility of re-powering. The operational lifetime consists of two main stages of 15 years; CfD years, t_b, which in principle would be covered by a potential CfD contract, and the merchant price exposure years, t_θ. The two periods utilise different electricity prices when multiplying the generation to calculate the yearly revenue. While the *merchant years* use the forecast wholesale electricity market price at year t, represented by θ_t, the CfD years use the unknown variable, referred to as the *minimum CfD bid*, represented by b_i, and calculated in Section 4.2.3. The revenues, as well as costs, are discounted by the WACC specified at the input stage. Therefore, where X_t is the total electricity in MW generated in a year, where t is the year, Eq. (5) represents how R_t the net cash flow is calculated for *CfD years*, which is $t \leq 15$, and during *merchant years* which is $t > 15$.

$$R_t = \begin{cases} X_t \cdot b_t - c_{i,t}(s_c^i), & \forall t \leq 15 \\ X_t \cdot \theta - c_{i,t}(s_c^i), & \forall t > 15 \end{cases} \tag{5}$$

In corporate finance theory, one should undertake a project if it gives a positive or zero NPV value [41]. Therefore, one can calculate a minimum acceptable b_i using Eq. (6), which gives discount equity return $NPV = 0$, as this is the minimum financial threshold required for projects to be undertaken [42]. The discount rate is represented by d.

$$NPV(b_i) = \sum_{t=0}^{N} \frac{R_t}{(1+d)^t} \tag{6}$$

4.2.3. Generation of CfD bid for each project

Once a CfD bid price is calculated for a player, it is then mapped to each agent, and agents then submit their bids $\mathbf{B}(C, b, DY)$ to the auction. Bids consist of a capacity C in (MW), a price b_i in (£/MWh), and a specified delivery year DY. The four flexible bids agents are allowed to submit must vary by different C or DY. As discussed in Section 4.2, $b_i(c_i, s_c^i, r_i, s_r^i)$ calculated for each player is a function of the total costs c, the total revenue generated r and their respective uncertainty s_c^i and s_r^i.

Using the theory described in this Section, and the life cycle stages illustrated in Fig. 4, an overall equation for deriving the minimum CfD bid for a player i can be derived, shown in Eq. (7). The equation considers four main states of an offshore wind farms life cycle, which is construction, generation under CfD contract, generation after expiry of CfD contract (explained in Section 4.2.2), and decommissioning of the wind farm. In each auction simulation, Eq. (7) is computed and

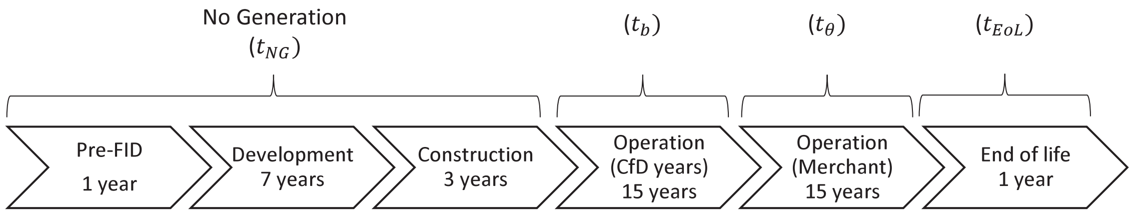


Fig. 4. Life stages and respective years t_x, of each project modelled [39].

Table 3
Table demonstrating the knowledge and capabilities of each category of agent in the model.

Capability/knowledge	Smart	Other
Competitor bid prices and capacity	Yes	No
Number of competing projects	Yes	No
Total capacity to be auctioned	Yes	No
Deviate CfD bid	Yes	No
Optimisation of $E[X]$	Yes	No

solved for b_i for each player, assuming $NPV = 0$. The auction is run many times to compute many different b_i values for varying s_c^i and s_r^i, giving $b_i(S_b^i)$, which characterises the uncertainty experienced with each players project costs.

$$NPV(b_i) = \underbrace{\sum_{t=0}^{t_{NG}} \frac{-c_{i,t}(s_c^i)}{(1+d)^t}}_{\text{No Generation}} + \underbrace{\sum_{t=t_{NG}+1}^{t_b} \frac{r_{i,t}(X_t, b_i, s_r^i) - c_{i,t}(s_c^i)}{(1+d)^t} + \sum_{t=t_b+1}^{T-1} \frac{r_{i,t}(X_t, \theta_t, s_r^i) - c_{i,t}(s_c^i)}{(1+d)^t}}_{\text{Operational}} + \underbrace{\frac{-c_{i,T}(s_c^i)}{(1+d)^T}}_{\text{End of life}} \tag{7}$$

where t is the year, T represents the lifetime of the wind farm that is assumed to be 42 years, t_{NG} is the non-generation lifetime assumed to be 11 years, and t_b is the CfD generation period assumed to be 15 years (see Fig. 4). $r_{i,t}$ is the revenue received by bidder i for their offshore wind project in year t, $c_{i,t}$ is the cost of offshore wind project for bidder i in year t, d is the discount rate assumed with a constant value of 6.3% for all players and years (see Section 5.1) and θ_t is the annual average price received by bidder i by selling electricity from its offshore wind project to the market in year t.

4.2.4. Game-theoretic deviation from mapped CfD bid for the smart player

There are two types of players characterised by the model: a *smart* player and *others*. The players differ based on their knowledge and capabilities, as shown in Table 3. The *other* players in the simulation bid truthfully and reveal their costs to the auctioneer. Bidding truthfully is how auction designers and policymakers would hope all players would act. However, the added capability that the smart player possesses allows optimisation of a bid price b_i based on increasing the expected value of its profits, $E[X]$, in £/MWh. The uncertainty means many possible probabilistic outcomes are feasible, and given the uncertain outcome, $E[X]$ gives a basis on which to select bidding strategies.

