DEALING WITH UNCERTAINTY WHILE DEVELOPING BID STRATEGY FOR CFD AUCTIONS.

Nicholas P. Kell[a,b,*], Ernesto Santibanez-Borda[b], Thomas Morstyn [a,c], Iraklis Lazakis[a,d], Ajit C. Pillai[a,e]

[a]Industrial Doctorate Centre for Offshore Renewable Energy, The University of Edinburgh, Edinburgh, UK
[b]EDF Energy R & D UK Centre, London, UK
[c]School of Engineering, The University of Edinburgh, Edinburgh, UK
[d]Department of Naval Architecture, Ocean, and Marine Engineering, University of Strathclyde, Glasgow, UK
[e]Renewable Energy Group, College of Engineering, Mathematics, and Physical Sciences, University of Exeter, Penryn, UK

Abstract

Offshore Wind installed capacity has grown dramatically in recent years. In the UK, this success can in part be attributed to the CfD (Contracts for Difference), the UK government's primary policy mechanism for subsidising low-carbon generation. This is a promising policy tool for achieving renewable targets. However, there are a number of risks involved for both auctioneer and bidders. Bidders are faced with many sources of uncertainty when analysing their project costs and future revenues, which is required in order to develop a bidding strategy. The uncertainty faced by auction participants can result in the non-realisation of projects, which poses a major risk to governments meeting their expansion targets. The auctioneer can take a number of measures to reduce the non-realisation of projects such as increasing the CfD contract length and limiting a wind farm's exposure to volatile wholesale electricity prices. In this paper, a sensitivity analysis is carried out on a stochastic, agent-based modelling approach, which utilises game-theoretic principles to generate optimum bid strategies for generators attempting to win a CfD contract. The sensitivity analysis is conducted by replicating the Allocation Round 3 (AR3) as a base case. This auction was held in 2019 in the UK. Empirically derived stochastic data obtained from a previously validated proprietary cost modelling tool is used to map each agent to a real-life project that participated in AR3. The results show the importance of estimating the capacity factor and capital expenditure and thus highlight where resources to reduce uncertainty should be focused by auction participants. This paper then analyses the effect of increasing CfD contract length on the uncertainty experienced by bidders. A trade-off appears between significantly reducing uncertainty for bidders and increasing the net present value of support payments to developers. The results also show that in a number of high-medium economic growth scenarios, governments can expect to receive net positive payments from awarding CfD contracts to fixed-offshore wind developers. Revenue generated can be used to further subsided *less-established* technologies and deliver savings for electricity consumers.

1 Introduction

Offshore Wind capacity has grown dramatically in Europe in the last decade, with cumulative offshore wind power capacity increasing from 5 GW to 28 GW in the years 2012 - 2021 (1). The majority of which have been installed in the UK (2). This has been possible due to the rapid cost reduction of offshore wind, whose success can be attributed in part to the financial support offered by the CfD support scheme. This is the UK government's primary policy mechanism for subsidising renewable energy generation and guarantees generators a fixed price for the electricity that they generate over a 15-year contract (3). The support mechanism reduces revenue risk by protecting developers from volatile wholesale prices and therefore reduces the cost of raising debt for financing projects. For many offshore wind developers, winning a CfD contract subsidy is considered the most viable route to market.

CfD contracts are awarded in competitive auction processes. Auctions enable policy-makers to control the expansion of renewable through the selection of the auctioned volume or a budgetary envelope (4). In the CfD auction, the auctioneer procures an amount of capacity from auction participants. Generators are required to submit a bid price for the capacity they wish to be subsidised or *sell*. Preparing an optimum bid for a project in these increasingly competitive auctions from a renewable developers' perspective is challenging. They must assess future revenues and cost streams for a project which is yet to be constructed and will have a generation period of up to 30-years. Therefore, there is significant uncertainty associated with bidding at auction. For example, there is uncertainty associated with one's own exact costs, those of the competition, future grid charges and future wholesale electricity prices (5). Getting one's bidding strategy correct is important. Developers who bid too high and fail to win a contract, are likely to incur project delays as they wait for the next allocation round. On the contrary, a contract-winning developer who does not quantify its own costs properly may bid too low and experience the winners' curse (6). Uncertainty experienced by participants can also have implications for policy-makers. It can lead to allocation inefficiencies and allow intrinsically worse sites to be awarded subsidies. This can lead to the non-realisation of projects, as winners whose uncertainty is reduced over time (e.g. receive better information on their own project costs), later discover that the project is economically unviable at the awarded CfD strike price. (7).

To better characterise this uncertainty, strategic analysis in the form of simulation allows for better bid preparation (8). The proposed paper presents an agent-based modelling approach, which utilises game-theoretic principles to generate optimum bid strategies for generators attempting to win a CfD contract. The model has use cases and potential implications for policy-makers and renewable generators alike and has been developed in partnership with industrial partners with active participation in CfD auctions.

In this paper, a sensitivity analysis of this model is produced, demonstrated by replicating the UK's Allocation Round 3 (AR3) which was held in 2019 as a base case. Empirically derived cost data obtained from a previously validated proprietary cost modelling tool (9) is used to map each agent to a real-life project that participated in AR3. Sensitivity analysis identifies the relative importance of inputs and characterises their impact. This highlights where resources to reduce uncertainty should be focused on by auction participants. This paper then highlights recommendations, evidenced by simulation, of how uncertainty can be mitigated by policy-makers to ensure value for money by electricity consumers. This is done by analysing the effect different CfD contract lengths have on reducing revenue uncertainty experienced by participants by decreasing their exposure during the lifetime of the offshore wind farm to volatile wholesale electricity prices.

The remainder of this paper is structured as follows: Section 2 discusses key elements of the CfD auction design and allocation process. Section 3 reviews the theoretical background and the state-of-the-art of dealing with uncertainty in renewable investment modelling. Section 4 gives an overview of the CfD bid simulation model. Section 5 details the approach and methodology of the analysis before introducing an offshore wind case study to which the methodology is applied. The results of the analysis are then presented in Section 6. Finally, Section 7 analyses the results before drawing conclusions and implications for the various stakeholders.

2 CfD auction design

The CfD is a private law contract between a generator and a government-owned company, the Low Carbon Contracts Company (LCCC). 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 at an agreed market reference price. If this reference price is below the strike price, the generator receives the difference. On the contrary, if the strike price is below the reference price, then generators pay back the difference to the LCCC. This means that the generator is guaranteed to sell the electricity at a fixed price (10). The CfD mechanism does not protect developers from potential negative prices, this is to encourage generators to act sensibly in helping to balance the grid (11). The strike price is however adjusted yearly to account for inflation and other minor adjustments, as outlined in a report issued by the LCCC (12).

The allocation process for CfD contracts is as follows: The process begins with National Grid inviting eligible applicants to bid for the available budget in each pot. In order to compete in the allocation process, bidders must first satisfy a number of pre-qualification criteria. These include that they must have obtained all the necessary consents for their site, as well as a grid connection agreement. Additionally, if the total capacity of the site exceeds 300 MW, then a supply chain plan which outlines how the project will promote competition, innovation, and skills in the supply chain must be submitted and approved.

