Simulating Renewable Energy Auctions for Offshore Wind

Nicholas Pietro Kell

Industrial Doctoral Centre for Offshore Renewable Energy

Doctor of Engineering

THE UNIVERSITY OF EXETER

2023

IDCORE

This thesis is submitted in partial fulfillment of the requirements for the award of an Engineering Doctorate, jointly awarded by The University of Edinburgh, The University of Exeter, and The University of Strathclyde. The work presented has been conducted under the industrial supervision of EDF Energy R&D UK Centre as a project within the Industrial Doctoral Centre for Offshore Renewable Energy (IDCORE).

Abstract

Renewable energy auctions seek to efficiently allocate subsidy support and trigger cost reductions in renewable technologies, including offshore wind. However, the design of these auctions to ensure efficient allocation of subsidy resources which successfully supports the realisation of renewable projects is challenging. Furthermore, due to the uncertainty associated with future cost and revenue streams, bidding into these auctions is risky for renewable developers. Simulation of renewable auctions can be used as a tool for analysing auctions. It allows for different auction rules to be tested and the effect on auctions can be analysed. Auction simulation also allows developers to characterise the uncertainty associated with their bid price and so can help with price discovery and strategic bidding. This thesis describes the design, development, and various applications of a novel modelling approach for simulating CfD auctions The modelling approach has use cases and implications for policymakers and renewable generators alike and has been developed in partnership with industrial partners with active participation in CfD auctions.

The developed methodology and analysis tool aims to replicate real-life auctions through the depiction of real offshore wind projects. A discounted cash flow model converts high-level cost estimates and macroeconomic data to estimate a bid price for each player. Stochastic cost data is used to generate a range of bid prices for each player, which characterises the uncertainty. An allocation mechanism then replicates the CfD allocation framework to determine an auction outcome. While the methodology is based on UK CfD auctions, the theory underpinning the model can be readily adapted to different auction types in varying geographies.

The application of the auction modelling tool in this thesis highlights key input sensitivities concerning bid price discovery, methodologies to better prepare bidding strategy and thus mitigate against the non-realisation of projects, and empirical analysis of previous auctions to provide strategic context. From a policy perspective, the applications explore policy recommendations concerning the effect of auction design changes on auction outcomes. For example, the effect of increasing the CfD contract length on reducing bidders' uncertainty and net support payments is analysed. Another application investigates the effect of different pricing rules has on outcomes and the incentive for developers to strategically bid.

Acknowledgements

Acknowledgement, with gratitude, is due to the following:

Dr Harry van der Weijde, Dr Thomas Morstyn, and Dr Iraklis Lazakis under whose supervision this work was carried out. In particular, Dr. Ajit Pillai, for his timely support, commitment, guidance, and insight I have developed my academic research skills and exceeded my own expectations. I would like to extend my gratitude to Prof. David Ingram, and Dr. Katrina Tait, whose passion for IDCORE has made this all possible.

EDF Energy R&D UK Centre, who hosted the three year industrial element of this Engineering Doctorate and in particular the individuals who supervised this work over that three-year period: Tariq Dawood, Ernesto Santibanez, and Marie Renner.

My parents who have supported me with whatever I have chosen to do, and encouraged me to pursue a doctorate. A special thanks to my brother, Dr. Alex Kell, for inspiring me to use computational methods to solve my research questions.

To my partner, Shauna Davidson, who provided great support, encouragement, and belief in me, made this process much more manageable.

I would also like to thank my IDCORE colleagues, for being a truly great bunch and for all those memorable experiences together. Similarly, thanks to my friends outside of academia for providing support, laughs, and a welcome distraction from the daily doctorate grind.

Funding for this work from the EPSRC and NERC for the Industrial CDT for Offshore Renewable Energy (EP/S023933/1) is gratefully acknowledged.

Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.
Parts of this work outlined in this thesis have been published:

- Chapter 3 & 4 are based on N. P. Kell, A. H. van der Weijde, L. Li, E. Santibanez-Borda, and A. C. Pillai, “Simulating offshore wind contract for difference auctions to prepare bid strategies,” Applied Energy, vol. 334, p. 120645, 2023

- Sections 4.2.3 & 4.4.1, and Chapter 5, are based on N. P. Kell, E. Santibanez-Borda, T. Morstyn, I. Lazakis, and A. C. Pillai, “Dealing with uncertainty while developing bid strategy for CfD auctions,” in 43rd IAEE International Conference, 2022.

- Chapter 6 is based on N. P. Kell, E. Santibanez-Borda, T. Morstyn, I. Lazakis, and A. C. Pillai, “Methodology to prepare for UK’s offshore wind contract for difference auctions,” Applied Energy, vol. 336, p. 120844, 2023.

All publications written as part of this work are appended in the Appendix.

Nicholas Pietro Kell

Contents

Figures and Tables

Figures

Tables

Acronyms

ABM Agent Based Model.
AE Adjustment Element.
AEP AEP.
AR Allocation Round.
ASP Administrative Strike Price.

BEIS Department for Business, Energy & Industrial Strategy.

CfD Contracts for Difference.
CHPQM Combined Heat and Power Qualifying Multiplier.
Climate Change Act CCA.

DE Differential Evolution.
DY Delivery Year.

ESCO Electricity System Operator.
European Union EU.

FCF Free Cashflow.
FIT Feed-In-Tariff.

GA Genetic Algorithm.
GSA Global Sensitivity Analysis.

IRR Internal Rate of Return.

LCCC Low Carbon Contracts Company.
LCOE Levelised Cost of Energy.
LCR Local Content Requirements.
LSA Local Sensitivity Analysis.

NPV Net Present Value.

O& M Operation and Maintenance.
OAT One-At-Time.
OFTO Offshore Transmission Network Operator.
OWCAT Offshore Wind Cost Assessment Tool.

PINS Planning Inspectorate.

PPA Power Purchage Agreement.
PSA Partical Swam Optimization.
PV Photovoltaics.

RES Renewable Energy Subsidy.
RL Reinforcement Learning.
RO Renewable Obligation.
ROC Renewable Obligation Certificate.
RQM Renewable Qualifying Multiplier.

SA Sensitivity Analysis.

TCE The Crown Estate.

UK United Kingdom.

VCA Value Chain Assessment.
VY Valuation Year.

WACC Weighted Average Cost of Capital.

YR1F Partial Year Generation Factor.
YRSE Year-Round-Shared Element.
YRSE Year-Round-Not-Shared Element.

Nomenclature

π	Auction Pay-off for Player
π_U	Pay-off for Player using Uniform Pricing
π_{PAB}	Pay-off for Player using Pay-As-Bid Pricing
θ_t	Wholesale Market Electricity Price
A_{sect}	Required Cross-Section
b_i	Bid Price Submitted by Player i
b_x	Bid Price x
BI	Budget Impact
C	Transmission Lost Multiplier
C	Wind Farm Capacity
C_I	Cost of Installation
c_i	Marginal Cost of Player i
C^{SS}_{cable}	Supply Cost for Export and Inter-Array Cables
c_{fab}	Unit Primary Cost of Steel
C^{PS}_{fnd}	Total Foundation Cost
C_{GIS}	Gas Insulated Switch Gear
$c_{i,TNUoS}$	TNUoS Costs
$c_{i,t}$	Cost of Offshore Wind Project
$C_{topsideplatform}$	Cost of Top-Side Platform for Substation
C_{trans}	Cost of Transformer
$C_{vessels}$	Cost of Vessels
C^{ref}_{WTG}	Turbine Unit Supply Cost
C^{S}_{WTG}	Total Turbine Supply Cost
C^{trans}_{WTG}	Transport Cost of Turbine to Fabrication Yard
cap_{WTG}	Power Rating of Turbine
d	Discount Rate
$d^{d_j}_{rotor}$	Wind Turbine Rotor Diameter
$d^{c_j}_{water}$	Water Depth
$E[X]$	Expected Value
f_{mat}	Material Conductor
h	Time of Installation Step
LF	Load Factor
m_j	Quantity of Primary Steel
$m^{e_j}_{topside}$	Mass of The Top Side of Turbine
N_{WTG}	Number of Wind Turbines Required

P	Probability of Success
p	Awarded Strike Price
q_i	Quantity of Capacity Units Demanded from Player i
$r_{i,t}$	Revenue Received by Bidder i for their Offshore Wind Project
R_t	Net Revenue During CfD Years
s_c^i	Uncertainty Associated to Cost
s_r^i	Uncertainty Associated to Revenue
SP	Strike Price
T	Lifetime of Wind Farm
t_b	CfD Generation Period
t_{NG}	Non CfD Generation Lifetime
$V_o p$	Rated Voltage
$W\%$	Winning Percentage at Bid Price x
X_t	Total Electricity Generated in a Year

Chapter 1

Introduction

1.1 Current State and Trends of Offshore Wind Energy

Governments worldwide have announced ambitious climate targets due to anthropogenic global warming. For example, the UK government introduced legally-binding carbon targets, as stated in the Climate Change Act (CCA), which committed the UK government by law to reducing greenhouse gas emissions by at least 100% by 2050, compared with 1990 levels [1]. In recent years, concerns with energy security and the volatility of fossil fuel prices have further accelerated decarbonisation and the push for renewables [2]. Global population increases and higher living standards have resulted in higher global energy demand [3]. As such, the EU has mandated that 43% of energy generation must come from renewable energy sources by 2030 [4]. Furthermore, the Paris Agreement has indicated that renewable energy sources must provide 65% of the world's primary energy supply by 2050 [5]. Therefore, strong drivers exist for governments and society to push for affordable, clean and reliable energy sources. This has resulted in intense interest in different renewable energy technologies.

Many different renewable energy technologies exist, which harness energy from several sources, including sunlight, wind, water movement, and geothermal heat. Installed renewable capacity has grown significantly in recent years and is expected to grow by over 50% over the next five years [6]. Growth markets include Europe, USA and Asia; particularly China, India, Japan and Taiwan. The rapid growth in renewables can be attributed to the rapid cost reductions achieved through technological advances, economies of scale and favourable government policy [7]. Wind energy has one of the highest expected growths of all renewable energy sources due to the abundance of wind resources and its rapid cost reduction, which allows it to compete economically with more traditional energy generation technologies such as nuclear, gas, and coal [8].

Development of the first onshore wind turbines began in the 1970s, with the first multi-megawatt turbine emerging in 1978 and full commercialisation achieved in the 1980s [9]. The offshore wind industry sought to leverage the technological advances from onshore wind and the oil and gas industry to harness higher and more consistent offshore wind resources. Furthermore, when compared to onshore, offshore wind had the additional benefits of higher public acceptability due to reduced visual impact and the possibility of larger capacity turbines. The first offshore wind farm to reach commercialisation was installed in 1991 in Denmark. The project was constructed approximately 2 km from the coast at water depths from 3 to 7 metres. The development consisted of 11 wind turbines with a cumulative installed capacity of 4.95 MW [10].

Since the first commercial offshore wind farm, the number and size of developments have been growing exponentially. The installed capacity of offshore wind reached 50 GW in 2022 and is expected to grow to 300 GW by 2030 [11]. A significant proportion of offshore wind technology has been deployed in Europe, especially in the United Kingdom, which accounts for 14 GW of installed capacity [12]. The UK has benefited from shallow water waters and a large wind resource.

The growth of the offshore wind industry has coincided with the rapid cost reduction of the technology. Technological innovation has been a big driver for the fall in generation costs. For example, the move towards larger turbines has resulted in economies of scale and savings in the balance of plant costs, as fewer turbine units are required to meet the required capacity. The development of bespoke vessels which can operate in a wider range of sea states has resulted in reduced Construction and Installation costs and Operation and Maintenance (O&M) costs. Improvements in the manufacturing processes for monopile and jacket foundations have reduced production and material costs. While technological innovation has certainly contributed to the success story of offshore wind (a full list can be found in [13]), it can also be attributed to favourable governmental policy. Government intervention has helped the wind industry during its nascent stages, providing market scale and clarity, de-risking investments to give confidence to investors, and facilitating technological advances. Capital grants have supported innovative demonstration profits, and fixed remuneration schemes have reduced project risk by providing revenue certainty. As a result, offshore wind is one of the renewable technologies at the forefront of the energy transition [14].

In the UK, offshore wind development is initiated by The Crown Estate (TCE). TCE is an independent organisation which owns the seabed rights and is responsible for managing development rights on the British coast. As part of its role, it identifies suitable sites for the development of offshore wind farms and awards development rights through a series of leasing auctions [13]. Suitable zones are identified based on characteristic site criteria such as wind speed, seabed conditions, water depth, and known site constraints such as environmental impacts, shipping routes and grid connection. So far, 43 GW of offshore wind development rights has been awarded in leasing auctions in UK waters [15]. For more recent allocation rounds (Round 3 onwards), if a developer is successful with their bid, they are awarded exclusivity development rights and must decide on a specific site within the awarded zone. Following this, developers can apply for a lease with the Planning Inspectorate (PINS), acquire the necessary grid permits from the National Grid, and proceed with the offshore wind farm's design and supply chain plan. After obtaining all the necessary consents, the developer can enter a separate auction to obtain a revenue support scheme for their project [13].

The UK government have implemented two main support mechanisms to expand the market penetration of offshore wind and promote its deployment [16], the Renewable Obligation (RO) and the Contracts for Difference (CfD) scheme. The RO scheme, introduced in 2002 in England, Wales, and Scotland, was designed to encourage the deployment of renewable technologies. The scheme obliged UK electricity suppliers to source a proportion of their electricity from renewable sources under the Renewable Obligation Certificate (ROC). The ROCs were issued to renewable generators as green certificates that can be sold on an open market and bought by suppliers to fulfil their RO. ROCs gave renewable generators a fixed level of support on top of the price they achieved on the wholesale electricity market [17]. The ROC was phased out in March 2017, during a transitional period where developers could apply for either ROC or CfD support [18]. The CfD eventually replaced the ROC, with the purpose of providing greater certainty and stability of revenues to electricity generators by reducing the exposure of electricity generators to volatile wholesale prices. CfDs ensure a fixed fee for each unit of electricity generated via a two-way payment mechanism (explained in detail in Section 2.1.1).

Revenue support schemes, such as the CfD, reduce the cost of raising the required capital from investors for their developments. Capital is not free, and investors require returns that compensate them proportionally to their level of investment risk [19]. To reduce the risk associated with offshore wind developments, governments have implemented CfDs to shield projects from selling electricity in volatile wholesale electricity markets, hedging their price risks with long-term support contracts. This provides revenue certainty, reducing the cost of borrowing and increasing the economic viability of projects. For large-scale, capital-intensive offshore wind projects, the reduction in the cost of borrowing is vital for offshore wind developments to meet the set investment criteria [19].

Developers must compete for revenue support schemes through government tenders in the form of "demand auctions" or "procurement auctions", whereby the government issues a call for tenders to procure a certain capacity or generation of renewable-based electricity. Project developers who participate in the auction submit a bid with a price per unit of electricity at which the project can be realised. The auctioneer evaluates the offers; typically, the lowest support price is the main winning criterium [20], and signs an agreement with the successful bidders. Auctions have a long and established history in the power sector, such as issuing capacity payments in Capacity Remuneration Mechanisms or contracting flexible demand response [21]. However, the use in awarding government support is novel, which increases the risk for policymakers and for developers attempting to secure financing for their projects.

1.2 Problem Statement: Renewable Energy Auction Simulation

Many jurisdictions are increasingly using auctions to allocate subsidy support and trigger cost reductions in offshore wind [22]. However, the successful design of auctions that ensures efficient allocation of subsidy resources and is effective at supporting the deployment of offshore wind is challenging. Policymakers have a wide range of design elements at their disposal, which can each significantly alter the auction dynamics and outcome. Furthermore, bidding into CfD auctions from a developer's perspective is challenging. Developers must determine a bid price which ensures economic viability for a project that starts generating in 4-5 years and has a lifespan of up to 30 years. Therefore, significant uncertainty is associated with future cost and revenue streams, which can lead to under or over-bidding. Bid too high and risk not being awarded a contract and experience project delays, or bid too low and then risk experiencing the winners' curse, potentially leading to unprofitable sites or the non-realisation of projects [23]. Developer's incentive to bid strategically and deviate from marginal cost further complicates the CfD auction process.

In order to address the issues concerning bidding into auctions and their design, simulation can be used as a tool for analysing auctions. Simulation can test auction design and its effect on allocation efficiency, allowing empirical testing of several different rule configurations, which helps inform policymakers on auction design. Renewable energy subsidy (RES) auctions have not yet converged onto one design; therefore, further research is warranted to explore rule design changes for policy recommendations [24]. Additionally, simulating the auction can be useful to test any rule changes or parameters set (e.g. budget impact) [25]. Given the auction framework set by policymakers, simulation can be of equal benefit to developers. Simulation can allow characterisation of the uncertainty inherent in determining bid prices, allowing the formulation of a bid which considers probabilistic outcomes. Auction simulation allows the testing of dominant strategies in varying bidder configurations, valuations and uncertainty. Therefore, developers can use simulation to test auction dynamics and identify the best bidding strategy. A well-thought-out bidding strategy can help prevent the winners' curse, mitigating the non-realisation of renewable projects [26].

Ensuring that auctions are well-designed and bidders possess the methodologies to successfully bid into these auctions is important for the continued growth of offshore wind. However, research on the simulation of auctions is limited. The literature survey suggests that there have been recent attempts to simulate renewable energy subsidy (RES) auctions to understand auction dynamics better and ensure allocation efficiency. However, most published work focuses on fictitious case studies and does not make recommendations for auction participants. Furthermore, the current literature does not use related academic subjects such as probability theory, game-theory or Monte Carlo sampling methods.

As auctions are becoming increasingly important to the successful deployment of renewable technologies, further research is warranted to make recommendations for developers and policymakers designing the auctions. Empirically simulating auctions is useful, owing to its flexibility, allowing a wide range of potential recommendations to be generated. However, current research in this area is limited. Therefore, expanding on existing simulation methodologies will allow policymakers to design better auctions and improve developers' ability to bid into the auctions which policymakers design.

1.3 Thesis Aim and Contributions

This work presented as part of this thesis aims to develop a novel modelling approach for simulating CfD auctions. The developed methodology will build on existing literature by utilising theory from relevant academic fields to simulate CfD auctions under a range of scenarios and inputs. The methodology is designed to have use cases and implications for policymakers and renewable generators alike. The main objectives are:

- develop a verified auction simulation tool for simulating CfD auctions under a range of inputs and scenarios
- identify key input parameters for estimating bid prices of specific offshore wind projects
- develop a computationally efficient financial analysis tool for estimating bid prices based on cost and macro-economic data
- develop an auction mechanism which replicates the CfD allocation framework
- identify key sources of uncertainty in determining a CfD bid price
- simulate past and future CfD auctions to inform future bidding strategy and CfD auction design
- provide insights into auction simulation, which can be used for leasing and subsidy auction in other markets

Compared to existing methodologies, the presented numerical framework includes additional detail to model specific offshore wind farms and simulate past and future CfD auctions. The model also allows for behavioural differences to be taken into account through a risk aversion parameter, which alters the bid profile of a specific competitor. Initial results from applications of the tool demonstrate that the model can replicate previous auctions well and predict future auction outcomes within a small margin of actual results.

1.4 Layout of Thesis

The thesis consists of eight chapters, which are listed and explained below:

Chapter 2: State-of-the-art in Auction Simulation
This chapter provides an overview of the relevant theory and background material which underpins the work carried out in this thesis. For example, a detailed overview of renewable energy auctions, cost modelling of offshore wind and auction simulation is given. Furthermore, a literature review sets this work in context with the current research concerning auction simulation, discussing the capabilities of each approach and critically assessing them. The future research direction is then explained, which is guided by the background and literature review material.

Chapter 3: Methodology of auction simulation tool
A detailed description of the novel modelling framework produced in this work is given in this section. The different elements of the model are explained and, where required, are justified using the material discussed in Chapter 2. This chapter demonstrates the governing equations and assumptions used in developing the model. The required inputs and parameters required to run an auction simulation, as well as detail of the outputs, are also given. Finally, the verification process used to ensure confidence in the model is discussed.

Chapter 4: Application I - Characterising uncertainty experienced by bidders
The model is demonstrated by re-creating and analysing Allocation Round 3 (AR3), which occurred in 2019. The model produces a distribution of most likely results, which better categorises uncertainty and, through comparison of AR3 and simulation results, demonstrates how developers can predict outcomes with reasonable confidence. This Chapter demonstrates how players can use probability theory to select an optimum bidding strategy which maximises expected profit while factoring in the uncertainty inherent in CfD auctions. Finally, a sensitivity analysis of inputs is conducted to identify where developers should allocate resources to reduce uncertainty.

Chapter 5: Application II - Studying the effect of CfD contract length on profitability and uncertainty
This chapter analyses the effect of increasing CfD contract length has on the uncertainty, profitability, and net support payments made to developers. To model the analysis, three different wholesale electricity forecast scenarios are compared. The trade-off between reducing uncertainty for bidders and increasing net present value of support payments is discussed.

Chapter 6: Application III - Predicting future CfD auctions
The most recent Allocation Round (2022), CfD auction for offshore wind is simulated. The simulation results obtained in this chapter have not been calibrated against the actual auction results and are based solely on information available before the auction. The results are then compared against the actual auction results to provide strategic context and to inform future

bidding strategies. Additionally, auction design rule changes are simulated to assess their impact on predicted auction outcomes and dynamics. The results of this analysis can be used by developers to understand auction design rule changes fully and for policymakers to test new auction formats and ensure allocation efficiency.

Chapter 7: Application IV - The effect of strategic bidding on allocation efficiency under different pricing rules

This chapter presents an empirical study to observe the effect of strategic bidding behaviour on the allocation efficiency (i.e. costs incurred by the tax payer) under the two most commonly used pricing rules: uniform and pay-as-bid. The study is conducted on two real life case studies which are based on the UK's CfD AR3 (2019) and AR4 (2022) for offshore wind.

Chapter 8: Discussion and Conclusion

The final conclusions of this work discuss recommendations for academia, industry and policymakers. The industrial impact is discussed, and the limitations associated to the work is explored. The thesis structure is presented in Figure 1.1.

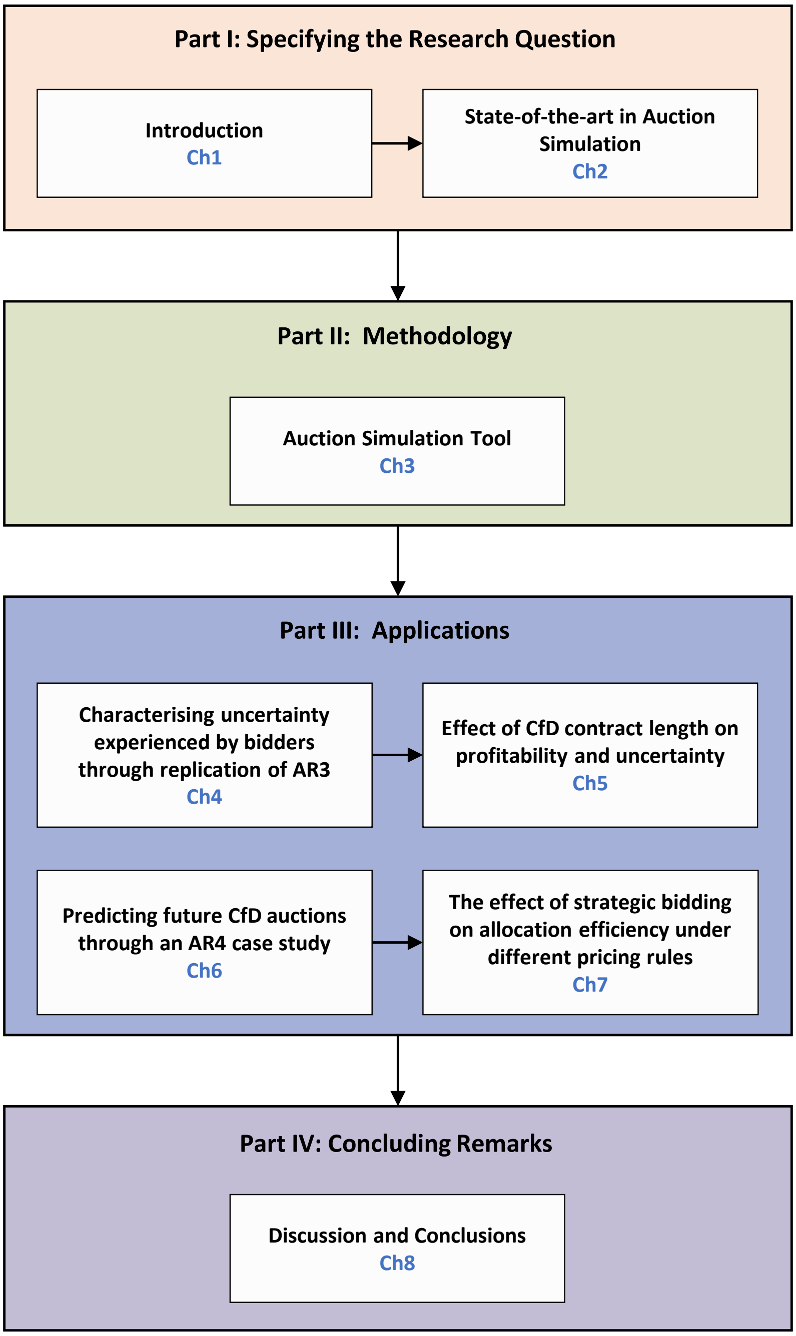


Figure 1.1: Relationship between thesis chapters

Chapter 2

State of the Art in Auction Simulation

This chapter provides an overview of the relevant background material which underpins the work carried out in this thesis. This chapter includes an introduction to renewable energy auctions, which includes a background into bidding into these auctions from a renewable developers' perspective and explains how the UK's CfD auction is an interesting case study which warrants further research. The relevant literature concerning auction simulation is critically reviewed, which has informed the future research direction section.

2.1 Renewable Energy Auctions

2.1.1 Background to Renewable Energy Auctions

To achieve ambitious renewable targets (as highlighted in Chapter 1), governments have implemented several support mechanisms to expand the market penetration of renewable electricity and encourage its deployment [22]. Such policies enable governments to achieve ambitious renewable energy expansion targets and thus reduce our carbon footprint.

The feed-in tariff (FIT) is an example of one of the main support mechanisms created by governments. FITs guarantee renewable electricity producers a fixed fee for their electricity and priority feed-in and dispatch; however, this discouraged generators from reacting to market price signals, so producers were not incentivised to curtail their energy. As a result of EU guidelines on state aid, many EU member states [27] and the UK have abolished renewable support policies such as the feed-in-tariff (FIT). Therefore, governments instead opted to replace FIT's and award support in auction processes, which based on retrospective analysis by multiple authors, provides better cost control, a lower support level, and a higher degree of efficiency [23, 28, 29]. Renewable energy generators must now compete for support through competitive government tenders, with the lowest support price primarily being the determining factor for awarding support [30].

An auction can be defined as a process of procurement via competitive bidding. Governments and private companies have used auctions to procure a number of goods and services, such as construction contracts, services, retail property, and equipment [31]. Procurement auctions, such as renewable energy auctions, are reverse auctions where multiple sellers compete to offer the lowest price. This differs from an ascending order, which can occur if an auctioneer sells a good or service to a number of buyers [32]. Governments will use auctions to procure a set amount of renewable electricity capacity, enabling governments to induce competition, reducing cost, and thus realising savings for taxpayers or electricity consumers [33]. Additionally, auctions allow developers to determine the support level required to facilitate their development, as they can submit a bid according to an estimation of their project costs, allowing price discovery. In the context of renewables, price discovery refers to the process by which the market determines the fair and equilibrium price for their electricity [34]. This reduces information asymmetry, which can occur if governments pre-determine support prices [30]. The risk of information asymmetry is present if there is an imbalance between the government and the developers on project costs or future revenue. As a result, governments may inflate support prices, where the governments perception of required prices is higher than the actual price required, resulting in inefficient use of taxpayers' money (public funds spent which do not maximise the benefits or value received by the public). On the other hand, governments may underestimate the required support prices, resulting in the non-realisation of projects.

Although auctions are commonly used in electricity markets, such as the day-ahead electricity market [21], the use of auctions in awarding government support is novel. As a result, several challenges are associated with their implementation. For example, auctions have facilitated a reduction in support costs and high project-realisation rates in some markets, such as the solar PV in South Africa [35], but failed on both of these aspects in other markets, such as the German onshore wind [36]. Further research is warranted to explore rule design changes for policy recommendations. Another prevalent issue is winner's curse, whereby a winning bidder regrets the award of the subsidy at a resultant price, leading to non-delivery of the project [37].

Key design features for renewable auctions

The support provided by governments, and issued through auctions, aims to provide revenue certainty or increased revenue by shielding developers from the volatility of wholesale electricity prices. Revenue certainty reduces project risk, and so decreases the cost of project financing. The main remuneration schemes include Contracts for Difference (CfD), one-sided sliding premiums, and fixed premiums. The three different mechanisms expose developers differently to the electricity markets. The CfD contract is between a producer and a designated government entity. The producer receives the difference when the electricity price is below the support price while returning revenues earned when the electricity price is above [38].

The CfD provides the most significant revenue stabilisation and price hedging among the different remuneration schemes applied in Europe [39]. Sliding premiums are similar to a CfD; a government entity pays the difference to the producer when the electricity price is below the support price. However, producers retain the excess revenues when the electricity price exceeds the support price [40]. Typically, when the one-sided sliding premium is allocated in a price-only auction, it attracts very low auction bids (developers are not forced to pay back), which increases the share of unsecured revenue. For example, recent offshore wind auctions in Germany and the Netherlands have attracted bids of zero (€/MWh) [41]. Analysis by Kreiss et al. [42] determined that low auction bids occur in auctions concerning one-sided sliding premium mechanisms as developers have an optimistic view of both the project costs and future wholesale electricity market prices. Finally, fixed premiums are payments on top of the market electricity price and, therefore, create the most significant exposure to electricity markets [43]. The different types of support mechanisms deployed by governments are illustrated in Figure 2.1.

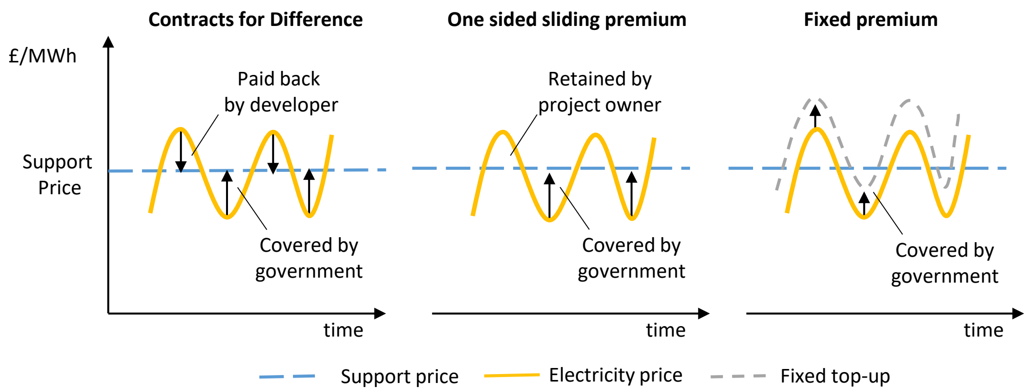


Figure 2.1: Common types of subsidy support schemes awarded at auctions

The pricing rule refers to how developers are renumerated based on their submitted bids. Two main pricing rules are used in multi-unit auctions: uniform and pay-as-bid pricing. In pay-as-bid schemes, winning bidders are awarded their bid price. On the other hand, winning bidders' remuneration in uniform pricing is determined by the last accepted or highest bid to be accepted. Governments can opt for a multi-technology auction, this is where projects from multiple renewable technologies (e.g. offshore wind, solar, and onshore wind) all compete in the same auction for the same subsidy budget pot. A multi-technology auction typically induces greater competition and a lower resultant auction price. However, some forms of renewable generation grouped with more mature technologies may be adversely affected. Physical pre-qualification comprises non-financial criteria bidders must fulfil to participate in the auction. Common examples of physical pre-qualification measures are the attainment of building permits or completion of conduction studies previous to the auction [30]. Financial pre-qualifications demand up-front payments from the bidders to participate in the auction. The pre-qualification payment is typically implemented as a non-interest-bearing deposit, a so-called bid bond. In case of non-realization of the contract within the grace period, the deposit is not refunded. The auctioneer claims penalties if a winning bidder does not complete its contract upon the end of the grace period. Penalties differ from financial pre-qualification as they can be non-monetary, such as exclusion from future auction rounds. Table 2.1 demonstrates the key auction design features for offshore wind subsidy auctions in several countries.

Table 2.1: Examples of offshore wind RES auction formats in different geographies [44].

	UK	Germany	Denmark	Poland
Price Rule	Uniform	Pay-as-bid	Pay-as-bid	Pay-as-bid
Support Type	CfD	Sliding Premium	Fixed Premium	CfD
Multi-technology	Yes	No	No	Yes
Physical Prequalification	Yes	Yes	Yes	Yes
Financial Prequalification	No	Yes	Yes	Yes
Penalty	Non-Stringent	Reduction of Support	Financial Penalty	Financial Penalty
Support Period	15 years	20 years	30 TWh	15 Years

2.1.2 Renewable Energy Auctions

RES auctions, such as the CfD auction, are a widely studied area of research. The main quantitative methods for analysing renewable energy auctions are econometric analysis, LCOE or NPV models, and simulation. The three main methods of analysis are discussed in this Section.

A number of authors apply econometric techniques to assess the effects of RES auction design on auction outcomes. In these studies, a large dataset of previous auction results is obtained from several countries. The data from past auctions (e.g. total subsidy payment, level of competition, auction rules) is obtained and typically compared to one another through econometric analysis (e.g. regression analysis). There are different types of regression analysis, such as linear regression, which finds the line of best fit to estimate the relationship between dependent variables. This can be done to answer several research questions, such as specific auction design rule changes and allocation efficiency analysis.

Casetta et al. [45] analyse the Italian auctions for onshore wind between 2012 - 2016 using standard ordinary least squares regressions. Their result shows that many auction design factors can induce competition and have a significant effect on lowering the awarded prices. Probst et al. [46] analyse the effect of local content requirements (LCRs) on India's awarded strike prices for solar auctions. Using regression methods, the authors demonstrate that LCRs dramatically increase the awarded prices. Matthäus et al. [47] also used a regression model to analyse the results of 94 worldwide RES auctions. The authors show that pre-qualification criteria and penalties positively affect realisation rates but increase the awarded support price. While econometric models are useful for analysing past auctions, their ability to predict future outcomes and trends is limited due to the rapid decrease in renewable costs (as discussed in Chapter 1). Furthermore, to obtain verified results, econometric analysis typically relies on large historical datasets, which are typically difficult to acquire, and there are issues related to data reliability. For new markets with poor data availability, this type of econometric analysis may not be possible.

Several articles analyse auction results and compare them to alternative support mechanisms. Shrimali et al. [48] analysed 20 RES auctions, largely from India, to test the effects of auction design on price effectiveness and utilise the findings to design India's auctions for RES support better. The authors determine that auctions are almost always more efficient at reducing support levels than administratively-set FITs. Winkler et al. [49] empirically compare the effectiveness of RES auctions in five countries to non-auction-based support schemes. They conclude that auctions can positively impact price efficiency, although not as a general trend. However, conducting regression analysis in this manner does not strictly prove causation, and although two data sets show an association, it may be spurious.

LCOE or NPV models are typically used to analyse renewable energy auctions. NPV (Net Present Value), and it is a financial metric used in capital budgeting and investment analysis. NPV is a measure of the profitability of an investment or project and helps in assessing whether a particular investment is economically viable [50]. The interpretation of a NPV calculation on investment decision is described in Section 2.1.5. NPV calculations typically uses cash-flow analysis. This is a financial management process that involves the examination of the inflows and outflows of cash within a business or individual's financial activities over a specific period of time. The time value of money is also taken into account, which considers the fact that present value of cash is greater than future cash. LCOE (Levelised Cost of Electricity), is a metric used in the energy industry to assess the cost of generating electricity from a particular source over the entire lifetime of a power plant. The levelised cost is expressed in terms of the cost per unit of electricity generated [51]. In analysis which uses LCOE or NPV models, historical data on the strike prices agreed upon in historic auctions is obtained and compared to the financial modelling of projects competing in the auction. This evaluates whether the auction was efficient at awarding subsidies and whether the projects are feasible at the realised subsidy price. When this data is compared on a country basis, researchers can determine which auction parameters drive low prices. This type of modelling can also help estimate future auction price trajectories.

Dobrotkova et al. [52] analysed the prices of utility-scale solar PV projects from auctions in developing countries. The authors use a simple financial model to obtain LCOE estimates for projects and explain whether projects are feasible at the resultant awarded auction prices. Butler et al. [53] use financial modelling of wind projects to compare the effectiveness of the German and the UK support schemes. Apostoleris et al. [54] use a similar approach to describe the factors that led to low-priced solar auctions in the Middle East, and whether the prices can be replicated elsewhere and further reduced. However, the financial models employed within this strand of literature are typically simplistic and do not consider the required number of assumptions for accurate conclusions to be drawn. Furthermore, these studies typically make significant assumptions regarding cost data for the different renewable technologies, which do not represent the reality of the developments. Although there is some value in financial modelling to assess the viability of renewable projects given an awarded subsidy price, their uses in assessing auction dynamics or informing auction design are limited.

Simulation of RES auctions involves creating a virtual model of the real-world auction, which is programmed into computer software. These models are frequently used to study how a system works, find optimal input parameters, learn the key features, and extract data from the system. Simulating RES auctions to test auction design empirically is a growing topic in literature, described and analysed in Section 2.3, which concerns the Simulation of Auctions. Simulating renewable auctions allows for greater flexibility in answering a wide range of research questions. The simulation environment can be altered to reflect the research question, and the outcomes can be empirically observed.

The UK CfD auction scheme, aimed at supporting renewable energy, is an interesting research case study for a number of reasons. Firstly, the UK's CfD mechanism has been used to procure 27 GW of renewable energy capacity [55], significantly more than comparative auctions in other geographies, with the resultant awarded prices consistently dropping and, as such, has attracted significant media attention. Secondly, as stated in Section 2.1.1, the CfD mechanism provides the greatest revenue certainty to developers and due to its success, is being discussed as a cornerstone for future European country's procurement of renewables [56, 57]. Finally, the UK CfD contract has unique design rules (e.g. uniform pricing rule), making it an interesting case study to analyse and compare with the design rules of other countries.