$E[X]$ is defined as the arithmetic mean of a large number of independently selected outcomes of a random variable. It can be defined by a random variable X with a finite list of possible outcomes $(x_1, \dots, x_k)$, each of which has a probability $(p_1, \dots, p_k)$ of occurring [44], as shown in Eq. (8). The outcomes and their probabilities can be summed together (shown in Eq. (9)) to obtain an expected value.

$$\mathrm{E}[X] = \pi_1 p_1 + \pi_2 p_2 + \cdots + \pi_k p_k. \tag{8}$$

$$\mathrm{E}[X] = \sum_{i=1}^{\infty} \pi_i \, p_i \tag{9}$$

The above equations are adapted to calculate the $E[X]$ of different bid prices. In the context of one auction simulation, π refers to the auction pay-off (calculated using Eq. (2)), and p_1 is either 0 or 1, dependent on whether the *smart* player was awarded a contract for that auction simulation or not. However, as $E[X]$ is probabilistic, the auction is repeated many thousand times, as competitor inputs are stochastic, so p_1 and π will vary with each auction run. Therefore, calculating $E[X]$ involves averaging over many thousand simulations. The number of simulations selected is determined from a convergence study, which is discussed in Section 5.

Therefore, to test for a bid price which maximises the $E[X]$ for the *smart* player, it deviates from the calculated b_i by a specified x amount, shown in Eq. (10). The model mechanics of determining a bid price which optimises E[X] is shown in Fig. 5.

$$b_x = b_i - x \tag{10}$$

The model collects information on the strike price, P, and whether the project was successful for each auction run. The smart player is able to predict P using its additional capabilities as highlighted in Table 3, it is then used to determine the auction pay-off. After simulating the auction thousands of times, the mean probability of being awarded a contract defined as $W\%$, at bid price b_x, can be computed. The expected value of auction profit can be calculated using Eq. (11).

$$E(b_x) = \sum_x [P(b_x) - b_i] \cdot W\%(b_x) \tag{11}$$

The $E[b_x]$ of various different bid prices are tested, in line with the user input testing range. To determine $E[b_x]_{max}$ the success of every bid price in its bid-test range is tested. Refer to Fig. 11(a) in the results section for a sample output.

4.3. Allocation mechanism

After completion of the first bid preparation stage, the allocation framework assesses the bids of all players. In this second stage, the model ranks bids in ascending order based on the bid price before accepting the required amount of capacity up to the maximum capacity specified in the *Model Set Up* stage (as described in Section 4.1). The process of ranking and sorting by the model (as shown in Fig. 2) is the same as described in Section 2.2; however, an overview of the model's allocation mechanism is given here.

The model replicates the uniform price auction format (as described in Section 3), assessing bids one at a time. If a bid is accepted, it elevates the clearing price of that delivery year to the price of the last accepted bid. All previously accepted bids will have their payment price elevated, which ensures that all successful bids of that delivery year receive the same price. Once the total maximum capacity for

Table 4
High-level overview of some of the publicly available site/project-specific input data which was used to generate cost estimations. A portion of the Seagreen project (360 MW) is connected to Cockenzie, the remaining to Tealing [43]. This split is represented in the calculation of wider TNUoS charges.

Project	Capacity (MW)	Average Depth (m)	Mean wind speed @ hh (m/s)	Distance to port (km)	Foundation type	Substation location
Doggerbank CB A	1200	23	10.68	200	Monopile	Creyke Bank
Doggerbank CB B	1200	26.5	10.68	185	Monopile	Creyke Bank
Doggerbank Teesside	1200	26	10.68	260	Monopile	Lackenby
Sofia	1400	28	10.68	220	Monopile	Lackenby
Seagreen[a]	1075	54	10.58	65	Jacket	Cockenzie[b]
East Anglia 3	1200	36.5	10.23	75	Monopile	Bramford
Inch Cape	1000	52	9.97	45	Jacket	Cockenzie
Moray West	800	45.5	10.12	70	Jacket	Blackhillock

[a]Only 454 MW of the project was awarded a CfD contract. The total capacity of the project is therefore used to generate cost estimates.
[b]Location is used to calculate TNUoS charges.

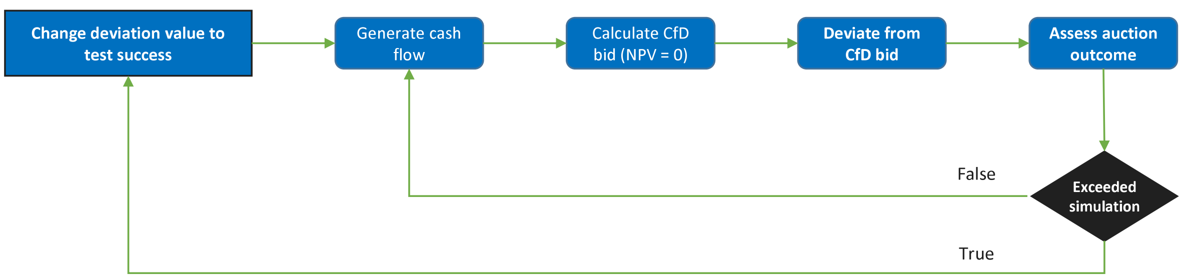


Fig. 5. Simplified flow diagram illustrating simulation for the *smart* player.

that delivery year is exceeded, then the bid which causes the capacity breach is rejected. A rejected bid results in the delivery year closing and removal from the bid stack of all bids submitted to that delivery year. The model can continue accepting bids for the second delivery year, accepting bids and updating the clearing price for that delivery year as described above. Once a bid is assessed and breaches the maximum capacity budget, the second delivery year also closes. Closure of the two delivery years results in the entire auction closing.