Developers submit bids that include the technology type, the price, capacity, and the delivery year of the project. In the UK scheme, applicants are permitted to submit up to a total of four *flexible* bids into the auction. These are sealed bids with varying capacities and/or Target Commissioning Dates, of which no more than two bids may have a Target Commissioning date in the same Delivery Year (13). National Grid then ranks all the submitted projects in the same pot based on their submitted bid price, regardless of the delivery year. The flexible bids of a project are considered if that project's costs exceed the budget cap when it is added to the cost of already awarded projects. If the flexible bids of this project also result in a budget breach, then the auction is closed and no other bids are considered.

In the unlikely case that 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 ASP is set by the auctioneer and is the ceiling price which can be awarded to a technology. More information on the UK implementation of CfDs for renewable energy can be found on the government website, as well as detail as to how the ASP is set (14).

3 Theoretical background and literature review

To understand the significance of uncertainty when making long term investment decisions in large capital-intensive renewable projects, it is important to first consider how CfD bids are calculated by generators and the relevant literature concerning renewable investment decision making.

A CfD bid price can determine the revenue stream for renewable projects for a significant proportion of a wind farm's lifetime. Therefore, it is important that CfD bids are carefully considered, allowing developers to cover costs and give investors the required return on their investment. In order to do this, all cost streams and revenue streams are analysed throughout the entire lifetime of the wind farm, up to 30 years. This is required to estimate the project's cash flow and then optimise a CfD bid price which gives a discount equity cash flow (NPV = 0). However, estimating the cash flow is challenging, as every cost stream and revenue stream component will have uncertainty attributed to it. For example, TNUoS (Transmission Network Use of System) charges which are levied on generators for use of transmission infrastructure must be forecast for the 30 year generation period of the farm. The future development of material costs is also an example of a key uncertainty.

Wholesale electricity price forecasts can also have a significant impact on one's calculated CfD bid. The CfD scheme lasts for 15 years, while the expected lifetime of an offshore wind energy asset is 30 years. After which the electricity output is sold at market price, this imposes significant uncertainty on future revenue streams. For this reason, forecasting future wholesale electricity prices is pertinent to predicting an optimum CfD bid price. Ioannou et al. (15) studied the effect electricity market price uncertainty has on the long term profitability of offshore wind developments. The analysis used different statistical techniques to predict future market prices, demonstrating how each different method yields vastly different profitability estimates.

Kreiss et al. (7) highlighted the impact of uncertainty on RES (renewable energy subsidy) auctions by using auction theory. It is explained that the non-realisation of projects, is a major risk for auctioneers achieving expansion targets. The main reason for the non-realisation of projects is due to uncertainties concerning bidders' project costs and revenue streams. The paper then discusses how auctioneers can take various measures to mitigate this uncertainty. One such measure discussed is the introduction of financial and physical prequalifications and penalties. However, there are other such mechanisms at the auctioneers' disposal in order to reduce uncertainty. One such method is to reduce generators' exposure to wholesale electricity prices by increasing the length of the CfD contract.

Analysis conducted by BEIS in 2013, (16) investigated the optimum CfD contract length. It found that a 15-year contract length was optimal as it provided the lowest NPV of support payments to developers. However, this work was done on the basis of offshore wind being a *less-established* technology, which at the time had high generating costs. Therefore, the principal role of the CfD was to act as a subsidy mechanism to allow offshore wind projects to be commercially viable. However, since then as the cost of offshore wind generation has plunged, the primary role of the CfD auction has switched from subsidising to providing revenue certainty. This means that as a result of the pay-back mechanism (as described in Section 2) under sustained periods of high wholesale electricity market prices the LCCC can feasibly expect to receive a net positive payment from developers during the CfD contract length. For this reason, it is worth repeating this analysis under a range of economic growth scenarios.

To the best of our knowledge, there is currently no published academic literature which characterises and quantifies the relative importance of inputs through a sensitivity analysis, in order to demonstrate how uncertainty affects CfD bid preparation. The literature survey suggests that there have been attempts to demonstrate how uncertainty related to specific inputs, such as future wholesale electricity price forecasts, can have on the estimated NPV of sites. However, to the best of our knowledge, no literature has combined a CfD auction simulation model with cost modelling data of actual sites, to explore how uncertainty can vary both the expected profitability of sites and the calculated CfD bid price. Furthermore, no recent published literature has analysed the effect of CfD contract length on the uncertainty experienced by participants and the NPV of support payments made by the government. The following gaps identified in the literature are therefore carried out in this paper, and the methodology is outlined in the below section.

4 Model methodology

This section gives an overview of the model which has been used to conduct the analysis as described in Section 1. The numerical framework recreates the CfD allocation mechanism as specified by the CfD allocation framework produced by BEIS (17) and explained in Section 2. It does this through the utilisation of the Python framework for agent-based modelling, Mesa (18). An overview of the model is given in this section. For a more detailed overview of the model, please refer to work produced by Kell et al. (19).

4.1 Model Overview

As discussed in Section 3, there is significant uncertainty associated with developing an optimum bidding strategy. Therefore, to better categorise this uncertainty, the model has been built with stochastic functionality. Therefore, each complete simulation typically contains over 20,000 auction runs to average over stochastic inputs. One auction run contains two main stages defined as Bid Preparation and Allocation Mechanism. This is highlighted in Figure 1, and is explained in greater detail in Sections 4.2 and 4.3. The model also has an additional feature which utilises game theory to optimise a bid price for a smart player. The methodology of this feature can be seen in Figure 1. This figure highlights an optimisation range to test, which is user input and gives the *smart* agent added flexibility to be able 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 and the associated bids that it expects. However, this feature is not utilised for the results of this paper due to the limited scope of this work. Expanded scope of work could investigate how uncertainty affects the strategic bidding (defined as bidding at expected value and not at cost) for a smart player. Therefore, assessing if uncertainty experienced by players encourages/discourages players to engage in strategic bidding.

To initiate the auction, the model uses a slight simplification, a ceiling strike price and the total capacity of electricity to be procured is specified by the auctioneer. In reality, participants in UK CfD auctions have to estimate which amount of tendered capacity is represented by the annual budget. There-

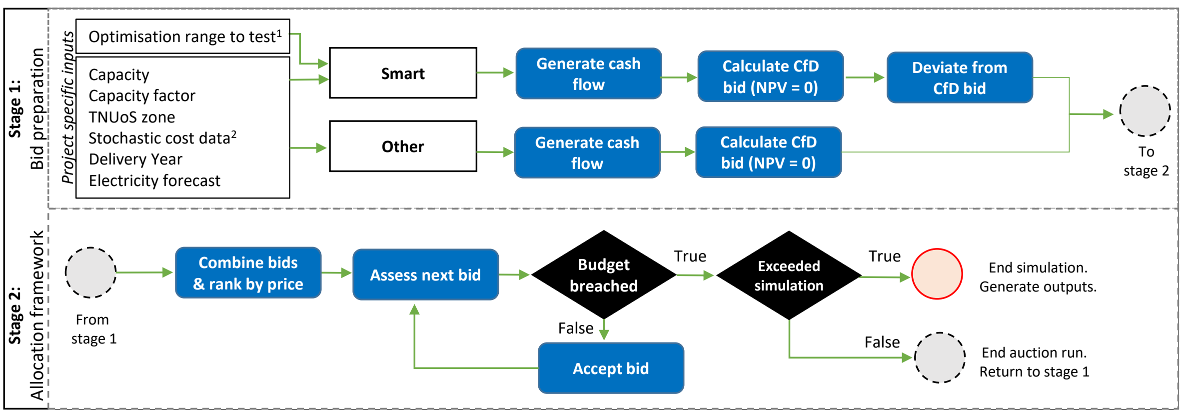


Figure 1: High-level flow diagram illustrating simulation process.
[1] This is the optimum bid price range to test.
[2] Stochastic cost data includes the DEVEX, CAPEX, OPEX and DECEX.