2.1.3 UK CfD Auction Background

The CfD auction scheme was introduced to the UK in 2014 as part of the Electricity Market Reform by BEIS (Department for Business, Energy & Industrial Strategy). It is one of the UK's primary subsidy support mechanisms for supporting low-carbon energy generation and is seen as 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 Figure 2.2, which is indicative of the falling cost of offshore wind energy generation. The Contract for Difference (CfD) Allocation Round (AR) 2 resulted in a low strike price of £57.5/MWh in September 2017, down from £114.39/MWh achieved in CfD AR 1 in February 2015. The strike price is defined as the price fixed by the auctioneer of security after receiving bids in a tender offer. In September 2019, in AR 3, prices dived to a value of £39.65/MWh, 60% lower than the target imposed to be met by 2020 [58]. Despite well-publicised commodity price increases, which put further pressure on the offshore wind supply chain, the awarded CfD strike price continued to fall to £37.35/MWh in 2022. As a result of the success of CfD auctions, the UK government have committed to staging a CfD auction every year, providing a greater level of certainty for the UK offshore wind industry. CfD auctions follow a uniform price format (explained in Section 2.1.1, and all successful bidders receive the same remuneration, determined by the highest successful bid. ASP refers to the (Administrative Strike Price). The auctioneer sets the ASP, the ceiling price awarded to a technology for a specific Allocation Round (AR). For further information on the methodology used to determine ASPs, refer to the UK Government website [59].

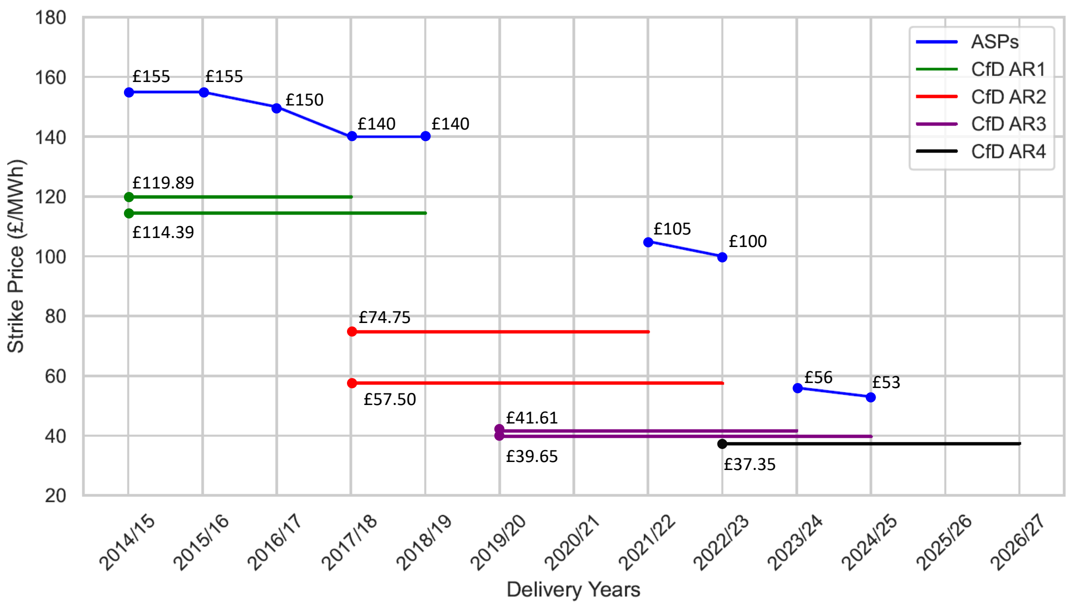


Figure 2.2: Offshore Wind CfD strike price historical results [60, 61, 62, 58], demonstrating sustained CfD strike price reduction.

In the UK, a CfD is a 15-year contract between developers of renewable projects and the Low Carbon Contracts Company (LCCC), a private company owned by BEIS. Under the agreement with the LCCC, a generator sells electricity under a Power Purchase Agreement (PPA) to a supplier or trader at a live market reference price. The LCCC then top up this payment or take payment from the generator, as explained in Section 2.1.1. This means that the generator is guaranteed to sell the electricity at the fixed strike price [63].

2.1.4 CfD auction design

The UK CfD auctions have a multi-unit, sealed-bid, uniform price (pay-as-cleared) format. A multi-unit auction is where several homogeneous items are sold [64]. 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 receive either the highest accepted bid, which can be their own, or zero. CfD prices are inflation tracked, this means that they increase with CPI (consumer price index) for the entirety of the 15-year contract length period. This is unique to other subsidy support mechanisms such as the Irish's ORESS-1 (Offshore Renewable Energy Support Scheme), which is only partially indexed to 30% of inflation [65]. A non-index linked subsidy auction adds uncertainty, as developers must estimate inflation and obtain a price that will be profitable during the duration of the subsidy contract.

The total CfD subsidy budget is divided into different technology pots. Table 2.2 illustrates the Allocation Round 4 (AR4) pot structure and allocated monetary budgets. Prices are shown in 2012, real terms, as this was the year that the auction was first introduced, so offers an easier method for comparing price changes throughout the years. AR4 is the most recently completed auction at the time of writing. Pot allocation is dependent on the UK Government's renewable energy policy. For example, a lack of government support for solar and onshore wind saw the withdrawal of funding for these technologies in previous auction rounds [66, 67]. Support for these technologies has been reinstated for AR4. The government can also ring-fence subsidy for particular technologies, this guarantees that subsidy is awarded to those technologies and is frequently done to support the deployment of less mature technologies. In AR4, only floating wind and tidal technologies received ring-fenced support.

The allocation process for CfD contracts is as follows: The process begins with the National Grid Electricity System Operator (National Grid ESO), inviting eligible applicants to bid for the available budget in each pot. National Grid ESO is the Delivery Body for the CfD scheme, responsible for running the CfD allocation process. Bidders must first satisfy several strict pre-qualification criteria to compete in the allocation process. For example, for large renewable development deemed Nationally Significant Infrastructure Projects, developers must obtain all the necessary consents for their site from the National Infrastructure Planning Inspectorate and a grid connection agreement with the network operator. Additionally, for offshore

Table 2.2: Budget (million £), in monetary terms [2012 prices], for AR4 [68].

	Delivery and Valuation Years					
	2023/4	2024/5	2025/6	2026/7	2027/8	2028/9
Pot 1 - Wind & Solar (M£)	10	10	10	10	-	-
Pot 2 (M£)	-	-	75	75	75	75
Minimum for Floating Wind (M£)	-	-	24	24	24	24
Minimum for Tidal Stream (M£)	-	-	20	20	20	20
Pot 3 - Fixed Offshore Wind (M£)	-	-	210	210	210	210

wind, developers must agree with the Offshore Transmission Network Operator (OFTO). For projects exceeding 300 MW, a *supply chain plan* which outlines how the project will promote competition, innovation, and skills in the supply chain must be submitted and approved. Other important considerations, such as local content, will also play a part in the eligibility of projects [69].

Prior to the auction, a budget notice is issued by BEIS, the auction organiser, which declares a capacity minima, capacity maxima, and total budget for the auction. Any singular project exceeding the capacity maximum is rejected. If a minimum capacity is set, then the lowest bids are automatically accepted up to the minimum, providing the bid price is equal to or below the ceiling price. Finally, a monetary budget dictates how many projects are accepted by assessing the budget impact of each project using a Valuation Formula (the Valuation Formula is presented and described in more detail below). Typically, the capacity maximum or budget notice is the limiting factor in determining the volume of capacity procured. For example, for the pot concerning offshore wind, in AR3 (2019), a capacity maximum was the limiting factor; this changed to a budget notice in AR4.

Budgets are capped annually, meaning 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. There are typically two delivery years in an AR available to generators for offshore wind, as shown in Table 2.3, which also illustrates the budget available and the amount of offshore wind procured for each past auction. The annual budgets shown are for total spending for all successful projects for that allocation round rather than for projects that start generating in a particular delivery year.

The budget impact of a project is calculated using the Valuation Formula, shown in Equation 2.1. The Equation has been taken from the Valuation Framework document produced by BEIS [68]. Where BI is the budget impact, SP is the strike price, RP is the reference price, LF is the given Load Factor for offshore wind, $YR1F$ is a factor applied to each project to account for partial year generation, C is the capacity, TLM is the Transmission Lost Multiplier, RQM is

Table 2.3: Budgets are available for each delivery year as set out by the Secretary of State for Energy in a budget notice [60, 61, 62].

	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 Renewable Qualifying Multiplier and determines the payments made to generators based on the renewable content of their fuels, and $CHPQM$ is the CHP Qualifying Multiplier which ensures that developers are producing good quality Combined Heat and Power.

$$BI = (SP - RP) \cdot LF \cdot YR1F \cdot C \cdot (Days_{yr} \cdot 24) \cdot (1 - TLM) \cdot RQM \cdot CHPQM \tag{2.1}$$

The values for each constant in the above equation are issued by BEIS for each auction round [68]. The parameters may change between auction rounds. Example parameters based on AR4 are shown in Table 2.4.

Table 2.4: Valuation formula parameters - Values are constant for all auction participants and are example inputs based on AR4 results [68].

Term	Value	Unit	
RP	32.85	£/MWh	*market reference price specific for the AR*
LF	63.1	%	*load factor estimate specific for technology*
YR1F	1		*factor to account for partial year generation*
Days	365		*days in a year*
TLM	0.9	%	*accounts for generated electricity lost in transmission*
RQM	1	-	*renewable qualifying multiplier*
CHPQM	1	-	*qualifying multiplier ensuring quality Combined Heat & Power*

Developers in the UK CfD auction submit up to four flexible bids. The flexibility applies to the bid's capacity, bid price and delivery year. Participants can only submit a maximum of two bids into each delivery year. The flexible bids allow players to submit a number of different capacities into the auction. Developers can, therefore, choose to submit multiple bids for varying proportions of their total consented capacity, reducing the bid's total budget impact and increasing the probability of being awarded a contract.

After receiving all sealed bids from all players, National Grid ESO combines all the bids (regardless of delivery year), arranged in ascending order based on the bid price to create a bid stack. The bids are then considered in the order of the bid stack, starting with the cheapest bid. If accepted, the auctioneer assesses the budget impact of the next bid. A bid is rejected if the addition of a bid results in a budget breach (as seen from Figure 2.3). If this occurs, the next flexible bid of this project is considered under the interleaving rule. For more detail on the UK CfD allocation mechanism, refer to the CfD allocation framework [67].

The interleaving rule allows the auctioneer to consider the flexible bids of developers. Under the interleaving mechanism, a participant's next flexible bid is considered after the original bid is rejected. In the illustrative example shown in Figure 2.3, Project D results in a budget breach, resulting in an interleaving loop forming which includes all bids between the first rejected bid and the next flexible bid of that project. Therefore, in this example, Project E1 and D2 are considered together, as E1's bid price is between D1 and D2, so it forms part of the interleaving loop. For D2 to be accepted, both E1 and D2 must fit into the budget and not result in a budget breach of VY1 or VY2 (Valuation Year 2). If either E1 or D2 results in a budget breach of either VY, then both bids are rejected, and the auction is closed. This is an example of unsuccessful interleaving. In this example, as Project C is the last accepted bid, it is the project which sets the strike price for both delivery years of the auction. However, if neither E1 nor D2 results in a budget breach, interleaving is successful, so both bids are accepted, and D2 becomes the strike price for both delivery years. If two bids are submitted with an equal bid price, and accepting both bids results in a budget breach, then the accepted bid is decided by a tiebreaker. During a tiebreaker, the Delivery Body must choose one of the Qualifying Applications at random [67].

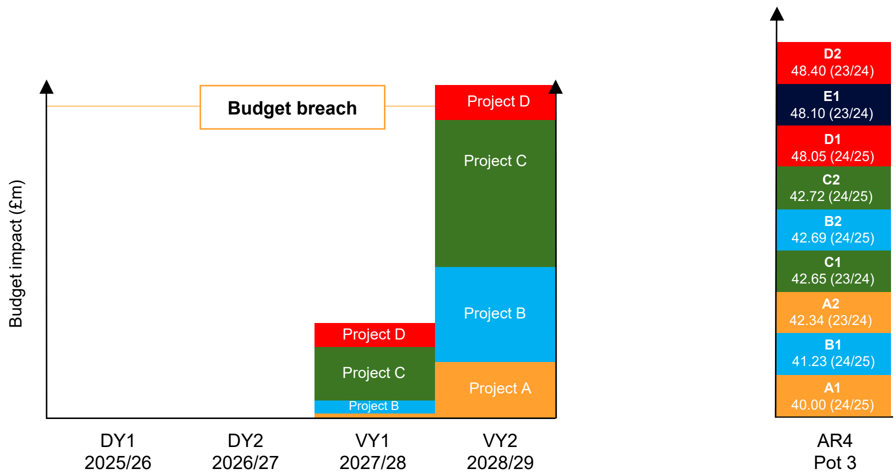


Figure 2.3: Illustration of how the stack of bids is assessed against a budget, resulting in a budget breach.

In the unlikely event that the total applications do not result in a budget breach, all applicants will be offered a CfD, non-competitively, at a technology-specific ASP. However, policymakers issue budgets considering the expected competition, meaning the probability of a non-competitive auction is remote.

The allocation framework rules between allocation rounds can change, impacting auction dynamics and auctions' competitiveness. One significant change from previous CfD auction rounds is simplifying the role of delivery years. In AR4, the whole auction closes if the monetary budget is breached in one delivery year. Therefore, a single strike price will apply across the auction (which is subject to ASPs). However, qualifying applicants will still bid into individual delivery years as before. In previous ARs, such as AR3, there were separate strike prices for each delivery year; this cannot happen in AR4. The two strike prices in previous auction rounds occurred because a budget breach would result in delivery year closure instead of entire auction closure. This meant that in the case of a budget breach, the auctioneer could continue allocating capacity to the other delivery year until a second breach occurred, resulting in auction closure [66].

The penalty for projects awarded a CfD contract and failing to deliver the project as agreed by the supply chain plan is considered non-stringent [70]. The penalty includes an exclusion for a project at the same location from future auctions for 13 months from the date of the breach of the contract. However, as CfD auctions previously occurred every two years, the penalty had virtually no effect. An overall diagram illustrating the allocation framework for CfD auctions can be seen in Figure 2.4. The diagram illustrates the decision making process for an auctioneer with respect to the different auction features as described in this section.

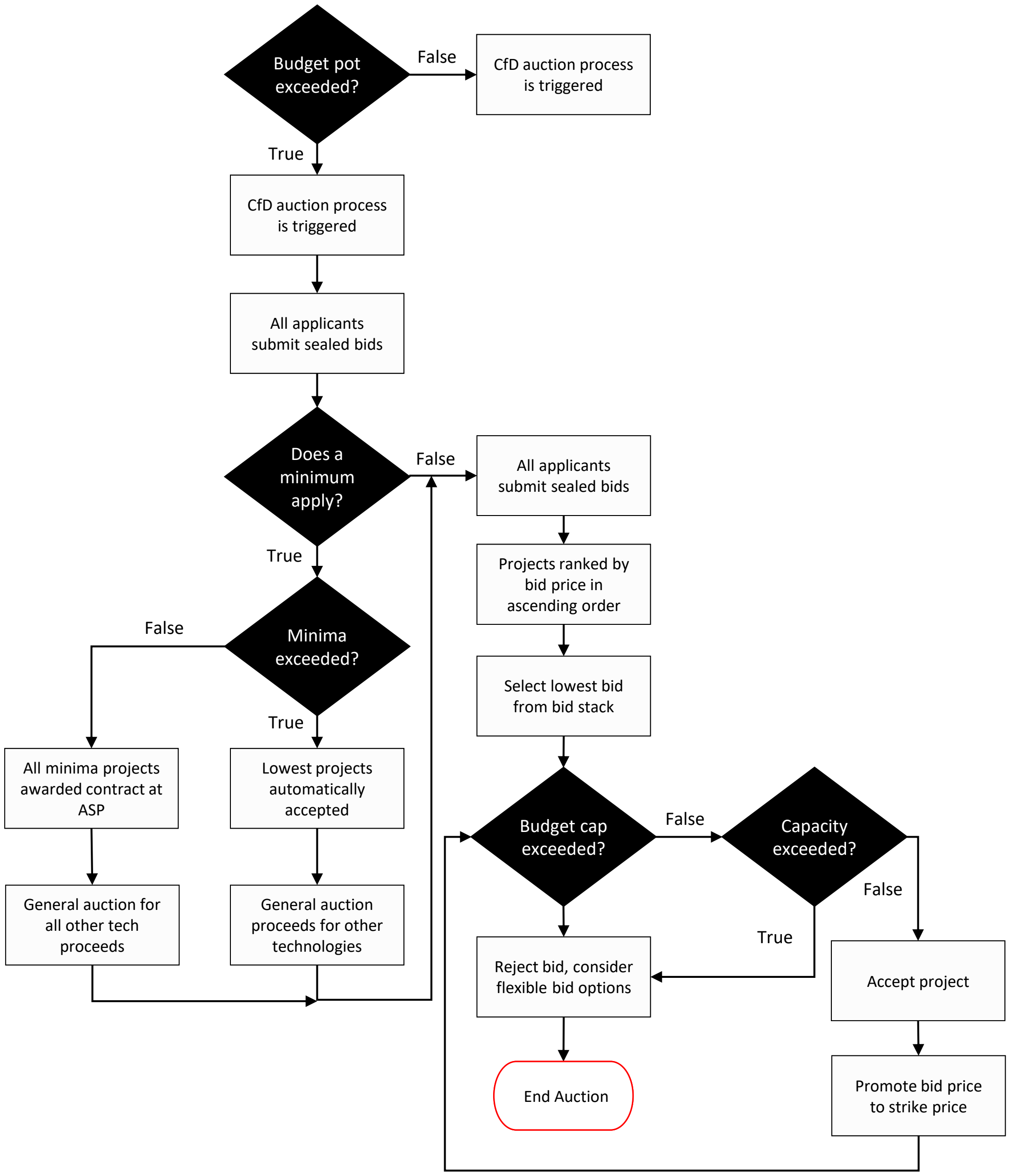


Figure 2.4: Allocation framework flow diagram for CfD allocation.

2.1.5 Bidding into Renewable Auctions

In order to design an effective RES auction, one must also consider the dynamics from the player's perspective. A well-designed auction must be transparent for players, and methods should exist for players to prepare their bids, which prevents the winners' curse and mitigates project non-realisation. 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.

There are two strands of financial theory that are relevant to this work: financial analysis and project finance. Financial analysis provides a comprehensive view of a company's financial health, project finance analysis narrows the focus to evaluate the financial aspects of a specific project, considering its unique risks, cash flow dynamics, and funding structure. Project finance analysis is often applied in sectors where large, capital-intensive projects are common [71].

The relevant corporate finance theory can further explain developers' motives for bidding in RES auctions. Offshore Wind developments are large capital-intensive projects where developers must raise significant capital before finalising investment decisions. Recent surveys on costs of capital of onshore wind energy projects across the EU have found shares of debt of between 55% and 80% [72, 73, 74], largely because debt is cheaper than equity, and so minimises project costs. To raise a high proportion of debt at preferred lending rates, banks typically require that projects have revenue certainty and are protected from merchant risk [65]. As described in Section 2.1.1, the various support mechanisms provide varying amount of protection from merchant risk.

The cost of capital is the cost under which lenders invest debt or equity into a company or project [75]. The overall cost of capital is weighted by the shares and cost of debt, which forms the weighted average cost of capital (WACC) [76]. Developers use the WACC to discount cash flows and calculate the Net Present Value (NPV). A positive NPV indicates that the project creates value and should be undertaken. However, in practice, companies only undertake projects which meet or surpass an internal hurdle rate (required IRR). Therefore, developers will ensure that a positive NPV is obtained when discounted by the required IRR. The hurdle rate is typically based on the WACC and is usually higher but, in some instances, can be lower depending on the strategic motivation of a company. For example, in project finance, hurdle rates can be lower than WACC if trying to gain a strategic advantage in a new market [19]. Therefore, in simulating auctions, it is the internal hurdle rates which can be set by developers and varied according to risk appetite [77]. The relationship between the cost of capital and hurdle rate, as well as the dynamic of varying one's hurdle rate in accordance with their risk appetite, can be seen in Figure 2.5. The risk appetite represented by the hurdle rate can vastly impact a developer's bid value in an auction. As a result, developers can alter their risk profiles and significantly alter their bid prices.

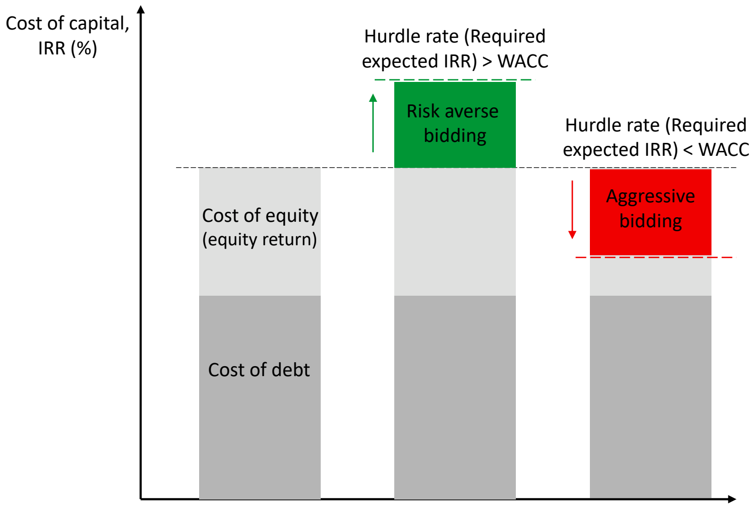


Figure 2.5: Effect of varying hurdle rates in accordance with bidding strategy. Adapted from [19].

An awarded support price can significantly affect the profitability of offshore wind developments. Therefore, bids must be carefully considered, allowing developers to cover costs and give investors the required return on their investment. Determining a bid price requires an analysis of costs and revenues throughout the entire lifetime of the wind farm. This is necessary to estimate the project's cash flow and then calculate a minimum price which satisfies the investment criteria. However, estimating cash flows accurately is challenging, as significant uncertainty exists. For example, uncertainty is associated with one's cost of components, such as foundation, cables and steel costs [78]. The uncertainty experienced by players bidding into auctions is explained and analysed further in Chapters 4 and 5.

There are several risks to consider while bidding at an auction. A developer can submit a very low bid price to ensure competitiveness and risk experiencing the winners' curse, where a bidder regrets the award of a contract at the resultant price, potentially leading to unprofitable sites and the non-realisation of projects [23]. Renewable energy developers must perform financial and strategic analyses to formulate a bidding strategy. Financial analysis relates to all known factors (e.g. seabed rental cost). Strategic analysis is associated with assessing uncertainties (e.g. level of competition, competition costs, future wholesale electricity market prices). This strategic element is crucial and is considered non-negligible [78]. Therefore, to determine a bid price, bidders must characterise the uncertainty to understand the auction dynamics and make predictions of the auction outcome. One way of achieving this is through auction simulation, which helps test the existence of dominant strategies in the presence of different bidder configurations, valuations and uncertainty [79].

Developers can use a number of academic theories (explained more broadly in Section 2.3.2) to help formulate an optimum bidding strategy. For example, developers can use Monte Carlo simulation. Monte Carlo simulation is a computational technique used to understand the impact of uncertainty and variability in a system. It involves the use of random sampling and statistical modeling to estimate complex mathematical outcomes. The underlying concept is to use randomness to solve problems that might be deterministic and is commonly used to inform decisions when there is considerable uncertainty [80]. Game theoretic principle can also be useful for developers. The subject is a branch of mathematics and economics that studies the strategic interactions among rational decision-makers. It provides a framework for analyzing situations where the outcome of an individual's decision depends on the decisions of others. Game theory is widely used in various fields, including economics, political science, biology, computer science, and psychology, to model and analyze decision-making in strategic situations. Rational decision-makers are individuals or entities who make decisions based on a systematic and logical evaluation of available information [81].

2.2 Financial Assessment of Offshore Wind

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. A cost modelling tool is required to estimate costs based on project and site-specific data. Estimating the life cycle costs for an offshore wind project is difficult. Cost modelling uses a number of assumptions for the development, construction, operation and decommissioning phases to estimate costs and identify key cost drivers. Even if a development is nascent, early-stage cost estimates are used to make investment decisions, authorise budgets, manage costs, and enhance negotiation skills with suppliers. A brief overview of the various cost modelling approaches has been summarised in this section.

2.2.1 Offshore Wind Cost Modelling

The first pieces of literature concerning offshore wind cost models were based on projecting onshore data to offshore [82]. Such models were a crude form of estimation, as they did not consider specific offshore wind parameters and so did not represent the harsh environmental conditions in which offshore wind farms operate. Later models, such as the UK Government's LCOE model, calculate the impact of innovations for an offshore wind farm reaching the Final Investment Decision (FID) in 2020. The model was developed to identify high-impact (significant LCOE reduction) technological developments [83]. The same model was extended using Monte Carlo simulation to propagate the uncertainty to the model output [84]. However, new environmental regulations, economic policies, technological advancements and financing structures have resulted in many new relationships that need to be considered to define risks and profitability for the next generation of offshore wind farms. Therefore, simple cost models, which do not consider financial modelling, are no longer suitable when using them as decision-making tools.

Shafiee et al. [85] developed a life cycle cost analysis framework for bottom-fixed offshore wind. The framework is divided into five life stages: predevelopment and consenting, production and acquisition, installation and commissioning, operation and maintenance and decommissioning. Later, a stochastic version of the same model was developed [86], to estimate cost uncertainties. However, these models lack the technological granularity and the financial model component to reflect the LCOE of offshore wind projects accurately. There are a number of commercial software that different developers have developed in the sector. One example is produced by DNV GL, which uses Value Chain Assessment (VCA) software to support investment decisions for offshore wind [87]. The VCA is a probabilistic tool that considers links between technology and finance and the relationships between several parts of the value chain. Furthermore, BVGA has a similar cost model, which it uses to track the impact of innovations on the LCOE and produce reports on technological innovation and cost reduction [88]. These two examples can represent the link that exists between technology and finance that is important for investors and shareholders for decision-making [89]. However, both tools are proprietary software, which cannot be used for research purposes, as the models are not widely available outside of their respective businesses. As a result, this work uses a cost modelling tool available at EDF, which is similar to the BVGA and DNV model discussed, as it considers the complex lifecycle of an offshore wind farm and factors in the relationship between technology and finance.

2.2.2 Overview of Offshore Wind Cost Modelling Tool

The Offshore Wind Cost Analysis Tool (OWCAT) has previously been developed at EDF Energy R&D UK Centre. The cost modelling tool produces rapid cost estimates using project-specific (e.g. wind turbine rating, foundation type, and cable export type) as well as site-specific (e.g. mean wind speed, average water depth, and distance to shore) data. The tool is typically used for comparative evaluation of multiple sites, evaluation of specific project layouts, and sensitivity studies on design/technology choices. Cost estimates from the model have been validated against detailed cost assessments from existing wind farm projects such as Navitus Bay, Courseulles-Sur Mer and Neart Na Gaoithe and have shown to produce cost estimates with an accuracy of $\pm$ 15% [90].

The cost modelling tool consists of three main modules, as highlighted by Figure 2.6: a wind farm layout and design module, a cost estimate module, and a financial module. The cost modelling tool can be run in either deterministic or stochastic modes. The deterministic mode assumes a single value for each input, producing deterministic outputs. The stochastic mode allows cost parameters to be represented by distributions, producing a matrix of estimated costs as outputs. The uncertainty band which creates the distributions for each cost parameter are obtained through expert interviews, and an upper, middle and lower estimate for each parameter is obtained. Stochastic values drawn from this model derive an empirical distribution of costs rather than assuming a specific distribution shape. The stochastic cost data generated by the cost model is empirical, meaning that the data does not fit a specific family of distributions. The cost data generated for each project are interdependent. For example, for each CapEx value calculated by the model, a corresponding capacity factor, OpEx, DevEx, and DecEx values, is calculated. This is because, for one iteration of stochastic cost estimations, a value for each cost parameter is selected and used throughout. In a second iteration of stochastic cost estimations, a different value for the same cost parameter is used throughout, which results in different interdependent cost estimates.

An overview of the three modules which make up the cost modelling tool is given in this Section. Only key equations and theories surrounding the main cost components are discussed in this Chapter. A detailed overview of the cost modelling tool is shown in work produced by Mora [89].

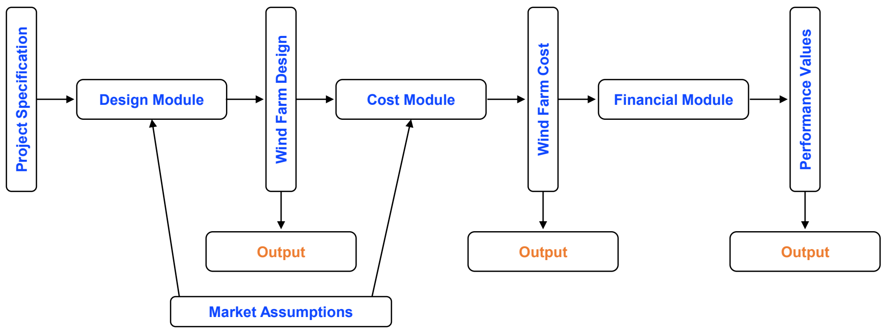


Figure 2.6: OWCAT high-level diagram

The inputs behind the modelling tool, such as cost values, correlations and other relationships, are informed by the EDF Group's procurement, engineering and energy economics teams. The assumptions are updated yearly to ensure data is accurate and reflects market conditions. The inputs can be categorised into the following:

- (i) Market Specification
- (ii) Project Specifications
- (iii) Technical Specifications
- (iv) Economic and Financial Specifications
- (v) Vessel Specifications
- (vi) Structural Masses and Electrical Component Database

(i) refers to the relevant market trends and forecasts such as cumulative installed capacity, future wind turbine ratings, and cost reduction scenarios. Market inputs are utilised to make estimates on the future cost of offshore wind and estimate costs for wind farms built several years into the future. (ii) represents the project-specific data intrinsic to a particular site. Such data include mean wind speed at a given reference height, average water depth, soil conditions, and distance from shore. (iii) refers to the chosen offshore wind technology, representing wind turbine rating, foundation type, export system, and inter-array cables. Further detail concerning the turbine, such as turbine spacing, availability, chosen installation vessel, and installation times, are all considered. (iv) addresses the reference year for real prices, route-to-market (CfD or wholesale markets) risk-free rate and cost of debt, depreciation, insurance, taxes, seabed rent and exchange rates. (v) consists of vessel costs and characteristics used for O&M, installing, and decommissioning an offshore wind farm. For example, data on a tug's day rate, vessel transit speed, vessel positioning time, vessel mobilisation time, percentage weather windows, and loading capacities are all included. Finally, (vi) contains all the engineering design data, such as foundation mass correlations and electricity system relationships, which is used to estimate CAPEX outlay.

Design Module

The design module fixes the project-specific inputs of the wind farm. To model a wind farm, the number and type of wind turbines, foundations, inter-array cabling and the export system must be defined. The design module of the tool must capture the interdependence of the various offshore wind components. For example, the foundations' size and weight depend on the type of turbine used. For this reason, the design module captures the same interactions as would occur between the various design teams of an offshore wind farm.

The overall design of the offshore wind farm includes wind farm layout, calculation of foundation masses, and inter-array and export system sizing. Additionally, it considers procurement, vessel charter model and an Annual Energy Production (AEP) calculation. Once the design is fixed, a procurement module identifies and stores the type, number of elements, and sizing of all required components for the design, such as wind turbines, foundations, the quantity of steel, length of cabling, and substations. Information is held in a procurement catalogue and fed into the cost module. The vessel charter design model follows the work of Kaiser et al. [91] and uses known relationships to calculate the required time (in hours) for each vessel type during the installation phase.

(i) Wind Turbine Supply

Associated costs to wind turbine supply significantly contribute to the total expenditure of wind farm projects. Wind turbine supply costs include the total cost of all components situated above the attachment point between the turbine and the foundation, including the transition piece. The turbine supply cost, C^{S}_{WTG}, is estimated from a unit cost per MW C^{ref}_{WTG}, the rated power of turbines used cap_{WTG}, and the number of wind turbines required, N_{WTG}. The unit cost used is a quote obtained from a turbine OEM. To estimate the transportation cost of the turbines from a fabrication yard to the installation port C_{WTG}^{trans}, the size of the turbine is multiplied by the vessel day rate and total estimated vessel days required. Larger turbines incur higher transportation costs, as they require greater deck space, meaning a higher number of trips from the fabrication yard to the installation yard is required. Therefore, the total wind turbine supply cost can be estimated from Equation 2.2.

$$C_{WTG}^{S} = N_{WTG}[cap_{WTG} \cdot C_{WTG}^{ref} + C_{WTG}^{trans}] \tag{2.2}$$

(ii) Foundations

To calculate the total foundation supply, foundation masses, m_j, are estimated from correlations to calculate the quantity of primary steel that is required for manufacturing. Foundation masses are estimated from data on water depth $d_{water}^{c_j}$, wind turbine rotor diameter $d_{rotor}^{d_j}$, and the mass of the topside of the turbine $m_{topside}^{e_j}$. The coefficients of these equations a_j, b_j, c_j, d_j, and e_j are calculated for each foundation type based on fitting Equation 2.3 to internal EDF proprietary data and using least square methods.

$$m_j = a_j + b_j[d_{water}^{c_j} \cdot d_{rotor}^{d_j} + m_{topside}^{e_j}] \tag{2.3}$$

Estimated foundation masses are converted into primary steel costs by multiplying the mass by the unit primary cost, c_{fab}, as shown in Equation 2.4. The unit primary cost differs for foundations and monopiles, as jacket supply costs are largely driven by fabrication costs due to the complexity of their structure. As a result, monopiles achieve higher rates of economies of scale than jackets.

$$C_{fnd}^{PS} = m_j \cdot c_{fab_j} \tag{2.4}$$

In addition to primary steel costs, the costs of secondary steel (e.g. boat-landings, ladders, internal platforms, and corrosion protection) are also estimated and included. The steel supply and fabrication, including welding and corrosion protection, are included for every item considered. The load-out and transportation to the installation port are considered, given assumptions on vessel transportation costs and distances from the foundation fabrication yard.

(iii) Electrical Infrastructure Supply

The supply costs for export and inter-array cables, C_{cable}^{SS} for a three-core conductor subsea AC cable, is shown in Equation 2.5. The equation is a function of the rated voltage V_op and the required cross-section, A_{sect}, of the conductor cores. Additionally, f_{mat} takes into account the material conductor, which takes a value of 0 for copper and 1 for aluminium. The equation has been derived by interpolating internal cost data sources and adjusted accordingly by inflation and exchange rates. The coefficients a, b, c, d, and e are obtained by minimising the difference between the model's estimated costs and the actual costs found from an internal procurement database.

$$C^{SS}_{cable} = a + bA^{C}_{sect} \cdot V^{d}_{op}(1 - ef_{mat}) \tag{2.5}$$

Subsea cables can be estimated using Equation 2.6, which sums the product of the total cable length l_{sect}, of each of the N_{sect} cable sections by the specific cost of that cable section C^{SS}_{cable}. In reality, the extra cable is ordered to account for potential damages during the installation phase and so is accounted for by the f_{spare} parameter. The length of each cable is calculated from the horizontal turbine spacing, the vertical direction (to and from the seabed, and estimated from the water depth). l_{sect} is increased by a small factor to take into account the added length needed for cable slack and snaking.

$$C_{cable} = \sum_{N_s ect} l_{sect}(1 + f_{spare})C^{S}_{cable}S \tag{2.6}$$

Offshore substation costs are calculated as a function of the cost of the topside platform $C_{topsideplatform}$, the jacket structure C_{jkt}, the transformers $C_t rans$, the Gas Insulated Switchgear C_{GIS} for array and export system, the Supervisory Control and Data Acquisition (SCADA) system C_{SCADA}, the Cross-linked Polyethylene (XPLE) set, C_{XLPE} and the overhead costs $C_{overheads}$. The equation is shown in Equation 2.7.

$$\begin{aligned} C_{HVAC_{on}} = C_{topsideplat} + C_{JKT} + C_{trans}N_{trans} + C_{GIS}(N_{MV_s} + C_{HV_s}) + C_{SCADA} \\ + C_{XLPE}N_{cables} + C_{overheads} + (N_{MV_s} + C_{HV_s}) + C_{XLPE}N_{cables} \end{aligned} \tag{2.7}$$

(iv) Installation

For all offshore wind components, the model estimates an associated installation cost. The exact method and parameters used for calculating installation costs vary depending on the type of component to be installed. Internal data is held on each component's installation requirements, vessel requirements, the total number of vessels required, and the estimated installation time for each component. The most significant cost associated with installation is the vessel charter cost, which can be estimated by Equation 2.8. The equation is based on the duration for each individual turbine installation process h_{WTG}, the number of wind turbines needed to be installed N_{WTG}, and the day rate of the vessel required C_{rate}. Additional costs for vessel mobilisation and demobilisation n_{mob} in days, required for the installation vessels to prepare for operation and transit from previous ports, must also be considered.

$$C_{vessels} = [n_{mob} + h_{WTG}N_{WTG}]c_{rate} \tag{2.8}$$

The procedure for estimating the installation cost for a component can then be estimated using Equation 2.9. Where C_I is the total installation cost, C_{prep} is the pre-assembly and pre-commissioning costs and is associated with storage and port costs, $C_{vessels}$ is the installation vessel charter cost, and is estimated from Equation 2.8, C_{comm} is the commissioning and completion cost, and the overhead costs $C_{overheads}$, which are scaled from internal data to match the offshore wind farm size, and relate to the design engineering for the installation phase.

$$C_I = C_{prep} + C_{vessels} + C_{comm} + C_{overheads} \tag{2.9}$$

(v) Capacity Factor

The calculation of the capacity factor assumes a logarithmic or power-law wind profile while using a Rayleigh or Weibull probability distribution to model wind speed at a reference hub height. Wind turbine power curves can either be provided by the Original Equipment Manufacturer (OEM), or theoretical power curves can be used. Wind speeds are discretised into bins according to wind speed to calculate the gross annual energy production. For each bin, the occurrence of the wind speed is calculated (based on a Weibull distribution) and then multiplied by the number of hours in a year (8760 hours) and the corresponding power output based on the power curve. The "power bins" are then summed and multiplied by the number of turbines to obtain gross AEP, as shown in Equation 2.10. Where n represents the individual bins, N_{WTG} is the number of wind turbines, T is the time length in hours of one year, $cdf(u_{n+1}) - cdf(u_n)$ is the occurrence of a wind speed bin and $P(u_n)$ is the power curve value at the same wind speed bin n.

$$AEP_{gross} = N_{WTG}T\int_0^{\infty} pdf(u)P(u)du \approx N_{WTG}\sum_{u_{bins}} T(cdf(u_{n+1}) - cdf(u_n))P(u_n) \tag{2.10}$$

Several loss factors are factored in to obtain AEP_{NET}. These are wake losses f_{wakes}, electrical losses f_{elec}, turbine availability f_{array}, and a degradation factor f_{exp}. More detail on how each of the individual losses is calculated can be found in the thesis produced by Mora [89]. Once AEP_{NET} is calculated, the capacity factor can be estimated. Capacity factor is defined as a dimensionless ratio of the wind energy output over a given period of time to the maximum possible energy output during that period.

$$AEP_{net} = AEP_{gross}(1 - f_{wakes}) \cdot f_{elec} \cdot f_{WTG} \cdot f_{array} \cdot f_{exp} \tag{2.11}$$

2.2.3 Cost Module

The procurement catalogue fed from the design module is input into the cost module. The cost module, which holds the cost component data, then aggregates the total cost of the different offshore wind components. The cost module calculates Development Expenditure (DevEx), Capital Expenditure (CapEx), Operational Expenditure (OpEx), and Decommissioning Expenditure (DecEx). DevEX concerns total costs incurred before financial close and final investment decision-making. Internal cost data is held on the associated DevEx costs for a 500 MW offshore wind farm. To compute DevEx, the cost data is scaled to the capacity of the estimated project. CapEx relates to the wind farm's total supply and installation costs, including wind turbine procurement, foundations, inter-array cable, substations, transition pieces and the associated installations. Additional indirect costs such as engineering, procurement, insurance, and project management costs are also included in the CapEx breakdown. OPEX includes any costs incurred during the operational period of the wind farm and is calculated using estimated equipment fault data, vessel data, transmission charges, insurance, taxes, and royalties. DecEx refers to decommissioning wind turbines, foundations, and onshore substations.