The outputs from one auction run of the model are as follows: A clearing price for each delivery year, successful projects, all project bids, and total capacity procured. From this, it is possible to draw out significant insights, as demonstrated in the results section.

4.4. Verification of model

There is limited value in using past auction results for validation purposes of this model. Currently, only the strike price and winners are published in the auction results [16,17]. No information is available on individual bids or details of what flexible bids may be submitted. Therefore, the model has undergone a systematic verification process to sufficiently test the model. During verification, testing fictitious test cases allows one to see if the model's outcome is as expected. The complexity of these test cases has increased until the required confidence in the model is achieved. Additionally, the model outputs are verified further through conversations with industrial and academic partners.

5. Case study and results

In this Section, a designed case study demonstrates the model's outputs. The case study described replicates Pot 2 of AR3, which concluded in 2019. This pot concerned offshore wind, remote island wind, and a small amount of biomass conversion technologies. First, Pot 2 of the auction is recreated and then the simulation results are compared to the actual auction results. The simulation does not consider non-offshore wind technology, as less than 5% was awarded to the other renewable technologies [17]. An additional case study (Case 2) is investigated to determine whether a project was able to win due to utilising more optimistic underlying assumptions than competitors. Therefore, we test the impact of modelling this project with a more optimistic view of future electricity prices. Forecasts are an important underlying assumption required in bid preparation and can significantly affect CfD bid values according to the literature [22]. Therefore, Case 2 assumes a 10% increase in this project's future electricity price forecast. All other parameters are kept constant.

5.1. Model set-up and case study assumptions

To demonstrate the game-theoretic nature of the model, East Anglia 3 acts as the *smart* player. According to post-auction analysis, this project may have narrowly lost out on being awarded a contract (see Fig. 8(a)). It is, therefore, interesting to explore if optimisation of their bid, based on estimations of competition, could have helped this project succeed. This project will therefore have additional capabilities and knowledge of other competitors' bids. It can thus use this competence to test for the existence of an optimum bid price that maximises $E[X]$.

For each project participating in AR3, the aforementioned cost modelling tool described in Section 4.2.1 generated 1000 empirical stochastic cost values. This number of total cost values is chosen as there is a strong convergence of results after 1000 simulations per bid price (see Fig. 6). This cost data was then input into the model. The range of bid prices tested is [−3,5], with an interval of 0.5. This range was chosen as it considers a wide possible bid range which also identifies a peak in the $E[X]$ graph (see Fig. 11(a)). The selected test range means that, in total, the *smart* player tested 17 bids. As there are 1000 auction simulations for every bid price tested by the model meaning that the output graphs are averages of 17,000 auction simulations. The projects modelled utilise publicly available site-specific and project-specific data to generate cost inputs from a stochastic cost modelling tool. Table 4 illustrates a high-level overview of the inputs used to generate the cost data. The generated cost data for each project is shown in Table 5, and the distributions for the stochastic inputs are shown in Fig. 7.

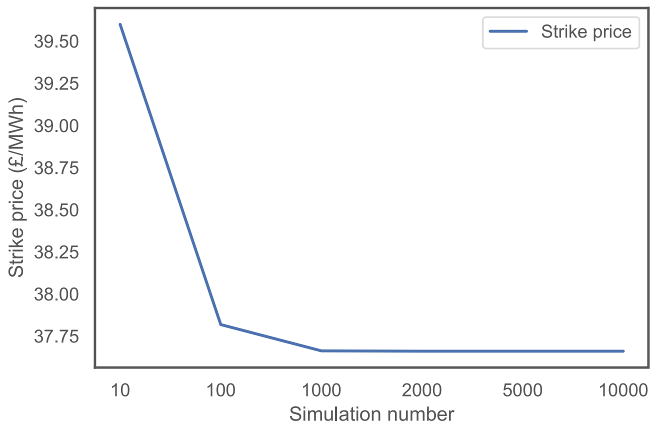


Fig. 6. Convergence of strike price results for the first delivery year, with varying simulation numbers.

The following assumptions are the author's own and are used to simulate the case study described in this paper. The assumptions are required to reduce the complexity surrounding unknowns of the auction process and do so without sacrificing too much detail of the auction design. For example, one cannot accurately guess what forecasts or WACC each player uses. Therefore, keeping these figures the same for all players is sensible.