4.2 Bid preparation

The bid preparation stage involves the conversion of the input project data into a CfD bid for each project. To do this the cost and revenue streams of every project are assessed for each auction simulation round.

The cost streams include capital, operational, decommissioning, development, rent, interest payment, tax, and grid charges. Revenue streams consist of CfD payments, contracted power, and market wholesale revenues. The discount equity (NPV = 0) cash flow is then calculated to derive a CfD bid for each agent. This is the minimum CfD incentive level required to meet the minimum equity return. This value is then mapped to each agent as its bid price.

Deterministic cost data is generated from a previously validated proprietary cost modelling tool. The model uses the publicly available site and project-specific data (e.g. mean wind speed, water depth, foundation type and soil conditions) to generate an overview of costs over the lifetime of the offshore wind development tool. The cost modelling tool has been validated to an accuracy of ± 15% (9).

4.3 Allocation framework

The allocation mechanism follows the bid preparation stage and assesses each bid before determining the winning bid. In this part, the model ranks bids before accepting the required amount of capacity according to its budget. The outputs from one auction run of the model are as follows: Clearing price, winning projects, all project bids, and total capacity procured.

5 Methodology of analysis & introduction of case study

To conduct the sensitivity analysis and then the CfD contract length analysis as outlined in Section 1, a base case must first be defined, which is described in this Section. The methodology and assumptions used to set up the CfD simulation model is also described here.

The analysis is conducted in 2012 real terms. This is because, in the CfD auction, bids, auction outputs, and ceiling prices are set in 2012 real terms. This means any inputs used in this case study have already had inflation up to the year 2012 discounted.

5.1 Case Study

The case study is based on Pot 2 of AR3 which concluded in 2019. Pot 2 was limited to offshore wind, remote island wind and biomass conversion technologies. In reality, the vast majority of capacity auctioned (95%) was awarded exclusively to Offshore Wind. Therefore, the other technologies can be ignored, and the budget is adjusted to account for this.

In AR3, the total capacity of competing projects was an estimated 9,543 MW of which 5,454 MW successfully secured a contract. The offshore wind projects which competed in AR3 are highlighted in Table 1. A high-level overview of the inputs used to generate the cost data can also be seen in Table 1.

5.2 Sensitivity analysis

To determine which cost and revenue streams are most important for bid preparation a local sensitivity analysis (LSA) has been conducted. This involves increasing or decreasing an input's value around a mean point whilst keeping all other inputs fixed at the base case. The main outputs of the model are measured and then analysed (22).

A base case is fixed for this one-at-a-time (OAT) sensitivity analysis. An overview of this base case, with the base inputs, is outlined in Table 1. In the first instance, a sensitivity analysis was conducted in order to observe the effect a change in input would have on the average bid price submitted by participants outlined in the Case Study. The bid price for participants is calculated as outlined in Section 4.2. The main inputs as shown in Table 1, are varied for all participants by ± 5%, ± 10% and ± 20%. Capacity is

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 Phase 1[1]	1075	54	10.58	65	Jacket	Tealing / Cockenzie [2]
East Anglia 3	1200	36.5	10.23	75	Monopile	Bramford
Inch Cape	1000	52	9.97	45	Jacket	Cockenzie
Moray Firth West	800	45.5	10.12	70	Jacket	Blackhillock

Table 1: A high-level overview of some of the publicly available site/project-specific input data was used to generate cost estimations.

excluded from this sensitivity analysis, this is because the costs generated by the cost model are reliant on a deterministic capacity value. The final value presented is the average of all bid prices submitted by participants after one of their inputs is changed.

To determine the effect that the inputs have on the auction clearing price, all projects are again considered. The base case which includes all competing projects and their associated inputs can be seen in Table 2. For one test, the same input for every project is varied by the same fluctuation. For example, the CAPEX for all 8 projects is adjusted by +20%, whilst all other inputs are kept constant. There are two clearing prices for every auction simulation and sensitivity tested. This is because as described in Section 4.1, for each auction run, two delivery years are modelled. Each delivery year has a separate clearing price and is irrespective of the other year. Therefore, the results presented are an average of both clearing prices.

5.3 *CfD contract length analysis*

The purpose of this analysis is to assess the effect of forecast wholesale electricity market price uncertainty on bid preparation. This is because it can have a significant effect on the overall bid price of a generator (as explained in Section 3). To analyse how this can be mitigated against policy-makers, we investigate what effect increasing the CfD contract length from 15 years to 20, 25 and 30 years has on the uncertainty experienced by bidders. The financial implications in terms of wind farm profitability and level of support payments of changing the CfD contract length are then analysed to compare contract lengths.

This analysis assumes that auction participants have deterministic costs associated with their developments (outlined in Table 2). However, each participant is assumed to have large uncertainty associated with future wholesale electricity market prices, which they must forecast to calculate the development's lifetime cash flow (which their bid price is calculated from). The forecast wholesale electricity market price for this simulation is the only parameter which is assumed to be stochastic for this analysis. For every simulation, there are 1,000 auction runs to average over stochastic inputs. An auction run is defined as the completion of one auction (as shown in Figure 1). A number of total auction runs were considered and tested until it was seen that there was a strong convergence of results after 1,000 auction

Project	Capacity (MW)	CF	DEVEX (£M)	CAPEX (£M)	OPEX (£M/year)	DECEX (£M)
Doggerbank CB A	1200	0.55	80	2400	22	77
Doggerbank CB B	1200	0.55	110	2400	22	72
Doggerbank Teesside	1200	0.53	86	2500	22	77
Sofia	1400	0.55	87	2600	26	87
Seagreen Phase 1	1075	0.56	76	2200	19	101
East Anglia 3	1200	0.53	80	2300	21	77
Inch Cape	1000	0.50	73	2000	17	74
Moray Firth West	800	0.53	66	1650	14	77

Table 2: Overview of inputs used to categorise each project and used as part of the case study. These values are based on 2019 costs and have been obtained from a proprietary cost modelling tool (9).

runs per simulation (see work produced by Kell et al. (19)).