2.2.4 Financial Module

The estimated cost outputs are fed into the financial model, which is the third module in the tool. The financial module calculates the various cash flows over the wind farm's lifetime, which is required to calculate financial performance indicators, such as LCOE. The financial structure to provide the initial capital investment is also considered. The outputs from the financial module allow for more detailed corporate and project finance modelling. LCOE can be calculated using Equation 2.12. Where FCF_t are the free cash flows incurred at different points in time, d is the minimum rate of return acceptable and acts as the discount rate, n is the total number of periods, and λ is an iterative value of the LCOE. λ starts with an initial guess and then optimises until the value converges towards the true LCOE.

$$LCOE = \sum_{t=1}^{n} \frac{FCF_t(\lambda)}{(1+d)^t} \tag{2.12}$$

2.2.5 Sensitivity Analysis

Sensitivity analysis (SA) methods explore model behaviour and allow comparisons with the system they represent. SAs can be used to understand the uncertainty associated with each input factor and identify inputs which most greatly affect the outputs. In the context of CfD auctions, as cost estimates and future revenues are uncertain, this is useful as it allows developers to allocate significant resources to reduce the uncertainty associated with the parameters which make up these main inputs. The number of stochastic inputs being sampled impacts the computational time for stochastic models. Therefore, sensitivity analysis can help reduce the number of variables allowed to be stochastic.

There are a number of different sensitivity methods which explore the sensitivity of input factors to model outputs. A number of reviews exist that compare different methods. For example, a detailed explanation of all types of SA methods exists in the textbook of Saltelli et al. [92]. A review of SA methods in the context of energy analysis can be seen in the work from Tian et al. [93].

The main methods of SAs are classed into two main groups; local sensitivity analysis (LSA) and global sensitivity analysis (GSA) [93, 92]. LSAs involve keeping the values of other input factors constant when studying the local sensitivity of an input factor. Global sensitivity analysis is the process of apportioning the uncertainty in outputs to the uncertainty in each input factor over their entire range of interest. For a given application, a number of different methods are possible. The chosen method depends largely on the computational size of the analysis, desired results, and whether the interactivity between inputs should be considered.

The most common method for conducting an LSA is to alter one input factor at a time (OAT) and record the effect on the output. This method involves selecting a base case of values for the model and displacing each input factor by a select percentage whilst keeping others at the base case. The outputs are then measured, and then conducting a regression analysis based on the output. Other SA methods exist that can consider the interaction effects of inputs, such as full factorial and fractional factorial, which are useful when there are few input factors (less than 10). Sequential Bifurcation and Morris Method can be used when there are many input factors (more than 10). For the purpose of this work, the interaction between inputs does not need to be considered, as inputs to the auction simulation tool are assumed to be independent variables. For this reason, an OAT sensitivity analysis is sufficient to demonstrate factor prioritisation.

Applications of SA in offshore wind include work by Martin et al. [94], which used the Morris method to determine the key sensitivities associated with the factors of O&M affecting operating cost and availability. Mora et al. [95] used GSA methods to rank the contribution of around 150 input parameters that influence the cost of offshore wind development. Furthermore, Santos et al. [96] used SA methods to determine the most important inputs affecting NPV, IRR, and LCOE for floating offshore wind. While both of these methods are valuable in assessing the sensitivities associated to the LCOE of offshore wind, they do not measure how the key inputs affect the auction bid price of projects, which is a different metric. LCOE and auction bid prices are different metrics, because bid price factors in estimates of future revenues.

To the best of our knowledge, no published academic literature currently characterises and quantifies the relative importance of inputs through sensitivity analysis to demonstrate how uncertainty affects the calculated bid price in a RES auction.

2.2.6 Future wholesale electricity prices

The CfD bid price can determine the revenue stream for a significant proportion of a wind farm's lifetime. However, as the operational lifetime of wind farms exceeds the CfD contract length, wholesale electricity price forecasts can impact one's calculated CfD bid. To estimate revenue for a wind farm's lifetime, one must forecast the price at which the electricity output is sold beyond the contract length; 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.

Distinct from most financial or commodity markets, the electricity market is a daily market that does not allow continuous trading. This is because operators require advance notice to verify the schedule conforms with the transmission constraints. The electricity market is deregulated and is characterised by extremely high volatility fluctuations in price throughout a given time period. A major factor for the volatility is the difficulty in storing electricity which magnifies the issues surrounding continuously matching production and consumption. Furthermore, electricity demand is highly inelastic, meaning there is relative insensitivity of demand to price fluctuations and supply constraints [97].

For energy companies, electricity price forecasts are a fundamental input in their financial decision-making assessments [98]. Attributed to the extreme volatility, predicting future wholesale electricity prices is challenging. In the literature, there are various methods for predicting future prices. For example, BEIS uses a dynamic dispatch model to estimate Great Britain's power sector up to 2050. The model uses a dispatch algorithm to model estimated electricity supply and demand across the country [99], the model is further explained in Section 5.2. Other examples include agent-based models, which can be seen in work from multiple authors [100, 101, 102], statistical approaches which use econometric techniques on historical data for days with characteristics to the similar predicted period, for example, Shahidehpour et al. [103], or artificial intelligence-based, which combine elements of learning, evolution, and fuzziness to create approaches that can adapt to dynamic systems [104, 81, 105]. A full review of the different methods used to estimate future electricity prices can be seen in work produced by Weron [106].

Kreiss et al. [42] 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 in 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, other such mechanisms at the auctioneers' disposal to reduce uncertainty are not considered. One such method is to reduce generators' exposure to wholesale electricity prices by increasing the length of the CfD contract.

Ioannou et al. [107] 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 method yields vastly different profitability estimates. This work is a useful first analysis of how different wholesale electricity market forecasts may affect the estimated NPV of future developments. However, the work does not investigate the effect of this uncertainty on investment decision-making or CfD bidding.

An econometric analysis conducted by BEIS in 2013, [108] investigated the optimum CfD contract length. It found that a 15-year contract length was optimal, giving developers the lowest NPV of support payments. However, this work was done based on the 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 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 2.1.2) 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. Economic growth scenarios refer to different possible trajectories or outcomes of a country's or a region's economic performance over a specified period. These scenarios are based on various assumptions about key economic factors such as investment, productivity, technological progress, government policies, and global economic conditions [109]. Furthermore, this work takes a different approach and uses empirical simulation to better study the effect on auction dynamics.

2.3 Simulating Auctions

2.3.1 Game Theory

Game theory principles can be integrated into simulation models, to explore how the dynamics evolve given different actors with individual objectives/knowledge bases. Therefore, game theory is an important strand of literature to consider for the present analysis; as it studies mathematical models of strategic interaction among rational decision-makers (defined in Section 2.1.5).

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 [110]. For example, Wu et al. [111] proposed a game-theoretic model which utilises 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 [112]. Mei et al. [113] 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. [114] utilise game theory to test the effect different bidding strategies have on the P2P solar transactive energy markets. Finally, Liu et al. [115] use game theory to study the main bidding mechanisms in electricity auction markets. These papers demonstrate how a game can be created between different non-cooperative players and how by assuming rationality, each player's possible action can be limited to a few possibilities. The literature above has demonstrated how, similarly, the CfD auction can be considered a game, as the auction outcome depends on the actions of two or more decision-makers (players). Furthermore, each player must act rationally in the auction to maximise their pay-off.

In game theory, Nash equilibrium has been used to analyze the outcome of strategic interaction and how conflict may be mitigated in a multi-objective environment. A multi-objective environment is an optimisation problem with more than one objective function to be optimised simultaneously. A Nash solution, also called an equilibrium, is a mixed strategy profile with the property that no single player can obtain a higher expected utility value by deviating unilaterally from this profile [116]. Therefore, identifying an equilibrium bidding strategy in an auction context can approximate the interaction and bidding strategies of non-cooperative players in a CfD auction. Several pieces of literature utilise the Nash equilibrium to determine strategic bidding in energy markets. Filho et al. [117] use comparative analysis of individual strategies of generating units in auctions, using a non-cooperative game theory approach. They find that their method best suits second-price auctions, where the highest bidder wins but only pays the price equal to the second-highest bid, and can be extended to more complicated networks with high precision. However, they find it impossible to use this methodology in more complex systems. For example, bidding within a stochastic and uncertain environment requires predictions for the behaviour of other actors. Kang et al. [118] demonstrate how all suppliers can attempt to estimate the others' bids using the concept of Nash equilibrium, as it assumes that all players are profit maximising.

The literature has demonstrated how game-theory can be a useful tool when modelling renewable energy auction. However, the literature review has demonstrated that game-theoretic literature is typically used in games with complete information, whereas, CfD auctions are games of incomplete information (as explained in Section 2.1.3. The challenges associated with game-theoretic studies of bidding strategies are they are mainly limited to situations of complete knowledge (players know their rival's precise characteristics and the various associated outcomes). Therefore, although it can aid decision making, it cannot be used alone to determine bidding strategy, due to the complex nature of renewable auctions.

Auction Theory

Auction theory utilises game-theoretic principles to study the dynamics of auctions. Auction theory provides a useful framework for studying RES auctions, as it assesses how players act in auction markets and the properties of auctions. Auction theory is used to analyse the game theoretic nature of auctions when bidding [23], and thus can be used as an effective way to model decision-making [119]. Auction-theoretic literature often focuses on the efficiency of a given auction design, optimal bidding, strategies and revenue comparison [120].

There is substantial literature which utilises auction theory to describe expected auction outcomes and optimum strategies for multi-unit auctions for electricity spot markets [121, 122, 110] has summarised the existing literature on auctions applied to energy markets from both a theoretical and economic point of view. For example, bidding behaviour in auctions is a well-studied area of research. Wilson et al. [123] were the first to formalise the multi-unit auction. They noted that an offer is made according to a private value, which is not known to competitors and is based on the knowledge of the bidder. Different auction formats can assist players in value discovery. Goeree et al. [124] used an auction theoretical model to demonstrate how uncertainty experienced by bidders harms allocation efficiency and efforts to reduce uncertainty by the auctioneer results in increased efficiency and sellers' revenue. As explained in Section 2.1.5, bidders are faced with significant uncertainty; therefore, according to Goree et al. [124], from a policymakers standpoint, the uncertainty experienced by developers should be mitigated to generate value for consumers. Kreiss et al. [23] auction theory to assess the impact of uncertainty on bidders and the implications of this on the non-realisation of projects. Further work by Kreiss et al. [23] used auction-theoretic analysis to describe the results of Germany's first offshore wind energy auction. Three out of four awarded projects achieved a subsidy of 0.0 ct/kWh. The analysis identifies the rapidly falling cost of offshore wind energy as the main driver. The paper describes that the auction design needs to be continually refined to remain efficient and incentivise further cost reductions.

According to auction theory, CfD auctions follow a uniform price format meaning all successful bidders have the same remuneration. 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 the auctioneer subsidises. C is the total capacity demanded, c_i is the marginal cost of player i producing a unit of electricity. Hence, the pay-off for player i, represented by π_i, for a particular bidding strategy for a uniform price auction can be represented by Equation 7.3. For more theoretical analysis on multi-unit, uniform price auctions, see, for example, Ausubel et al [125] or for a further explanation of the format of CfD auctions, see Section 2.1.4.

$$\pi_i = \begin{cases} [b_j - c_i] \cdot q_i(C; \mathbf{B}), & \text{if } b_i \leq b_j \\ [b_i - c_i] \cdot q_i(C; \mathbf{B}), & \text{otherwise} \end{cases} \tag{2.13}$$

Wolfram et al. [126] demonstrate that in multi-unit auctions, such as in electricity spot markets, developers typically strategically bid to increase their auction pay-off. In auction theory literature, bid shading is where a bidder places a bid below their true value to increase their expected pay-off [125]. This is a well-studied auction dynamic in multi-unit auctions [127, 128]. In CfD auctions, where the auctioneer attempts to procure capacity at the best price, developers can shade by increasing their bid above the minimum CfD bid price calculated. This adds further complexity to the auction as participants may deviate from cost. According to the literature, the incentive for players to shade their bid can vary depending on the number of units sold [129]. In a multi-unit auction, bidders with a large demand for units will receive a higher auction pay-off if the auction price is reduced [125].

Auction experiments suggest that the winners' curse is a prevalent problem for inexperienced bidders. The winners curse for inexperienced bidders has been reported under several auction conditions, and for various subject conditions [130]. Kagel and Levin [131] discuss auctions for moderately experienced bidders who had participated in at least one prior first-price common value auction experiment. In small groups (auctions with fewer than 3-4 bidders), the winners' curse goes away, and experienced bidders earn a positive auction pay-off. However, in larger groups (auctions with 6 or 7 bidders), profits earned by experienced bidders are significantly higher than those earned by inexperienced bidders, although the winners' curse still exists.

In the context of renewable subsidy auctions, auction-theoretic literature provides a good basis for understanding the objective functions of developers and the various strategies they can deploy. In the past, it has been used to explain previous renewable auction results, justify auction design, and used in decision-making for future auctions. Therefore, in the context of CfD auctions, the literature survey has shown how auction theory can be a useful tool to answer the research questions and set the framework for the simulations.

Allocation Effectiveness and Efficiency

Auction theoretic literature on renewable subsidy auction largely examines the auctions effectiveness and efficiency by comparing auctions across multiple jurisdictions [132, 20, 133] or their use in single markets [53, 134, 135]. Efficiency and effectiveness are often used as criteria to assess the performance of renewable support schemes.

Effectiveness relates to the extent at which an objective is met. Within renewables, effectiveness refers to the renewable capacity installed or renewable electricity generated in a given period (e.g. the number of allocated projects which successfully met their target commissioning window within a set timeframe) as a result of the auction issued subsidy [136]. Effectiveness is assessed positively if the target are reached or over-achieved [136]. To reach a high level of effectiveness, auctions should be designed accordingly. First, auction volumes and awarded capacities need to be aligned to extension targets. Secondly, the design of the auction should adequatly incentives successful auction participants to realise their projects as awarded [137].

Efficiency is reached when the specified expansion target by a jurisdiction is achieved at the lowest possible cost. Within renewable energy generation, efficiency can signify a number of different things. Static efficiency or macroeconomic efficiency is defined as the minimisation of the overall costs of installing a certain renewable capacity or the cost of producing a certain amount of electricity at a given point in time. Dynamic efficiency looks at the future cost of renewables, so support schemes can be dynamically efficient if they successfully contribute to the static efficiency in the longer term.

According to the literature, efficiency of support schemes are impacted by the technologies in which the support scheme supports and the choice of allocating subsidies. Additional selection criteria, apart from discrimination based on price typically reduce macroeconomic efficiency [138]. Technology-neutral auctions focus on static efficiency, while technology-specific auctions include considerations regarding dynamic efficiency. Auctions, which harness competition to drive down costs, can significantly influence the development of subsidy payments, if the competition on the market is sufficient [139]. The multiple studies which look at both effectiveness and efficiency [140, 141, 135] typically show a mixed success of auctions ability to distribute renewable support. In some countries, where macroeconomic efficiency has been proven to be high (as a result of low support levels), many projects have not been realised [20].

2.3.2 Simulation and Agent-Based Models

A computer simulation is a virtual model of a system programmed into computer software. These models can be used to study how such a system works. Simulations are flexible and allow parameters to be varied to predict how a system might behave [142]. Simulations are particularly beneficial when real-life experiments are challenging. For example, there is a high financial cost of experimentation, or adverse outcomes may have significant consequences. Additionally, for systems that operate on long timescales, such as CfD auctions, one may not be able to repeat experiments in a controlled environment. Simulation has the dual benefit of minimising the risk of real decisions in the physical system and allowing practitioners to test less risk-averse strategies [143].

Within auction simulations, the most commonly used method to simulate autonomous, interacting players who operate in the same environment is agent-based models (ABM). These can be built to model systems with many heterogeneous agents. Due to the numerous and diverse actors involved in auctions and electricity markets, ABMs have been utilised to address market power and auction simulation phenomena. Li and Shi [144] show that agent-based simulation is a viable modelling tool that can provide useful insights into complex interactions among a number of different market participants.

Within energy research, ABM has frequently been used to model the electricity (spot) market. EMLAb Generation Model by TU Delft [145] is an open-source ABM toolkit that integrates short-term daily electricity trading and long-term investment decisions. Another similar use of ABM is the closed source PowerACE [146]. Furthermore, a strand of literature focuses on using ABMs to simulate complex interactions in the broader electricity market. For example, Kiose et al. [147], and Widergren et al. [148] modelled transmission system operators, generators, regulator institutions, and consumers as different agents to analyse their respective interactions and their competing objective functions. ABM has also been used to assess and analyse different market design elements and their effects on awarding a limited subsidy budget to a pool of competing renewable developments. For example, Weidlich et al. used ABM to compare the effect of pricing rules (uniform versus pay-as-bid) in an electricity market model [148]. While electricity markets is adjacent but different to CfD auctions, there are similarities. For example, an electricity market often exists in an auction format, made up of many competing players who must compete based on price. Therefore, this strand of literature demonstrates that ABMs can be applicable to CfD auctions, which takes into account the same considerations.

Bidding in Auctions Under Uncertainty

Uncertainty analysis consists of quantitatively evaluating uncertainty in model components and the representation of the level of certainty for each output. In the context of CfD auctions, developers are faced with significant uncertainty associated with their own costs and those of the competition, as explained in Section 2.1.5.

A number of different approaches exist to model uncertainty in auctions. The first is the use of Monte Carlo simulation (defined in Section 2.1.5) within ABM. Schweizer et al. [149] were among the first to analyse bidding under uncertainty. In their experiments, agents are uncertain about their true valuations and draw estimates from a probability distribution defined on an interval around a true value. Monte Carlo methods can be used within ABM to characterise uncertainty. In agent-based models of auctions, Monte Carlo methods are frequently applied to assign valuations to agents. For example, Gode and Sunder [150] simulate a double auction market by agents with zero intelligence, who draw their bid value from uniform distributions regardless of true valuation. Cai and Wurman [151] apply a probabilistic Monte Carlo approach to sequential, multi-unit, sealed-bid auctions. The agents sample the valuation space of the opponents and solve the incomplete information game that results from the sample. Their work demonstrates that stochastic sampling is useful if the problem is difficult or impossible to solve. In the context of CfD auctions, Monte Carlo sampling from distributions can be used by agents to determine an estimate for their valuation (bid price) from a distribution of cost and revenue streams.

Significant literature concerning bidding in auctions under uncertainty utilises Reinforcement Learning (RL) to identify optimal bidding solutions. In RL an agent interacts with an environment to maximise the cumulative reward gained from an environment by taking specific actions. In other words, the agent adjusts its actions based on its previous actions and observations that arise from its actions. Wu et al. demonstrate how RL can be used to determine optimal bidding strategies for electricity markets. The RL algorithm determines an optimum strategy for an individual bidder, given the significant uncertainty associated with the competitor's bidding price [152]. Liang et al. [153] use the RL algorithm to model the bidding strategies of various generation companies. The authors demonstrate that the RL algorithm can converge to a Nash equilibrium even with imperfect information. While RL has proven to converge quickly on local optima under incomplete information, its use cases within CfD auctions are limited. This is because the convergence to a solution is dependent on learning received from previous attempts. As explained in Section 2.1.4, the auction is one-shot, meaning that learning between rounds is not possible.

A separate strand of literature utilises heuristic optimisation, a family of optimisation approaches designed for solving a problem when classic methods are too slow to find an approximate solution. For example, in situations with many strategic bidders, Monte Carlo sampling from cost distributions and then analysis to determine a Nash equilibrium bidding strategy may be too computationally expensive. The use of various heuristic optimisation techniques to solve a described problem relating to the simulation of auctions has been assessed in the below section.

2.3.3 Heuristic Optimisation Approaches

As introduced in Section 2.3.1, an equilibrium exists between players where the maximum auction pay-off between players is extracted from the auction, given the number of strategic players. In the empirical simulation of renewable energy auctions, determining an equilibrium bidding strategy for various players based on their cost and revenue assumptions is a computationally expensive task. A heuristic is a time efficient algorithm that provides an acceptable solution in an acceptable time scale by iteratively improving a candidate solution with regard to a given quality measure. A key advantage of heuristics is that they can search large spaces of candidate solutions to find high quality or near-optimal solutions at a reduced computational cost.

The motivation for using a heuristic method for this work is to allow faster discovery of optimal bidding strategies, which allows for more complex case studies to be designed and explored. Additionally, heuristic optimisation techniques are readily applicable to different use cases. For example, their use cases expand to various scientific fields such as biomedical science, design of communication networks, control, electronics and electromagnetics, finance and economics, and robotics [154] The following heuristic methods, Genetic Algorithms, Particle Swam Optimisation and Differential Evolution have been considered, as these are the algorithms most commonly employed in related optimisation problems [155]. Therefore, their use cases in related literature has been explored to determine the most suitable method for the optimisation problem.

Genetic algorithms

Genetic algorithms (GA) are a class of evolutionary algorithms inspired by the principles of biological evolution [156]. In a GA, the functional behaviour of genetic operators is mimicked to create variations in a population, which is then subjected to selection pressure in a competitive environment [157]. Survival of the “fittest" solutions under selective pressures leads to the convergence of a solution. To date, GAs have been applied as an optimisation method in a variety of scientific fields, such as in material science [158], structural design [159], and wind farm layout optimisation [160]. The basic theory underpinning a genetic algorithm, which shows the key features of selection, crossover, and mutation are show in Figure 2.7.

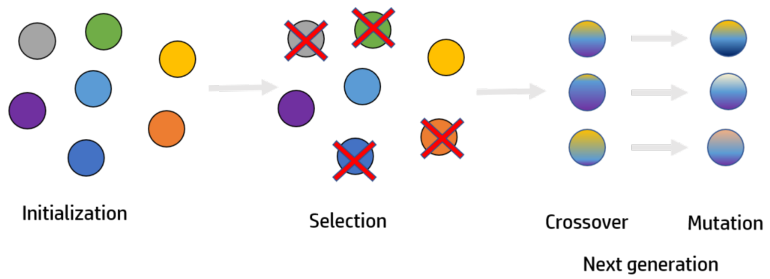


Figure 2.7: Basic Genetic Algorithm [157]

Within energy, GAs have been applied extensively within energy markets. For example, Azadeh et al. [161] utilise GAs to optimise profit-maximising generation companies' bidding strategy. Two scenarios are modelled: profit maximisation is considered without considering the rival's profit function, and profit maximisation are by considering both rivals' bid and profit functions. As this is a multi-objective problem, it is difficult to solve with traditional optimisation techniques. The GA is demonstrated to converge on local optima quickly and demonstrate optimal bidding strategies. Meng et al. [162] also use a genetic algorithm optimisation approach to make dynamic pricing decisions in the day-ahead energy market. The authors model the day-ahead market and propose a two-level optimisation model. They model the price responsiveness of different customers using the optimisation algorithm and then optimise the dynamic prices that the retailer sets to maximise its profit. They confirm the feasibility and effectiveness of their technique through simulation. GAs ability to converge rapidly on optimum solutions in adjacent research areas is evident in the literature.

Particle Swam Optimisation

Particle swarm optimization (PSO) is another example of a heuristic algorithm, which is similar to a genetic algorithm in that the optimisation problem is initialised with a population of random solutions. However, a key difference is that each candidate solution (referred to as a particle) is also assigned a randomized velocity and then flown through the problem hyperspace. Each particle's movement is influenced by its local best-known position. Still, it is also guided toward the best-known positions in the search space, updated as other particles find better positions. This is expected to move the swarm toward the best solutions. Figure 2.9 highlights how over time, particles with a given velocity converge onto a single solution.

While the use cases of PSO are widespread, there is a strand of literature which has applied PSO's to solve game-theoretic optimisation problems within an auction context. For example, Bao et al. [163] use PSO's to determine the Nash equilibrium bidding strategy for multiple bidders in a multi-round auction. The PSO algorithm successfully identified the Nash equilibrium (described in Section) point for a multi-round auction. However, the authors noted that the algorithm had difficulty converging on an optimised solution, and the computational time

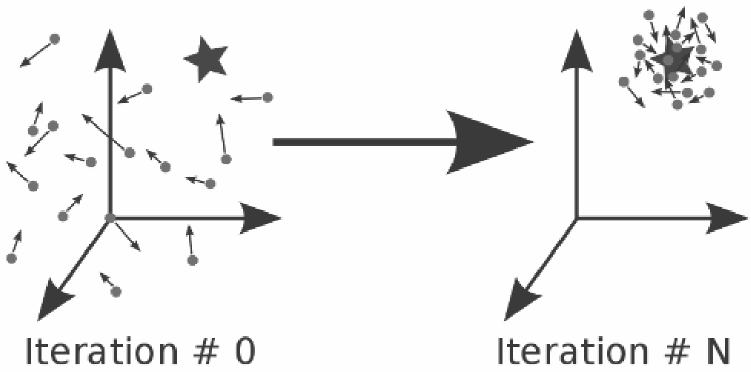


Figure 2.8: Particle Swam Optimisation [154]

to reach an optimum should be reduced. Yucekaya et al. [164] studied strategic bidding in electricity markets using PSO. The work notes that to maximise profit, utility companies need suitable bidding models that consider power operating constraints and price uncertainty within the market. A PSO is used to determine bid prices and quantities that maximise expected profits and is shown to outperform bidding at marginal cost. Similarly, Kumar et al. [165] utilise PSO to determine the optimal bidding strategy in a competitive electricity market between generating companies and consumers. In the above examples, it is observed that less fit solutions evolve due to the algorithm getting stuck in local minima due to insufficient kinetic energy.

Differential Evolution

Differential Evolution (DE) differs from standard genetic algorithms as it incorporates within the population phenomena from PSOs, such as assigning a target and unit vector. These capabilities allow differential evolution to converge faster to solutions at the cost of poor exploration. Like the other heuristic optimisation approaches, DEs have been applied extensively in a variety of scientific fields [166]. Differential Evolution converging onto one point is shown in Figure 2.9.

Within related energy literature, DEs have been similarly applied to investigate strategic bidding in energy markets. For example, Angatha et al. [167] used DE to determine the optimum bidding strategy in a non-cooperative day-ahead electricity market. The DE is shown to determine a solution; however, it is stated that the algorithm should only be applied when the optimisation problem has only one or a few local minima. Essiet et al. [168] explore the use of DEs to optimise energy consumption for smart homes. The results show that the proposed algorithm can optimise energy usage by balancing load scheduling and renewable sources' contribution. However, the DE has only been extended to balance the demand for one consumer, and when there are many consumers present, the computational demands may be excessive.

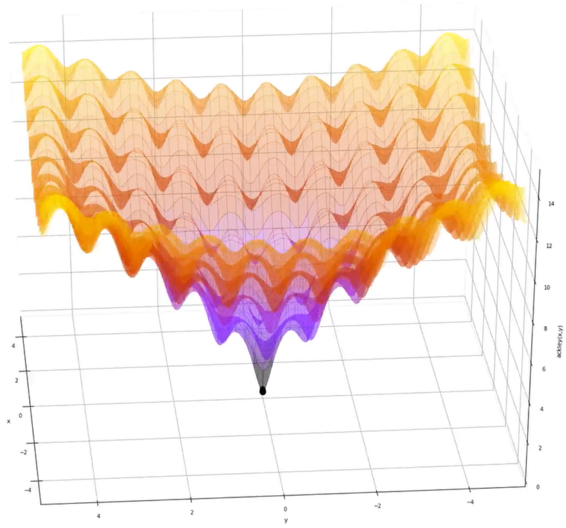


Figure 2.9: Differential Evolution outline [154].

2.3.4 Simulating Renewable Energy Subsidy Auctions

A small strand of literature is the most relevant to our work, which concerns the simulation of auctions through agent-based models. Anatoloitis et al. [169] are the first to use ABM in simulating RES auctions. A model was developed to test the allocation efficiency of two major auction formats, pay-as-bid versus pay-as-clear, for German onshore wind power auctions. Welisch et al. [170] used the same ABM to empirically test the effect of non-realisation penalties on developers bidding truthfully and revealing their costs. Furthermore, Lundberg [171] used a simplistic ABM to examine how an auction design structure to help small-scale actors affects actor diversity, bidding behaviour, and the risk of participants incurring the winners' curse. However, these works focus on a recurring auction (i.e. not a one-shot auction as the CfD), which introduces learning opportunities for developers between rounds.

There are several limitations associated with the previously developed models. The previous models assume fictitious case studies with approximations of the likely competition. For example, these fictitious case studies do not properly represent the correct number of players acting in an auction. Basing case studies on real-life auctions is important as it allows a better characterisation of agents and, therefore, a realistic depiction of auction dynamics and outcomes. The current literature assumes a bid price based on the LCOEs of the technology. This is an oversimplification, as LCOE differs from the calculated CfD bid price of developers [26]. To better approximate bid prices, models should enhance the agent's utility function by incorporating further parameters, which optimise future costs and revenue. Moreover, the uncertainty experienced by bidders should be better approximated. Many previous models assume either a deterministic bid price or a random draw from a normal distribution. In reality, from a developer's perspective, there are many sources of uncertainty which can be better characterised by considering the sources of uncertainty individually. Finally, current literature assumes that players bid accordingly to their cost, therefore, do not consider the strategic incentive for developers to shade their bids to maximise auction pay-off.

2.4 Future Research Direction & Gaps Identified

The literature survey has demonstrated that renewable energy auctions are increasingly being used globally by governments to procure renewable capacity. However, designing auctions is complex, as many design configurations exist which have a significant effect on auction outcomes. As a result, auction design has not converged onto one design. Furthermore, bidding into auctions from a developer stand point is tricky. This is because there is significant uncertainty, and the consequences of submitting an incorrect bid is high. Therefore, further research is required to make recommendations on auction design and bid preparation.

A comparison of the various quantitative methods for studying renewable energy auctions has been discussed. The three main methods used are: econometric analysis, LCOE or NPV models, and simulation. Literature has shown while there are merits in using all three methods, there is greater flexibility in answering a range of questions using simulation techniques. This is because simulation can incorporate elements of financial modelling and econometric analysis, to answer a range of different questions.

The findings from the literature survey demonstrate that CfD auctions can be represented as a game of incomplete information, as the outcomes are dependent on two or more decision-makers. However, the representation of CfD auctions as a game is complicated as the auction is a multi-objective problem. While game theory is valuable for determining bid strategies for more simplistic case studies, literature has shown that its uses are limited within uncertain and complex environments. Therefore, in the context of this work, game-theory will be used as a useful tool in simplified examples where auction participants are aware of the characteristics of their competitors.

ABMs have been applied successfully in a number of adjacent auctions/markets, and have demonstrated promising results. It can also be used alongside uncertainty analysis, such as Monte Carlo simulation, in order for agents to determine an estimation for teir bid price from a distribution of cost data.

The literature survey demonstrates that there have been recent attempts to simulate RES auctions. However, as discussed in Section 2.1.2, there are several features and phenomena of a real-life auction which are not considered by current literature. Expanding current models would allow a better approximation of real-life auctions. Firstly, there is scope to produce a stochastic model that would allow better characterisation of the uncertainty experienced by auction participants. For example, a model can sample 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 of many thousand auction simulations, which estimate the most likely auction outcomes. Coupling an auction simulation tool with a cost modelling tool allows for real auctions and players to be simulated. Secondly, game theory and probability theory elements can be incorporated to allow auction participants to test various bidding strategies, allowing agents to deviate from bidding at cost. For example, the model can determine a bid price for auction participants, maximising players' expected pay-off.

Additionally, current literature focuses on fictitious case studies and does not make recommendations for auction participants. To the best of our knowledge, no published literature has used auction simulation and estimated project-specific costs to predict and analyse a CfD auction result and then make recommendations evidenced by simulation for auction participants. A well-thought-out bidding strategy can help prevent the winners' curse, mitigating the non-realisation of renewable projects, a major risk to governments meeting their deployment targets [23].

RES auctions are a relatively novel concept, with their use gradually becoming much more widespread. There is a growing strand of literature which addresses research questions surrounding these auctions, however, only a few limited examples use simulation to empirically analyse auctions. Therefore, there is an opportunity to expand on current methodologies (such as from the work from Anatoloitis et al. [169]) for simulating RES auctions. The methodology would have use cases and implications for policymakers and developers alike. For example, auction design rules which are poorly or have not yet been researched can be simulated and the effect on auction efficiency observed. For developers, the tool can prepare methodologies to select optimum bid strategies through the simulation of CfD auction dynamics.

Chapter 3

Methodology

A novel numerical framework has been developed as part of this thesis to study CfD auctions. This chapter introduces the agent-based auction modelling tool and gives a detailed review of the tool's methodology. The model's methodology has been informed by the research carried out in Chapter 2, and applications of this numerical framework under various scenarios and inputs have been used in this thesis to generate recommendations for policymakers and developers. The contribution of this chapter is a detailed outline and justification of the model's methodology.

3.1 Introduction

Renewable Energy Auctions are central to governments meeting their own low-carbon procurement targets. As discussed in Chapter 2, auctions have not yet converged onto one design. Therefore, further research is warranted to explore rule design changes for policy recommendations [24]. Simulation can test auction design and its effect on allocation efficiency, allowing empirical testing of several different rule configurations, which helps inform policymakers on auction design. Additionally, simulating the auction can be useful to test any rule changes or parameters set (e.g. monetary budgets) [25].

The model can be used by the following users:

- **Policy experts** - to test the effect of different auction design rules or auction set-ups on auction efficiency and effectiveness, and therefore, provide quantitative analysis to inform policy decisions.
- **Developers** - auction participants can use the methodology to prepare better auction strategies, which prevents the winners' curse and mitigates project non-realisation.

As described by the literature survey in Chapter 2, previous models which study RES auctions have not attempted to enhance agents' utility functions by assigning agents to real and non-theoretical projects.

The present model seeks to address the gaps identified in Chapter 2 by using inputs from a proprietary cost modelling tool and incorporating a number of theoretical elements not previously considered by related models. Firstly, the model uses inputs from a proprietary cost modelling tool alongside economic data to estimate bid prices for real offshore wind development. Secondly, the model is stochastic, which allows for better characterisation of the uncertainty experienced by auction participants. Finally, it incorporates game theory and probability theory elements to allow auction participants to test various bidding strategies. For example, the model can determine a bid price for auction participants, maximising players' expected pay-off.

CfD auctions are simulated through the depiction of auction players, characterised by real offshore wind projects. A discounted cash flow model converts high-level cost estimates and macroeconomic data for each wind farm to estimate a bid price for each player. The tool assesses submitted bids by auction players by replicating the CfD auction allocation framework. After bids are assessed, and an outcome is determined, information on the winning bids and auction clearing price is gathered to generate outputs. Figure 3.1 illustrates the overall structure of the chapter in relation to the auction simulation process. The process diagram shows that the model can be split into six main individual functions. The model is initiated, which starts the process of configuring the inputs to the correct format and creating and assigning the developers to an individual agent. The bid preparation stage involves cash flow analysis to estimate a minimum CfD bid price for each developer, before the bids are sorted, and the subsidy is allocated in the allocation mechanism section. If the termination criteria are not met, the process repeats using different inputs for each agent, as explained in the stochastic functionality section. Furthermore, a bid price can be optimised for a smart player under the game-theory analysis. Once the termination criteria are met, the simulated auction results, which include the successful projects, individual bids, and clearing price, are then processed and represented in graphical form.

3.2 Overview of Auction Simulation Tool

In this Section, the architecture of the auction simulation tool is detailed. The tool was created using the Python programming language, and the core of the model has been built from scratch, which builds on the Mesa framework [172]. The model has been developed starting with simple deterministic examples, and then slowly integrating additional capabilities such as Monte-Carlo sampling and financial analysis.

The model created as part of this work is made up of three main parts:

- Generation of Agents
- Bid Preparation
- Auction Mechanism

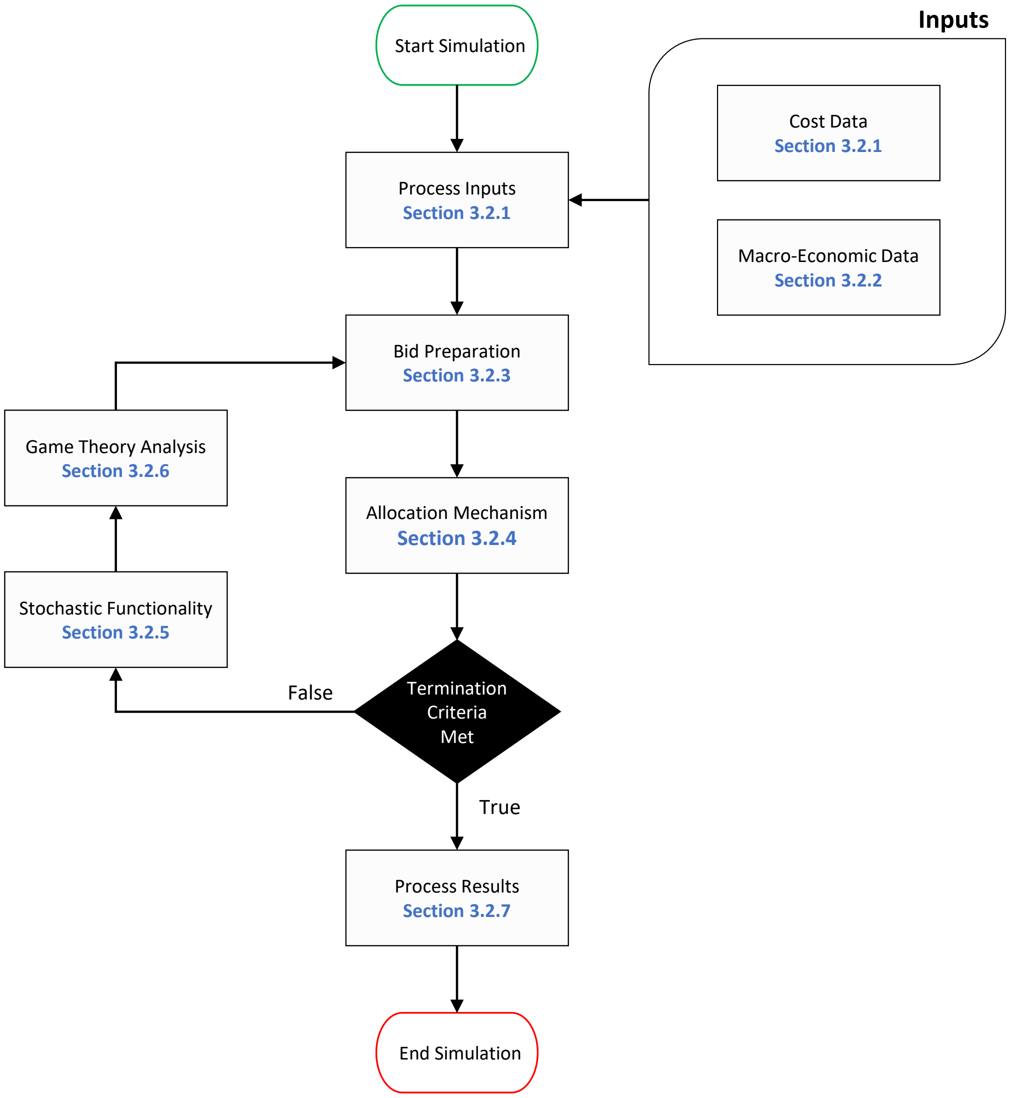


Figure 3.1: Structure of the methodology chapter

A high-level overview of the deterministic version of the numerical framework is shown in Figure 3.2, which highlights the process for one auction run. The generate agents stage of the model creates the required number of players in the auction and assigns the relevant inputs to each agent. Assigning inputs to each agent characterises agents as a specific offshore wind project. The bid preparation stage uses the inputs for each agent and performs the relevant financial analysis to generate a cash flow over the entire lifetime of the wind farm. A minimum CfD bid is calculated from the cash flow, which meets the set investment criteria (i.e. internally set IRR). Once a bid price is calculated for each agent, the model replicates the auction allocation framework to determine the auction outcome. The model can also be run stochastically, explained in detail in Section 3.2.5, which is used to generate probabilistic outputs and allow for game-theoretic analysis of strategic bidding, explained in Section 2.3.1.