1. **All players use the same forecast wholesale electricity market prices** — Future wholesale electricity prices 30 years into the future are extremely difficult to predict. Therefore, forecasts can vary significantly between developers and impact CfD bids significantly. All players use the same curve to keep calculations relative, with an average market price forecast of £55 MWh for the next 30 years.
2. **Agents do not submit flexible bids** — Although the model can handle flexible bids, it is not considered for simplification purposes. In reality, players can submit variations of their primary bid by varying the total amount of capacity in their bid. However, the actual flexible bids submitted by each player for each project cannot be predicted with significant confidence. Doing so would only increase the uncertainty associated with the inputs. Therefore, only two bids per player are submitted (one for each delivery year), with the capacity of this bid equal to either the entire size of the consented project (for unsuccessful projects in AR3) or the amount of subsidy awarded (for projects which were successful in AR3). However, for Seagreen Phase 1, which achieved a partial capacity award, bids submitted are for 454 MW; however, the full capacity of the site determines the CfD bid price.
3. **Total capacity budget available is 5500 MW** — Based on the total amount of awarded subsidy for the AR3 offshore wind pot, this is likely to be a close estimate of the total capacity budget available at AR3. This budget is split evenly between two delivery years, assuming that policymakers would like to evenly stagger the amount of capacity that comes online between two delivery years. A capacity budget is used instead of a monetary budget for the reasons described in Section 4.1
4. **Exclusion of Remote island wind projects** — Remote island wind was able to compete against the offshore wind in AR3. These projects were awarded 275 MW of capacity, significantly smaller than the total budget. Therefore, these projects have been excluded from this simulation, and the available budget is slightly adjusted to account for this.
5. **The discount rate assumed for all players is 6.3%** — Discount rates used by different players are likely to vary based on risk appetite and business models. Variation between players cannot be predicted; therefore, all players use the same central discount rate, based on official 2020 BEIS estimates [45].
6. **Each player submits the same bid into both delivery years** — In CfD auctions and therefore represented through this simulation, each delivery year is essentially a separate auction, with each delivery year attempting to procure a certain amount of capacity. Therefore, to maximise the possibility of being awarded a subsidy, players are likely to submit bids into both delivery years to maximise the subsidy for which they compete. Furthermore, as delivery year options are only one year apart, cost degression resulting in CfD bids decreasing in the second delivery year is considered negligible. Therefore, the CfD bid submitted for all players for both delivery years is the same for both capacity and price.
7. **An administrative ceiling price set at £56 MWh** — This is the same as the ASP published by the UK government prior to AR3 concluding [20].

In Case 2, the Seagreen project uses a 10% increase in forecast wholesale electricity market prices. Case 2 tests the hypothesis that Seagreen was awarded a subsidy in AR3 and could do so by utilising more optimistic underlying assumptions, despite potentially higher generation costs.

5.2. Simulation results

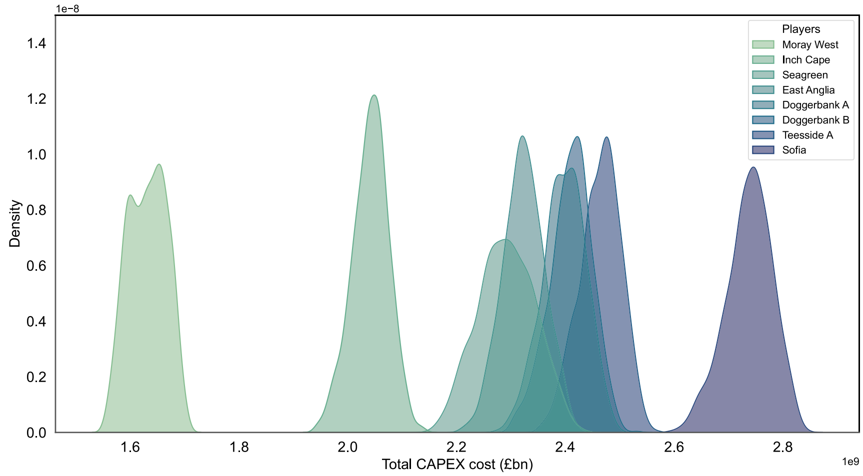
Fig. 8 illustrates the most likely clearing prices predicted by the stochastic simulations. The figures show the most likely clearing price for the 23/24 delivery year, with a 22.5% probability of occurrence is £38/MWh. The most likely clearing price for the 24/25 delivery year with a 22.5% probability of occurrence is £42/MWh. There is approximately a 10% increase in strike price predicted from the first delivery year to the second. Additionally, the range of clearing prices obtained from the simulation is £30.31/MWh to £43.77/MWh, with a standard deviation of 1.78 for delivery year 23/24. For delivery year 24/25 the range is £34.89/MWh to £50.24/MWh, and with a standard deviation of £1.98/MWh for 24/25.

In Case 2, Seagreen modelled with a 10% increase in forecast wholesale electricity market prices. Fig. 9 demonstrates that the predicted clearing price is largely unchanged, and the most likely outcome is a strike price of £38/MWh and £42/MWh for delivery years 23/24 and 24/25, respectively. The simulated clearing price range for Case 2 is between 30.65 and 44.64, with a standard deviation of 1.77 for delivery years 23/24 and a range of between 34.90 and 50.54, with a standard deviation of 1.98 for 24/25.

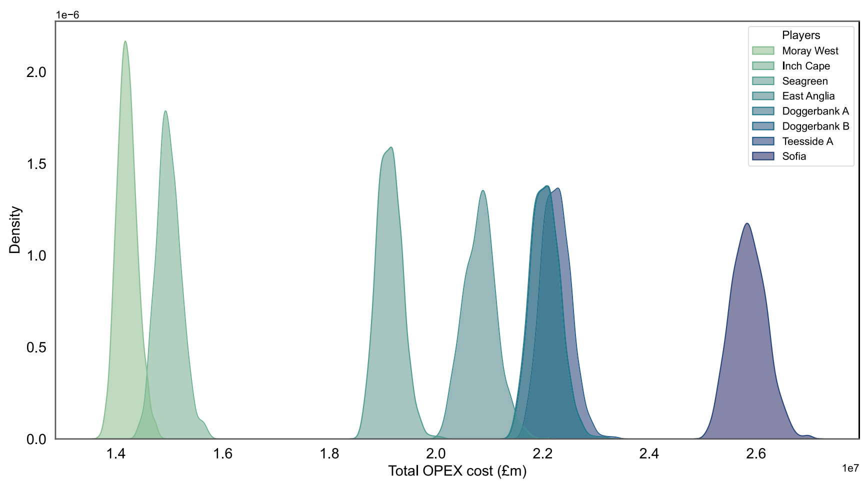
Fig. 9 illustrates the spread of bid prices submitted by each project. The figures are in ascending order, sorted by the median bid price; this demonstrates the merit order of projects. In both cases, the Doggerbank projects have the lowest bid prices. Conversely, the three Scottish projects have a significantly higher spread of bid prices. Between these two projects, there is a spread of close to £10 - £20 MWh in median bid prices.