In this analysis, there are three potential future electricity price scenarios modelled: low economic growth, medium economic growth and high economic growth. All forecasts are publicly available from BEIS, and are based on outputs from a Dynamic Dispatch Model (23). This is a comprehensive integrated power market model which aims to forecast Great Britain's power market over the medium to long term. It considers electricity demand and supply on a half-hourly basis for sample days to generate forecasts for the future. Projects which bid into AR3 are likely to go online in or around 2025 and are expected to have a project lifetime of 30 years. Therefore, developers are required to produce forecast wholesale electricity market prices up to approximately 2060 to calculate cash flows. BEIS forecasts are only available up to 2040, it is very challenging to forecast future electricity prices beyond this time period. Therefore, it is assumed in this study that the electricity price beyond this period will remain unchanged. This ensures that the relative difference between the three economic growth scenarios remains constant.

The wholesale electricity forecasts produced by BEIS are based on 2016 real values (this allows for a more accurate comparison of future prices, by accounting for inflation). As CfD bid prices are submitted in 2012 real values (as explained in Section 5), the forecasts from BEIS are converted to 2012 real values, using historical inflation data from the ONS (24). The resultant three curves used in this analysis can be seen in Figure 2.

5.4 Monte Carlo sampling of future wholesale electricity prices

Using the same methodology as outlined in Section 4.2, each participant calculates an optimum bid, which is a function of their input costs and other parameters (as shown in Table 2). Monte Carlo Sampling is used to determine the future wholesale electricity price used for that auction run. The forecast electricity market price is sampled from the curves illustrated in Figure 2 and each sample is a mix of varying contributions of each of the three curves. This means that for each auction run, a different forecast electricity price curve is generated for each project, using varying weightings of the three curves shown in Figure 2. Each project in each auction run has a different curve, and the same project will have a different curve in each auction run. This means that over the course of the simulation, the bids produced by a project will vary as a result of the stochastic wholesale electricity market price input. It

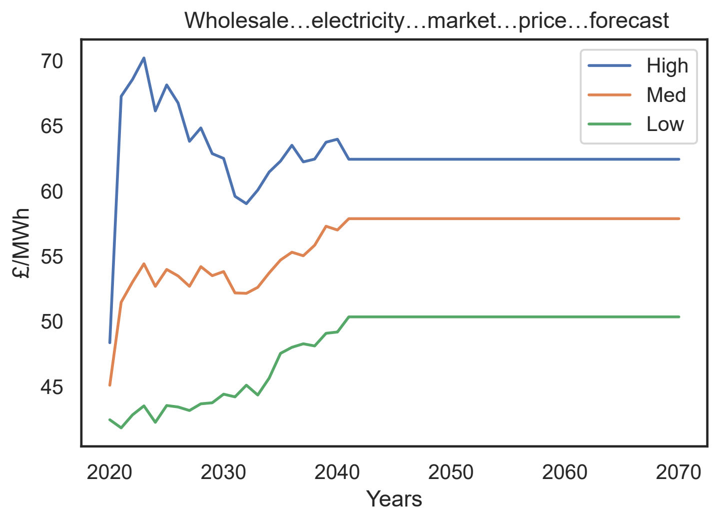


Figure 2: Illustration of the three wholesale electricity price curves used in the model. BEIS forecast data is up until the year 2040, with data beyond predicted using an inflation multiplier

is assumed in this analysis, that auction participants have access to these curves produced by BEIS, and this gives them some indication of future trends in future electricity prices. However, participants have no indication of whether the economy will experience high, average, or low future growth. Therefore, stochastic sampling from all three curves will give an approximation of bids which can be submitted by participants.

The analysis is repeated when the CfD contract length is changed from 15 years to 20, 25 and 30 years. This decreases the overall contribution of the forecast market wholesale electricity price curves toward the overall cash flow of projects and thus reduces the uncertainty in forecasting a project's cash flow. Results from this analysis are based on 4,000 auction runs (1,000 auction runs per CfD contract length tested). The main outputs analysed are auction clearing price, winning projects and project bid prices'.

5.5 NPV calculation

To compare the effect that different contract lengths has on policy-makers objectives, an NPV analysis is conducted on contracts that in the simulation were awarded a CfD contract. The NPV of support payments made to generators and the NPV of developers' projects is assessed.

A scenario-based approach is adopted to calculate NPV values. This is to show which contract length gives the lowest NPV of support payments and the highest level of NPV for developers, given a low, medium or a high economic growth scenario. The same forecast scenarios are used as in Figure 2. This analysis assumes that developers have already bid into the auction using a forecast wholesale electricity market price and have been awarded a CfD contract at a known CfD bid price. In this analysis, CfD contracts are awarded using a fixed strike price for is entire life. This allows for revenues to be analysed in real terms.

To calculate the NPV of support payments and NPV of developments, a discount rate of 3.5% and 6.3% have been used respectively. The social discount rate is fixed by HM Treasury (25). The 6.3% WACC (weighted average cost of capital) is taken from estimates from BEIS (26). This is because there is a difference between social and private discount rates. A developer whose offshore wind farm is protected under a CfD contract receives support payments for the duration of the CfD. However, when assessing these payments in *present value* terms investors apply a higher discount rate, which is in line with the cost of raising debt and expected return on equity. The social discount rate is calculated differently and is based on a *time preference* (16). This captures the fact that people generally place more value on present costs and benefits than on future ones.

5.51 NPV support payments

To calculate the NPV of support payments, the total amount of money received or payments given per financial year for each auction run is calculated. This involves calculating the cash flows of net payments between the LCCC and the generators for the duration of the CfD contract, for all winning projects of that auction run. Equation 1 is used to calculate the sum of NPV support payments to one project. Where C_p is the clearing price, P_p is the power price for that year, C is the capacity of the farm, C_f is the capacity factor, h_{year} is the number of hours in a year, t is the number of timer periods, and i is the discount rate.

$$NPV = \sum_{n}^{t=1} \frac{(C_p - P_p)(C \times Cf) \times h_{year}}{(1+t)^i} \tag{1}$$

5.52 NPV developers

A cash flow is calculated for each project which was awarded a CfD in the simulation carried out in Section 5.1. The NPV of developments awarded a subsidy is calculated in the same manner as described in Section 5.1. However, instead of optimising a CfD bid to meet minimum equity returns (NPV = 0), the clearing price agreed at auction is used to calculate net revenues. The cash flow is adjusted depending on the CfD contract length tested. For example, for a 20-year CfD contract length, 20 years of revenue is calculated using the clearing price, and 10 years of revenue (assumed 30 year lifetime of the offshore wind farm) is calculated using the forecast wholesale electricity market price forecasts displayed in Figure 2. For each contract length, three economic growth scenarios are modelled (as explained in Section 5.4). This means that for every contract length analysed, there will be 3 resultant NPV developer values generated.

6 Results

The results produced by the methodology can be divided into two main sections: sensitivity analysis and CfD contract length analysis. The sensitivity analysis concerns how uncertainty associated with the inputs to the CfD simulation model can affect participants' bid prices and thus auction outcomes. The CfD contract length analysis demonstrates the effect on bid preparation and NPV of support payments if governments were to try to mitigate against this uncertainty by increasing CfD contract length.