The model utilises cost data and analyses costs in 2012 in real terms. This is because, in the CfD auction, bids, auction outputs, and ceiling prices are set in 2012 real terms. This means any costs or analysis used within this thesis have already had inflation up to the year 2012 discounted. As discussed in Section 2.1.3, CfD bid prices are inflated by CPI. This feature of inflating 100% of bid price by CPI is unique to the CfD, and offers better protection to developers than a non-indexed bid price. For example, the Irish equivalent subsidy scheme ORESS-1, which is also a CfD, only index's bid prices to 30% of inflation.

Developers typically assume that costs also increase with CPI, in reality, this assumption is a proxy for a full set of complex indexes (steel, fuel, commodities, various labour indices etc). Modelling ones own cost increases using CPI is a rough assumptions, which is commonly used by industry, particularly in the absences of detailed index estimates for various indeces. By modelling the auction in real terms, the assumption is that cost and revenue inflation is forecasted consistently (both revenue and costs increase with CPI). If the subsidy/revenue inflation differed from the cost model inflation then there would be a mismatch, and the bid price would change. For example, if the cost inflation is higher than revenue inflation, then the bid price would increase to compensate. However, bidders exposure to cost inflation risk is mitigated as contingency assumption would account for inflation risk on construction contracts. Additionally, the expectation is bidders would hedge inflation risk for the contract period as part of the funding process. Therefore, for the purpose of this research it is justifiable to develop a real cash flow model, as revenue and cost index's are assumed to be the same.

3.2.1 Starting Auction Model

A run script initialises the model. The script contains the parameters required to run an auction simulation and formats and exports the simulation output as a .csv file after the simulation is completed. When the model is run stochastically, the total number of auction runs carried out in a simulation is specified in the run script. The number of auction runs used for each case study follows best practices and is determined through a convergence study. For an example application, such as replicating a previous auction round, numerous auction runs are tested until the awarded strike price results are converged. As an increased number of auction runs results in greater computational times, strike price convergence can optimise a trade-off between the accuracy of results and computational expense. An example is shown in Figure 3.3, where the total number of auction runs chosen 1,000, as it is the point at which there is a strong convergence of results.

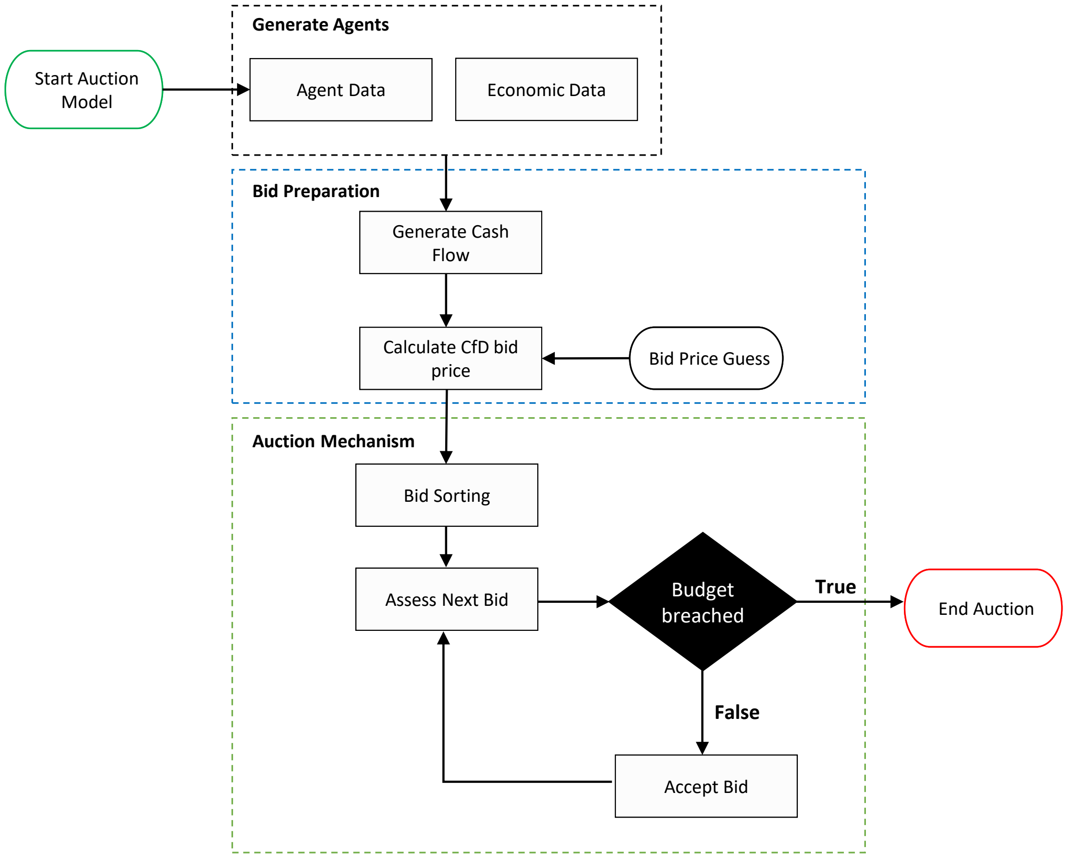


Figure 3.2: High-level flow diagram of model

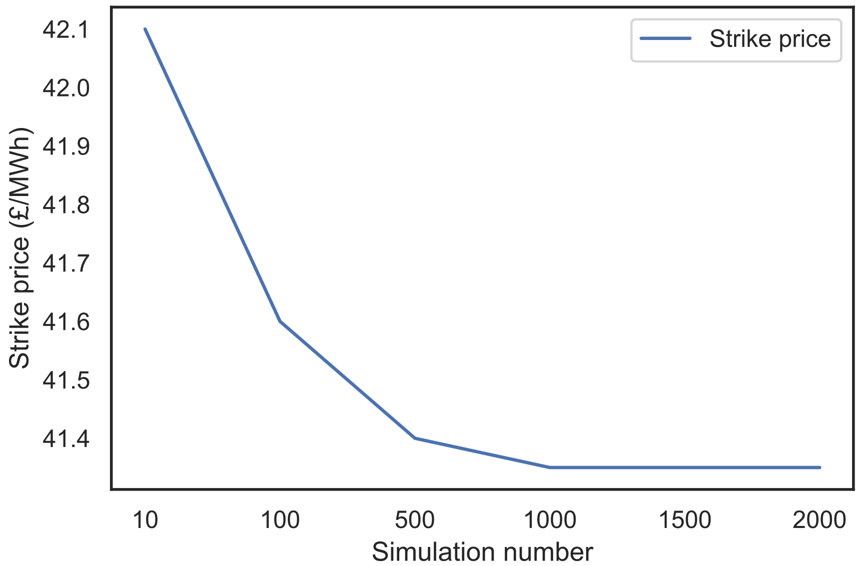


Figure 3.3: Convergence of strike price results with varying simulation numbers.

A key parameter set is the ceiling strike price, issued by BEIS prior to the auction and refers to the ASP (described in Section 2.1.4). A further parameter determines the volume of capacity to be procured. As discussed in the CfD auction design in Section 2.1.4, a number of auction types can occur depending on the budget notice. The auction types are minima only, monetary budget, and maximum only. Typically, a capacity cap or the monetary budget is the limiting factor. If the limiting factor in procuring capacity is the monetary budget, then an auction with respect to this budget will occur. On the other hand, if the limiting factor is a capacity cap, then an auction in relation to a capacity occurs. In the model set-up, the type of auction format is specified, and a corresponding monetary budget or total capacity cap is given.

If the monetary budget is the limiting factor in determining the volume of procured capacity, then the budget impact of each individual bid must be calculated. For this reason, the auction model assesses each bid and its impact on the budget before deciding whether to accept or reject it. The model considers the budget impact of each bid through the utilisation of the Valuation Formula, which has been introduced in Section 2.1.4.

3.2.2 Generate Agents

The theory underpinning ABM and its various applications have been introduced in Chapter 2. The literature survey has demonstrated that ABMs are well suited to model CfD auctions, as it allows agents with different levels of intelligence to be modelled, which introduces additional behavioural dynamics and allows for game-theoretic phenomena to be studied. Additionally, ABM methods for studying renewable energy auctions are not dependent on large amounts of historical data such as the other quantitative methods for analysing renewable auctions (as discussed in Section 2.1.2).

The auction modelling tool models each offshore wind farm project as a separate agent. A single developer may have multiple projects and, as a result, be represented by a number of agents.

Inputs for each Agent

An input file imports the required data for each agent from an external spreadsheet file. Each agent is assigned a unique id; the number of unique ids specified in the input file determines the number of agents initiated in the auction simulation. Each agent must have the required inputs to generate a bid price; if not, an error is returned. An example of the inputs required to initiate an agent is shown in Table 3.1.

The project costs (CapEx, DevEx, OpEx, and DecEx) and Capacity Factor are generated from the cost modelling tool described in Section 2.2.2. The capacity of each project can be obtained from various sources such as PINS [173], and 4C Offshore's database [11]. The discount rate is the return to investors from the offshore wind farm development. Discount rates used by different players are likely to vary based on risk appetite and business models. Variation between players can not be predicted with significant confidence; therefore, all players are typically modelled using the same central discount rate of 6.3%, based on BEIS estimates [174]. The effect that the discount rate has on calculated bid prices has been investigated in Chapter 4. However, analysis of previous auction bidding behaviour can be used to inform estimates of discount rates, such as whether a project has been unsuccessful in the past. Additionally, estimates on capital costs, as described in Section 2.1.5, can be considered to estimate discount rates for various players.

Table 3.1: Illustrative inputs for one participating agent.

Input	Example data	SD of stochastic inputs
Unique id	1	-
Capacity (MW)	1000	-
Capacity Factor	0.55%	0.025%
DevEx (£M)	100	-
CapEx (£M)	1000	23
OpEx (£M /year)	15	0.175
DecEx (£M)	75	-
Discount Rate	6.3%	-
Electricity forecast	Curve 3	-
Delivery Year	1	-
TNuOS Zone	Zone 7	-

The model assumes a 15-year period of exposure to market electricity prices due to a fixed CfD contract length of 15 years and a total operational period of 30 years [67] (the project life cycle for each project is explained further in Section 3.2.3. Therefore, agents must 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 Figure 3.4. Typically, different electricity price curves are derived by modelling different scenarios. Factors such as renewable energy penetration, total demand, technological advances, load factors, and carbon fuel costs make up these different scenarios [175].

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 depend on the grid's electricity make-up and the geographical spread between supply and demand [176]. The exact figure for an electrical system as complicated

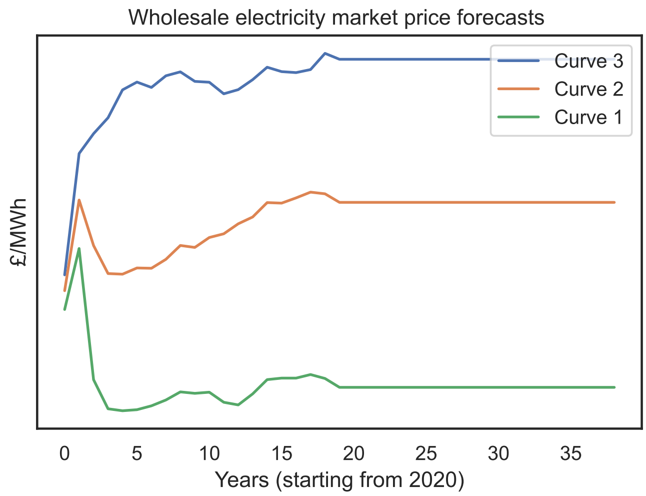


Figure 3.4: Illustration of the three wholesale electricity price curves used in the model. The curves are proprietary, so some information has been redacted.

as the UK can not be estimated for a 40-year time horizon. National Grid ESO currently only gives forecast prices up to 5 years in advance [177]; therefore, to gain an estimate for the entirety of the project, the last forecast given is extended in a flat, straight line, for 40 years from the last forecast.

Equation 3.1 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 [177]. 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, LF, 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.

$$c_{i,TNUoS} = LF \times ((YRSE \times Cf) + YRNSE + AE) \tag{3.1}$$

Risk Aversion

As described in Section 2.1.5, developers may have different tolerance to risk, which impacts their bidding behaviour. The appetite for risk by different players is captured in the model through the discount rate and electricity price curve parameters. The assumptions for each player in the auction simulation tool can be adjusted accordingly to capture differences in risk. Typically, a competitor analysis assessment can inform the varying risk appetite of players in an auction. For example, competitor analysis may explain past bidding behaviour, corporate strategy, and project details which may inform the characterisation of the risk appetite of each player.

A risk-averse player with a negative outlook on future electricity prices would be assigned Curve 1 in Figure 3.4. 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 contract. However, determining which curve each player uses in an auction is challenging to predict; therefore, a scenario based approach can be adopted to investigate the effect of different participants using different types of curves.

3.2.3 Bid Preparation

The bid preparation stage prepares a bid tuple to be submitted into the auction by each agent. The bid tuple contains a unique id, capacity, delivery year, and bid price. 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 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.

Generation of cash flow

As discussed in Section 2.1.5, companies can estimate a minimum CfD bid price through discounted cash flow models, utilising project finance theory to assess investments. The bid preparation stage utilises corporate finance theory and expectations on returns (as highlighted by Section 2.1.5) to estimate a bid price for each player. The level of detail of the cash flow model matches that of other models used for research on CfD auctions, such as by BEIS for CfD contract length analysis [108]. Additionally, the outputs from this module have been verified against a proprietary corporate financial model, the results are shown in Section 3.2.8.

Each auction simulation round assesses every project's costs and revenue streams. 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.

Figure 3.5 illustrates a typical life stage cycle of offshore wind development and their respective lengths [178]. The life stage periods are used to calculate each project's cash flow. The life stage and its constituent periods are user input and can be the same or varied for each project. In reality, not all wind will have the same project life cycle. There are a number of explanations why project life stages will differ between projects, such as project delays in the development phase, complex site conditions resulting in construction delays, or optimistic forecasts on the total operational period. Additionally, some projects may have factored in the possibility of re-powering their site, where instead of decommissioning, turbines are replaced with more powerful and efficient models [96]. While it may be possible to determine the length of the development or construction period for some projects, estimating each player's project life stages beyond this point introduce further uncertainty; therefore, the same operational period is typically considered for all projects.

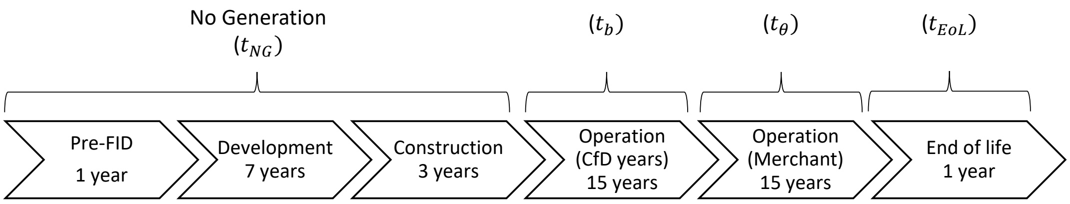


Figure 3.5: Life stages and respective years t_x, of each project modelled [15].

The DevEx cost is spread equally across the Development Period and assumes all costs incurred prior to financial close. 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 includes wider TNUoS charges and a BSUoS (Balance Service Use of System) charge. BSUoS charge is levied on generators to cover the day-to-day operation of the transmission system [179], estimated by the cost modelling tool and included in the annual OPEX cost. The model includes a 2% [15] 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 profits [180]. The tax calculation is simplified, as it does not include capital allowances. Capital allowances refer to a form of tax relief that businesses can claim on qualifying capital expenditures. The purpose of capital allowances is to provide businesses with tax relief for the wear and tear or depreciation of qualifying capital assets over time and so can spread the cost over several years through capital allowances, reducing their taxable liability. This simplification is justifiable, as the analysis looks to compare the main differentials between projects to build merit order of projects, and so reduces the complexity of the bid calculation to allow for increased computational time and uncertainty analysis over many thousands of simulations.

Developers could consider DEVEX as a sunken cost, and look to not include it as a cost which should be recovered in their bid price. This is because it is a cost incurred regardless of whether the project is constructed or not (i.e. it is not part of the investment decision). However, this work assumes DEVEX is included as a cost which developers look to recover in the bid preparation stage. This follows typical industrial practice [108]. The justification for this is that for developers with many projects, disregarding DEVEX amongst many projects would have a cumulative financial impact. Therefore, DEVEX is seen as value at risk and developers will look to recover the costs.

Revenue is calculated using the generation (MWh/year) from the project's capacity, multiplied by the hours in a year and the project's capacity factor. A capacity factor for each site is estimated using the cost modelling tool and calculated in the Design Module (described in Section 2.2.2). The lifetime of the wind farm T, includes the pre-operational years and typically assumes that no agents are 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 known as the *minimum CfD bid*, represented by b_i, and calculated in Section 3.2.3. The revenues and costs are discounted by the discount rate specified at the input stage. Therefore, where X_t is the total electricity in MW generated in a year, where t is the operational year, Equation 3.2 represents how R_t the net cash flow is calculated for *CfD years*, which is $t \leq 15$, and during *merchant years* which is $t > 15$. s_c^i is the uncertainty of these costs. Where s_c^i and s_r^i differ for each player and are empirical distributions on an interval $[-\bar{s}, \bar{s}]$. The uncertainty values are +/- range from the median cost or revenue value. The realisation of s_c^i is unknown before the auction. Still, 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.

$$R_t = \begin{cases} X_t \cdot b_t - c_{i,t}(s_c^i), & \forall t \leq 15 \\ X_t \cdot \theta_t - c_{i,t}(s_c^i), & \forall t > 15 \end{cases} \tag{3.2}$$

In corporate finance theory, one should undertake a project if it gives a positive or zero NPV value. A positive NPV value indicates that the project creates value for the business. Therefore, one can calculate a minimum acceptable b_i by setting Equation 3.3 to zero, as this gives discount equity return ($NPV = 0$), and is the minimum threshold required for projects to create value [181]. The discount rate is represented by d.

$$NPV(b_i) = \sum_{t=0}^{N} \frac{R_t}{(1+d)^t} \tag{3.3}$$

Algorithm 1 Calculating minimum CfD bid price from discounted cash flow

Require: Discount rate and project cash flow.

for all agents **do**
    create initial CfD bid price guess
    compute cash flow with CfD bid price guess
  cash flow is equal to zero
  create bid tuple
end for
return bid tuple

Generation of CfD bid for each project

Once a CfD bid price is calculated for a player, it is 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. 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. The four flexible bids agents can submit must vary by C or DY. The flexible bids submitted for each developer are considered for each different case study, and are based on assumptions regarding submitted capacity bids. As discussed in Section 3.2.3, $b_i(c_i, s_c^i, r_i, s_r^i)$ 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 Figure 3.5, an overall equation for deriving the minimum CfD bid for a player i is shown in Equation 3.4. In each iteration of the bid preparation stage, this equation is computed and solved for b_i for each player, assuming $NPV = 0$. For the stochastic simulations, which are described in greater detail in Section 3.2.5, 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 categorises the uncertainty experienced with each players project costs.

$$\text{NPV} = \underbrace{\sum_{t=0}^{t_{NG}} \frac{-c_{i,t}(s_c^i)}{(1+d)^t}}_{\text{No Generation}} + \underbrace{\sum_{t=t_{NG}+1}^{t_b} \frac{r_{i,t}(X_t, b_i, s_r^i) - c_{i,t}(s_c^i)}{(1+d)^t} + \sum_{t=t_b+1}^{T-1} \frac{r_{i,t}(X_t, \theta_t, s_r^i) - c_{i,t}(s_c^i)}{(1+d)^t}}_{\text{Operational}} + \underbrace{\frac{-c_{i,T}(s_c^i)}{(1+d)^T}}_{\text{End of life}} \tag{3.4}$$

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 Figure 3.5). $r_{i,t}$ 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, 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.

The computational algorithm, which calculates a CfD bid price for each agent, starts with an initial guess obtained from a random generation function between the range of $[0, 100]$ and then iterates through the bid prices until the true bid price value is discovered, which returns a discount equity return. The process of determining a CfD minimum bid price from the calculated discounted cash flow can be seen in Algorithm 1.

3.2.4 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 2.1.3).

The model replicates the uniform price auction format, assessing bids one at a time and demonstrated in Algorithm 2. The algorithm assesses all submitted bids to ensure that they meet the given requirements (below the ceiling bid price and above zero), then sorts bids in ascending order. 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 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 algorithm 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 and the algorithm ending. This is the AR3 mechanism, which has been updated for the AR4 auction case study, introduced and described in Chapter 6.

Algorithm 2 Determining winning bids

Require: All submitted bid tuples which include: bid price (£/MWh), Capacity (MW), and delivery year.

```
for all agent bids do
    check all bids are below ceiling price limit
    check that bid price is above zero
    sort by price in ascending order to create a bid stack
end for
for all agent bids do
    select first bid in bid stack
    calculate the budget impact of bid
    evaluate total budget impact
    if cumulative budget impact is less than total monetary budget then
        accept bid
        promote clearing price to last accepted bid
        remove other flexible bids from same player
    else consider flexible bids of rejected player
        identify interleaving loop
        calculate cumulative budget impact of accepting interleaving loop
        if cumulative budget impact is less than total monetary budget then
            accept bids
            promote clearing price to last accepted bid in loop
        end if
    end if
end for
return uniform price
```

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 significant insights, as demonstrated in Chapters 4-7. The algorithm for determining the winning bids is shown in Algorithm 3.

Algorithm 3 Allocation of subsidy mechanism for an auction w.r.t. budget

Require: All submitted bids and the uniform price obtained from Algorithm 2.

```
for agent bid tuples do
    if bid price is equal or less than uniform price then
        add one to counter
        copy tuple to Winners
    end if
end for
return Winners
```

3.2.5 Stochastic Functionality

The model is predominantly used as a stochastic model, which uses cost distributions to produce stochastic outputs that better characterise the uncertainty experienced by participants at an auction. 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 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. A sensitivity analysis conducted in Chapter 4 explores the impact of this simplification. 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.

The motivation for developing a stochastic model is due to the significant uncertainty bidders face while bidding at auction. The uncertainty associated with their b_i is captured by the uncertainty associated with the cost component $c_i(s_c^i)$ and the revenue component $r_i(s_r^i)$. 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 required bid price developers should achieve at auction for their project to meet the set investment criteria. Let p denote the strike price of the auction, q_i represent the quantity of electricity procured by the auctioneer (MW/h) from player i, then the pay-off for a winning player i is

$$\pi_i(c_i, s_c^i, r_i, s_r^i) = q_i \cdot (p - b_i) \tag{3.5}$$

Costs are incurred throughout the lifetime of the wind farm. Therefore, the true profitability will not be known until the entire project is realised. As a result, it is valuable to understand how the bidding strategy and profitability of the project vary with these uncertain costs. Depending on s_c^i and s_r^i, which are realised long after the auction, 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 characterising 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.

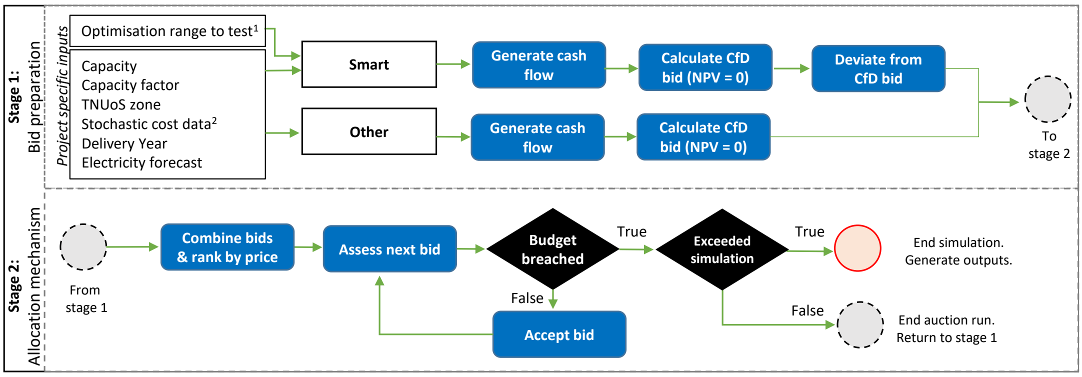


Figure 3.6: High-level flow diagram illustrating one auction run process.

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. Sampling from the distributions allows for multiple values of b_i to be calculated. Producing an empirical distribution of b_i values for each player, spread over $[-\overline{S}, \overline{S}]$. Therefore, the following relationship depicted in Equation 3.6 highlights the basis for Monte Carlo sampling from cost distributions to characterise the inherent uncertainty by determining a distribution of different bid prices.

$$b_i(S_b^i) = b_i(c_i, s_c^i, r_i, s_r^i) \tag{3.6}$$

3.2.6 Game Theory

As discussed in Section 2.3.1, the CfD auction can be considered a game, as the auction outcome depends on the strategic actions of two or more rational decision-makers (players). To maintain auction efficiency (as defined in Section 2.3.1, auctioneers hope that developers bid truthfully and reveal their costs. However, the literature highlights that strategic bidding to maximise auction pay-off is common in renewable energy auctions [23, 49]. Increasing the model's capabilities to include game-theoretic phenomena allows players to bid strategically. The type of strategic bidding investigated by the game-theory feature is bid shading. In auction theory literature, bid shading is where a bidder places a bid below their true value to increase their expected pay-off [125]. This is a well-studied auction dynamic in multi-unit auctions [127, 128]. In the context of CfD auctions, where the auctioneer is attempting to procure capacity at the best price, developers can shade by increasing their bid above the minimum CfD bid price calculated.

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 3.2. 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 will act. However, the smart player's added capability allows for the 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 for selecting bidding strategies.

Players are assumed to be rational and will not bid below their minimum calculated CfD bid price, as this would risk a negative pay-off and a loss on the overall project. However, players may bid above their bid price, and shade their bid to increase auction pay-off (as discussed in Section 4.1). Strategic players who can not increase their auction pay-off due to having a high-cost bid price above the other players do not attempt to shade their bids and bid their cost price.

Table 3.2: Table demonstrating the knowledge and capabilities of each category of agent in the model.

Capability / Knowledge	Smart	Other
Competitor bid estimates 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

The basis for selecting expected value as the metric for comparing optimum bidding strategies can be explained mathematically. $E[X]$ is defined as the arithmetic mean of a large number of independently selected random variable outcomes. It can be defined by a random variable X with a finite list of possible outcomes $(x_1, ..., x_k)$, each of which has a probability $(p_1, ..., p_k)$ of occurring [182], as shown in Equation 3.7. The outcomes and probabilities can be summed together (shown in Equation 3.8) to obtain an expected value.

$$\mathrm{E}[X] = \pi_1 p_1 + \pi_2 p_2 + \cdots + \pi_k p_k. \tag{3.7}$$

$$\mathrm{E}[X] = \sum_{i=1}^{\infty} \pi_i p_i \tag{3.8}$$

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, 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 has been discussed previously in Section 3.2.1.

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 Equation 3.9. The model mechanics of determining a bid price optimising $E[X]$ is shown in Figure 3.8.

$$b_x = b_i - x \tag{3.9}$$

The model collects information on the strike price, P, and whether the project was successful for each auction run. The smart player can predict P using its additional capabilities as highlighted in Table 3.2, which 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 Equation 3.10. This is the additional profit extrapolated from the auction per unit of generation output.

$$E[b_x] = \sum_{x} [P(b_x) - b_i] \cdot W\%(b_x) \tag{3.10}$$

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 Figure 4.9 in the results section for a sample output.

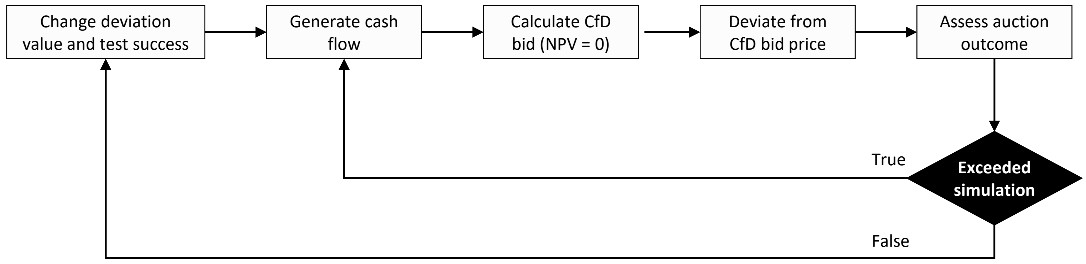


Figure 3.7: Simplified flow diagram illustrating simulation for the *smart* player.

Genetic Algorithm

When there are two or more strategic players, they must submit a bid into the auction with the knowledge that other players are also attempting to increase their auction pay-off. Therefore, the *smart* player can no longer assume that all players are bidding at their cost bid price, so a multi-objective optimisation problem occurs. Instead, a *smart* player assumes that other strategic players are attempting to maximise their own auction pay-off. As game theory dictates that all players are rational, profit-maximising decision-makers, each strategic player will assume that other *smart* players select a bid price which maximises their individual pay-off. Therefore, there is an equilibrium where a bid price exists between the two *smart* players, which maximises their collective auction profit.

Computationally, it is possible to optimise bids for each player using an iterative method, where many bids in a range are tested using a for loop, as described in Section 2.3.1. For examples where there are many strategic players, the model empirically tests various bid prices for each smart player until an equilibrium is found. Therefore, when there are six strategic players in a deterministic problem, where each player can deviate from its cost bid price by an integer value between $[0, 3]$, there are 729 (equivalent to 3^6) different bid configurations in which the model must test. In reality, the equilibrium point is unlikely to be an integer value between $[0, 3]$, meaning that the model must test a much greater number of bid configurations. For example, if one intends to find the equilibrium bid price to 1 decimal place for a known range of $[0, 3]$, then there are 739 million (equivalent to 30^6) possible bid configurations which must be empirically tested. The number of bid configurations expands exponentially if the costs associated with each participant are assumed to be stochastic. As a result, there is an optimisation problem where the equilibrium bid configuration for the various *smart* players should be determined to the required number of decimal places.

As discussed in Section 2.3.3, a number of other optimisation approaches exist, such as reinforcement learning, particle swarm optimization, and differential evolution; however, not all optimisation methods are equally applicable to a given problem. For this work, GA has been chosen due to its flexibility to be applied to a variety of problems, ability to find good solutions with a limited number of simulation runs, ability to find global optima, and because GA has been shown to perform well in a number of related problems (as highlighted by Section 2.3.2).

A genetic algorithm optimises bidding strategies when there are two or more strategic players. As described above in Section 2.3.1, strategic bidders in this research are defined as bidders who attempt to deviate from their marginal cost bid price (calculated in the Bid Preparation stage) and shade their bid to maximise their auction pay-off. The number of strategic bidders can be varied incrementally from zero to all players.

The optimisation is initialised by generating a population P_0, which is made up of randomly generated solutions. The outputs of the simulations for each of the individuals in P_0 are then evaluated. For a population to evolve, the fitness of each solution is evaluated by a fitness function. A subset of these individuals $C_{t+1} \subset P_t$ are chosen for mating. This subject of individuals is chosen proportional to their fitness, where fitter individuals have a higher chance of reproduction to create an offspring group $C^{'}_{t+1}$. This offspring group is generated through a combination of the parameters of two-parent individuals (crossover) and the introduction of natural variability (mutation). Furthermore, elitism allows some individuals with the highest fitness values to survive. This is useful to ensure that the best-performing parameters do not disappear and that there is no deterioration in performance over the generations. Therefore, a new population P_{t+1} is created by merging individuals from P_t and $C^{'}_{t+1}$. The process of generating new populations in this manner is repeated until results converge on one solution for a minimum of 10 iterations. The solutions presented in the Results section are based on three separate runs, initialising the population each time and then averaging over the independent optimisation runs. This helps ensure that the solutions have not converged too early on an optimum and that the solution is robustly independent from the random seeding of the initial population.

The parameters chosen for the problem outlined were a population size of 100, a crossover probability of 50%, a mutation probability of 20% and elitism of 5%. The population size was selected as it provides a diverse range of solutions in the initial population while also limiting computational time. The crossover and mutation probabilities are chosen due to recommendations found in the DEAP evolutionary computation framework [183]. Simulation results can be repeated, and the results presented an average of these results. Repeating simulation allows a comparison of optima obtained from the GA; this helps identify whether the solutions have converged early.

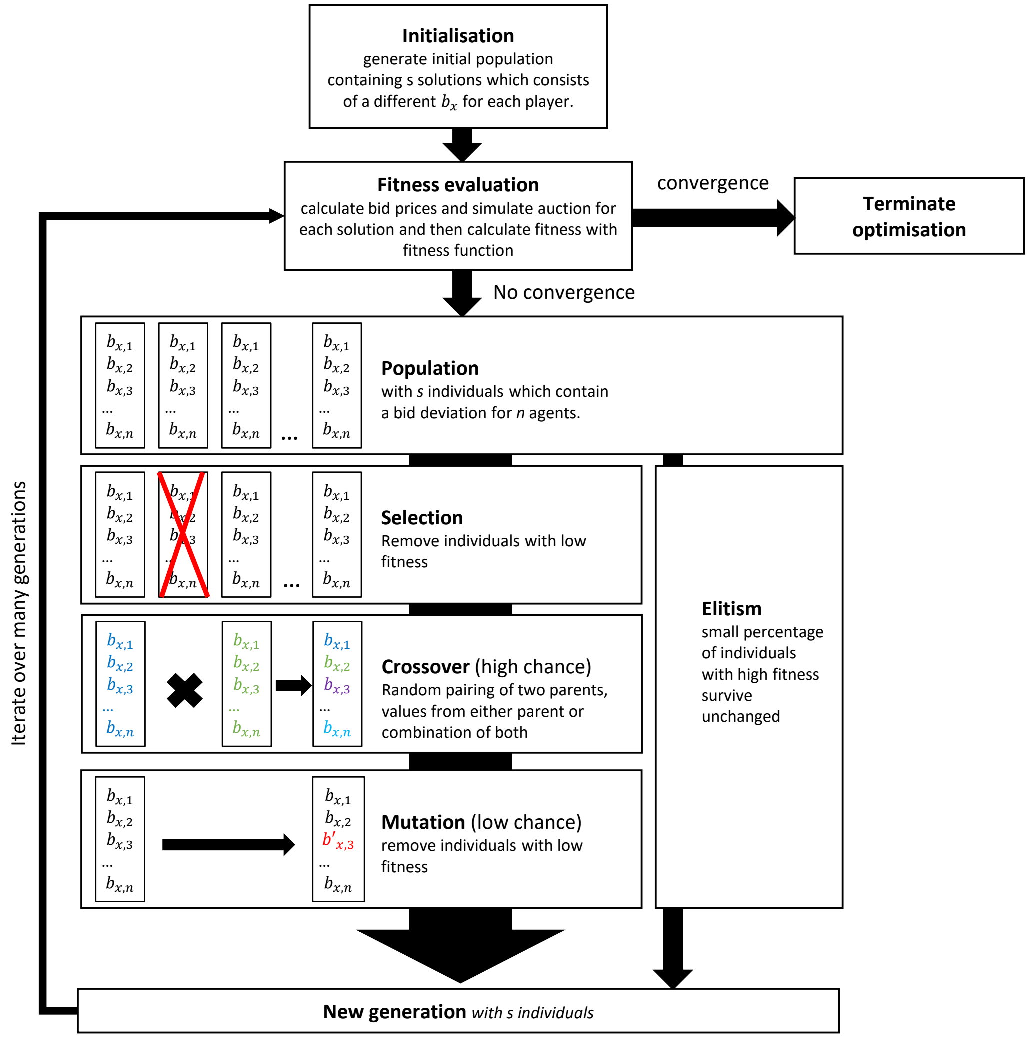


Figure 3.8: Conceptual representation of the genetic algorithm as an optimization procedure for determining strategic bidding behaviour. Adapted from Fischer et al. [184].

Fitness Function

A fitness function is used to assess the relative merit of each solution. The GA seeks to identify the solutions which maximise the output generated by the fitness function. The fitness function used in this study calculates the total auction pay-off extracted by the strategic players. The total auction pay-off received by each agent is a quantifiable metric for auction inefficiency, as it is assumed that each strategic maker is a profit-maximising rational decision-maker. This is because agents extract additional profit through strategic bidding and exploitation of the auction mechanism [23]. If a player is unsuccessful in the auction, the payoff is zero.

The pay-off for player i, represented by $\pi_{i,U}$, for a particular bidding strategy for a uniform price auction can be represented by Equation 3.11. Let $\mathbf{B} \equiv (b_i, b_j)$ denote a bidding profile of submitted bids into the auction from two players i, j. Let q_i indicate the number of capacity units from player i, which the auctioneer subsides. C is the total capacity demanded, c_i is the marginal cost of player i producing a unit of electricity.

$$\pi_{i,U} = \begin{cases} [b_j - c_i] \cdot q_i(C; \mathbf{B}), & \text{if } b_i \leq b_j \\ [b_i - c_i] \cdot q_i(C; \mathbf{B}), & \text{otherwise} \end{cases} \tag{3.11}$$

The pay-off for each player is calculated for each solution using Equation 3.11, which is summed to calculate the total pay-off. The GA then discriminates against solutions based on the total pay-off calculated. A penalty is applied if a strategic player fails to be awarded a contract to ensure that the GA does not maximise the total auction pay-off for only one player. The penalty reduces the fitness function of a solution by an arbitrarily chosen large number, ensuring that these solutions are not chosen. This ensures that the GA finds the equilibrium bidding strategy for all strategic players, and the GA does not maximise total auction pay-off by only increasing the pay-off for one player.