For Case 2, seen in Fig. 9, Seagreen's median bid price decreases from £53.15 MWh to £50.52 MWh. This is a 5% reduction in the median bid price. As a result, it goes up one place higher in the merit order of projects.

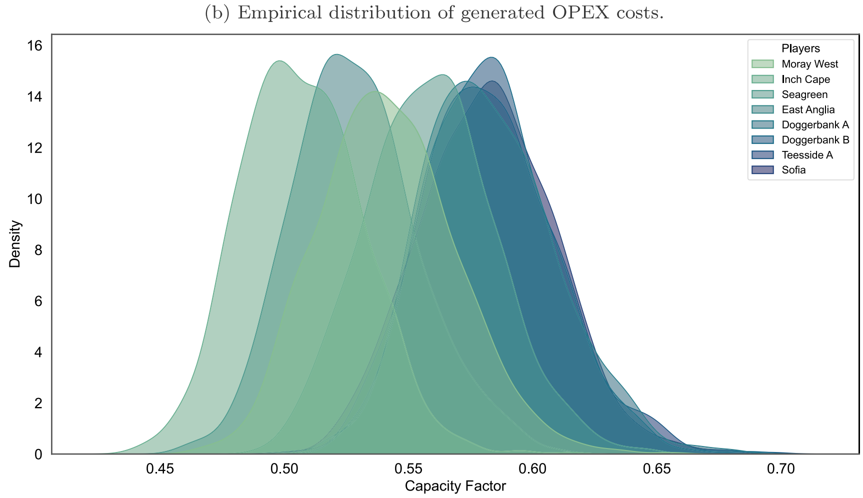
The translation of median bid prices into the probability of being awarded a subsidy is seen in Fig. 10. Sofia, Doggerbank A and Doggerbank B are predicted to be successful with high certainty (>92%). On the other hand, the three Scottish-based projects with the highest bid prices have a very low chance of success (<1%). Fig. 11(b) shows the effect that an increase in forecast electricity prices has on the probability of success. Increasing this assumption by 10% for the Seagreen project increases the probability of success by 5 p.p.



(a) Empirical distribution of generated CAPEX costs.



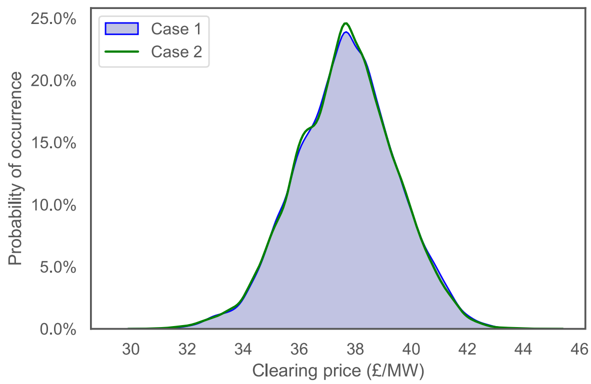
(b) Empirical distribution of generated OPEX costs.



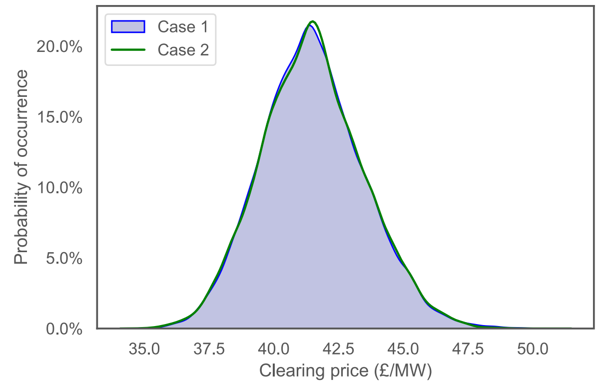
(c) Empirical distribution of generated Capacity Factors.

Fig. 7. Distributions of stochastic inputs for each player in case study.

Fig. 11(a) identifies an optimum bid for the smart player based on the objective function, which is $E[X]$. $E[X]$ is calculated based on the smart player's perception of the level of competition and competitors' project costs and assumptions, as outlined in Section 4.2.4. The peak on the graph is evidence of the highest $E[X]$ and, therefore, the optimum bidding strategy according to E[X]. According to $E[X]$, the optimum bidding strategy is for East Anglia 3 to increase its minimum CfD bid price by + £2.5/MWh. In monetary terms, this would lead to an increase in expected profits of approximately £9 million per year for the 1200 MW site and £135 million additional expected profit during the 15-year contract length of the CfD and £135 million in additional profits during the 15-year contract length of the CfD. There is an obvious trade-off, as the resultant increase in expected profit results in a decrease in the probability of winning by 25%. The estimated



(a) First delivery year



(b) Second delivery year

Fig. 8. Histogram illustrating the expected clearing price for the two delivery years of AR3 based on empirical stochastic cost data.