6.1 Sensitivity analysis

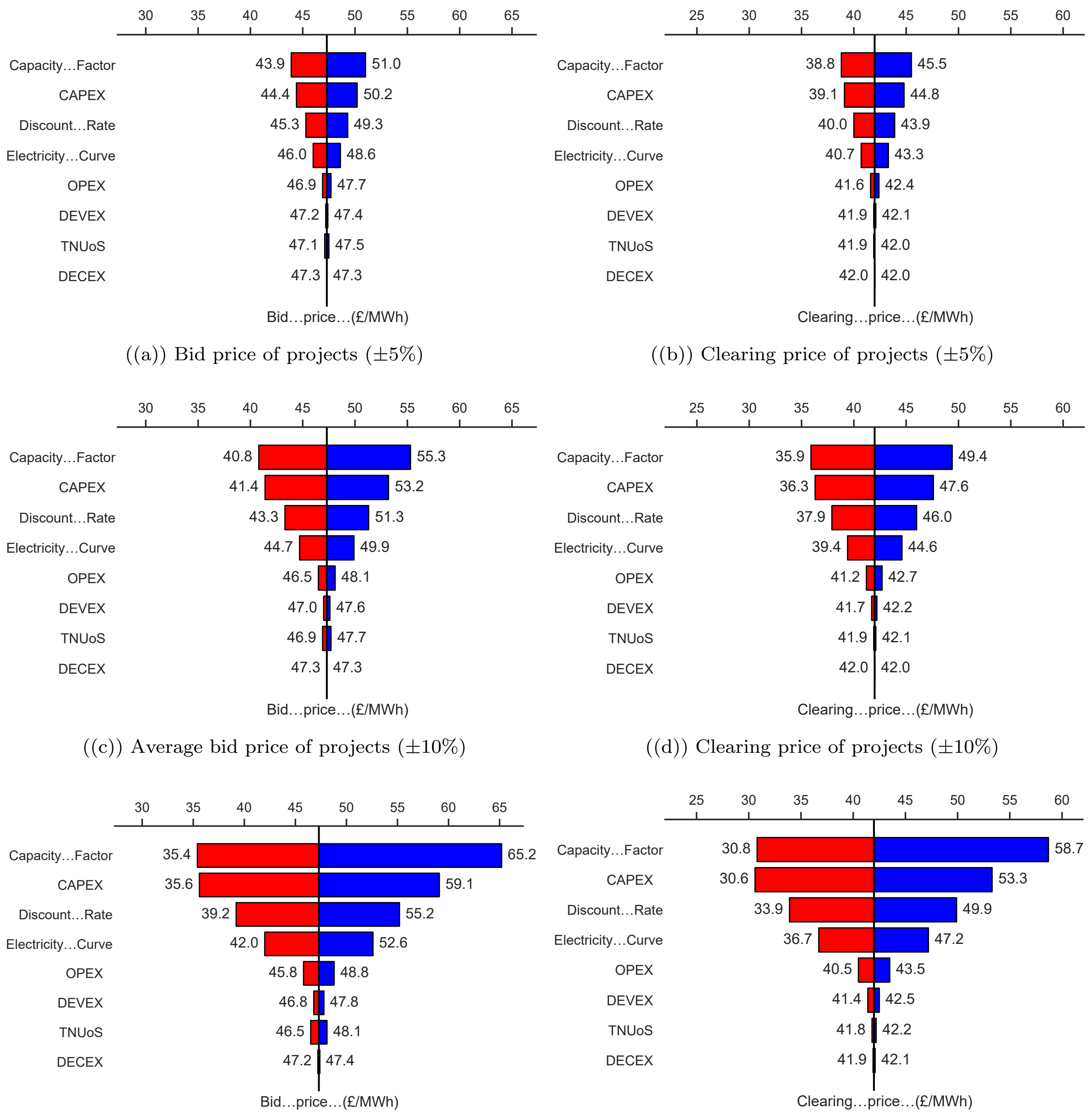
The results in this subsection show which inputs have the most impact, and thus where resources should be allocated to reduce uncertainty. Figure 3 demonstrates how the main outputs of the model change with varying inputs.

As expected, there is a correlation between the average bid price and the clearing price of the auction. This means that the most sensitive inputs which affect bid price the most, also affect clearing price the most. It can be seen clearly from the graphs that the largest sensitivity is Capacity Factor and then CAPEX (Capital Expenditure). A 10% change in Capacity Factor and CAPEX has a 17.7% and a 13.5% change on clearing price respectively. The Discount Rate used in calculating the cash flow and future wholesale electricity price forecasts is also a key sensitivity. All four inputs are key sensitivities and can have a noticeable effect on the bid price and clearing price. This highlights the importance of reducing uncertainty on these four main inputs. OPEX (Operational Expenditure), TNUoS, DEVEX (Development Expenditure) and DECEX (Decommissioning Expenditure) comparatively have a much smaller effect on the bid price and therefore clearing price. A 10% change in inputs for these four parameters affects the clearing price output by between 1.8%-0.2%.

6.2 CfD contract length analysis

Governments can directly aim to mitigate against the uncertainty surrounding forecast electricity curves, which is extremely challenging to accurately forecast and is a sensitive input in bid preparation (as can be seen in Figure 3). Policymakers can mitigate this by varying CfD contract length, thus minimising the exposure wind farm projects have to wholesale market prices. The results of an analysis of the effect CfD contract length has is shown in this subsection.

From Figure 4 it can be seen the effect that CfD contract length has on auction outcomes. The variation in bid price is demonstrated for one project only. The general trend is that a longer CfD contract length results in participants submitting higher bid prices. The mean bid price (£/MWh) for each contract length is 35.5, 40,0, 43.0, and 46.0 for contract lengths 15, 20, 25 and 30 years respectively.



((a)) Bid price of projects (±5%)

((b)) Clearing price of projects (±5%)

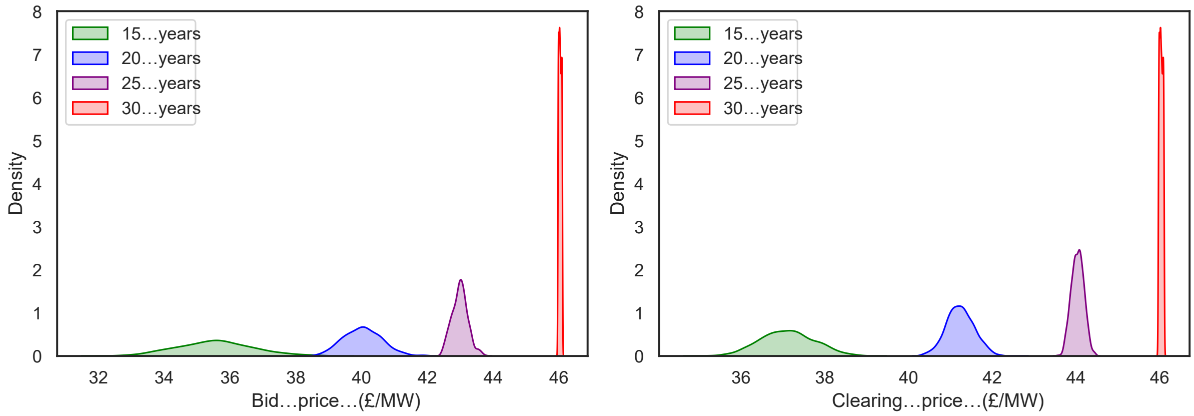
((c)) Average bid price of projects (±10%)

((d)) Clearing price of projects (±10%)

((e)) Average bid price of projects (±20%)

((f)) Clearing price of projects (±20%)

Figure 3: OAT sensitivity analysis results illustrate how the average bid price of projects and clearing price changes with a change in each of the main inputs.