3.2.7 Process results

The main outputs from the auction simulation are strike price, list of successful bidders, total capacity procured, and each project's individual bid price. As the auction is repeated many thousands of times, this data is obtained for each auction run. The data is processed in a "process results" script which is executed after the termination criteria for the simulation is met. The final outputs are a representation in graphical form of the many thousand auction simulation results.

3.2.8 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 [61] [62]. 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 test the model sufficiently. During verification, the bid preparation stage and the allocation mechanism were tested independently.

The bid price estimates generated from the model were benchmarked against bid estimates from a commercially used project finance tool. The benchmarking tool is a detailed discounted cash flow model, which considers macroeconomic factors and detailed debt structuring to estimate minimum CfD bid prices for each project and has been validated by industry experts.

EDF uses the tool to assess investment opportunities and determine the required CfD bid prices, based on a number of financial assumptions, for its existing projects. It is not possible to use this tool, as the computational times are too large for a single run, and the model is proprietary. The benchmarking process involves generating project costs using the cost modelling tool outlined in Section 2.2.2 and utilising the data to generate estimated bid prices. An overview of the costs used for the benchmarking exercise can be seen in Table 3.3. The cost data has been chosen as they are estimates for real offshore wind projects, and are based on the AR3 CfD Pot 3 auction round. Therefore, the cost data tested is typical and representative of the data that will be studied using the presented auction modelling tool. For a full explanation of the assumptions behind the cost data, please refer to Section 4.2.1. A number of other assumptions were used, such as forecast electricity price curves and discount rates. The inputs to the two models were the same, allowing for a direct comparison of the results.

Table 3.3: Costs assumptions used for bid price benchmarking exercise

Project	Capacity (MW)	DEVEX (£m)	CAPEX* (£m)	OPEX* (£m/year)	DECEX (£m)	Capacity Factor*
A	1200	80.1	2398.0	21.8	76.4	0.555
B	1200	104.5	2410.9	21.9	76.7	0.555
C	1200	86.4	2506.5	22.1	76.5	0.554
D	1400	120.9	2775.9	25.6	90.5	0.554
E	1075	68.3	2242.6	18.9	60.3	0.505
F	1200	79.8	2321.1	20.9	80.2	0.527

The results from the benchmarking exercise for the bid preparation module can be seen in Figure 3.9. The results show that, on average, the results from the auction simulation tool are 2% higher than the benchmarking tool. The maximum difference between the two estimates for the same project is £0.78, with the lowest difference being £0.46. Differences in results is largely attributed to the difference in debt structuring between the two projects (this is discussed in more detail in Chapter 8). Importantly, the merit order of projects estimated between the two tools remains unchanged, and the relative difference between projects is also similar. Keeping the relative difference between projects is important, as it means that there is a consistent estimate of the merit order of projects based on the input cost data.

The allocation mechanism has also been tested from fictitious test cases; one can see if the model's outcome is as expected (i.e. the lowest bidding projects are awarded a subsidy and the budget utilisation of each project is as expected). The complexity of these test cases has increased until the required confidence in the model is achieved. The tests ensure that the lowest bidders are sorted as winners, and the maximum amount of capacity is awarded given the inputs to the model. This is because as described in Section 3.2.3, the bid prices are calculated and then each project is passed on to the allocation mechanism. Table 3.4,

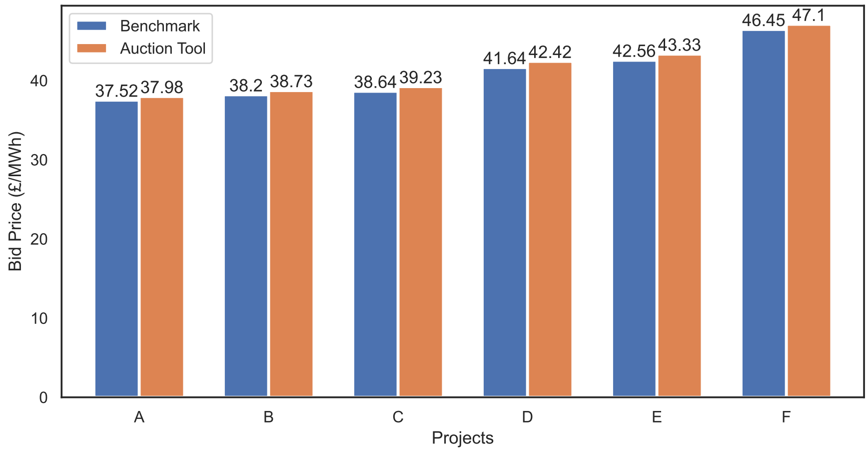


Figure 3.9: Relative difference between bid estimations.

3.5, 3.6 illustrates the basic set-up of the verification test, and then the expected results, which have been determined by running the set-up through the model, and then verified using hand calculations. The projects, capacities and bid prices are fictitious and are not based on any specific offshore wind project. However, the examples are intended to represent a realistic offshore wind CfD auction, by having a limited number of participants, a likely range of capacities, and a realistic spread of bid prices.

The verification set-up outlined in Table 3.4 has been designed to test the simple allocation of subsidy and ensure the budget utilisation of each bid is calculated correctly. Table 3.5 increases the complexity by utilising a larger spread of bid prices, including bids above the ASP (ceiling price). Running this scenario with a large budget ensures that only bids below the ceiling price are accepted, and any other bids are filtered out. Table 3.6 increases the complexity by also setting up a scenario where a flexible bid should be accepted. As discussed in Section 2.1.3, if a budget breach occurs then flexible bids are considered. The three scenarios as demonstrated by the tables replicate the various scenarios that the allocation mechanism will be required to resolve.

Table 3.4: Verification of winner determining and budget calculation.

Project	Capacity (MW)	Bid (£/MWh)	Budget (£m)	Winners	Procured Capacity	Clearing Price	Budget Impact
Set-up				Verified Outputs			
A	500	36	100	A	1400	37.2	93
B	600	36.5					
C	300	37.2					
D	250	40					
E	400	42					

Table 3.5: Verification ceiling strike prices and allocation mechanism.

Project	Capacity (MW)	Bid (£/MWh)	Budget (£m)	Winners	Procured Capacity	Clearing Price	Budget Impact
Set-up				Verified Outputs			
A	500	39	100	A	500	39	25
B	600	40					
C	300	41					
D	250	42					
E	400	43					

Table 3.6: Verification of flexible bids and allocation mechanism.

Project	Capacity (MW)	Bid (£/MWh)	Budget (£m)	Winners	Procured Capacity	Clearing Price	Budget Used
Set-up				Verified Outputs			
A	500	37.0	150	A	500	38.2	140
B	600	38.0		B	500	38.2	
C	300	36.5		C	600	38.2	
D	250	38.2		D	125	38.2	
E	400	39.6					

3.3 Conclusion

This chapter 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 cost estimations for real offshore wind projects, thus allowing past and future auctions to be simulated. A high-level overview of the cost modelling tool has also been given. A discounted cash flow model analyses costs and future revenues and calculates a minimum CfD bid price based on an equity return basis. This chapter shows that an allocation mechanism can replicate the CfD allocation framework and determine the award of subsidies. The basis for Monte Carlo sampling is demonstrated from cost distributions to generate probabilistic outputs and how quantifying uncertainty can reduce the risk of the winners' curse.

Moreover, this section outlines how ABMs, used for simulating the interactions of autonomous agents acting in the same environment, can be used to model the intended problem. It is shown that agents can be differentiated based on additional capabilities and knowledge of the competition projects, so one can attempt to optimise a bid price based on $E[X]$. A GA optimises bid prices for each player when multiple strategic players exist.

The subsequent four chapters present applications of the model, which demonstrate how policy recommendations can be generated and methodologies to influence bidding strategies can be generated.

Chapter 4

Characterising uncertainty experienced by bidders through replication of AR3

Previous chapters have described the building of an auction simulation tool which can be used to study UK CfD auctions. This chapter aims to demonstrate the model by replicating the offshore wind AR3 (2019) pot, utilising high-level cost modelling distribution data to estimate bid prices for competing projects. Simulating past auctions is useful for developers and policymakers; it allows testing whether the auction was efficient at allocating resources and will enable developers to test hypotheses that can inform future bidding strategies. The uncertainty experienced by bidders, identified as a major risk to the realisation of projects, is explored in this chapter. This case study addresses research gaps identified in the literature review, by combining a CfD auction simulation model with cost modelling data of actual sites to explore how uncertainty experienced by developers can be characterised and affect the expected profitability of sites and the calculated CfD bid price. In addition, current literature has not analysed past CfD auctions to provide strategic context.

4.1 Introduction

The challenges and associated risks from a bidders perspective have been introduced in previous chapters. As stated, a significant proportion of this risk is attributed to the uncertainty experienced by developers. There are also implications for policymakers and consumers due to the uncertainty bidders face at the CfD auction. During the auction, there is a potential economic risk of auction inefficiency [24]. 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 [23]. This could hinder the auction effectiveness, as projects which have intrinsically higher generation costs, are typically less likely to be delivered at the same price when compared to lower cost-generation assets, especially if macroeconomic environments are less favourable.

To better characterise this uncertainty, strategic analysis in the form of simulation allows for better bid preparation [25]. This chapter presents an application of the ABM approach detailed in Chapter 3 and replicates the CfD Allocation Round 3 (AR3) held in 2019. The previously validated proprietary stochastic cost modelling tool described in Section 2.2.2, generates cost data for each participating wind farm project. A sensitivity analysis shows which cost and revenue streams are most important for bid preparation and thus highlights where auction participants should focus resources to reduce uncertainty. The results can also inform the stochastic simulations and identify which input to prioritise in the stochastic, uncertainty analysis.

The methods described in this Chapter 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 results from the simulation are compared to the actual results of AR3 to test whether the auction successfully allocated subsidy to lower cost generators and assess how accurately developers can predict auction outcomes prior to the auction.

The present work demonstrates a novel approach utilizing auction simulation and estimates of project-specific costs to support analysis of past auctions, providing strategic context and recommendations. The literature survey (guided by Chapter 2) 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. However, this work can be expanded as existing literature on this subject does not consider several features and phenomena of a real-life auction, as explained in Section 2.4.

The remainder of the chapter is structured as follows. The analysis methods are outlined in Section 4.2. The results for both the sensitivity analysis are presented in Section 4.3.1 and Section 4.3.2, respectively. An analysis and wider implications of the work are discussed in Section 4.4. Finally, the work is concluded in Section 4.5.

4.2 Case Study Definition

4.2.1 Allocation Round 3 - Model Set Up

In this Section, a designed case study demonstrates the methodology presented in Chapter 3. 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 [62]. An additional case study (Case 2) is investigated to determine whether a project could win due to utilising more optimistic underlying assumptions than competitors. Therefore, this work tests the impact of modelling this project with a more optimistic view of future electricity prices. Forecasts of wholesale electricity prices are an important underlying assumption required in bid preparation and can significantly affect CfD bid values according to the literature [23]. Therefore, Case 2 assumes a 10% increase in this project's future electricity price forecast. All other parameters are kept constant.

4.2.2 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 Figure 4.7). 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 $E[X]$.

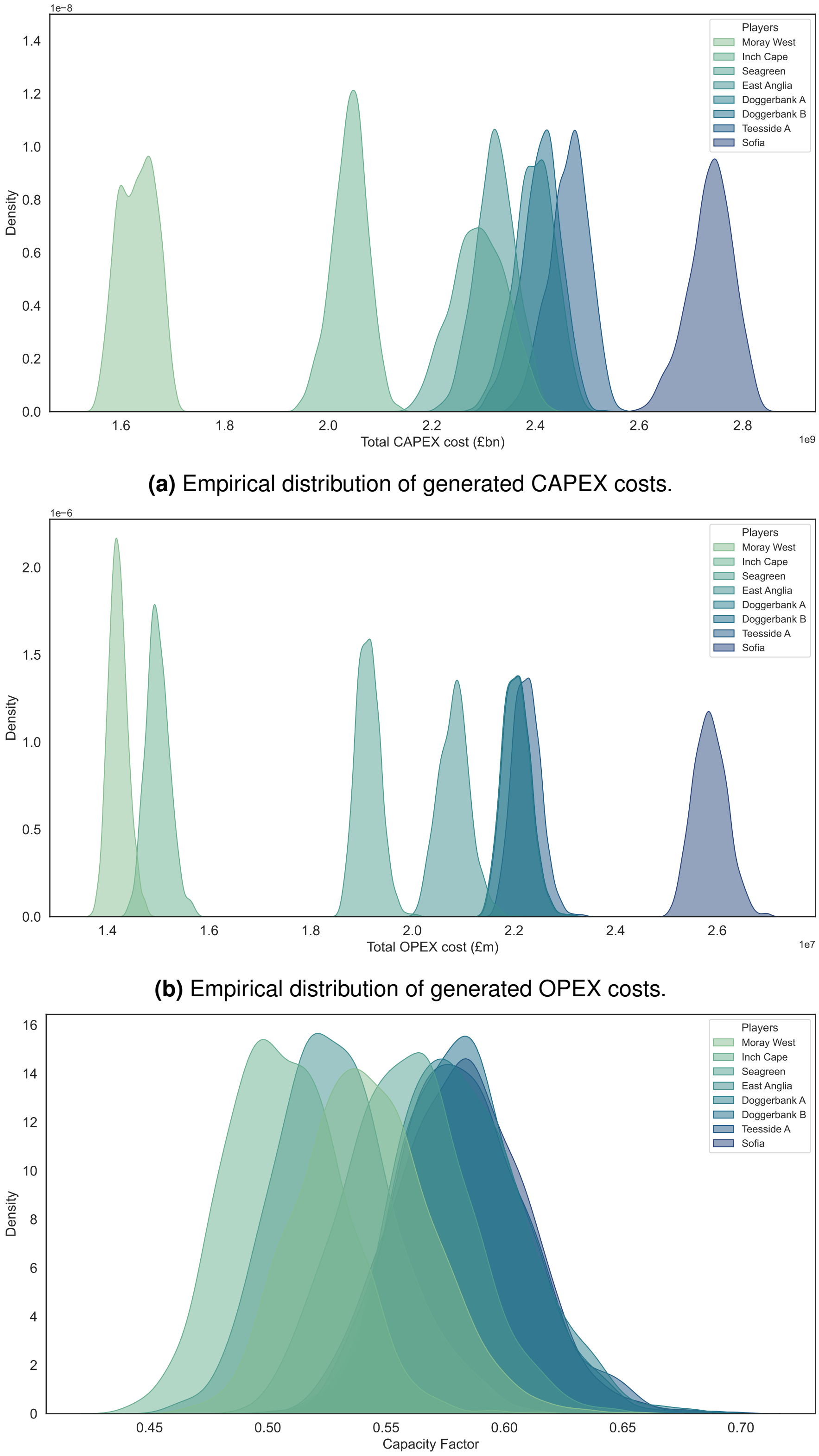
For each project participating in AR3, the cost modelling tool generated 1000 empirical stochastic cost values. This number of total cost values is chosen as there is a strong convergence of results after 1000 simulations per bid price (as discussed in Section 3.2.1). This cost data was then input into 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 bid range which also identifies a peak in the $E[X]$ graph (see Figure 4.9). The selected test range means that, in total, the *smart* player tested 17 bids. As there are 1,000 auction simulations for every bid price tested by the model, the output graphs are averages of the 1,000 auction simulations made per bid. The projects modelled utilise publicly available site-specific and project-specific data to generate cost inputs from a stochastic cost modelling tool.

Table 4.1 illustrates a high-level overview of the inputs used to generate the cost data and formulate the price scenarios for each project in this study. The generated cost data for each project is shown in Table 4.2. As described in Section 2.2.2 & 3.2.3, these costs have been developed using a cost modelling tool using site specific information to estimate costs using known relationships. Using a verified cost model to generate costs reduces subjectivity in estimating costs and bases them on known information about each site.

The distributions for the stochastic inputs are shown in Figure 4.1. This figure demonstrates the costs which have been estimated for each project using the stochastic cost modelling tool. The results show that Sofia has a significantly higher CAPEX and OPEX than other projects, largely attributed to the increase in project size. The distributions associated with different projects vary because there is more uncertainty associated with the inputs of some of the projects than others. The geographical location of the offshore wind farms that competed in AR3 is shown in Figure 4.2. The 28 TNUoS zones outlined by National Grid ESO are also displayed on the map. A sensitivity analysis has been conducted to identify the most sensitive parameters to include stochastically. This has been informed by the Sensitivity Analysis outlined in Section 4.2.3. The rationale for making some inputs stochastic is to find a trade-off between incorporating the appropriate amount of uncertainty and computational times, the explanation and justification of this is explained in Section 3.2.5.

Table 4.1: High-level overview of some of the publicly available site/project-specific input data which was used to generate cost estimations. [1] Only 454 MW of the project was awarded a CfD contract. The total capacity of the project is therefore used to generate cost estimates. [2] Location is used to calculate TNUoS charges. A portion of the Seagreen project (360 MW) is connected to Cockenzie, the remaining to Tealing [185]. 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
Doggerbank CB A	1200	23	10.68	200	Monopile
Doggerbank CB B	1200	26.5	10.68	185	Monopile
Doggerbank Teesside	1200	26	10.68	260	Monopile
Sofia	1400	28	10.68	220	Monopile
Seagreen[1]	1075	54	10.58	65	Jacket
East Anglia 3	1200	36.5	10.23	75	Monopile
Inch Cape	1000	52	9.97	45	Jacket
Moray West	800	45.5	10.12	70	Jacket



(a) Empirical distribution of generated CAPEX costs.

(b) Empirical distribution of generated OPEX costs.

(c) Empirical distribution of generated Capacity Factors.

Figure 4.1: Distributions of stochastic inputs for each player in Case Study

Table 4.2: Overview of cost input data used to generate a bid price for each player. Inputs marked *, show the median data for stochastic inputs, distribution of stochastic data is shown in Figure 6.1.

Project	Capacity (MW)	DEVEX (£m)	CAPEX* (£m)	CAPEX* (£m/MW)	OPEX* (£m/year)	DECEX (£m)	Load Factor*
Doggerbank CB A	1200	80.1	2398.0	1.99	21.8	76.4	0.555
Doggerbank CB B	1200	104.5	2410.9	2.00	21.9	76.7	0.555
Doggerbank T	1200	86.4	2506.5	2.01	22.1	76.5	0.554
Sofia	1400	120.9	2775.9	1.98	25.6	90.5	0.554
Seagreen	1075	68.3	2242.6	2.08	18.9	60.3	0.505
East Anglia 3	1200	79.8	2321.1	1.93	20.9	80.2	0.527
Inch Cape	1000	60.2	2039.0	2.03	14.8	58.4	0.505
Moray West	800	55.5	1645.9	2.06	14.0	52.0	0.532

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.

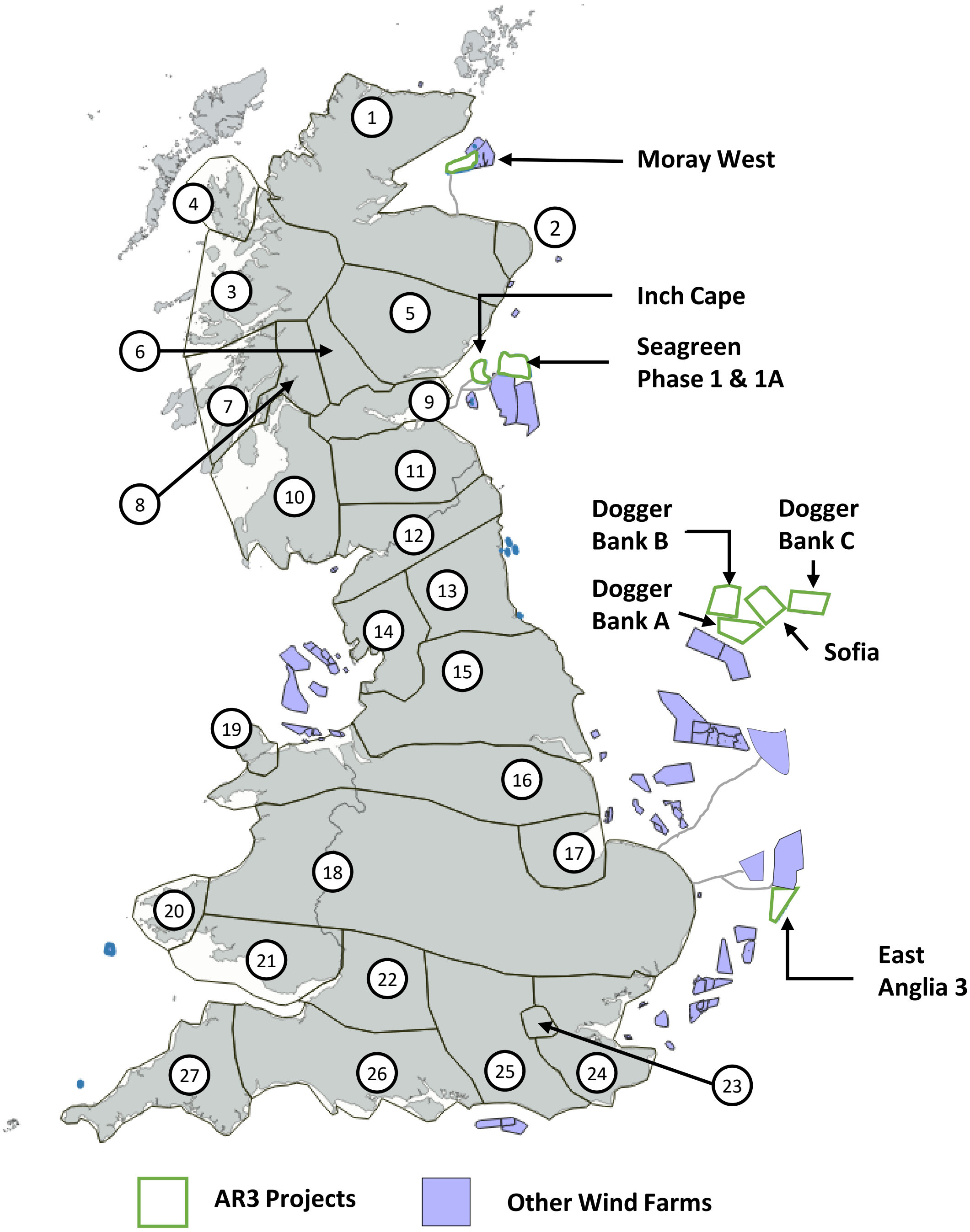


Figure 4.2: Geographical location of Offshore Wind Farms which participated in Pot 3 AR3. The 28 TNUoS zones, as outlined by National Grid ESO, are displayed on the map.

3. **Total capacity budget available is 5,500 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, as the factor limiting effect for AR3 was the capacity budget [67].
4. **Exclusion of Remote island wind projects and Forthwind offshore wind project** - 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. Additionally, a 12 MW site competed in AR3 and successfully achieved a contract. This project is excluded to reduce the complexity in the number of competitors, as the project is comparatively very small and so its impact on auction dynamics are near negligible.
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 can not be predicted; therefore, all players use the same central discount rate, based on official 2020 BEIS estimates [174].
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 [186].

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.

4.2.3 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 [187].

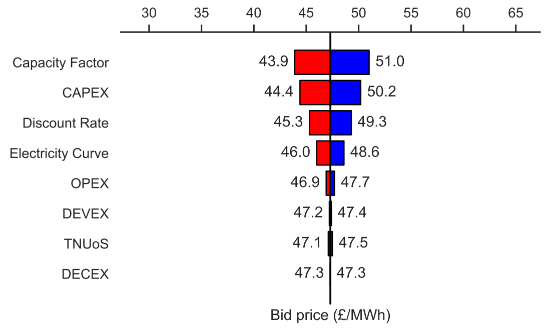
A base case is fixed for this one-at-a-time (OAT) sensitivity analysis. An overview of this base case, with the base inputs, has already been outlined in the previous section. In the first instance, a sensitivity analysis was conducted to observe the effect a change in input would have on the average bid price submitted by participants outlined in the Case Study. The bid price for participants is calculated as outlined in Section 3.2.3. The main inputs as shown in Table 4.1, are varied for all participants by $\pm$ 5%, $\pm$ 10% and $\pm$ 20%. Capacity is 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.

All projects are again considered to determine the effect the inputs have on the auction clearing price. For one test, the same input for every project is varied by the same fluctuation. For example, the CAPEX for all eight projects are adjusted separately 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 4.2.1, two delivery years are modelled for each auction run. Each delivery year has a separate clearing price irrespective of the other year. Therefore, the results presented are an average of both clearing prices. The sensitivity analysis has been conducted on all projects in the AR3 case study, and so the results presented are an average of the estimated bid prices for all projects. Additionally, a sensitivity on clearing price is the observed effect in which the same amount for the same input varies for every project.

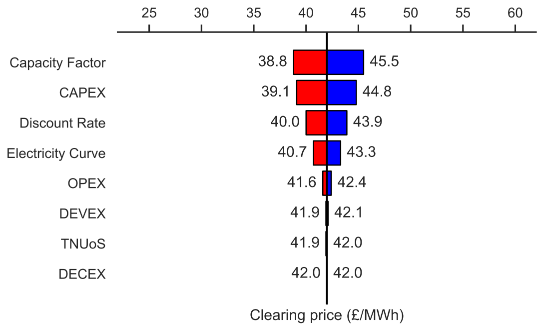
4.3 Results

4.3.1 Sensitivity analysis

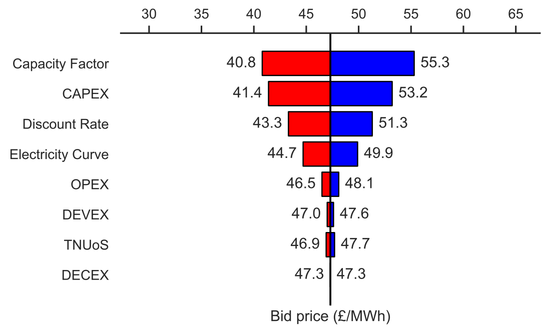
The results in this subsection show which inputs have the most impact and, thus, where resources should be allocated to reduce uncertainty. Figure 4.3 demonstrates how the main outputs of the model change with varying inputs, as shown in the Tornado diagrams. A Tornado diagram is a bar chart that visually displays the magnitude of each risk in descending order. More detail on the figures is given below.



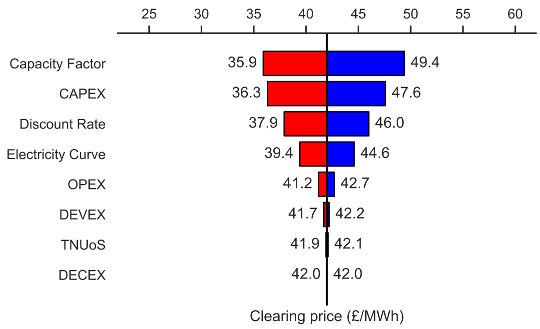
(a) Bid price of projects (±5%)



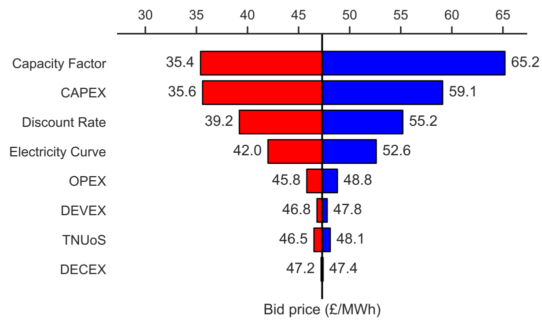
(b) Clearing price of projects (±5%)



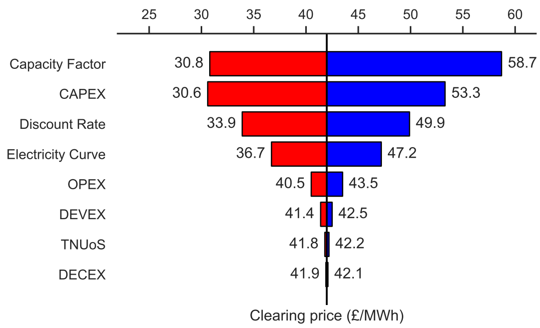
(c) Average bid price of projects (±10%)



(d) Clearing price of projects (±10%)



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



(f) Clearing price of projects (±20%)

Figure 4.3: 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.

As expected, there is a correlation between the average bid price and the auction's clearing price. This means that the most sensitive inputs, which affect the bid price the most, also affect the 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%.

Figure 4.4 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 3.2.3.

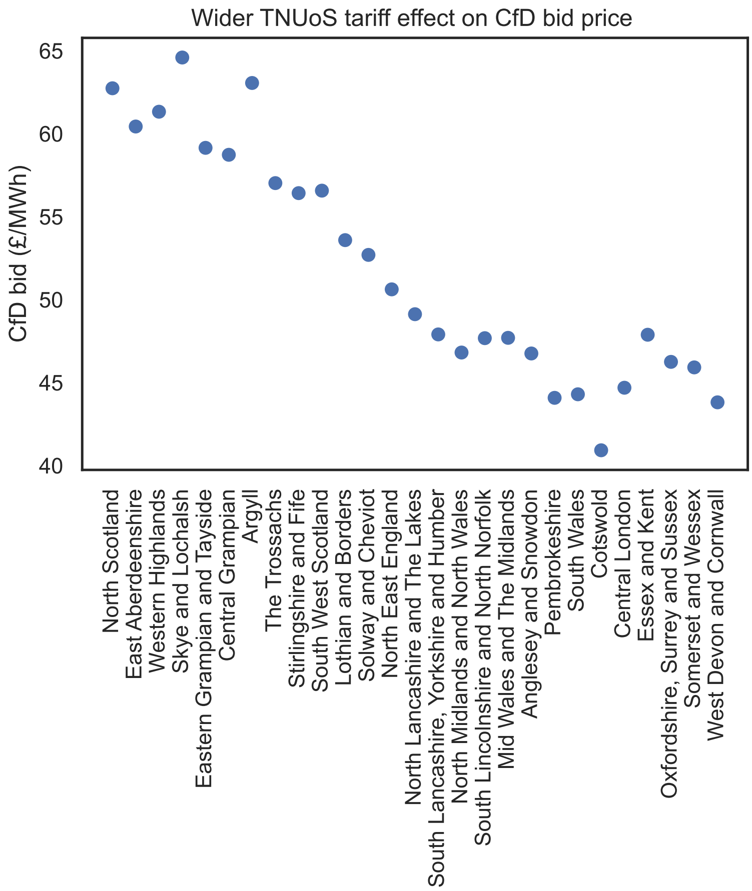


Figure 4.4: Effect of geography on CfD bid as a result of transmission charges, which vary significantly by geography.

4.3.2 Auction Simulation

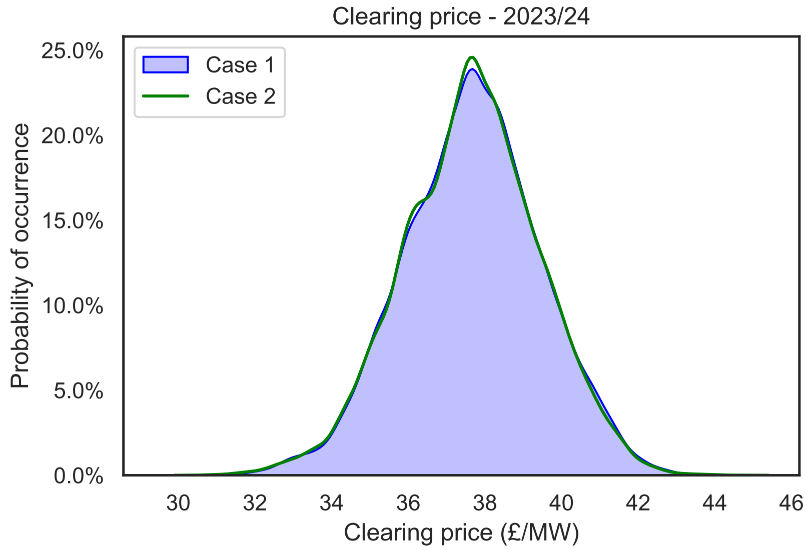


Figure 4.5: Estimated clearing price for first delivery year

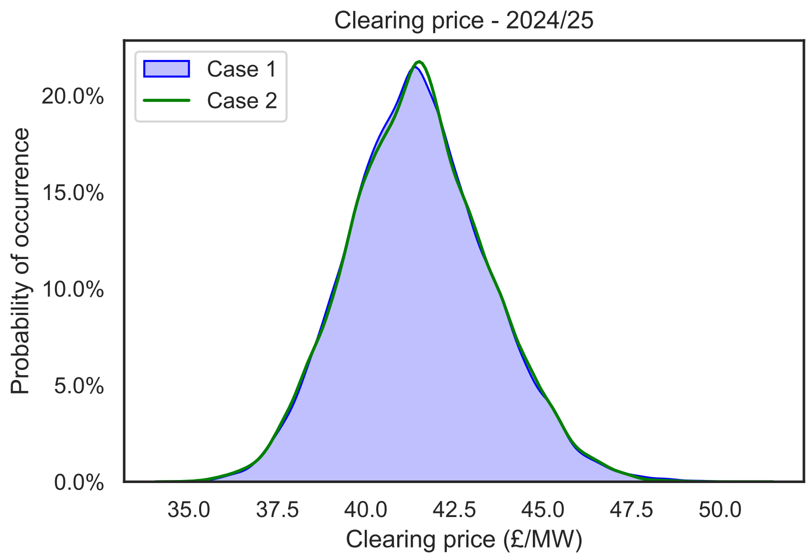


Figure 4.6: Estimated clearing price for second delivery year

Figure 4.5 and 4.6 illustrate 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

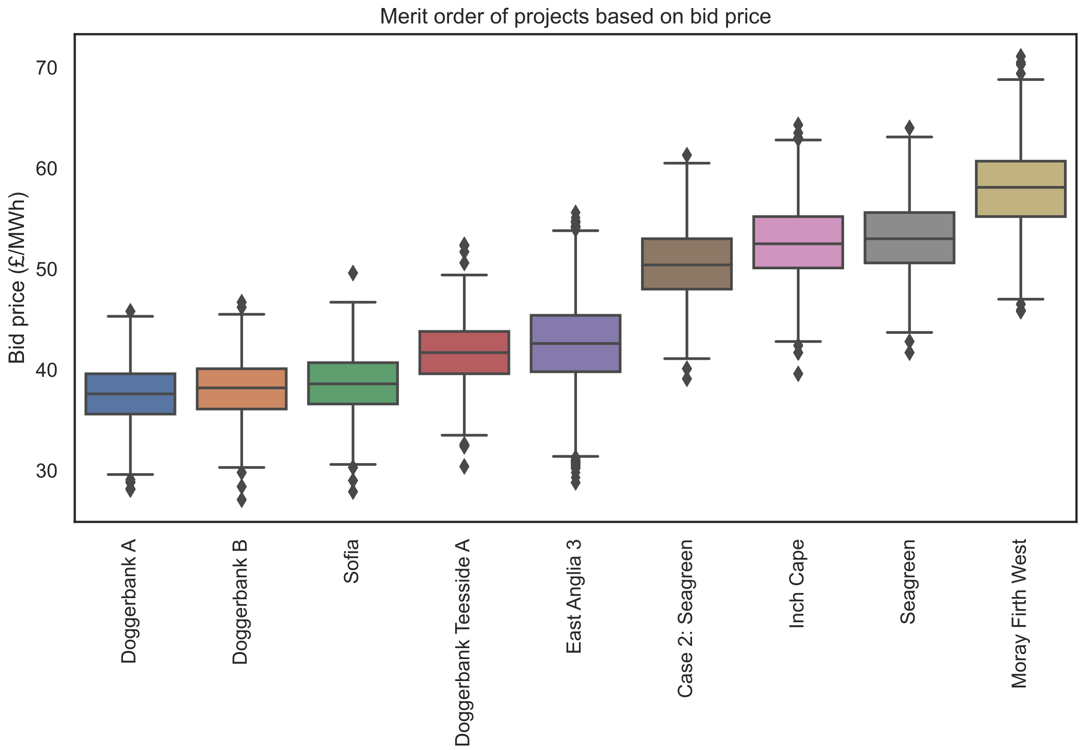


Figure 4.7: Box diagram illustrating the merit order of projects which bid into the offshore wind AR3 pot, in ascending order. For Case 2: Seagreen, the project is based on the Seagreen project, but modelled with a 10% increase in forecast electricity market price.

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 to 43.77, with a standard deviation of 1.78 for delivery year 23/24. For delivery year 24/25 the range is 34.89 to 50.24, and with a standard deviation of 1.98 for 24/25.

In Case 2, Seagreen modelled with a 10% increase in forecast wholesale electricity market prices. Figure 4.5 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.

Figure 4.7 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.

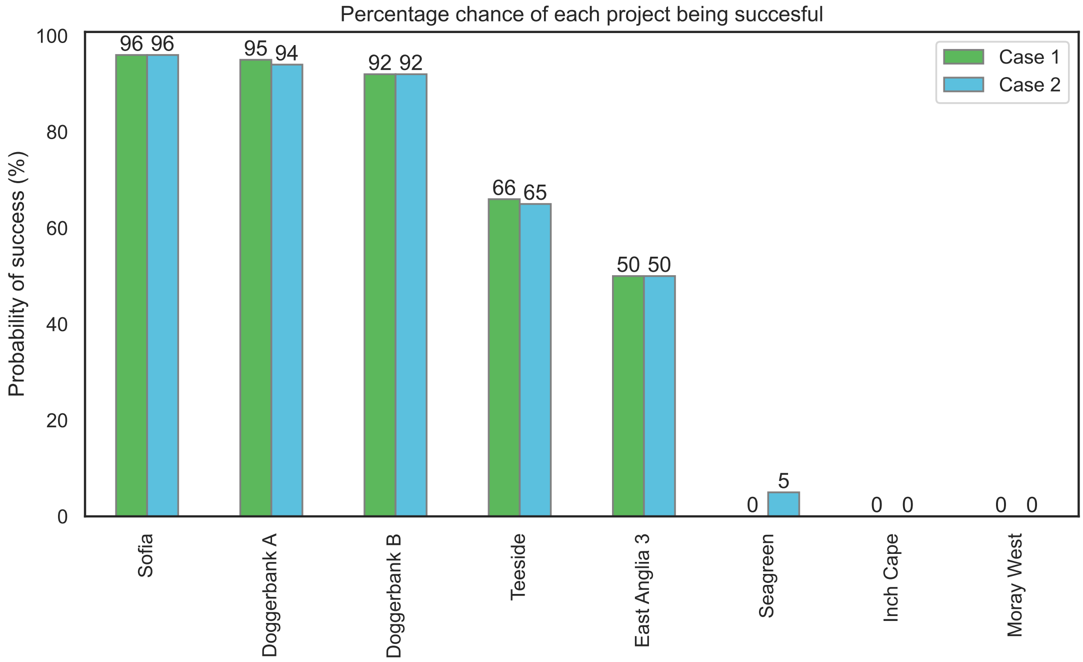


Figure 4.8: Effect of geography on CfD bid as a result of transmission charges, which vary significantly by geography.