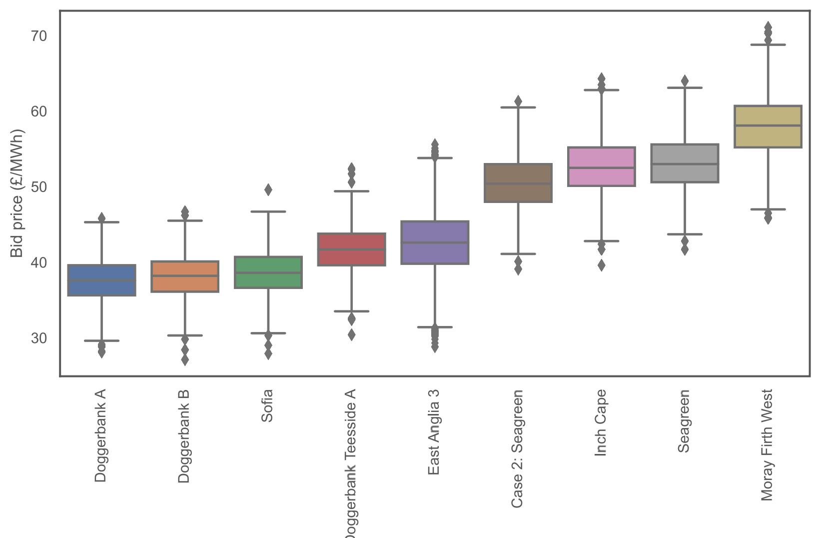


Fig. 9. Box diagram illustrating the merit order of projects which bid into the offshore wind AR3 pot, in ascending order. For Case 2: Seagreen, the project is based on the Seagreen project, but modelled with a 10% increase in forecast electricity market price.

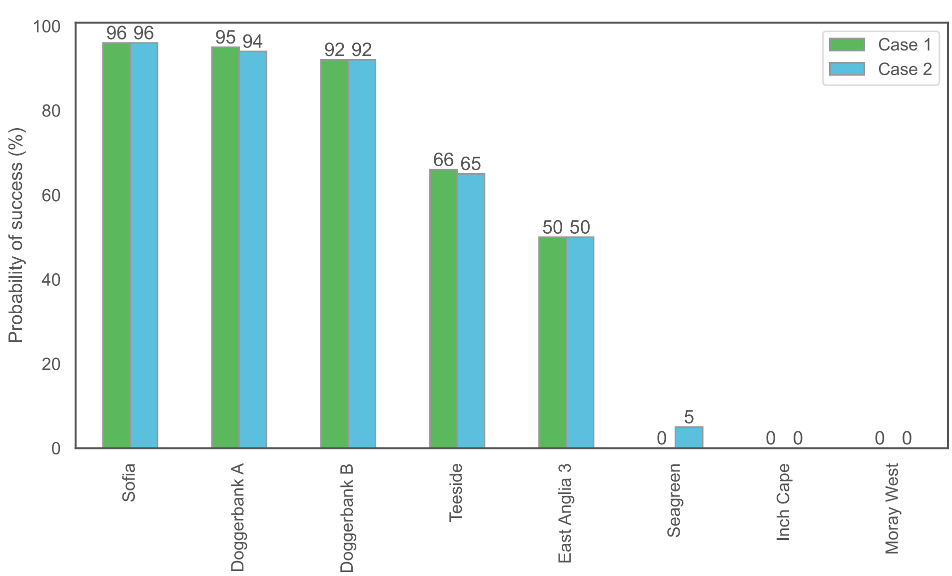
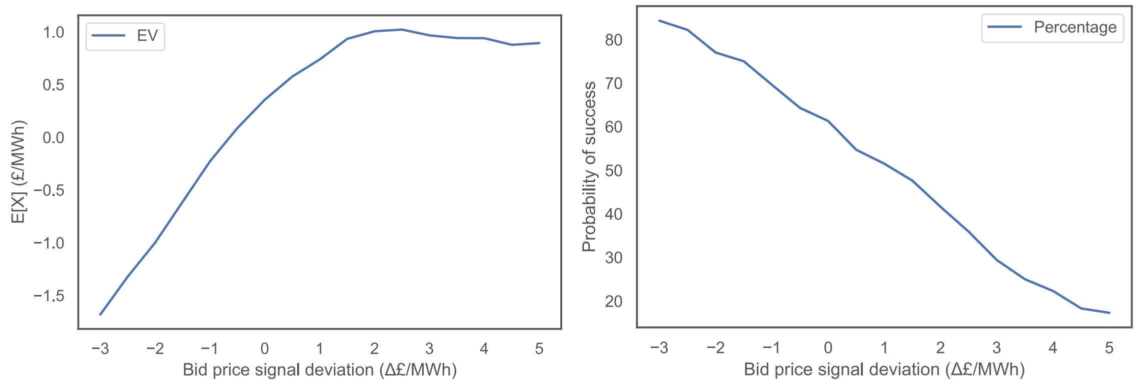


Fig. 10. Percentage win rate of different projects estimated by the stochastic simulations.



(a) Expected Value optimisation plot

(b) Probability with change in bid price

Fig. 11. 11(a) Graph illustrating how expected value changes with deviations from cost. When bid price signal deviation is equal to zero, the *smart* the player is considered to be bidding at cost. 11(b) Graph illustrating the linear relationship between the increase in the bid price and the probability of being awarded a subsidy.

Table 5
Overview of cost input data used to generate a bid price for each player.