((a)) Effect of contract length on bid price demonstrated for one player.

((b)) Effect of contract length on auction clearing price.

Figure 4: Histogram illustrating the expected clearing price for the two delivery years of AR3 based on empirical stochastic cost data.

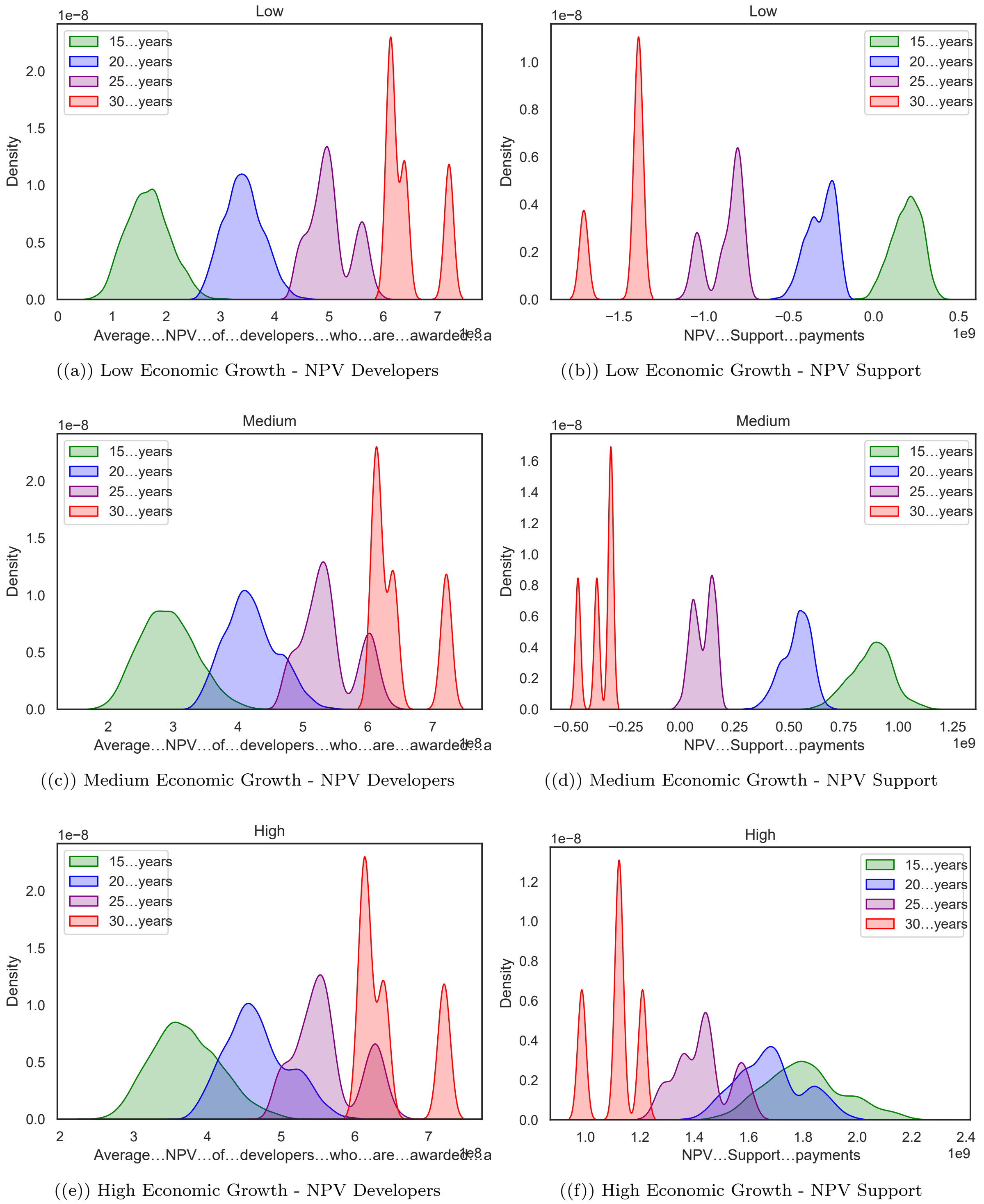
Figure 5 demonstrates the effect of an increased CfD contract length on net payments to developers and the NPV of wind farm projects. From the results, it can be seen that the general trend is that for an increase in contract length, there is an increase in expected NPV for developers and an increase in subsidies paid to developers. When a low economic growth scenario is modelled, there is an estimated net payment (negative NPV Support Payments) to developers for CfD contract lengths of 30, 25 and 20 years. Net payment to developers is seen in the medium economic growth scenario with a 30-year contract length only. In the high economic growth scenario, all contract lengths result in governments receiving net payments from developers. Although there is a large uncertainty associated with the estimates produced in the high economic growth scenario. It can be seen from the Contract Length Analysis, that developers receive a positive NPV in all scenarios. They can expect an increase in NPV with increasing contract length and with a higher economic growth scenario modelled.

7 Discussion of results

There are two main sets of results to analyse and then discuss. The first concerns the results from the sensitivity analysis which has demonstrated the key inputs in bid preparation and found that Capacity Factor, CAPEX, and Forecast Wholesale Electricity Prices are key sensitivities. Following on from this, a scenario-based analysis has been conducted to analyse how governments can help mitigate this uncertainty by limiting developers' exposure to volatile wholesale electricity prices, which was found to be a key sensitivity.

7.1 Sensitivity analysis

Capacity factor as expected is a significant sensitivity. This is because it is a vital variable in the revenue component of the cash flow, as it is used to determine what percentage of total capacity is converted into electrical energy on an hourly basis. The outputs of the model are very sensitive to any variation in capacity factor. CAPEX also is a large uncertainty, as it is a significant up-front cost which is incurred early on in the project's lifetime, so is not heavily discounted. As these inputs have a large impact, then in order to reduce the uncertainty associated with one's bid, then it is worth aiming to reduce the



((a)) Low Economic Growth - NPV Developers

((b)) Low Economic Growth - NPV Support

((c)) Medium Economic Growth - NPV Developers

((d)) Medium Economic Growth - NPV Support

((e)) High Economic Growth - NPV Developers

((f)) High Economic Growth - NPV Support

Figure 5: OAT sensitivity analysis results, illustrate how the average bid price of projects and clearing price changes with a change in each of the main inputs.

uncertainty associated with the cost parameters which make up the calculation of capacity factor and CAPEX. For capacity factor, they are mean wind speed, turbine availability, wake and electrical losses. For CAPEX: turbine unit costs, steel cost, substation cost. Therefore, significant resources should be allocated to improve the accuracy of these cost components through better measuring or other means.

It can be seen that the discount rate or WACC (Weighted Average Cost of Capital) which is used to calculate the cash flow, required to optimise a CfD bid price, can have a significant effect on the bid price. This is a different type of input from the others considered in this study, as it is predominantly calculated from the cost of financing the development, expected returns and perceived risk of investment. This means that independent developers are likely to face higher financing costs than a utility or oil major, this means that they will require a higher strike price to meet the same level of return as a utility (16). This makes smaller investors less competitive in the CfD auction, where participants must compete on price.