For Case 2, seen in Figure 4.7, 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 Figure 4.8. 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%). Figure 4.8 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.

Figure 4.9 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 2.3.1. The peak on the graph is evidence of the highest $E[X]$ and, therefore, the optimum bidding strategy according to $E[X]$. The effect that an increase or decrease in bid price has on the probability of winning can be seen in Figure 4.10. 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.

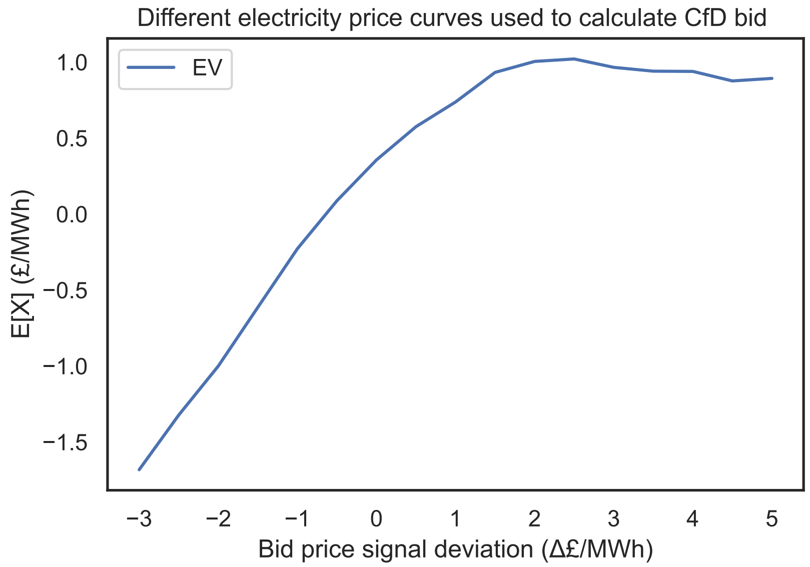


Figure 4.9: Change in expected value with deviations from cost. When bid price signal deviation is equal to zero, the *smart* player is considered to be bidding at cost.

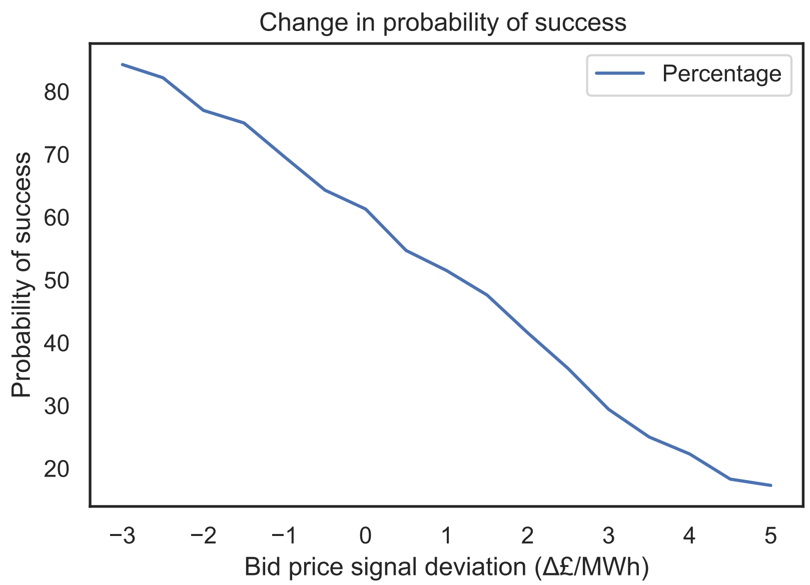


Figure 4.10: Relationship between the increase in the bid price and the probability of being awarded a subsidy

4.4 Discussion and analysis of results

4.4.1 Sensitivity Analysis

The 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 model outputs 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 uncertainty associated with the cost parameters which make up the calculation of capacity factor and CAPEX. For the 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 [108]. This makes smaller investors less competitive in the CfD auction, where participants must compete on price. Wholesale electricity price forecast is a key sensitivity, and significantly affects the calculated bid price of projects. It is challenging to determine which forecast a developer may use, as this can not be estimated from the known site or project-specific conditions, like other costs. Therefore, although the sensitivity to bid price is less for this input, the uncertainty associated with determining an accurate forecast is greater. This means that the actual effect of the wholesale electricity price curve may result in greater uncertainty than better-estimated inputs such as CapEx, or capacity factor.

OPEX is commonly referred to in the literature as making up 33% of total wind farm costs [188]. However, it can be seen from Figure 4.3 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 are small when compared 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 compared to other costs incurred. Additionally, DECEX costs are incurred at the end of a project's lifetime and are negligible in terms of real value. Although which TNUoS zone a wind farm is in can significantly affect the calculated minimum CfD bid 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.

4.4.2 Auction Simulation

There are two main auction results to analyse and then discuss. The first is determining whether the strike prices agreed upon 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 [61]. Secondly, does the award of subsidies in AR3 follow the estimated merit order of projects, as predicted by the auction simulation tool? In other words, was the allocation process at AR3 successful in allocating subsidies to the projects with the lowest generation cost (highlighted as one of the aims of auction design in Section 2.3.1)?

To compare the simulation results to the actual outcome of AR3, which concluded in 2019, a short overview of the auction results is given in Table 4.3. AR3 procured 5,775 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 [62]. A total of 3,034 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. These outcomes are some of the highest probabilities as predicted by the simulation, which demonstrates there is good agreement between the model and actual results. 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

Table 4.3: 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. * Only 454 MW of capacity was awarded for a total project size of 1075 MW [62]

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*	41.611
East Anglia 3	Scottish Power	1400	-
Inch Cape	Red Rock Power	754	-
Moray West	EDP Renewables	850	-

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 was successful at awarding subsidies to the estimated lowest-generation projects based on the merit order (as highlighted in Figure 4.7). 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. Figure 4.4 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 4.1. Due to the importance of winning a CfD contract 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 Figure 4.7, 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. Its position on the merit order can be attributed largely to the higher TNUoS charges. The analysis shown in Figure 4.4 results in an £11.25/MWh increase in CfD bid price when comparing the Seagreen projects to Doggerbank AB. 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 a 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 2,254 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.

Finally, the optimum bidding strategy is for East Anglia 3 to increase its minimum CfD bid price by + £2.5 / MWh. Compared to bidding at cost, 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 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 percentage chance of East Anglia 3 being awarded a subsidy at a + £2.5 / MWh price deviation is 36%. It is an operational decision by developers to analyse on a case-by-case basis to assess their level of risk, which is acceptable for an increase in reward.

The results from the simulation are close to the actual AR3 results while assuming in the simulation that players bid at cost. However, one can not 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.

4.5 Conclusion

This chapter has focused on analysing the AR3 offshore wind pot to demonstrate the uncertainty experienced by auction players while bidding into a CfD auction. The effect of the uncertainty has been characterised by conducting a sensitivity analysis on the AR3 case study. The model utilises a proprietary cost modelling tool to generate stochastic cost estimations for projects which competed in the offshore wind pot of AR3. Furthermore, the auction simulation tool has been demonstrated through a real-life case study. 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 optimising 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 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 in clearing price, respectively. This means that in bid preparation, significant resources should be allocated to reducing the uncertainty associated with costing parameters which make up these main inputs. Additionally, the wholesale electricity price curve is also a key sensitivity and is very challenging to estimate, therefore, uncertainty associated with this value can significantly affect the calculated bid for each project. A study on the wholesale electricity price curve, and the effects of uncertainty on profitability is investigated in Chapter 5.

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 before 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 the 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. The auction outcome 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 AB. This is likely to be a notable barrier for Scotland-based projects to be awarded CfD subsidies in future auctions.

Chapter 5

Studying the effect of CfD contract length on profitability and uncertainty

Methods for developers to characterise the uncertainty present at the auction have been identified in previous chapters. However, policymakers are also incentivised to mitigate against uncertainty. A sensitivity analysis carried out on the AR3 case study identified the forecast wholesale electricity price curve as a key sensitivity, which, as discussed, is more challenging to estimate compared to other inputs. Policymakers can increase the CfD contract length to mitigate the exposure to volatile wholesale electricity prices and thus reduce uncertainty. This chapter investigates the effect of an increase in CfD contract length on profitability and the uncertainty experienced by bidders.

5.1 Introduction

As highlighted in previous chapters, RES is a useful policy tool for governments to support the expansion of low-carbon electricity-generating technologies. However, several risks are associated with bidding at auctions from a government's and a player's standpoint. A major risk for governments, with respect to meeting expansion targets and the acceptance of auctions, is the risk of non-realisation; awarded bidders do not realise their projects [20]. Non-realisation can occur due to the significant uncertainties developers face while bidding into the auction (as described in Chapter 4) [42]. The uncertainties experienced by developers can result in developers under-bidding and experiencing the winners' curse. Policymakers can reduce the non-realisation risk by introducing several measures which reduce the uncertainty experienced by developers.

Policymakers can alter the auction design rules to reduce uncertainty for developers. For example, physical prequalifications are project-specific requirements that must be fulfilled to participate in an auction. For example, prequalification criteria could include detailed supply chain proposals, feasibility studies, land-use plans, or technological experience. Having stringent prequalification criteria also introduce sunken costs, increasing the threshold for participation in the auction. As a design rule mechanism, physical prequalifications or penalties are already well-researched in literature [169, 42, 170].

As presented in Section 2.1.1, auction design rules and renewable support differ between countries due to varying policy goals. In addition, the type and duration of subsidy support available for developers differ between countries. For example, the UK CfD contract provides revenue certainty for a 15-year period. In comparison, German offshore wind support auctions provide a sliding premium support mechanism for a 20-year period [24]. A longer support period provides greater revenue certainty for developers. However, the type and duration of support have not converged onto a single best solution.

As highlighted by Section 2.2.6, forecasting a wholesale electricity market price is pertinent to calculating a CfD bid. This is further evidenced by the analysis conducted in Chapter 4, which demonstrates that forecast electricity price curves are a key sensitivity in preparing a bid price. Unlike cost estimates, which can be based on site characteristics or supplier contracts, it is very challenging to predict future prices. Therefore, it is a key source of uncertainty that can be mitigated by increasing CfD contract length and limiting exposure to volatile wholesale electricity prices.

This chapter presents recommendations, evidenced by simulation, of how policymakers can reduce uncertainty to increase the realisation rate of projects and ensure renewable deployment targets are met. 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. In addition, further financial analysis calculates the effect of varying CfD contract lengths on offshore wind profitability and net support payments made by governments.

The literature survey conducted in Section 2.2.6 has guided this work. It suggests that there have been attempts to demonstrate how uncertainty related to specific inputs, such as future wholesale electricity price forecasts, can affect a site's estimated NPV. However, literature is yet to explore how uncertainty concerning forecast electricity prices can have an effect on the expected profitability of sites and the calculated CfD bid price. Furthermore, the effect of CfD contract length on the uncertainty experienced by participants and the NPV of support payments made by the government is yet to be researched. Therefore, the following gaps identified in the literature are investigated in this chapter.

The remainder of the chapter is structured as follows: Section 5.2 outlines the methodology and case study. The results are presented and described in Section 5.3. Finally, Section 5.4 analyses the results before drawing conclusions and implications for the various stakeholders.

5.2 Case Study Methodology

A base case must first be defined to conduct the CfD contract length analysis as outlined in Section 5.1. The Case Study utilised is based on Pot 2 of AR3, which concluded in 2019 and is the same as outlined in Section 4.2.2. The justification for replicating a previous auction, is that it is a better representation of competition and so can better replicate auction dynamics.

5.2.1 CfD contract length analysis

This analysis aims 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 developer (as explained in Section 2.1.5). To analyse how this can be mitigated against policy-makers, this work investigates 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 regarding 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. In reality, and as explained in Section 3.2.5 developers costs are better represented by stochastic inputs, which take into account the uncertainty associated to other developers costs and one's own cost. However, this analysis deviates from the model's methodology as outlined in Chapter 3, and assumes each participant is assumed to have large uncertainty associated with future wholesale electricity market prices. Developers must forecast future electricity prices to calculate the development's lifetime cash flow (from which their bid price is calculated). The forecast wholesale electricity market price for this simulation is the only parameter assumed to be stochastic. This is so the uncertainty associated to the future electricity market prices can be observed in isolation and prevents uncertainty associated to other inputs propagating into outputs. For every simulation, there are 1,000 auction runs to average over stochastic inputs. An auction run is defined as completing one sample auction run, which outputs a clearing price and list of subsidised projects. 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 runs per simulation (see Section 4.2.2).

In this analysis, three potential future electricity price scenarios are modelled: low, medium, and high economic growth. All forecasts are publicly available from BEIS, and are based on outputs from a Dynamic Dispatch Model [99]. This comprehensive, integrated power market model 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 [178]. 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 2.1.3), the forecasts from BEIS are converted to 2012 real values, using historical inflation data from the ONS [189]. The resultant three curves used in this analysis can be seen in Figure 5.1. These curves are the base load electricity prices, and are used in the absence of publicly available capture price for offshore wind. This has limitations compared to estimating the average electricity price that a project achieves according to its technology (wind or solar PV) and geographic specific renewable energy resources. For example, the base load price does not take into account cannibalisation of renewables price. Cannibalisation of renewable prices is the phenomenon where variable renewables depress wholesale power prices at times of high output [190]. This means that the base load prices are likely higher than the capture price for offshore wind. However, given the uncertain nature of forecasts that bidders use, with many using internal forecasts base load price is a useful proxy for weighted average capture price. This is justifiable given that the purpose of this analysis is to compare different CfD support period lengths, and since this same assumption is used for all CfD contract lengths tested, it will still allow for a fair and accurate comparison.

5.2.2 Monte Carlo sampling of future wholesale electricity prices

Using the same methodology as outlined in Chapter 3, each participant calculates an optimum bid, which is a function of their input costs and other parameters. Monte Carlo Sampling determines the future wholesale electricity price for that auction run. The forecast electricity market price is sampled from the curves illustrated in Figure 5.1, and each sample is a mix of varying contributions of each of the three curves. This is achieved by randomly sampling three weightings for each curve, and constraining the sum of these weights to one. Therefore, each auction run generates a different forecast electricity price curve for each project, using varying weightings of the three curves shown in Figure 5.1. 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 the bids produced by a project over the simulation will vary due to the stochastic wholesale electricity market price input. It is assumed in this analysis that auction participants

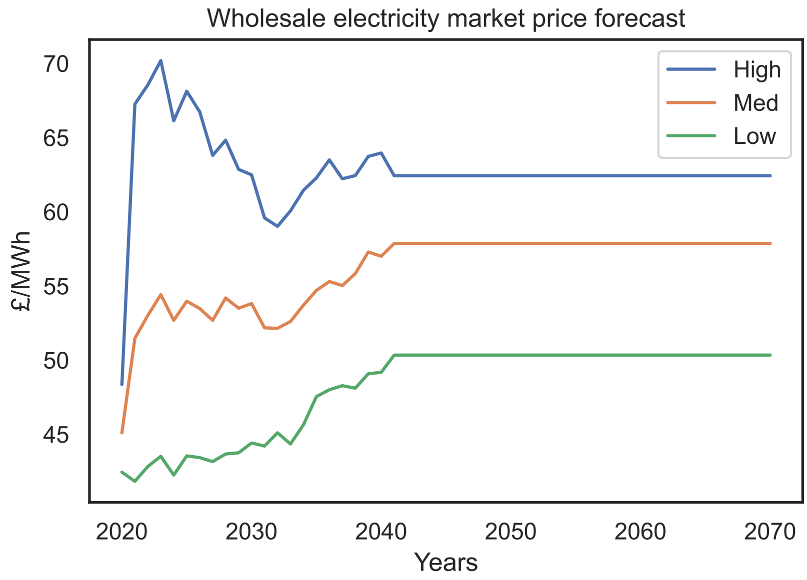


Figure 5.1: Illustration of BEIS's wholesale electricity price curves used in case study.

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 approximate bids that participants can submit.

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 future 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 prices, winning projects and project bid prices'.

5.2.3 NPV calculation

To compare the effect that different contract lengths have on policymakers' 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.

However, from a policymaker's perspective, NPV of support costs to developers is not the only consideration in determining CfD contract length. It is also important to consider the effect of contract lengths on the estimated NPV of offshore wind developments. Any changes to the CfD scheme which detrimentally affect the profitability of projects may have a detrimental effect on the realisation of projects.

A scenario-based approach is adopted to calculate NPV values. This shows which contract length gives the lowest NPV of support payments and the highest NPV for developers, given a low, medium or high economic growth scenario. The same forecast scenarios are used in Figure 5.1. 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 their 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 [191]. The 6.3% WACC (weighted average cost of capital) is taken from estimates from BEIS [174]. 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* [108]. This captures the fact that people generally place more value on present costs and benefits than on future ones.

The WACC used for the period of CfD contract length is the same as for the period not covered by a CfD contract. A CfD contract improves revenue certainty, so in a levered project, where debt is used in the project, lenders will reduce the cost of their finance due to the reduced risk (as explained in Section 2.1.5). However, this analysis assumes unlevered financing (as explained in Section 3.2.3), as financing structures of competitor projects are difficult to assume and so can be represented by a standard WACC assumption for each competitor. Therefore, it is also challenging to assume the delta between WACC's assumed for CfD and merchant years in an unlevered project. Additionally, an unlevered bidder may have a blended WACC that would account for both merchant and subsidy revenues and may not have two WACC's for each revenue period [65]. For this reason the WACC assumed in this analysis is the same as dictated by BEIS (explained above), which is constant throughout the years.

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 5.1 calculates the sum of NPV support payments to one project. Where P is the clearing price, θ is the average weighted capture price for offshore wind during the year period 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 d is the discount rate.

$$NPV = \sum_{n}^{t=1} \frac{(P-\theta)(C \cdot C_f) \cdot h_{year}}{(1+t)^d} \tag{5.1}$$

NPV developers

A cash flow is calculated for each project awarded a CfD in the simulation carried out in Section 5.2.1, using the same method described in Section 3.2.3. The NPV of developments awarded a subsidy is calculated using Equation 5.2, which is an adaptation of the overall equation presented in Chapter 3. To determine the NPV for each developer, the work assess the *true* NPV value using the awarded CfD bid price and one of the three wholesale forecast price curves as shown in Figure 5.1. This means that for every contract length analysed, three resultant NPV developer values will be generated. 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 ten 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 5.1.

$$\text{NPV} = \underbrace{\sum_{t=0}^{t_{NG}} \frac{-c_{i,t}}{(1+d)^t}}_{\text{No Generation}} + \underbrace{\sum_{t=t_{NG}+1}^{t_b} \frac{r_{i,t}(X_t,P)-c_{i,t}}{(1+d)^t} + \sum_{t=t_b+1}^{T-1} \frac{r_{i,t}(X_t,\theta_t)-c_{i,t}}{(1+d)^t}}_{\text{Operational}} + \underbrace{\frac{-c_{i,T}}{(1+d)^T}}_{\text{End of life}} \tag{5.2}$$

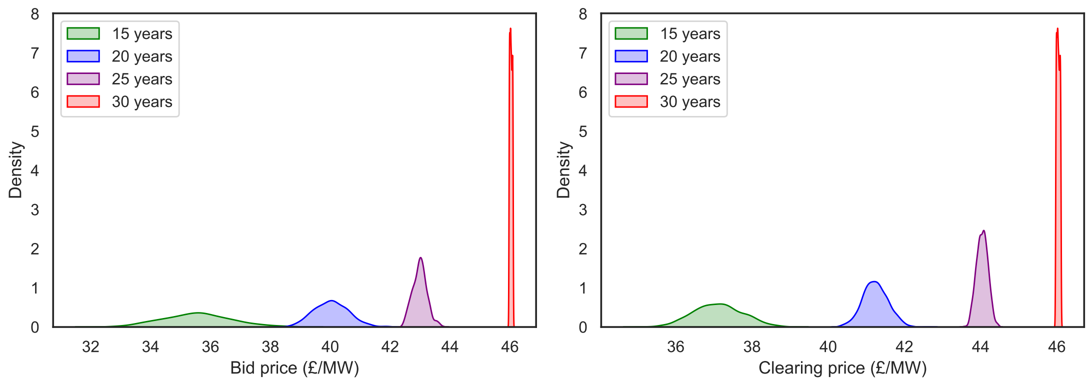
Where t is the year, T represents the lifetime of the wind farm that is assumed to be 42 years, t_{NG} is the non-generation lifetime assumed to be 11 years, and t_b is the CfD generation period assumed to be 15 years. $r_{i,t}$ is the revenue received by bidder i for their offshore wind project in year 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, 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, and is dictated by the three economic growth scenarios (outlined in Section 5.2.2).

5.3 Results

The results show that governments can mitigate against the uncertainty surrounding forecast electricity curves, which is extremely challenging to forecast accurately and is a sensitive input in bid preparation (as seen in Figure 4.3). Policymakers can mitigate this by varying CfD contract length, thus minimising wind farm projects' exposure to wholesale market prices.

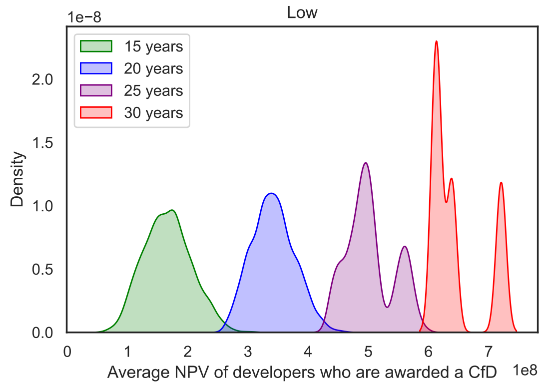
From Figure 5.2 the effect that CfD contract length has on auction outcomes can be seen. The variation in bid price is demonstrated for one project only. The general trend is that a longer CfD contract length results in participants submitting higher bid prices. The mean bid price (£/MWh) for each contract length is 35.5, 40,0, 43.0, and 46.0 for contract lengths 15, 20, 25 and 30 years, respectively. This means that the resultant expected clearing price for each CfD contract length also increases.

Figure 5.3 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.

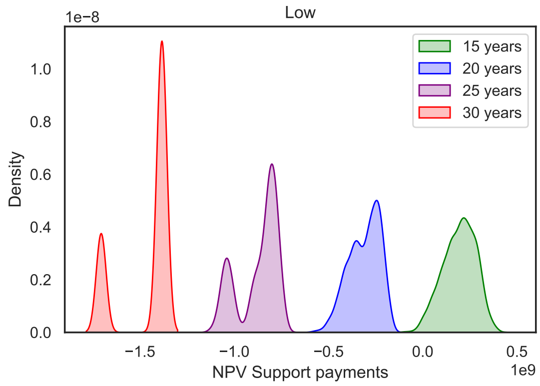


(a) Effect of contract length on bid price. **(b)** Effect of contract length on clearing price.

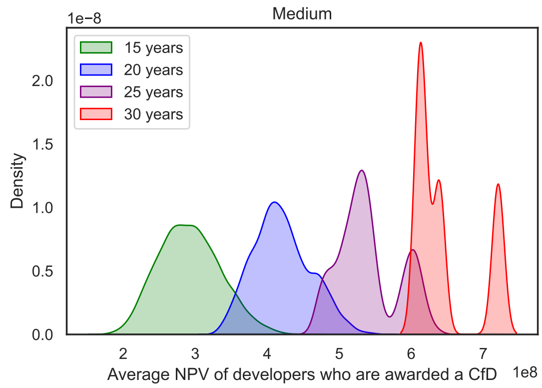
Figure 5.2: Effect of contract length on auction dynamics



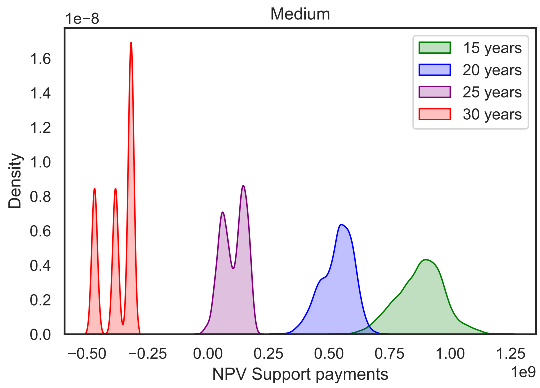
(a) Low Economic Growth - NPV Developers



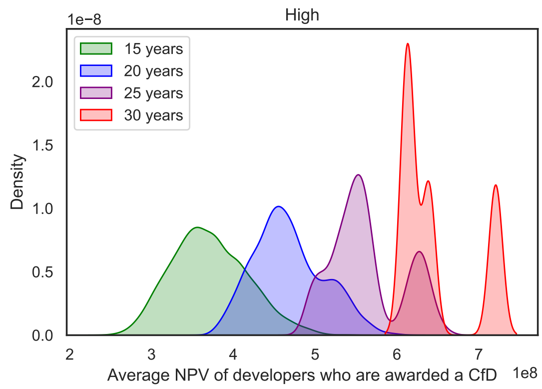
(b) Low Economic Growth - NPV Support



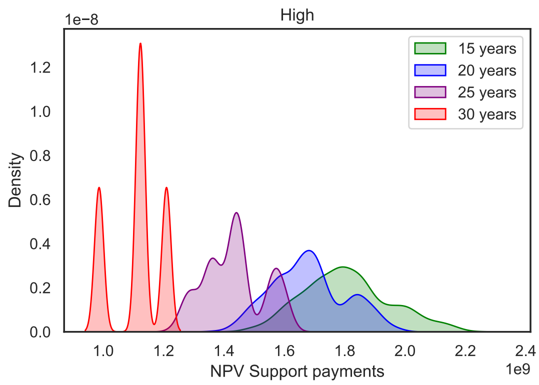
(c) Medium Economic Growth - NPV Developers



(d) Medium Economic Growth - NPV Support



(e) High Economic Growth - NPV Developers



(f) High Economic Growth - NPV Support

Figure 5.3: Effect of CfD contract length on NPV

5.4 Discussion

The results presented in Section 5.3, demonstrates that the auction strike price increases with an increase in CfD contract length. This is because, under the modelled scenario, generators have an optimistic view of future electricity prices. This can be explained because developers have an average cost of generating electricity for each unit of generation 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, the CfD bid price varies 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 Figures 5.4) and 5.5. 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, shown in Figure 5.2, is an increasing CfD bid price with an increasing contract length.

As described in Section 5.2.3, the WACC assumptions for each revenue period has been kept constant. In reality, developers may assume a higher hurdle rate for a project not covered by a CfD versus merchant. Although the delta is difficult to assume, if a lower hurdle rate for CfD years is assumed than a merchant period, than the differences between contract lengths in Figure 5.2a would be reduced, meaning that a longer CfD period would result in a reduced delta between CfD bid prices. However, the differences between bid price averages for each contract length is significant and so the main trends as discussed in Results 5.3 would still hold true. This is because the main factor that would affect the delta between bid prices for each CfD contract length is a developers future view on merchant price (as described above).

The results shown in Figure 5.4 are estimations of the LCOE of the projects outlined in the Case Study in Section 4.2.2. The LCOEs have been calculated using the high-level inputs as specified in previous chapters and through the use of the financial element of the model as described in Section 3.2.3. 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 5.5 was produced by sampling for 1,000 curves as described in Section 5.2.2. The average of those curves is then calculated and used to produce the density plot.

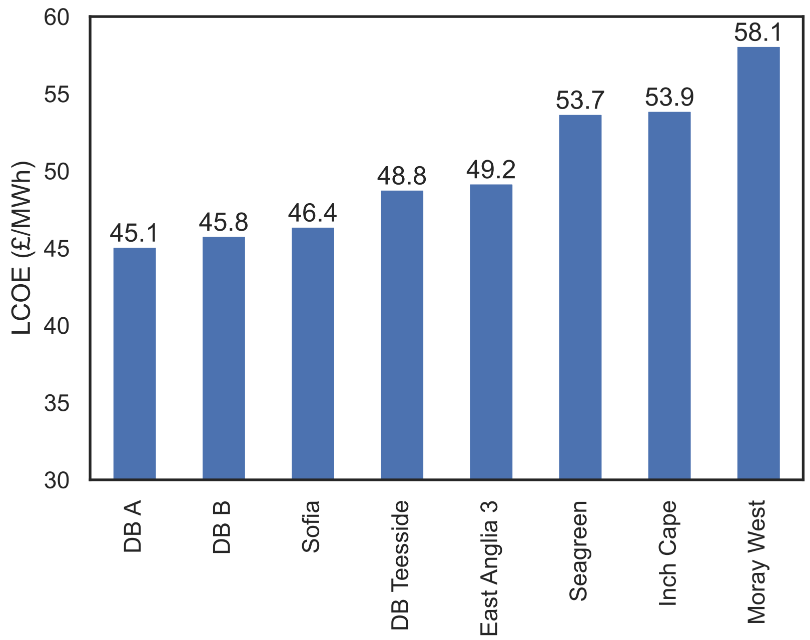


Figure 5.4: LCOE estimation for projects outlined in Case Study

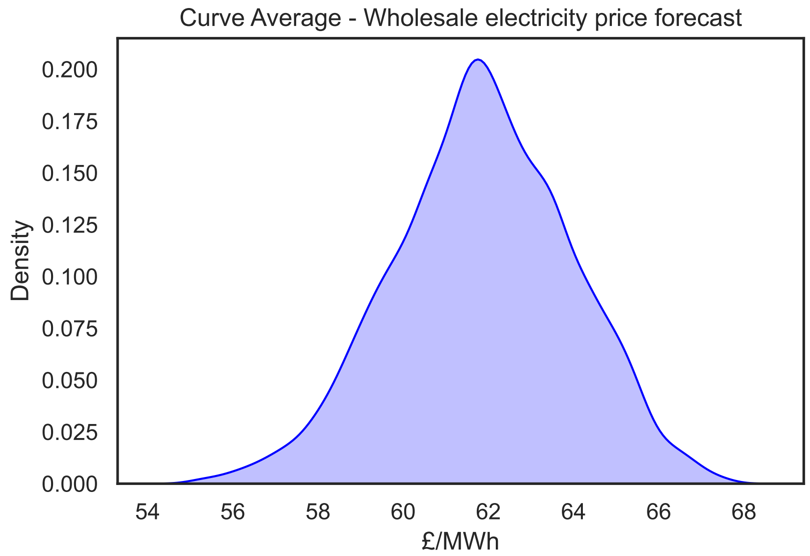


Figure 5.5: Average value of electricity during merchant exposure

Although Figure 5.2a represents how bid price changes for a single project, it can be seen from Figure 5.2b 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 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 5.1.

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 in Figure 5.5). The general trend as highlighted in Section 5.3, 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 5.2a) 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 in 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 the risk experienced by increasing CfD contract length may reduce the cost of borrowing and thus further reduce the generation costs of offshore wind projects.

5.5 Conclusion

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 a decrease 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.

Chapter 6

Predicting future CfD auctions through an AR4 case study

This chapter aims to build on the previous applications of the auction simulation tool and demonstrate a methodology for policymakers to design and for developers to prepare for upcoming ARs. This chapter simulates AR4 (held in 2022), the most recent CfD auction for offshore wind, using data only available prior to the auction. A number of different bidding strategies are empirically tested, and auction design rules are simulated to test auction efficiency. The results show that policymakers face a trade-off between increased risk of non-realisation and minimising subsidy payments (i.e. minimising cost to tax-payer).

6.1 Introduction

The most recent CfD auction, the fourth auction to occur, is known as Allocation Round 4 (AR4) [68], which is the focus of the Case Study presented in this work. AR4, held in 2022, was the first to occur in three years. A three-year gap between rounds resulted in greater competition from projects unsuccessful in AR3 and new entries in AR4. For the projects who were unsuccessful in AR3, a three-year delay in construction as they awaited the next AR led to increasing pressure on the feasibility of their projects and a change in their risk appetite. Ahead of the auction, fixed offshore wind was allocated to its own dedicated pot, meaning it did not need to compete with other technologies. No maximum capacity cap was applied to the auction, unlike AR3, and so a monetary budget of £210m was applied to the auction [67].

In order to demonstrate the auction simulation tool and its use cases for future auction rounds, AR4 has been simulated prior to the auction using only information available before the auction. This methodology details an approach that developers can use throughout the lifecycle of a bidding process. The methodology includes an assessment of the competitiveness of the auction through analysis of the monetary budget, simulation of the auction to help define a dominant bidding strategy, and post-auction analysis of the results to provide strategic context and recommendations for future rounds.

Simulation can also be used to test auction design and its effect on allocation efficiency, allowing empirical testing of several different rule configurations, which helps inform policymakers on auction design. Renewable energy subsidy (RES) auctions have not yet converged onto one design, as highlighted by Section 2.1.1; therefore, further research is warranted to explore rule design changes for policy recommendations [24]. Additionally, simulating the auction can be useful to test any rule changes or parameters set (e.g. monetary budget) [25]. This is useful for both policymakers and developers. Policymakers can use the simulation results to empirically test that the auction is well-designed and successfully induces competition. From a developer's perspective, it allows for the effect of auction design rule changes on auction dynamics to be studied and well understood.

Preparing a CfD bid is challenging. As discussed in Section 2.3.1, the developer's incentive to bid strategically and deviate from marginal cost further complicates the CfD auction process. From an auctioneer's standpoint, strategic bidding, whereby developers do not reveal their actual cost, is an example of auction inefficiency [42]. One form of strategic bidding is shading, where players increase their bid above cost to increase their expected pay-off [192]. Simulation routed in game-theoretic principles can help quantify the likelihood of each player engaging in this strategic behaviour.

The simulation results obtained in this chapter have not been calibrated against the actual auction results and are based solely on information available before the auction. The results are then compared against the actual auction results to help inform future bidding strategies. Developers can use the methodology to prepare better auction strategies, which prevents the winners' curse and mitigates project non-realisation. Policymakers can also use the methods described to test new auction formats and ensure allocation efficiency.

This chapter introduces a novel methodology for studying CfD auctions dynamics. As highlighted by the literature review chapter, several novel elements are associated with the methodology that do not feature in the few studies conducted on Renewable Energy Subsidy (RES) auctions or adjacent auction modelling literature. Firstly, previous work, such as Anatolitis et al. [193] and Welisch et al. [18], assumed that developers reveal their actual value and bid at cost. However, this methodology incorporates game and probability theory elements to allow developers to shade their bids. Secondly, this work simulates auction design rule changes to test the effect on allocation efficiency by depicting real auction players characterised by real offshore wind projects. Basing case studies on real auctions allows for a realistic depiction of competition. Finally, the presented methodology uses auction simulation to analyse past auction results, which can be used to understand auction behaviour and inform future bidding strategies. It also enables policymakers to make conclusions on the auction's effectiveness at allocating resources.

The remainder of the chapter is structured as follows: Section 6.2 details the assumptions used and the methodology carried out. The results are presented and described in Section 6.3, and then compared to the actual AR4 results. Finally, Section 6.4 discusses the wider implications of the results before drawing conclusions.

6.2 Case Study Methodology

This section explores the assumptions and methods used to conduct the analysis as outlined in Section 6.1. The auction simulation tool, as outlined in Chapter 3 has been used to conduct the analysis. To carry out the simulation, the Allocation Framework published for AR4 has guided the set-up of the simulation [67]. As there is no capacity cap, a monetary budget will determine the auction's outcome. Therefore, the model uses the Valuation Framework and parameters specific for AR4 to assess the budget impact of each bid (as explained in Section 2.1.4). Furthermore, the role of delivery years has been simplified for AR4. This change has, therefore, also been implemented in the numerical framework, meaning that the auction will close once the budget has been breached in any delivery year. This means that one strike price will be issued for all projects regardless of the delivery year they bid.

Affordable Capacity

The monetary budget issued by BEIS gives an indication of affordable capacity if used alongside the Valuation Framework Formula (outlined in Section 2.1.4). Therefore, an affordable capacity analysis can be used to estimate the competitiveness of the auction based on the monetary budget and the expected eligible capacity competing. Six months prior to the auction the government issued a revised budget revision for Pot 3, increasing the budget by £10m to £210m. This budget revision's effect on auction dynamics is analysed in Section 6.3. Therefore, the affordable capacity for the old and new budgets is analysed. Using the known budget and constants outlined in Table 2.4 it is possible to solve for C, capacity, with a range of SP, strike price, values using Equation 6.1.

$$C = \frac{BI}{(SP - RP) \cdot LF \cdot YR1F \cdot (Days_{yr} \cdot 24) \cdot (1 - TLM) \cdot RQM \cdot CHPQM} \tag{6.1}$$

Game-theoretic methodology

The model has demonstrated how the incentive to engage in strategic bidding (e.g. bid shading) depends on the player and its project. The model is run seven times (once for each player), altering the smart player for each simulation. This means that only one player at a time will have additional capabilities (described in Section 3.2.6 and shown in Table 3.2) and, therefore, knowledge of other competitors' bids. Therefore, only one player at a time uses its additional competence to test for the existence of a bid price that maximises E[X].

When running the model for each smart player, the smart player's costs are assumed to be deterministic. This is because the game-theoretic simulations are computationally expensive, and stochastic bid prices for the smart player would require many more thousand auction simulations for results to converge. If it can be assumed that the smart player's costs are known, then computational times are reduced significantly. Therefore, a deterministic cost modelling tool (OWCAT) [90] has been used to generate input data for the project, acting as the smart player. The *other* players will utilise stochastic cost data to generate bid prices. This cost modelling tool has been described previously in Chapter 2).

Players are assumed to be unwilling to reduce their bid price below the minimum CfD bid price calculated, which gives them a minimum equity return. In doing so, the developer would risk not meeting the hurdle rates required for the project, which could result in non-realisation. For this reason, the players only consider increasing their bids beyond the minimum acceptable CfD bid price. Therefore, the players observe the effect of increasing their bid price by a maximum of £5/MWh, with an interval of £0.50/MWh. This range was chosen as it considers a wide possible bid range which also identifies a peak in the E[X] graphs produced in the results (see Figure 6.8). Each player observes the success of 10 bid prices beyond their minimum calculated CfD bid price. For every bid price tested by the model, 1,000 auction simulations are generated. This auction simulation number is chosen because there is a strong convergence of results after 1,000 simulations per bid price (as explained and demonstrated in Chapter 3.

Delivery year rule change

AR4 delivery year rules stipulate that if the monetary budget is breached in one delivery year, the whole auction closes. Therefore, a single strike price applies across the auction (subject to ASPs). This reduces the strategic complexity of the auction, as it means that the success of a bid is irrespective of what delivery year it bids into.