Project	Capacity (MW)	DEVEX (£m)	CAPEX[a] (£m)	OPEX[a] (£m/year)	DECEX (£m)	Capacity factor[a]
Doggerbank CB A	1200	80.1	2398.0	21.8	76.4	0.555
Doggerbank CB B	1200	104.5	2410.9	21.9	76.7	0.555
Doggerbank Teesside	1200	86.4	2506.5	22.1	76.5	0.554
Sofia	1400	120.9	2775.9	25.6	90.5	0.554
Seagreen	1075	68.3	2242.6	18.9	60.3	0.505
East Anglia 3	1200	79.8	2321.1	20.9	80.2	0.527
Inch Cape	1000	60.2	2039.0	14.8	58.4	0.505
Moray West	800	55.5	1645.9	14.0	52.0	0.532

[a]Inputs marked, show the median data for stochastic inputs, distribution of stochastic data is shown in Fig. 7.

percentage chance of East Anglia 3 being awarded a subsidy at a + £2.5/MWh price deviation from the minimum calculated bid price is 36%. It is an operational decision by developers to analyse on a case-by-case basis to assess their appetite for risk.

5.3. Comparison of auction results and numerical prediction results

There are two main auction results to analyse and then discuss. The first is determining whether the strike prices agreed at auction align with simulation results. Strike prices from AR3 were lower than analysts anticipated, a 30% reduction compared to the lowest clearing price achieved in AR2. Secondly, does the award of subsidies in AR3 follow the estimated merit order of projects? In other words, was the allocation process at AR3 efficient in allocating subsidies to the projects with the lowest generation cost?

To compare the simulation results to the actual outcome of AR3, which concluded in AR3, a short overview of the auction results is given in Table 6. There is currently no published literature which has been analysed using simulation of the described case study (AR3) or a CfD auction results. For this reason, comparison with previously available work is not possible. AR3 procured 5775 MW of capacity across all pots, with 95% of capacity awarded to offshore wind. For a full results list, refer to the UK government announcements [17]. A total of 3034 MW of eligible Offshore Wind projects were unsuccessful in obtaining a CfD in AR3. The likelihood is that the unsuccessful projects: East Anglia 3, Inch Cape, and Moray Firth West, will re-attempt to win a CfD subsidy by participating in AR4.

The two strike price results agreed at auction for AR3 are £39.650 /MWh and £41.611/MWh for the delivery years 23/24 and 24/25, respectively. The model replicates these results well. The model predicts these clearing price outcomes for each delivery year with a 14% and 22% probability (see Fig. 8). These outcomes are some of the highest probabilities as predicted by the simulation, which has a large possible strike price range due to the high level of stochasticity of the inputs to the model. As predicted by the simulations, the mean price for both delivery years is £37.675/MWh and £41.495/MWh, a 5% margin of AR3 results. Suggesting that developers, through the utilisation of cost modelling tools and publicly available information, are likely to be able to predict the clearing price with some confidence before entering the auction. Predictions of clearing prices will help formulate a bidding strategy. For example, a risk-averse bidder could adjust their bid to below the central expected clearing price to increase their chances of winning. However, developers must have confidence in their predictions and must be able to make reasonable assumptions on competition, project costs, and future wholesale electricity market price predictions.

The outputs of the model suggest that the CfD auction is reasonably efficient at awarding subsidies based on a merit order (as highlighted in Fig. 9). The model predicts three of the winning projects (Doggerbank CB A, Doggerbank CB B, and Sofia) to win with high certainty. This is because all three sites have preferable site characteristics (e.g. high mean wind speeds, mean depths) and low grid charges and therefore are likely to have the lowest generation costs. All three Scottish projects (Moray Firth West, Inch Cape, and Seagreen) are unlikely to win. As the site characteristics modelled for the Scottish and Doggerbank projects are similar, it would appear that a key differential to the merit order of projects appears to be the geographical spread of wider TNUoS charges. Transmission costs are significantly higher in unsuccessful projects. Fig. 12 supports this statement, as it highlights the sensitivity of location on CfD bid price. A one-at-a-time sensitivity analysis generates outputs for this graph, as all input parameters are kept constant with varied locations. TNUoS is calculated in the model as described in Section 4.2.1. Fig. 12 shows that CfD bids are significantly higher in Scotland than in England & Wales as a result of the higher TNuOS charges. This example utilises the inputs for the Seagreen project as highlighted in Table 4. Due to the importance of winning a CfD contract

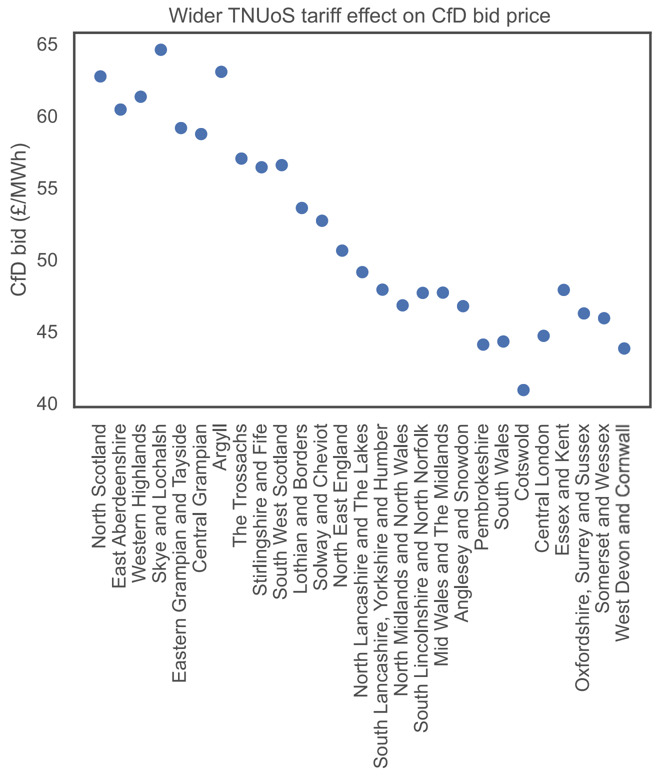


Fig. 12. Effect of geography on CfD bid as a result of transmission charges, which vary significantly by geography.