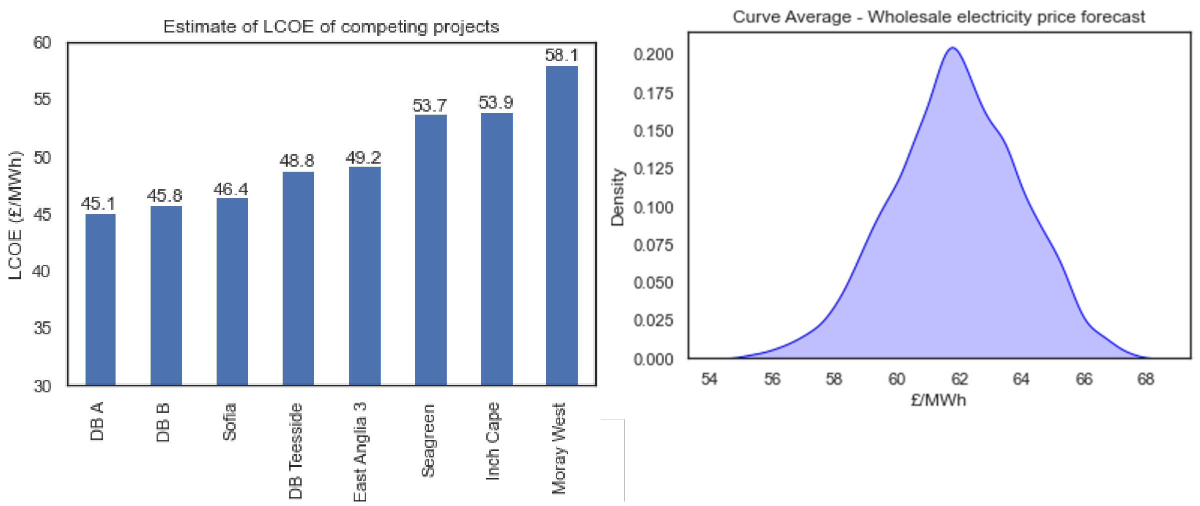
OPEX is commonly referred to in the literature as making up 33% of total wind farm costs (27). However, it can be seen from Figure 3 that the outputs of the auction are not sensitive to a change in OPEX. This is because although the total nominal value of OPEX costs over the lifetime of a project is large, the cost is spread over the entire wind farm's life, meaning that it is heavily discounted. This means that the OPEX costs in real terms are small when comparing it to large upfront costs such as CAPEX.

There is little sensitivity associated with DEVEX, TNUoS, and DECEX. This is particularly because DEVEX and DECEX have a small nominal value when compared to other costs incurred. Additionally, DECEX costs are incurred at the end of a project's lifetime and so are negligible in terms of real value. Although which TNUoS zone a wind farm is in can have a significant effect on the calculated minimum CfD bid (as demonstrated by work produced by Kell et al. (19)) the outputs of the model are not sensitive to changes in TNUoS grid forecasts. This is because although TNUoS fees are significant for some locations, for the zones tested in our case study they are comparatively small. This means when the sensitivity change is applied, there is a relatively small change in the whole number of the TNUoS. For these reasons, the results show that variation in these input parameters has a very small impact on outputs and that uncertainty in these parameters can be safely ignored. This is known as factor fixing. This should allow for strategy teams preparing CfD bids to reduce model complexity and focus resources on reducing uncertainty on more significant inputs.

7.2 Contract Length Analysis

As explained in Section 6.2, the auction strike price increases with an increase in CfD contract length model. This is because, under the modelled scenario, generators have an optimistic view of future electricity prices. This can be explained because developers have a net present cost of electricity generation for a generating plant over its lifetime. This means that for developers to cover costs and give an adequate return on investment, they must sell their electricity for an average price throughout the lifetime of the wind farm. This is equivalent to the LCOE (levelised cost of energy) of the wind farm. This differs from the calculated minimum CfD bid, because the bid price factors in future revenues beyond the CfD contract length, which is dependent on the wholesale electricity price forecast selected. In cases where for the years that the wind farm is exposed to market prices, the average of those years as predicted by the forecast electricity price curve used, is higher than the LCOE of the wind farm, then there is downward pressure applied on the minimum CfD bid price. This is because in the simulation CfD bid price is varied in order to generate the same revenue within the project's lifetime (required to give NPV

= 0). In this simulation, developers have sampled from three forecast curves (produced by BEIS) which typically results in a curve that has on average a higher price per MW/h than the LCOE of the wind farm (this can be seen from Figure 6). Therefore, if the CfD contract length is increased, this reduces the exposure to the high market wholesale prices and therefore puts less downward pressure on the CfD bid price. The expected result, which can be seen in Figure 4, is that there is an increasing CfD bid price with an increasing contract length.



((a)) LCOE estimation for projects outlined in Case Study ((b)) Average value of electricity during merchant exposure

Figure 6: Demonstration of how project LCOE's (2019 costs in 2012 real terms) is typically lower than the forecast wholesale electricity market price, which is used to calculate the electricity price during years of merchant exposure and is used to calculate CfD bid.

Figure 6 supports the above explanation. The results shown in Figure 6(a) are estimations of the LCOE of the projects outlined in the Case Study in Section 5.1. The LCOE's have been calculated using the high-level inputs as specified in Table 2 and through use of the financial element of the model as described in Section 4.2. The results are deterministic, as they do not include the stochastic sampling of future wholesale electricity market forecast curves as was done previously. This is because LCOE calculations do not factor in revenue streams. Figure 6(b) was produced by sampling for 1,000 curves as described in Section 5.4. The average of those curves is then calculated and then used to produce the density plot.

Although Figure 4(a) represents how bid price changes for a single project, we can see from Figure 4(b) that the same is true for other projects. This is because the same dynamic as explained above, is true for all For technologies with high generation costs (e.g. floating wind), a longer CfD contract would likely lead to a lower overall clearing price.

Another noticeable difference between contract lengths is that the spread of bids by auction participants is significantly reduced with an increase in contract length. This is because generators have significant uncertainty associated with future prices, therefore, reducing their exposure to this unknown by increasing CfD contract length reduces the significance of future prices on their calculation of CfD bid. This demonstrates that governments can successfully mitigate against uncertainty by adjusting contract length. This limits developers to downside risk as a result of bid uncertainty. As a result, governments will reduce the potential risk of non-realisation of projects as explained in Sections 1 and 3.

It can be seen from the results that governments under a number of scenarios can expect to receive net payments from developers (as a result of the pay-back mechanism) who are awarded a CfD. This is because strike prices agreed for offshore wind are low, and future wholesale electricity market prices in most scenarios are consistently above CfD prices (as shown from Figure 2. The general trend as highlighted in Section 6.2, is that an increase in CfD contract length increases the net payments to generators or decreases payments received from generators. In other words, increasing CfD contract length results in less favourable financial returns for governments. This can be largely attributed to the likely higher strike prices which occur as a result of increasing CfD contract length (as seen in Figure 4(a)) and the longer time period in which governments are providing subsidies. This means that there is an increase in the government's exposure to volatile wholesale prices.