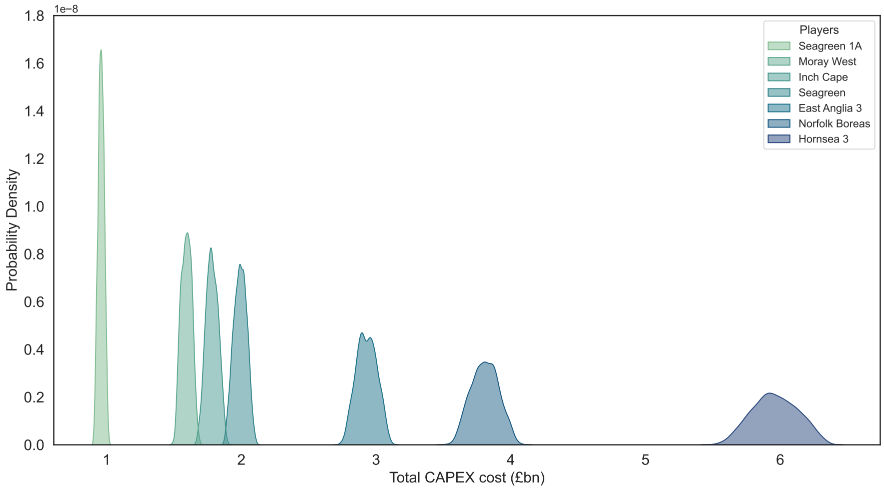
To model the effect the rule change has on the auction outcome, the case study described in Section 6.2.1 is modelled with AR3 delivery year rules and compared to the AR4 rules. To model the AR3 delivery year rules, a similar procedure as described in Chapter 5.2.1 is followed. The budget impact of each bid is assessed using the Valuation Formula; however, the delivery year that the bid is submitted determines which reference price is used to calculate the budget impact. For example, if the bid is submitted into the first delivery year, a reference price of £38.77/MWh applies. Similarly, if the bid is submitted into the second delivery year, a price of £32.85/MWh applies. Once the £210m budget is breached in either of these delivery years, that delivery year is closed, and all other bids associated with that delivery year are removed from the bid stack. Allocation continues to the other delivery year until the £210m budget for that year is breached; the last accepted bid into that delivery year sets the strike price. The auction then closes. As the reference price for the second delivery year is significantly lower, the budget impact is greater, meaning the second delivery year is likely to close first. The results generated from the simulation using AR3 delivery year rules are compared to those from AR4.

6.2.1 Case Study Description

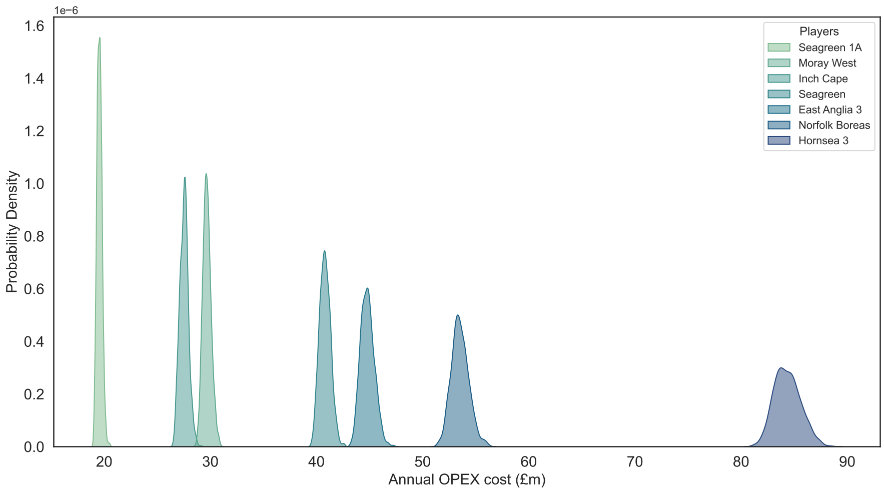
The eligible projects expected to compete in AR4 are first introduced in this Section. As projects must have obtained the necessary consent and approval from the UK government, details surrounding eligible projects are publicly available on the Planning Inspectorate (PINS) website [173]. The consenting documents outline a significant amount of information for each project, such as allowable build-out capacity, cable landfall point, export type and maximum turbine rating.

The project costs are modelled using publicly available site-specific and project-specific characteristics, which can be seen in Table 6.1. The data presented in this Table has been obtained from various sources such as PINS [173], and 4C Offshore's database [11]. Using this publicly available information, cost data is generated for each project using a previously validated proprietary stochastic cost modelling tool. The costs generated from this costing tool have been validated to an accuracy of $\pm$ 15% [90].

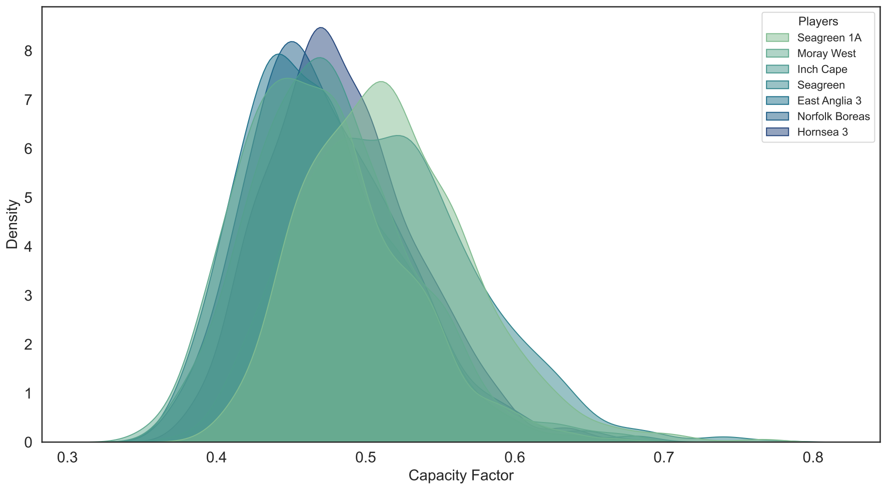
Stochastic cost data is used to better categorise the uncertainty associated with projecting costs. The cost model produces stochastic outputs based on uncertainties associated with the individual cost parameters. Stochastic values drawn from this model are used to derive an empirical distribution of costs rather than assuming a specific distribution shape. The cost distributions used for the AR4 prediction can be seen in Figure 6.1. As described in Chapter 4, the results have been obtained from a stochastic cost modelling tool. However, the spread of projects is much wider on the distributions, this is because the capacity of projects which competed in AR4 varies more significantly than AR3 (as shown in Figure 6.1). The uncertainty associated with the CAPEX and OPEX costs for larger projects is greater because, for example, there are a greater number of turbines for larger projects, so the distribution of total wind turbine costs is wider. This can be seen by comparing the distributions between Seagreen 1A and Hornsea 3. The median bid price extracted from the stochastic cost distributions for each project is shown in Table 6.2. The geographical spread of projects and their respective constituent TNUoS zones can be seen in Figure 6.2.



(a) Empirical distribution of generated CAPEX costs.



(b) Empirical distribution of generated OPEX costs.



(c) Empirical distribution of generated Capacity Factors.

Figure 6.1: Distributions of stochastic inputs for each player in the case study.

Table 6.1: High-level overview of some of the publicly available site/project specific input data which was used to generate cost estimations [173] [11].

Project	Capacity	Average depth (m)	Mean wind speed @ hh	Distance to port (km)	Foundation type	Export type
Hornsea 3	3000	38	10.47	250	Monopile	HVDC
Norfolk Boreas	1800	33	10.30	92	Monopile	HVDC
East Anglia 3	1480	39	10.23	80	Monopile	HVDC
Moray West	850	45.4	10.13	70	Monopile	HVAC
Inch Cape	1000	52	9.97	45	Monopile	HVAC
Seagreen 1A	500	54	10.55	65	Jacket	HVAC
Seagreen	1075	54	10.55	65	Jacket	HVAC

Table 6.2: Overview of cost input data used to generate a bid price for each player. Inputs marked *, show the median data for stochastic inputs, distribution of stochastic data is shown in Figure 6.1.

Project	Capacity (MW)	DEVEX (£m)	CAPEX* (£m)	CAPEX (£m/MW)	OPEX* (£m/year)	DECEX (£m)	Capacity Factor*
Hornsea 3	3000	172.6	5052.6	1.68	83.2	232.0	0.508
Norfolk Boreas	1800	134.1	3034.2	1.69	52.6	132.4	0.511
East Anglia 3	1480	121.3	2039.4	1.67	44.4	106.8	0.531
Moray West	850	92.2	1524.3	1.79	29.3	72.1	0.535
Inch Cape	1000	99.9	1783.8	1.78	27.7	78.4	0.527
Seagreen 1A	500	71.2	939	1.88	19.4	56.8	0.507
Seagreen	1075	107.1	1953.1	1.81	40.4	91.9	0.507

In addition to generating cost data for each project, several other inputs are required to estimate the CfD bid price of different projects. Financial assumptions such as WACC, IRR, and gearing ratios required for detailed financial modelling, are difficult to assume with any confidence for each player, so they are left generic for all developers. Hence, the site/project characteristic data is the key driver of differentiation between projects and determines the estimated bid price merit order of projects.

The following additional assumptions are the author's own and are made to simulate the AR4 auction. The assumptions are required to reduce the complexity surrounding unknowns of the auction process and do so without sacrificing the detail of the auction design.

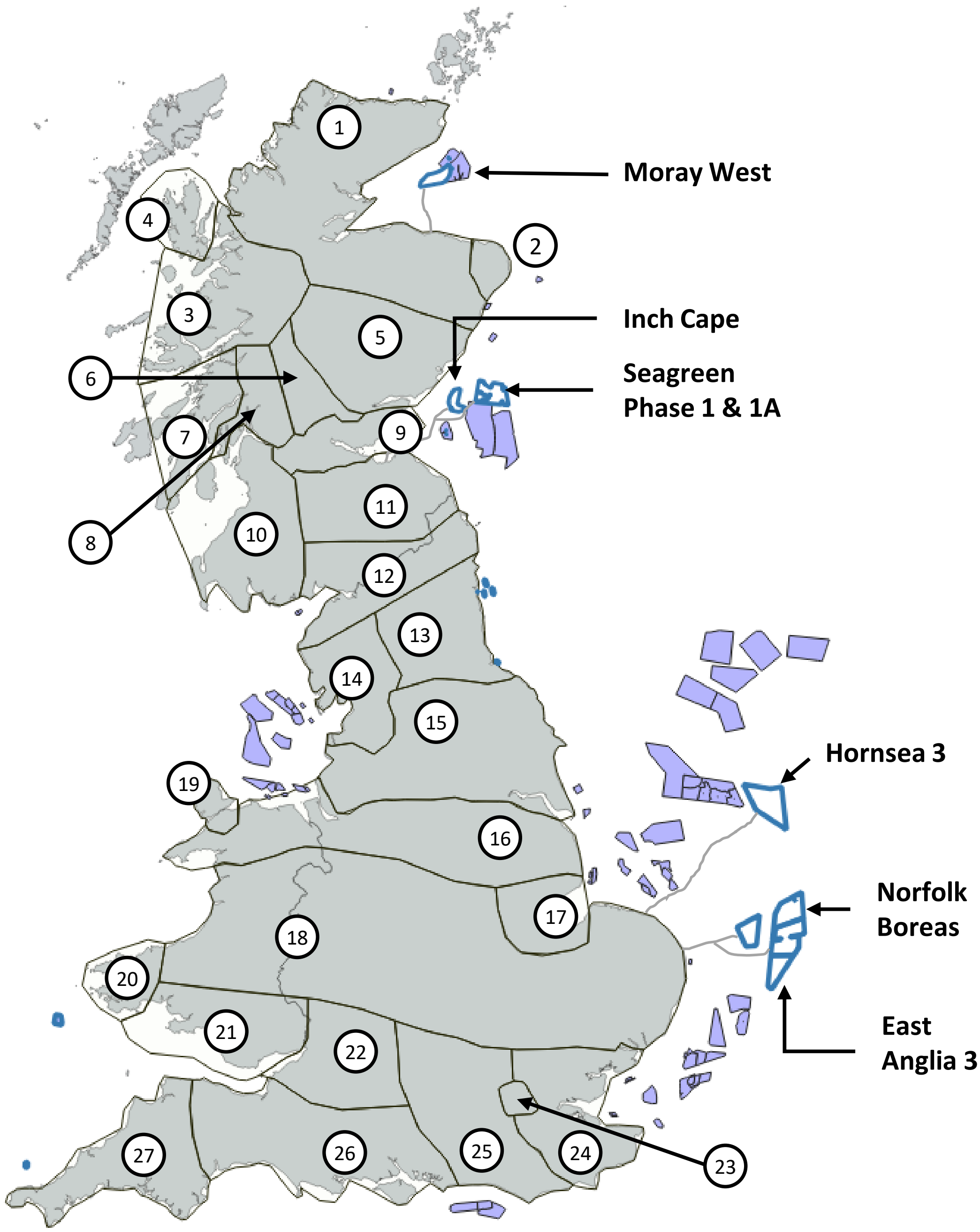


Figure 6.2: Geographical location of Offshore Wind Farms expected to compete in Pot 3 AR4. The 28 TNUoS zones, as outlined by National Grid ESO, are displayed on the map.

1. **Forecast wholesale electricity market price** - Future wholesale electricity prices 30 years into the future are extremely challenging to predict. Forecasts will differ between developers and can impact the calculated CfD bid. As it cannot be estimated which forecast each player may use, to keep calculations relative, all developers use the same curve, which has an average market price forecast of £55/MWh for the next 30 years. This is based on the medium economic growth forecast produced by BEIS [99].
2. **TNUoS forecasts** - Transmission Network Use of System (TNUoS) charges over the operational lifetime of a wind farm are required to estimate total costs. TNUoS charges are levied on generators as a cost for transmitting electricity on the electricity grid. The charges reflect the cost of building and maintaining transmission infrastructure. National Grid ESO provides forecasts only up to 2027/28. Therefore, this final forecast is extrapolated from the last forecast in a straight line to provide estimated charges for the entire 30-year wind farm period. All projects will derive their TNUoS charges from the same forecast.
3. **Discount rate** - Discount rates used by different developers are likely to vary based on risk appetite and business models. Variation between developers can not be predicted; therefore, all developers are modelled using the same central discount rate of 6.3%, based on BEIS estimates [174].
4. **Flexible bids** - Developers can submit variations of their primary bid by varying the total amount of capacity of their bid. Flexible bids trigger the interleaving rule (as explained in Section 2.1.4). Flexible bids submitted by each player for each project are difficult to predict. However, as large eligible projects compete in AR4, the interleaving rule is expected to be of more importance (discussed in Section 2.1.4). For this reason, it is assumed that each player submits two bids, one at their total consented capacity and one at half this value.
5. **Real terms** - The auction modelling tool is set to analyse revenues and costs in 2012 in real terms, as this is the reference year used in the CfD auction.

6.3 Results

6.3.1 Affordable capacity results

Figure 6.3 shows the relationship between affordable capacity against strike prices. The intersection between the vertical lines and the curve shows how much capacity will be afforded at different strike prices of interest. It can be seen by comparing the £210m and £200m budget lines that the budget revision has made a marginal difference to the expected outcome of the results. The first vertical line represents the strike price which would be achieved if all 9,250 MW of eligible projects (as depicted in Table 7.1) receive a CfD. This strike price is £36.85/MWh and £36.80/MWh for the £210m and £200m budgets, respectively. This is the coexist price and acts as a bid floor, the minimum price developers bidding in the auction will achieve. The coexist strategy is possible in AR4 as there is no capacity maxima cap and because a monetary budget determines the allocation process (as discussed in Section 2.1.4). As the coexist price is a function of the total eligible capacity expected to bid into the auction, developers must accurately predict the capacities of other competing projects. This price would remain true considering the assumptions based on the eligible projects and their build-out capacities are valid. The second vertical line depicts the total affordable capacity if the same average strike price of £40.63/MWh, achieved in AR3 (2019), occurs again in AR4. However, a repeat of the 2019 CfD strike price is unlikely, as historically, the price has decreased between auction rounds [60, 61, 62, 58]. Under this scenario, 4,950 GW of offshore wind capacity would be procured for the revised budget, compared to 4,600 MW for the previous budget. The final vertical line on Figure 6.3 shows the minimum amount of capacity that the auctioneer will procure. This represents the ASP set before the auction at £46/MWh and is the maximum strike price awarded to offshore wind generators. Under this scenario, a total of 2,915 MW and 2,800 MW will be procured for the revised and old budgets.

Figure 6.3 also demonstrates to developers and the auctioneer the expected effect of increasing the budget by £10m. It shows that the change in capacity procured and strike price is marginal. Therefore, it is unlikely that developers will aim to significantly change their bidding strategy due to the revised budget notice. However, suppose the government's intention by issuing the budget notice is to dramatically increase the amount of offshore wind capacity procured in line with their renewable targets. In that case, a larger increase in a budget revision is required.

Bidding at the coexist price depends on a developer's estimated costs, financial assumptions, risk appetite, outlook on future wholesale electricity prices, and eagerness to be awarded a CfD contract. If winning a CfD contract in AR4 is imperative to the project's viability, then there are several financial levers, such as sell-downs, project financing and hurdle rates that developers can adjust to reduce their CfD bid.

6.3.2 Stochastic results

Figure 6.4 highlights the most likely strike price, which is the subsidy priced given to each successful developer and has been predicted by the stochastic simulations of AR4. The peak in the graph illustrates that the most likely strike price is between £37.50/MWh - £40.50/MWh, as this is the area where the majority of the density lays. The most likely strike price, with a 14% probability of occurring, is £39.26/MWh. The simulated strike price range for AR4 is between £25.30/MWh and £48.24/MWh, with a standard deviation of £3.13/MWh.

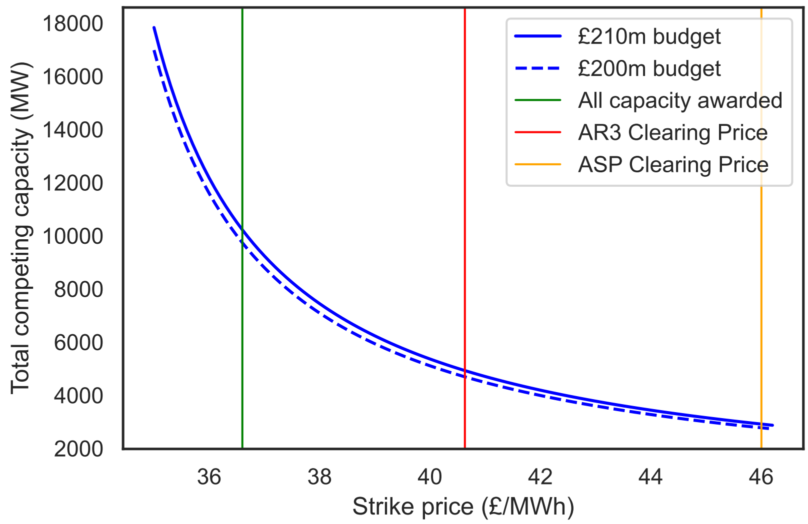


Figure 6.3: Affordable capacity by the auctioneer due to the budget notice. The intersection of vertical lines and curves illustrates affordable capacity at three different strike prices.

A developer could use the predicted strike price probability density graph to determine where the strike price is most likely expected to fall and then bid below this value to increase the probability of being awarded a contract. It will also indicate to developers the competitiveness of their site and whether the hurdle rate should be altered (as described in Section 2.1.5) to increase/decrease profitability to alter their CfD bid price closer to the estimated strike price.

The results indicate that the estimated procured capacity ranges from 1,500 to 8,000 MW (Figure 6.5). The median result from the simulation is that 3,450 MW will be procured. This is considerably lower than the 9,600 MW of eligible capacity. However, there is a 35% possibility that greater than 4,000 MW of capacity will be procured and a 14% probability that greater than 5,000 MW will be procured.

Figure 6.6 illustrates the spread of bid prices submitted by each project. The figures are in ascending order, sorted by the median bid price for each project; this demonstrates the bid merit order of projects based on the assumptions outlined in Section 6.2.1. It can be seen that Hornsea 3 has the lowest expected bid price. Conversely, three Scottish projects have a significantly higher spread of bid prices. There is a spread of close to £10/MWh - £20/MWh in median bid prices between Hornsea and the three Scottish-based projects (Seagreen, Seagreen 1A and Moray West). This can be attributed mainly to the geographical spread of grid connection TNUoS charges (shown in Figure 6.2), which are significantly higher in Scotland than in the rest of Great Britain. Based on analysis carried out on TNUoS charges (shown and discussed in Chapter 4), the differences in charges account for £14.30/MWh of the difference in CfD bid between the Hornsea 3 and Moray West project.

The translation of median bid prices into a probability of being awarded a subsidy can be seen in Figure 6.7. It can be seen that Hornsea 3, Inch Cape and East Anglia 3 are predicted to be successful with a reasonable amount of certainty (>70%). On the other hand, Moray West and Seagreen 1A are predicted to win a low amount of certainty (<30%).

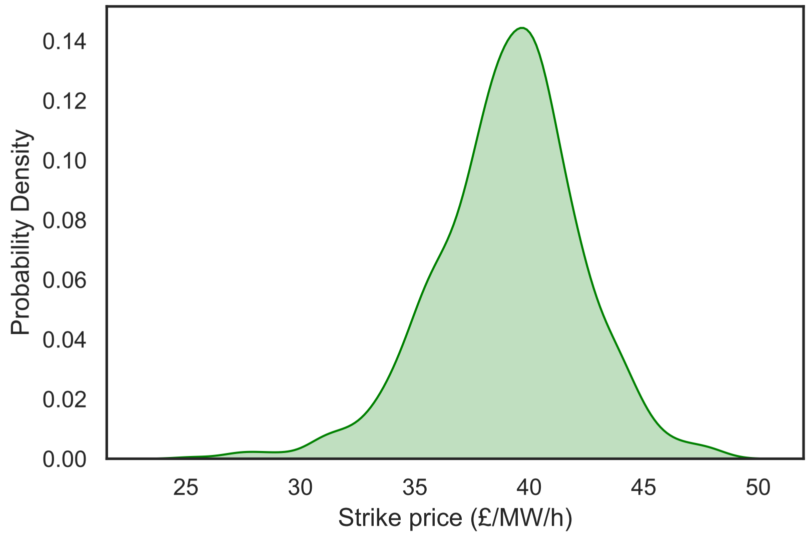


Figure 6.4: Stochastic results indicating the estimated likely strike price for AR4

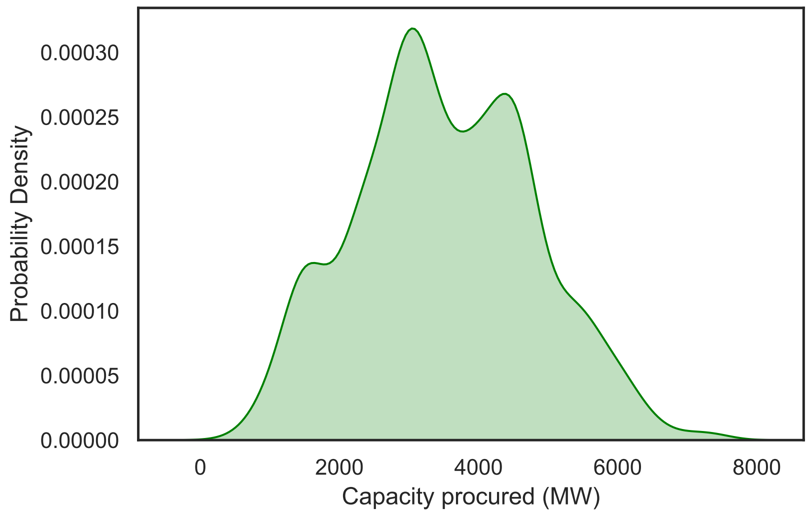


Figure 6.5: Estimated total capacity procured by the auctioneer in AR4

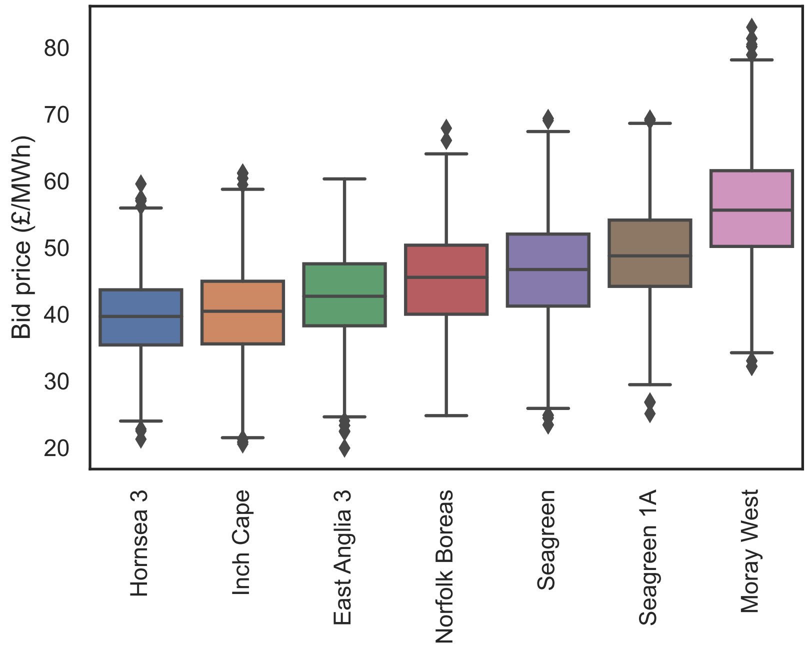


Figure 6.6: Estimated merit order of projects competing in AR4. The bid spread for different projects due to stochastic cost data is also illustrated.

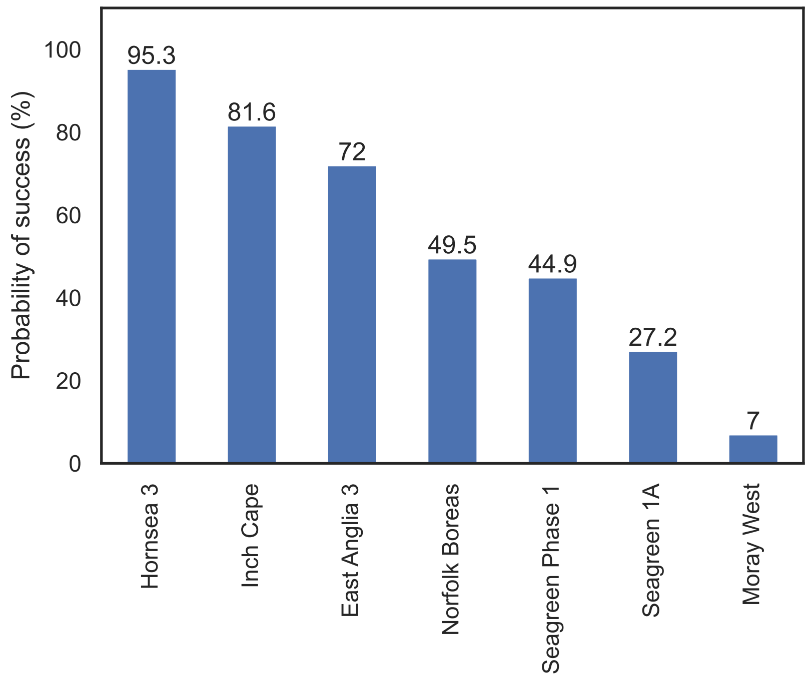


Figure 6.7: Probability of each project successfully being awarded a subsidy

6.3.3 Game-theoretic bidding behaviour results

The game-theoretic bid shading analysis has quantified the incentive for different developers to deviate from cost and shade their bids. Figure 6.8 shows how the optimal bid with respect to the E[X] of auction pay-off and the incentive to engage in bid shading (described in Section 2.1.5) depends on the developer in the Case Study. The incentive is defined as how high developers can increase their expected E[X] of auction pay-off by increasing their bid beyond the minimum calculated CfD bid price. It can be seen from the results presented in Figure 6.8 that the incentive to engage in strategic bidding varies for each player and their project. Results show that Hornsea 3 has the largest incentive to bid shade, as identified by having the largest E[X] peak. This is because the optimum bid price is not only the furthest away from the cost price at a bid price signal deviation of £3.00/MWh but also gives the player the highest E[X] of approximately £2.00/MWh. This is mainly due to its position of having the lowest minimum CfD bid price but also because it has the largest budget impact as it attempts to procure the most capacity from the auctioneer. This result is consistent with auction-theoretic literature, where in uniform price, multi-unit auctions, the incentive to shade depends on the units demanded and the bidders' market power [125]. Inch Cape, which also has a low median bid price (see Figure 6.6), is incentivised to bid shade; this is because it can optimise its bid by increasing its bid price by £2.50/MWh and achieve an E[X] of auction pay-off of £1.70/MWh. Developers such as Moray West and Seagreen 1A, defined as unlikely to win by the model, have minimal incentive to engage in bid shading behaviour. Therefore, projects with a high estimated median bid price and, therefore, unlikely to win cannot increase their E[X] of auction pay-off by increasing their bid price further.

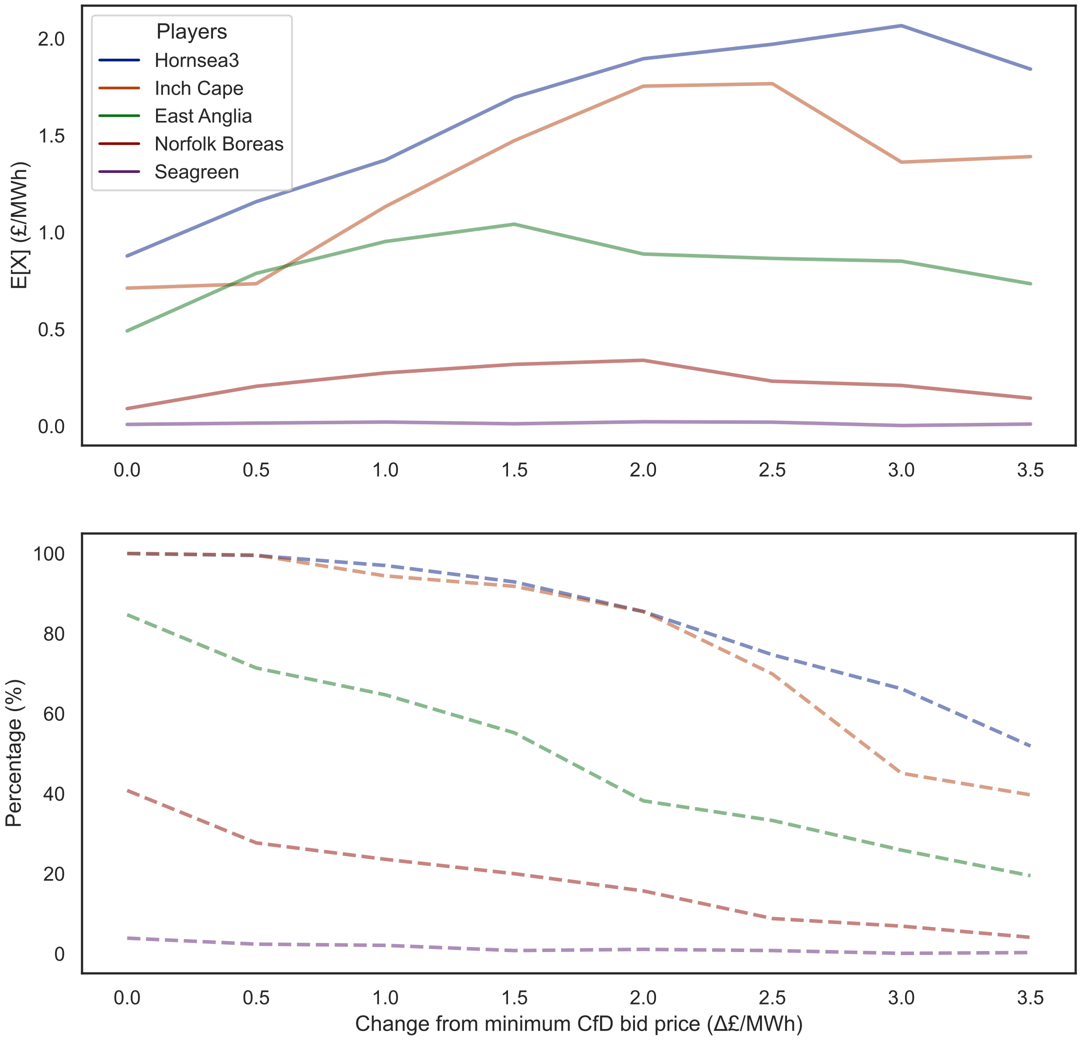


Figure 6.8: Incentive for different players to engage in bid-shading is highlighted by the change in E[X]. The effect of bid-shading on the probability of winning is also shown.

6.3.4 Delivery year rule change results

Figure 6.9 and 6.10 demonstrate the effect changing the purpose of delivery years (this rule change is explained in Section 2.1.4) has on the auction outcome. The new rules for AR4 drastically reduce the volume of capacity procured and the expected strike price. The median strike price estimated if the old delivery year rules are applied is 4,650 MW. This is a 1,300 MW increase from what has been predicted using the new rules predicted by AR4. The median strike price predicted by the model is £43.78/MWh, compared to £39.26/MWh, which has been predicted using the new rules.

The results demonstrate that the delivery year rule change is likely to put further downward pressure on CfD bid prices, which will likely impact the profitability of offshore wind developments. Therefore, this rule change can be considered less preferential for developers as it increases the budget impact of projects and reduces the total amount of capacity procured. However, as one strike price is issued for both delivery years, there will be some reduction in the strategic complexity of the auction, as developers will now not need to consider which delivery year it is preferential to bid into.

The difference between estimated results for both rule formats can be explained due to how each bid's budget impact is assessed. A reference price is used to calculate the budget impact of each bid. The reference price corresponds to the first and second delivery years, which are £38.77/MWh and £32.85/MWh, respectively. Applying AR3 rules, bids are assessed against the delivery year in which they are submitted. This means any bid accepted into the second delivery year will have a larger budget impact due to the first term of the Valuation Formula: *Budget Impact = (Strike price - reference price)*. Once there is a budget breach, this delivery year closes; however, bids can still be accepted into the first delivery year. Bids submitted into the first delivery year are then assessed using the higher £38.77/MWh reference price and are accepted until there is a second breach for that delivery year. As a result, far more capacity is procured as the reference price of £38.77/MWh now sets the affordable capacity.

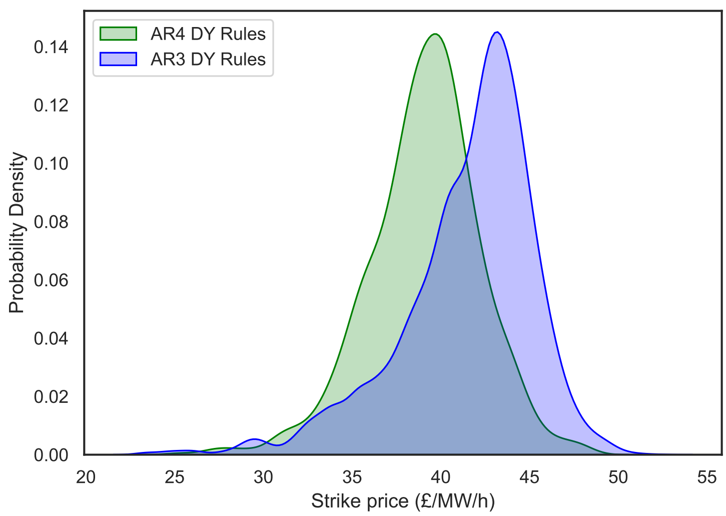


Figure 6.9: Delivery year rule change effect on *first* delivery year

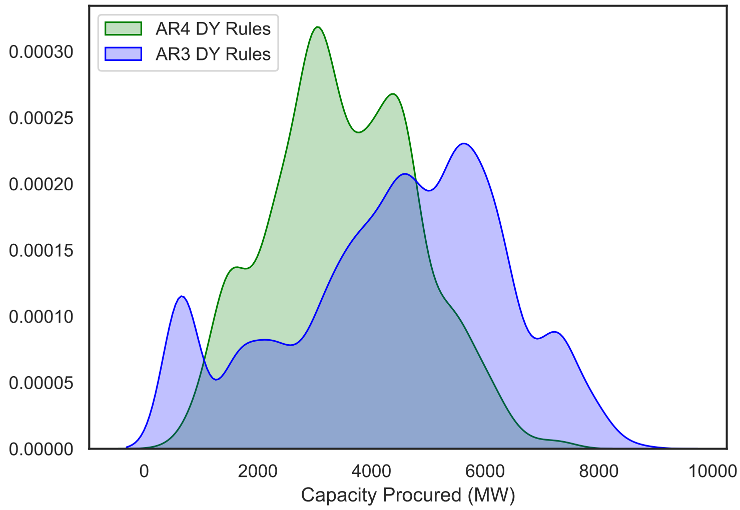


Figure 6.10: Delivery year rule change effect on *second* delivery year

6.3.5 Summary of AR4 Outcome

Table 6.3 gives an overview of the CfD AR4 Offshore Wind auction results, issued by the UK Government after the completion of the CfD auction round. A full list of results for AR4 can be found on the UK government CfD website [58]. The strike price of £37.35/MWh awarded at AR4 is an 8% further reduction in CfD strike price from AR3 (demonstrated in Figure 2.2). A total of 6,994.34 MW of offshore wind capacity was procured. It can be seen that five out of seven of the eligible projects were successful in being awarded a contract at a strike price of £37.35/MWh. East Anglia 3, Inch Cape and Moray West, who were unsuccessful in being awarded a contract in AR3, were successful in this auction. SSE's Seagreen projects were the only non-successful projects and failed to win a subsidy for its 1,120 MW of eligible build-out capacity.

Four out of five successful projects were awarded contracts for over $\geq$75% of their total build out-capacity. Moreover, three out of five projects were awarded a contract for their total build-out capacity. This demonstrates that hedging against volatile electricity prices through securing a CfD contract is still the preferred route to market for developers.

Table 6.3: Overview of AR4 Pot 3 auction results [58]. Successful projects are shown with a strike price.

Project	Owner(s)	Eligible Capacity (MW)	Capacity (MW)	Strike Price (£/MWh)
Inch Cape	Red Rock Power	1080	1080.00	37.35
East Anglia 3	Scottish Power	1373.34	1373.34	37.35
Norfolk Boreas	Vattenfall	1800	1396.00	37.35
Hornsea 3	Ørsted	2852.00	2852.00	37.35
Moray West	Ocean Winds	510	294.00	37.35
Seagreen 1A	SSE	1075	-	-
Seagreen	SSE	500	-	-
Total		**8735**	**6994.34**	

Coexist price

The estimated competing capacity used for the pre-auction analysis was estimated from the consenting documents available on the National Planning Inspectorate Website. The consenting documents stipulate the maximum build-out capacity of the wind farms. Typically, developers will build out to this maximum capacity but may differ slightly due to turbine power ratings and other limitations. As a result, the eligible capacities have been updated in Table 6.3. As developers typically aim to have a CfD cover the entirety of their site, the auction results represent the best estimate for the actual capacities of each of the consented sites. Additionally, Moray West signed a PPA (power purchase agreement) for 350 MW of its capacity at an undisclosed price [194]. This reduces the amount of capacity Moray West will likely bid from 850 MW to 510 MW. Therefore, the actual eligible capacity for each site has been updated post-auction and can be seen from Table 6.3.