Table 6
A high-level overview of AR3 Pot 2 auction results. Successful projects are shown with a strike price. Successful Remote Island Wind projects have been excluded.

Project	Owner (s)	Capacity (MW)	Strike price (£/MWh)
Doggerbank CB A	SSE & Equinor	1200	39.650
Doggerbank CB B	SSE & Equinor	1200	41.611
Doggerbank Teesside	SSE & Equinor	1200	41.611
Sofia	Innogy	1400	39.650
Seagreen	SSE	454[a]	41.611
East Anglia 3	Scottish Power	1400	–
Inch Cape	Red Rock Power	754	–
Moray West	EDP Renewables	850	–

[a]Only 454 MW of capacity was awarded for a total project size of 1075 MW [17].

for developers, this is evidence that TNUoS charges may act as a barrier to the delivery of renewable projects in Scotland.

Considering the significant impact TNUoS zones have on CfD bids and the merit order as highlighted in Fig. 9, it is surprising that Seagreen was awarded a subsidy. In Case 1, Seagreen was only expected to win in 0.4% of simulations. This is potentially an example of auction inefficiency, where a project low down on the merit order was able to be awarded a subsidy ahead of East Anglia 3, which has a lower estimated generation cost. This auction inefficiency should be mitigated by the auctioneer to generate better value for electricity consumers. Its position on the merit order can be attributed largely to the higher TNUoS charges. The analysis shown in Fig. 12 results in an £11.25/MWh increase in CfD bid price when comparing the Seagreen projects to Doggerbank A&B. This represents approximately 70% of the cost difference between the projects.

Several potential rational answers explain how Seagreen may have been awarded a subsidy. Firstly, Seagreen may have strategically bid into the auction by bidding significantly below cost to gain subsidy for a proportion of the consented project. Secondly, the developer may have chosen more optimistic bid assumptions considerably. Thirdly, SSE, the owner of this project which secured a CfD for 2254 MW of projects in which they have equity, was able to realise significant savings during procurement (e.g. cables, turbines) due to economies of scale. Lastly, inaccuracy in site assumptions and the cost modelling tool used to cost the Seagreen project could have underestimated its position on the merit order of projects.

Due to uncertainty in understanding Seagreen's exact project cost, it cannot be said with any definitive confidence whether they were successful in bidding strategically or if economies of scale impacted their success. However, results show that utilising more optimistic underlying bid assumptions such as forecast wholesale electricity market prices can increase the probability of winning. For example, doing this with Seagreen resulted in the median bid price of the project decreasing by £2.2/MWh, although it did not move substantially up the merit order. However, the percentage chance of Seagreen winning increases to 5.2%. Therefore, it is feasible that Seagreen could have been awarded a subsidy by using more optimistic assumptions; however, the probability is remote. In this simulation, more drastic changes in the Seagreen underlying bid assumptions are required to position itself higher up the merit order and increase the likelihood of winning.

The results from the simulation are close to the actual AR3 results while assuming in the simulation that players bid at cost. However, one cannot conclude that it is typical for players participating in CfD auctions to bid at cost. This is because the actual cost of players is difficult to determine (due to the number of bid assumptions required, e.g. WACC and forecast wholesale electricity market prices). One would have to obtain from each developer their underlying cost value and bid assumptions to determine whether players bid truthfully and bid at cost at AR3.

6. Conclusion

This paper has introduced and described the methodology behind a novel stochastic, game-theoretic modelling approach, which provides insights into the CfD auction and assists bid preparation. The model utilises a proprietary cost modelling tool to generate stochastic cost estimations for projects which competed in the offshore wind pot of AR3. Several assumptions, such as discount rate, forecast wholesale electricity market prices and TNUoS forecasts, have been assumed for all players. Assessment of revenue and cost streams over a project's lifetime allows for the optimisation of a CfD bid price for each player. Finally, based on a *smart* player's additional capabilities and knowledge of the competition's projects, it has attempted to optimise its bid price based on E[X].

The simulation of this CfD auction has demonstrated that developers would have been able to predict the strike price of the auction with reasonable confidence prior to bidding. This means that they would have been able to adjust their bids according to their risk appetite. A method of quantifying this risk-reward trade-off through optimisation of expected profits has been demonstrated. Analysis shows projects could increase their total profits by £135 million over the length of the CfD in return for a decrease in the probability of winning by 25 pp. The results show that the allocation of subsidies in AR3 does not strictly follow the merit order of projects. Auction inefficiencies may suggest that some projects were successful in strategically bidding into the auction.

Three projects in Scotland had a significantly higher mean CfD bid of approximately £15/MWh on average, thus hindering the probability of success at auction. This is largely attributed to the higher TNUoS charges incurred by Scotland-based projects. Transmission charges account for an extra £11.25/MWh on generation costs compared to the transmission charges incurred by Doggerbank A&B. This is likely to be a notable barrier for Scotland-based projects to be awarded CfD subsidies in future auctions.

Interesting model expansions could include increasing the *smart* game-theoretic capabilities to all players and observing what effect it will have on the auction outcome if all players attempt to optimise based on E[X]. Finally, further research could assess the impact of human behavioural processes and the effect this has on individual players and the auction outcome as a whole.

CRediT authorship contribution statement

Nicholas P. Kell: Conceptualization, Methodology, Software, Validation, Investigation, Data curation, Writing, Visualization. **Adriaan Hendrik van der Weijde:** Supervision, Review & editing. **Liang Li:** Supervision, Review & editing. **Ernesto Santibanez-Borda:** Supervision, Review & editing. **Ajit C. Pillai:** Supervision, Review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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