The trends relating to the effect of CfD contract length on the estimated NPV of developers and estimated NPV support payments made by the government, which are discussed in the above paragraphs, will hold true irrespective of what forecast wholesale electricity price curve is used. As long as the same forecast electricity market price curve is used within the same (low, medium or high) economic scenarios, then the relative difference for NPV values between contract lengths will remain the same.

It can therefore be seen from the analysis that although increasing CfD contract length mitigates against some of the uncertainty experienced by generators, policy-makers are not financially incentivised to do so. This is because increasing CfD contract length increases the expected clearing price of auctions significantly, which results in increased subsidy payments to developers. Increasing CfD contract length, however, would be beneficial for generators, as it reduces their exposure to volatile wholesale market electricity prices, allows them to achieve higher strike prices, and increases the actual NPV of their projects. Further to this, there are additional further potential benefits. Reducing risk experienced by increasing CfD contract length, may reduce the cost of borrowing and thus further serve to reduce the generation costs of offshore wind projects.

8 Conclusion

This paper has described the challenges of submitting bids into CfD auctions as a result of the uncertainty faced by bidders, who must accurately forecast their cost and revenues for projects that go online in 4-5 years' time and have a 30-year generating period. This uncertainty has been categorised through conducting a sensitivity analysis on a described case study and through the utilisation of a stochastic CfD auction simulation model. The uncertainty described can also act as a major risk to governments' long term renewable deployment targets, as a result of non-realization: awarded bidders do not realise their projects as a result of the winners curse. Therefore, it is in the interest of the auctioneer to attempt to minimise uncertainty experienced by bidders. As a result, a scenario-based analysis has analysed the effect of increasing CfD contract length (from the current 15 year period). This could be used as a tool by policymakers to mitigate against uncertainty generated by having to predict future wholesale electricity prices.

The sensitivity analysis has demonstrated that Capacity Factor and CAPEX are the most sensitive inputs to the model. A 10% change in Capacity Factor and CAPEX has a 17.7% and a 13.5% change on clearing price respectively. This means that in bid preparation, significant resources should be allocated to reducing the uncertainty associated to cost parameters which make up these main inputs. Forecast wholesale electricity market curves are also a key sensitivity and can cause significant variation in auction outcomes. Therefore, to mitigate against this uncertainty, the effect of increasing the CfD contract length from 15 years to 20, 25 or 30 years has been assessed. The overall trend is that increasing CfD contract length decreases the uncertainty associated with this parameter. Therefore, an increase in CfD contract length successfully reduces the overall uncertainty experienced by bidders in the CfD auction. However, doing so would increase the expected clearing price of CfD auctions and increase the governments' downside risk to volatile wholesale electricity prices. As a result, there is an increase in net payments to generators or decreases in net payments received from generators. In other words, an increase in CfD contract length results in less favourable returns for governments. The results also show that for mature renewable technologies, such as offshore wind, in medium/high economic growth scenarios governments can expect a positive NPV of support payments from developers. Meaning, that additional funds generated could be used to further subsidies *less-establish* technologies, or to pass on additional savings to energy consumers.

Interesting expansions of this work could include conducting the sensitivity analysis on the individual cost parameters which make up the high-level inputs as described in Section 4.1. This would give strategy teams a more detailed focus on where resources should be allocated to reduce uncertainty. Finally, further research could be used to assess the effect of CfD contract length on a case study involving *less-established* technologies which have higher generating costs.

Acknowledgments

The authors wish to acknowledge funding for this work from the EPSRC and NERC for the Industrial CDT for Offshore Renewable Energy (EP/S023933/1).

A.C. Pillai acknowledges support from the Royal Academy of Engineering under the Research Fellowship scheme (2021-2026) award number: RF02021075.

References

[1] Statista, "Cumulative offshore wind power capacity installations in europe from 2012 to 2021."

[2] Statista, "Cumulative installed capacity of offshore wind in the united kingdom (uk) from 2009 to 2020."

[3] BEIS, "Contracts for difference - government website," 2022.

[4] "Auctions for the support of renewable energy in germany," standard, Aures, 2019.

[5] E. H. Bowman and G. T. Moskowitz, "Real options analysis and strategic decision making," vol. 12, pp. 772–777, 2001.

[6] M. Welisch, "The importance of penalties and pre-qualifications: A model-based assessment of the uk renewables auction scheme," *Economics of Energy and Environmental Policy*, vol. 7, pp. 15–30, 2018.

[7] J. Kreiss, K. M. Ehrhart, and M. C. Haufe, "Appropriate design of auctions for renewable energy support – prequalifications and penalties," vol. 101, pp. 512–520, Elsevier Ltd, 2017.

[8] NERA, "Gale force competition auctions and bidding strategy for offshore wind," 2018.

[9] E. B. Mora, J. Spelling, and A. H. van der Weijde, "Global sensitivity analysis for offshore wind cost modelling," *Wind Energy*, vol. 24, pp. 974–990, 9 2021.

[10] BEIS, "Contracts for difference and capacity market scheme update 2020," 2020.

[11] BEIS, "Cfd: Ar4 consultation final stage impact assessment," 2020.

[12] "Guidance on strike price adjustments under contracts for difference and investment contracts low carbon contracts company," 2017.

[13] BEIS, "Contracts for difference scheme for renewable electricity generation," 2021.

[14] BEIS, "Contracts for difference - methodology used to set administrative strike prices for cfd allocation round 4 methodology used to set administrative strike prices for cfd allocation round 4," 2021.

[15] A. Ioannou, A. Angus, and F. Brennan, "Effect of electricity market price uncertainty modelling on the profitability assessment of offshore wind energy through an integrated lifecycle techno-economic model," vol. 1102, Institute of Physics Publishing, 10 2018.

[16] "Contract length analysis for feed-in tariff," 2013.

[17] BEIS, "Contract for difference: Final allocation framework for allocation round 5.," 2022.

[18] "Mesa: Agent-based modeling in python 3+," 2016.

[19] N. Kell, A. H. Weijde, L. Li, E. Santibanez-Borda, and A. Pillai, "Game-theoretic methodology and simulation of renewable energy subsidy auctions for preparing bid strategy," *Pre-Print*, 2021.

[20] DECC, "Contract for difference: Final allocation framework for the october 2014 allocation round.," 2014.

[21] M. Welisch, "Auctions for allocation of offshore wind contracts for difference in the uk," *Energy Economics Group*, 2019.

[22] A. Saltelli, *Global sensitivity analysis: the primer*. John Wiley, 2008.

[23] BEIS, "Department of energy & climate change - dynamic dispatch model," 2021.

[24] ONS, "Consumer price inflation."

[25] M. Freeman, B. Groom, and M. Spackman, "Social discount rates for cost-benefit analysis: A report for hm treasury 1 a summary report from two workshops on recent advances in social discounting practice and theory."

[26] BEIS, "Electricity generation costs," 2020.

[27] T. Stehly, P. Beiter, and P. Duffy, "2019 cost of wind energy review," 2019.