Using the same methodology outlined in Section 6.2, the new coexist price is £37.23/MWh. As the coexist price is a function of total eligible capacity, developers can raise this price by reducing the total capacity submitted in their bid. For example, Moray West submitted a bid of 294 MW instead of the total 510 MW that they were eligible to submit. This means Moray West's view on total submitted capacity is reduced by 216 MW to 8,520.34 MW. The new coexist price for this calculated amount of eligible capacity is £37.35/MWh, the same price as the auction results.

The budget impact of all successful bids is £172 million; approximately £38 million of additional subsidy budget was unused. This unused budget represents an extra £0.63/MWh possible increase in strike price, or a further 1,524 MW of total capacity subsidised. The inefficient use of budget by developers is a disadvantage of adopting a risk-averse bidding strategy, such as bidding at the coexist price. This *optimum* price was not achieved as winning developers would have factored in Seagreen and Seagreen 1A bidding into the auction when calculating the coexist price. In reality, Seagreen and Seagreen 1A, the only unsuccessful projects, either did not adopt the coexist strategy or did not submit bids into the CfD auction. As the auction is sealed-bid, the successful developers would not have known the bid price of either Seagreen or Seagreen 1A.

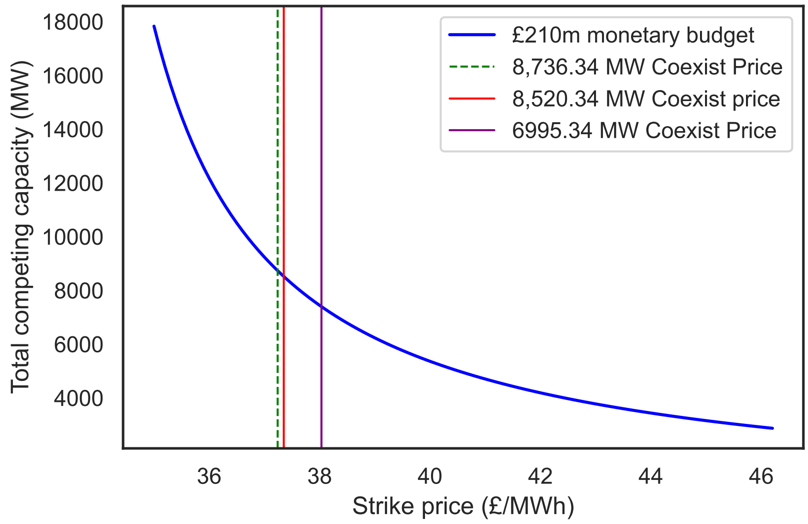


Figure 6.11: Post-auction analysis of affordable capacity results and identification of coexist price.

6.4 Discussion

The award of subsidy largely follows the estimated merit order of projects as shown in Figure 6.6. The four cheapest projects, Hornsea 3, Inch Cape, East Anglia 3 and Norfolk Boreas, as predicted from the stochastic simulations, were all awarded a CfD contract. The three projects Hornsea 3, Inch Cape and East Anglia, which won a contract to cover the entirety of their build-out capacity, are the three projects estimated to win with the highest certainty (as demonstrated in Figure 6.7. This demonstrates that the actual auction results well replicate the pre-auction prediction of the likely winners (demonstrated in Table 6.3). However, Moray West, which is predicted by the simulations to have a very low chance of winning, was awarded a contract. This can be explained in parts due to the project's hybrid financing approach. As the PPA price is unknown, it is difficult to model the CfD bid price required by the project. This introduces more uncertainty and further complexity associated with estimating auction outcomes.

The strike price AR4 result achieved of £37.35/MWh is 5% lower than the most likely estimate from the stochastic simulations. The AR4 result is obtained in approximately 11% of auction simulations. There are several possible explanations for this, owing to the limitations of the model. Firstly, the model relies on inputs from a cost assessment tool, which is used to generate cost data for each site. As the outputs from the auction simulation depend on the cost assessment tool, any inaccuracy in cost estimation for the offshore wind farms would lead to incorrect auction predictions. Secondly, the case study uses the same wholesale electricity price forecast for all developers. In reality, developers may use more or less optimistic forecasts than the one used in the simulation. Therefore, the simulation does not capture the effect of using different wholesale electricity price forecasts. Thirdly, developers bid according to their cost bid price in the stochastic simulations. In CfD auctions, developers can strategically bid lower than their estimated minimum CfD bid price to guarantee themselves an award of a contract. One form of strategic bidding is to vary the required IRR of the development to bid at the coexist price. This work does not consider lowering the bid price below the minimum CfD bid price.

6.5 Conclusion

This chapter has introduced a novel methodology for developers and policymakers to analyse CfD auctions. The analysis is useful for developers to prepare a dominant bidding strategy, which mitigates the winners' curse and so reduces the risk of non-realisation and is valuable for policymakers to test allocation efficiency. A previously validated stochastic cost modelling tool, which utilises the publicly available site and project-specific data, generates stochastic cost estimates for the different competing projects in a Case Study. The Case Study replicates AR4 with information only available to developers before the auction. Cash flow analysis over the lifetime of the projects is used to estimate a distribution of CfD bid prices for each player. The auction is simulated thousands of times using the different estimates of CfD bids, which produce stochastic auction outputs, which categorise the significant uncertainty experienced by developers. Developers can use the outputs to determine a bid strategy in the context of the given probabilities. The chapter has demonstrated how each developer's incentive to deviate from cost differs. The incentive to deviate from cost is achieved through identifying a bid price which maximises the expected value of auction pay-off for each player. Finally, the effect of a rule change on this auction has been investigated. This rule change simplifies the role of delivery years and is analysed by modelling the auction using AR3 rules and then comparing it to the results of the AR4 simulation. This gives developers and policymakers a deeper understanding of what effect this change will have on auction dynamics. Finally, the actual AR4 results are compared to the stochastic pre-auction simulations.

The simulation of this CfD auction has demonstrated that the most likely strike price, as predicted by the analysis, is £39.26/MW, 5% lower than the actual auction results. Post-auction analysis has demonstrated that the strike price was largely determined by a risk-averse coexist strategy, with projects bidding at a price which would ensure the award of a CfD. The analysis successfully identified the most likely winners of the auction. Estimated merit orders are useful to assess their projects' competitiveness and align their bidding strategy accordingly. The results of the game-theoretic simulations have found that players have the incentive to engage in bid shading, where the level of incentive varies between projects. The projects lower down on the merit order (i.e. cheapest projects) have a larger incentive to deviate from cost in an attempt to increase pay-off. Shading one's bid decreases the allocation efficiency, as it increases total subsidy payments, and should be mitigated against policy-makers, such as by introducing stringent pre-qualification criteria which result in significant sunken costs. Finally, an analysis of the delivery year rule changes demonstrates that it makes the auction more competitive for developers and puts further downward pressure on CfD bid prices. Excessive downward pressure on awarded CfD bid prices increases the risk of the non-realisation of projects. Therefore, policymakers face a trade-off between increased risk of non-realisation and minimising subsidy payments (i.e. minimising cost to tax-payer).

Chapter 7

The effect of strategic bidding on bidding behaviour under different pricing rules

This chapter tests the effect of varying levels of strategic bidding by more than one player on bidding behaviour and subsidy utilisation of the auction under the two most common pricing rules: uniform and pay-as-bid. Literature is inconclusive on the effect of the pricing rule in renewable energy auctions. The AR3 and A4 case studies, introduced in previous chapters, are used as the basis for the analysis.

7.1 Introduction

As auctions are central to the government's renewable energy expansion targets, designing efficient auction allocation processes is key. Renewable energy auctions have not yet converged onto one design, attributable partly to governments' aim to tailor different design elements to meet their deployment and development objectives. As such, a steadily growing amount of auction theoretic literature analyses the efficiency and effectiveness of renewable energy auctions through country-level case studies, as highlighted by the literature review.

The differences between effectiveness and efficiency has been previously defined in Section 2.3.1. According to the literature, effectiveness of auctions in procuring enough renewables to meet expansion targets. Efficiency concerns minimising support expenditure (i.e. procuring capacity at a low auction price). To maintain allocation efficiency, auctioneers hope that developers bid truthfully and reveal their costs. However, the literature highlights that strategic bidding to maximise auction pay-off is commonplace in renewable energy auctions and adjacent auctions [123, 42, 25]. In multi-unit auctions, which concerns the auction of several homogeneous items, inefficiencies arise as bidders shade their bids (i.e. increase their bid price above cost to increase auction pay-off) and so may lose to bidders with higher generation costs [195]. Therefore, policymakers should mitigate against strategic bidding by carefully selecting the various design elements of the auction.

An important auction design choice is the effect of the pricing rule on auction efficiency. Currently, two main pricing rules are used in multi-unit auctions: uniform and pay-as-bid pricing. In pay-as-bid schemes, winning bidders are awarded their bid price. In uniform pricing, winning bidders' remuneration is determined by the last accepted or highest bid to be accepted. Literature is inconclusive on the effect of the pricing rule on bid prices in renewable energy auctions. Strands of literature report that uniform pricing incentivises players to reveal their real costs and reduce bid prices. This is contradicted by other strands of research, which highlight that shading your bid is a dominant strategy [125, 123]. Pay-as-bid may incentive strategic bidding, as bidders are incentivised to estimate the level of competition to shade their bid. However, few papers empirically assess the effects of the pricing rule on renewable energy auction outcomes.

This chapter contributes to the literature by conducting an empirical study to observe the effect of strategic bidding behaviour on allocation efficiency (i.e. costs incurred by the taxpayer) under the two most commonly used pricing rules: uniform and pay-as-bid. The study is conducted on two real-life case studies building on the work from the previous three chapters, and analyses the two case studies previously introduced, UK's CfD AR3 (2019) and AR4 (2022) for offshore wind. Basing case studies on real examples provides a realistic depiction of competition and players. The case studies are replicated using an agent-based modelling approach designed to replicate CfD auctions. The number of strategic bidders per simulation is varied using a genetic algorithm (GA) to optimise a bid price for each strategic player. Strategic players aim to shade their bid given knowledge about the auction, the competition and their estimated costs, while the other bidders bid truthfully and reveal their costs. This also allows for the effects of strategic bidding on auction dynamics and outcomes to be studied.

Furthermore, the effect of the different pricing rules on strategic bidding is investigated. An analysis of the individual bids will highlight the varying incentive to bid strategically under the two pricing rules. It will also highlight whether the auction pay-off for individual players is greater under a certain price rule and whether the bidding dynamics between players alter. Therefore, developers can also use this work to understand the difference between the two pricing rules and whether their behaviour should adapt between uniform and pay-as-bid priced auctions.

7.2 Case Study Methodology

The auction simulation tool as described in Chapter 3, is used to carry out the analysis outlined in Section 7.1. As there are two or more strategic players in this analysis, the GA outlined in Section 3.2.6 is used to determine the equilibrium bidding strategy for the strategic players. As defined in Section 2.3.1, the equilibrium bidding strategy is obtained when no single player can obtain a higher expected utility value by deviating from this profile. Players are assumed to be rational profit-maximising decision-makers; therefore, it limits each strategic player to adopt the equilibrium bidding strategy determined by the GA. The same GA set-up as outlined in Section 3.2.6 is used to run the analysis.

7.2.1 Strategic bidding

Strategic players are defined in this chapter as players who attempt to deviate from their marginal cost bid price (calculated in the Bid Preparation stage) and shade their bid to maximise their auction pay-off. In a real auction, the number of strategic players is unknown, so to observe the effect of strategic bidding on auction efficiency, the number of strategic bidders is varied. For both Case Studies (outlined in Section 7.3), the number of strategic bidders varies from zero to all by increasing the number of strategic bidders incrementally by one per simulation.

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 will act. As the model uses deterministic inputs for the players, it has a deterministic estimated bid price. Therefore, there is only one equilibrium bidding strategy for one set-up of strategic players.

Players are assumed to be rational and so will not bid below their cost bid price, as this would result in a negative pay-off and a loss on the overall project. Strategic players who can not increase their auction pay-off due to having a high-cost bid price above the other players do not attempt to shade their bids and bid their cost price.

The number of strategic players varies to analyse the effect of strategic bidding behaviour on allocation efficiency under the two pricing rules. The players are sorted from the lowest estimated bid price to the highest bid price to create a bid stack. Following the order from the bid stack, the number of strategic players varies from zero and is increased incrementally by one until all players bid strategically. This means that the project with the lowest bid price is ultimately the first strategic bidder; similarly, the project with the highest bid price is the last player to be made strategic.

As stated previously, strategic bidders can not bid lower than their CfD bid price. As a result, players who cannot increase their auction pay-off bid at their cost bid price. Therefore, although in the AR3 case study, there are eight players in total, only four of the players have a low enough bid price that they can bid strategically in a profit-maximising manner. This is a key reason why the merit order determines the order in which players are made into strategic bidders. However, to investigate whether the order in which players are made strategic has a material impact on results, the simulations are repeated with every possible order. The results are shown in Section 6.3.

Pay-as-bid versus Uniform pricing

The simulation is repeated separately under pay-as-bid and uniform rules to analyse the difference between the two pricing rules. The auction simulation tool as described in the methodology section, utilises the uniform pricing rule, as determined by the CfD allocation framework [67]. As a result, a pay-as-bid version is created for this analysis. Pay-as-bid auctions to allocation renewable subsidy support are seen in German, French, and Danish auctions, as discussed in Section 2.1.1. The pay-as-bid model assesses bids using the budget impact equation described in Section 2; however, the clearing price is not elevated to the last accepted bid. This means that the budget impact is calculated using the bid price instead of the clearing price. Therefore, Equation 7.1 modifies the Valuation Formula shown in Equation 2.1. In the modified equation, for a player i, the bid price, b_i, is used instead of the strike price, SP, to calculate the budget impact. Furthermore, the capacity for the player C_i is used instead of the cumulative capacity of the player's bid and the capacity of already accepted projects. Therefore, the budget impact for each project is calculated individually, and the total budget impact, BI, is calculated by summing each accepted project's budget impact. As shown in Equation 7.2. If the addition of BI_i to BI results in a budget breach, then the project in consideration is rejected and the auction closes.

$$BI_i = (b_i - RP) \cdot LF \cdot YR1F \cdot C_i \cdot (Days_{yr} \cdot 24) \cdot (1 - TLM) \cdot RQM \cdot CHPQM \tag{7.1}$$

$$BI = \sum BI_i \tag{7.2}$$

As described in Section 2.3.1, the fitness of each solution is determined by the pay-off achieved by all strategic players. The pay-off is the additional profit extracted from the auction, reducing the auction's allocation efficiency (as described in Section 7.1. The auctioneer hopes to minimise the total cumulative pay-off, as it hopes to award subsidy at a price equivalent to each bidder's marginal cost. The pay-off for player i, represented by $\pi_{i,U}$, for a particular bidding strategy for a uniform price auction can be represented by Equation 7.3. Let $\mathbf{B} \equiv (b_i, b_j)$ denote a bidding profile of submitted bids into the auction from two players i, j. Let q_i indicate the number of capacity units from player i, which the auctioneer subsides. C is the total capacity demanded, c_i is the marginal cost of player i producing a unit of electricity.

$$\pi_{i,U} = \begin{cases} [b_j - c_i] \cdot q_i(C; \mathbf{B}), & \text{if } b_i \leq b_j \\ [b_i - c_i] \cdot q_i(C; \mathbf{B}), & \text{otherwise} \end{cases} \tag{7.3}$$

Similarly, the pay-off for player i, represented by $\pi_{i,PAB}$ for a pay-as-bid price auction, can be represented by Equation 7.4. Unlike uniform price auctions, for contract-winning agents, the bid price of one agent does not affect the price received by other agents.

$$\pi_{i,PAB} = [b_i - c_i] \cdot q_i(C; \mathbf{B}) \tag{7.4}$$

7.3 Case Studies used to investigate Strategic Bidding

The analysis is carried out on two past auction case studies. Replicating previous auctions helps depict a realistic set of players and level of competition. The case studies are AR3 and AR4, which occurred in 2019 and 2022, respectively. After profiling each wind farm project, costs and revenue streams can be estimated using project-specific and site-specific data. The same data as outlined in Chapter 4 and 6 is used for this analysis. An overview of the data used in this analysis and the projects considered for both case studies is shown in Table 7.1.

A number of projects (East Anglia 3, Moray West, Inch Cape, and Seagreen) competed in both ARs. While the same project-specific and site-specific data has been used for both ARs, the calculated bid prices and the generated cost inputs which are shown in Table 7.1 are different. As explained in Section 2.2.2, the cost modelling tool used to generate inputs for the auction simulation tool is continuously updated in line with changing technology and cost reduction assumptions. Therefore, different cost estimates are obtained for the same offshore wind project modelled in 2019 compared to 2022. The bid prices have been calculated using the bid preparation stage of the auction simulation tool, as described in Section 3.2.3. The order of projects presented in the table is arranged in ascending order, the merit order of projects and, therefore, the order in which projects are made strategic in the analysis.

In addition to the cost data for each project, other inputs are required to estimate a realistic CfD bid price for each player. The forecast electricity curve utilised by each player is unknown, and as discussed previously, it can significantly affect CfD bid price. Therefore, the same medium curve as shown in Figure 5.1 is used for all projects. Similarly, financial assumptions such as WACC, IRR, TNUoS charges, and gearing ratios required for detailed financial modelling

Table 7.1: High-level overview of some of the publicly available site/project-specific input data used to generate cost estimations.

Project	Capacity	Average depth (m)	Mean wind speed @ hh (m/s)	Distance to port (km)	Foundation type	Export type
			AR3 Projects			
Doggerbank A	1200	23	10.68	200	Monopile	HVDC
Doggerbank B	1200	26.5	10.68	185	Monopile	HVDC
Doggerbank T	1200	26	10.68	260	Monopile	HVDC
Sofia	1400	28	10.68	220	Monopile	HVDC
			AR4 Projects			
Hornsea 3	3000	38	10.47	250	Monopile	HVDC
Norfolk Boreas	1800	33	10.30	92	Monopile	HVDC
Seagreen 1A	500	54	10.55	65	Jacket	HVAC
			Competed in both			
East Anglia 3	1480	39	10.23	80	Monopile	HVDC
Moray West	850	45.4	10.13	70	Monopile	HVAC
Inch Cape	1000	52	9.97	45	Monopile	HVAC
Seagreen	1075	54	10.55	65	Jacket	HVAC

are difficult to assume with any confidence for each player, so they are left generic for all players. The same assumptions for the financial data are used as in the previous Chapters. Therefore, the site-specific and project-specific data, as well as the TNUoS charges, act as the key difference between the bid price for each player.

To run the AR3 and AR4 case studies, the auction set-up parameters, as outlined in Section 3.2.1, need to be outlined. The Allocation Frameworks have determined the parameters used for each respective auction. This includes a ceiling strike price of £53/MWh and £46/MWh for AR3 [59] and AR4 [186], respectively. For the AR4 case study, a monetary budget of £210m was applied, as determined by the budget notice and discussed in Section 6.1. However, AR3 was determined by a maximum offshore wind capacity cap of 5,500 MW, as the monetary budget was not the limiting factor. To compare the budget utilisation percentage for each pricing rule, the capacity cap was converted to an equivalent monetary budget. This was done by ensuring that in the deterministic mode, a similar amount of capacity was procured as when the model was run using a capacity cap. The equivalent monetary budget set was £230m, which ensured similar results from both the capacity cap and monetary budget. In reality, as long as a consistent monetary budget is used for both pricing rules in the AR3 case study, then the precise value used is not important. This is because it is not the total amount of capacity procured under each pricing rule which is analysed but rather the budget utilisation percentage for the different pricing rules, considering the same projects bidding into both.

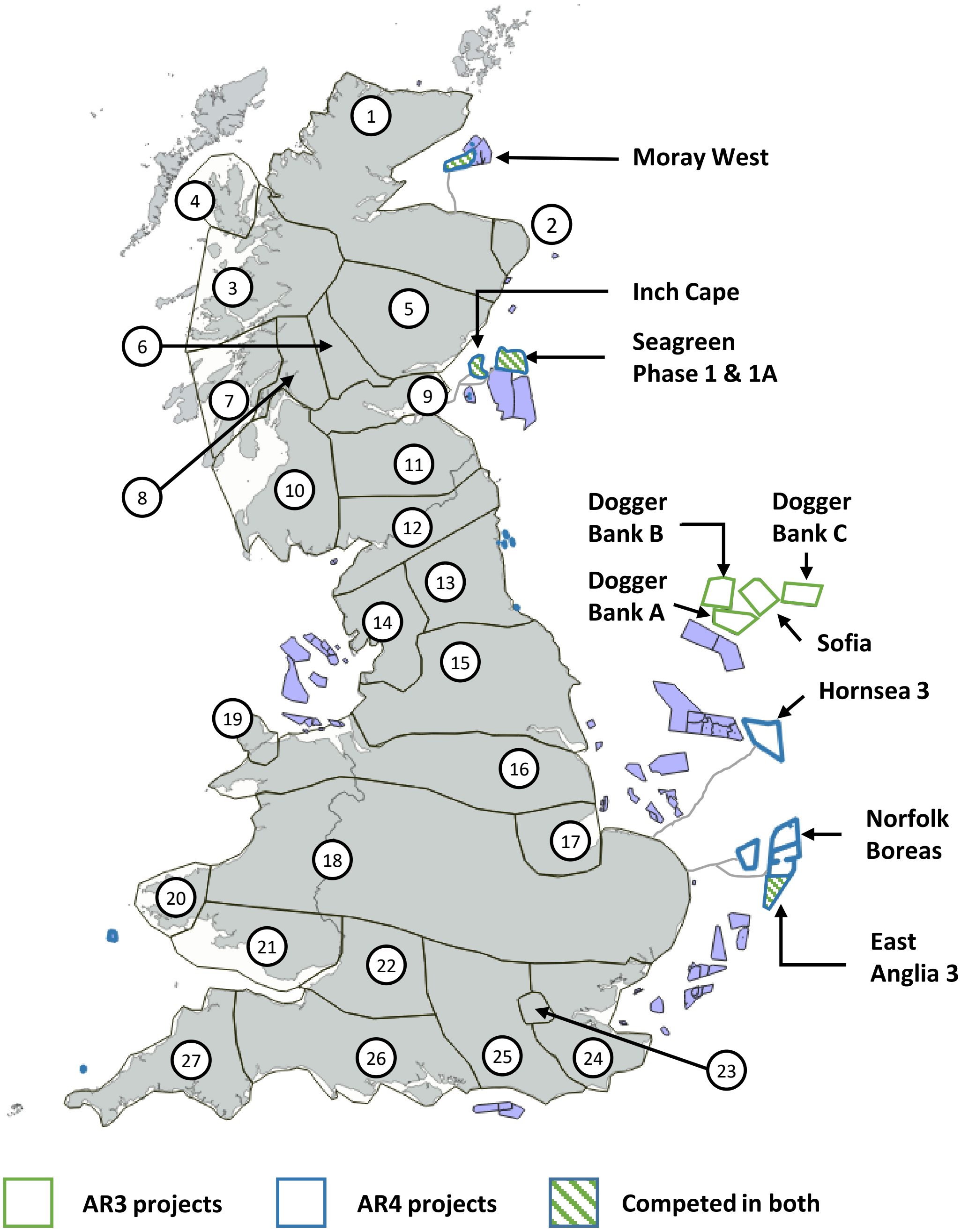


Figure 7.1: Geographical location of Offshore Wind Farms for both AR3 and AR4 case studies. The 28 TNUoS zones, as outlined by National Grid ESO, are displayed on the map.

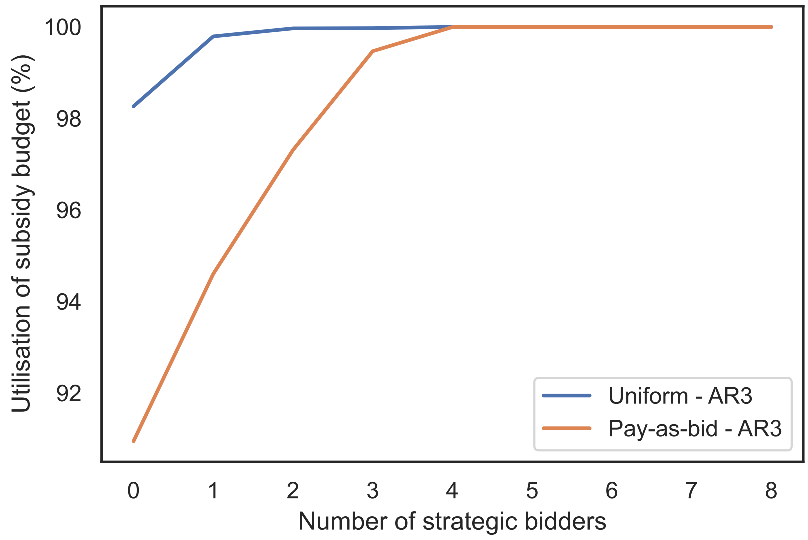


Figure 7.2: Percentage of budget utilisation for AR3

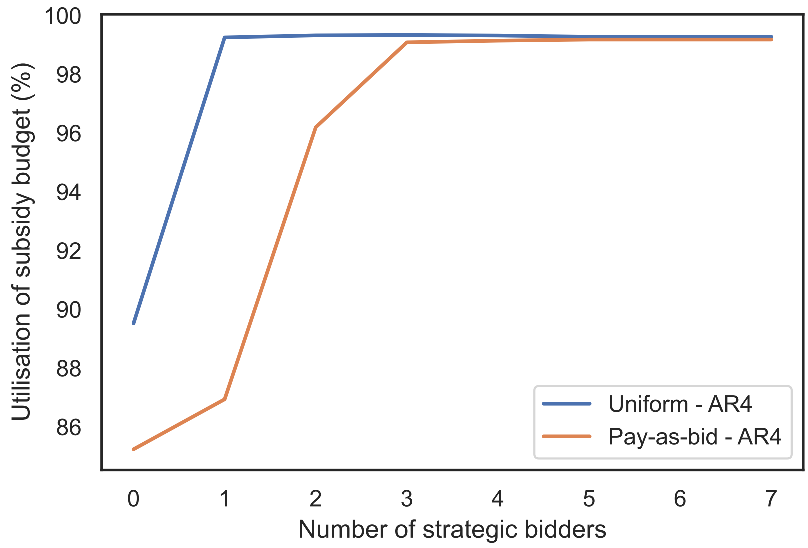


Figure 7.3: Percentage of budget utilisation for AR4

7.4 Results

7.4.1 Allocation efficiency

Figure 7.2 shows the effect the number of strategic bidders has on subsidy payments for both auction formats for AR3. As expected, the results show that total payements decreases as strategic bidders increase. This can be seen as both the subsidy budget utilisation and the total auction pay-off extracted from the auction increase. The results show that with no strategic bidders, the budget utilisation for the AR3 case study is approximately 8% lower for pay-as-bid compared to uniform. The results show that pay-as-bid has a consistently lower subsidy utilisation rate when there are few strategic players. Under the uniform pricing rule, a strategic player who successfully shades their bid and, as a result, is the price setter inadvertently also increases the pay-off for other players. In the AR3 case study, going from zero to one strategic player, the subsidy utilisation rate increases by 1.5% for uniform and 2% for pay-as-bid. For this reason, even one strategic player can dramatically reduce the static efficiency of the auction. However, once a significant proportion of players are strategic, there is no difference between the static efficiency under both pricing rules, as the entirety of the subsidy budget is utilised for both pricing rules. This is because the maximum amount of pay-off is extracted from the auction.

It can be seen by comparing Figures 7.2 and 7.3 that a similar trend is also seen using data from AR4. The utilisation of the subsidy budget is consistently higher under the uniform pricing rule, irrespective of the number of strategic players. Under zero strategic players, the utilisation budget is 86% and 90% for pay-as-bid and uniform, respectively. For the uniform pricing rule, when there is one strategic player, the subsidy budget peaks at 99%, and there is no change with any increase in the number of strategic players. As expected, for the pay-as-bid auction rule, an increase in the number of strategic bidders results in an increase in the utilisation of the subsidy budget. For both pricing rules, the subsidy budget utilisation increases with an added number of strategic players before plateauing, where there are four strategic players. This is the same for both case studies.

The results show that there is an incentive to bid strategically under both pricing rule formats. However, the incentive to bid strategically is higher in pay-as-bid auction formats. The subsidy budget utilisation average between both case studies under zero strategic bidders is 86% and 90% for pay-as-bid versus uniform, respectively.

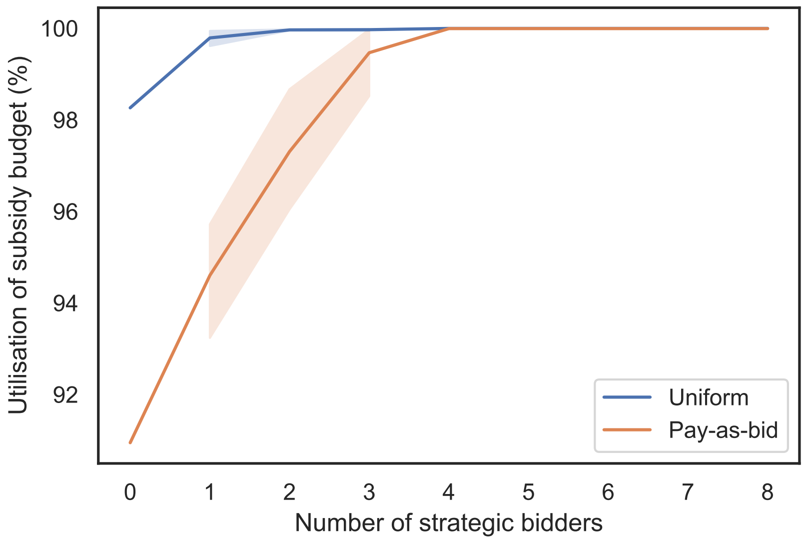


Figure 7.4: Effect of chosen order for strategic bidders based on AR4 case study

As described in Section 7.2.1, the order in which players are made strategic is assessed to see whether it affects any of the trends described above. It can be seen from Figure 7.4, that the chosen order in which players are made strategic has some effect on the observable utilisation of the subsidy budget, but the same overall trends between the pay-as-bid and uniform pricing rules remain. The shaded area in the Figure represents the spread which is present depending on which players are strategic. This means that with fewer strategic bidders, the utilisation of the subsidy budget is lower for pay-as-bid. The order in which players are made strategic bidders has a greater effect on the pay-as-bid auction rule and a negligible effect on the uniform pricing rule. The order has a greater effect on pay-a-bid, become some players can achieve a greater auction pay-off than others, which results in higher utilisation of the subsidy budget. Under the uniform pricing rule, even a player who can only increase their pay-off marginally inadvertently also increases the pay-off for other players, resulting in a higher utilisation of the subsidy budget.

7.4.2 Effect of pricing rule on strategic bidding

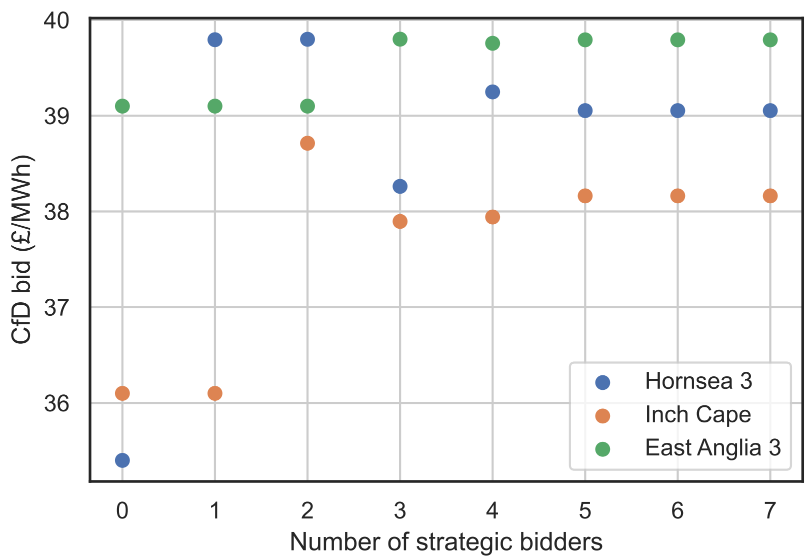


Figure 7.5: Bid price distribution for strategic players for **uniform**

The bid prices for each simulation for the winners from the AR4 case study can be seen in Figures 7.5 and 7.6. It can be seen from the diagrams that Hornsea, Inch Cape, and East Anglia 3 are the winning projects as determined by the GA for all the simulations, regardless of how many strategic bidders there are present in the auction. This is because these projects have the lowest calculated bid price. As the number of strategic bidders increases, the other projects lower down the merit order of projects (Norfolk Boreas, Seagreen, Seagreen 1A, and Moray West) also become strategic bidders. However, a key assumption (as discussed

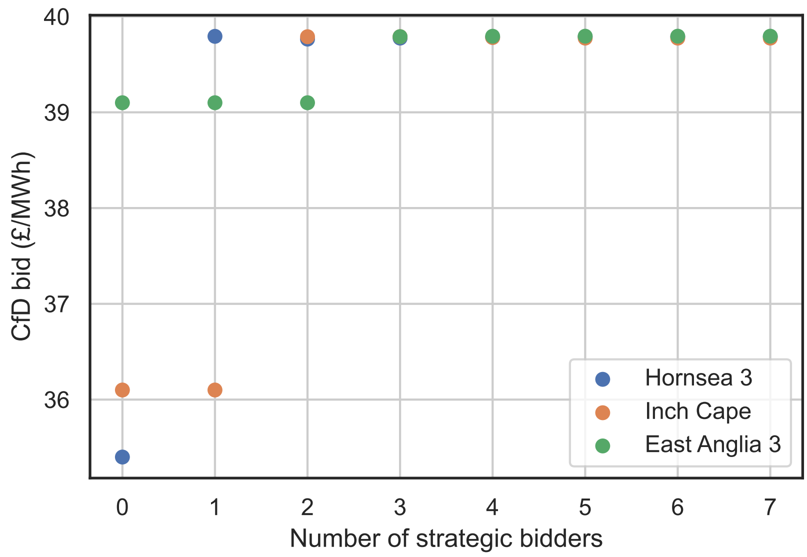


Figure 7.6: Bid price distribution for strategic players for **pay-as-bid**

in Section 7.2.1) is that players are profit-maximising decision makers, so players will not bid below their calculated CfD price. Therefore, these players do not have a material effect on the auction outcome. Although these projects can bid higher than their calculated CfD bid price, their optimal solution is to bid at a cost price.

As the order of players made strategic follow the merit order of projects, Hornsea 3 is the first strategic bidder, Inch Cape is second, and East Anglia 3 is third. This means that when there are no strategic bidders, all players bid at cost. Hornsea 3 is the only profit maximiser when there is one strategic bidder. Inch Cape and Hornsea 3 are strategic bidders when there are two strategic bidders. Finally, all three players are profit-maximising when there are three or more strategic bidders. It can be seen from the results that under the pay-as-bid pricing rule, the three strategic bidders submit the same bid price when they are all profit maximising. This shows that strategic players are incentivised to bid close to one another to maximise their respective auction pay-offs under this pricing rule. Literature has highlighted that in pay-as-bid auction formats, developers are incentivised to deduce rivals' bidding prices and bid close together to maximise auction pay-off [196]. In uniform pricing auctions, the bid spread of the profit-maximising projects is less grouped than pay-as-bid and more spread out. This is because, under the uniform pricing rule, the highest accepted bid determines the remuneration for other players. Therefore, players can bid lower with the expectation that another player's bid will be higher and set the clearing price.

Under both pricing rules, the maximum strike price awarded is 39.79 £/MWh. The total remuneration for both schemes is the same when there are three or more strategic players, as discussed in Section 7.4.1. This can be explained because, under the pay-as-bid pricing rule, all players bid at the maximum of 39.79 £/MWh. Under the uniform pricing scheme, one player bids 39.79 £/MWh, which determines the remuneration for all other players. The maximum bid price seen by all players is the maximum price which players can achieve while still winning a contract. This is determined as the next project, Norfolk Boreas has a bid price of £39.80. Therefore, if the strategic bidders bid higher than this value, they would be unsuccessful.

7.5 Discussion

The results show that in an auction with fewer strategic bidders, the pay-as-bid auction format results in lower utilisation of the subsidy budget compared to the uniform pricing rule. However, there is no difference between the two pricing rules when there are more than four out of eight strategic bidders and three out of seven strategic bidders for the AR3 and AR4 case studies, respectively. It can be seen from the results that developers have a greater incentive to shade their bids in pay-as-bid when compared to uniform, as developers can increase their auction pay-off more significantly. However, players are still incentivised to shade their bids in uniform-priced auctions. Previous chapters have identified methods which can assist developers in identifying an optimum bid shading strategy.

From an auctioneer's standpoint, the number of strategic bidders is unknown in a real-world auction. Therefore, different levels of strategic bidding have been tested. In the context of this work, strategic developers have been assumed to be profit-maximising players, all players can be assumed strategic. Although players are incentivised to shade their bids, according to the literature, a player's ability to be strategic depends on knowledge of their own bid price and their knowledge of the bid price of other players [197]. This is because research has shown that where there is significant uncertainty about the true value of the item being auctioned, players risk experiencing the winners' curse [198]. In CfD auctions, as discussed in previous chapters, significant uncertainty is attached to one's own costs and those of the competitors. Therefore, this hinders the ability of players to bid strategically and shade their bids, so players are less likely to adopt an aggressive strategy. Given the assumption about players' behaviour in CfD auctions, governments may realise lower subsidy budget utilisation by the same pool of projects by adopting a pay-as-bid pricing rule.

On the other hand, as discussed in Section 2.3.1, auction effectiveness is the ability of the auctions to support the deployment of renewable technologies and mitigate against the non-realisation of projects. The results show that the uniform pricing rule will likely lead to higher overall subsidy payments. As a result, governments need to pay more subsidies, and average profits for developers are higher when using uniform pricing. This may result in higher effectiveness as a higher degree of projects become economically viable, and therefore, projects are more likely to be realised. Additionally, the results have shown that players have a greater incentive to bid speculatively in pay-as-bid auctions. Speculative bidding may result in developers bidding too high and failing to secure a CfD contract. This could result in the non-realisation of projects. For these reasons, it can be argued that although uniform-priced auctions may result in a higher subsidy payments, the format is better at mitigating speculative bidding and also can result in higher awarded prices, and so could result in higher effectiveness at supporting the deployment of renewable technologies. Although, effectiveness of an auction is dependent on a number of factors (e.g. protection against inflation, penalities for non-delivery etc) and not just the awarded price. Kreiss et al. [42], does argue that a uniform pricing auction results in lower non-realisation rates as a result of higher prices.

As a result, although policymakers can potentially realise lower prices under pay-as-bid auctions, it encourages speculative bidding. Therefore, this increases the risk of good offshore wind projects (i.e. low generation costs) overbidding and failing to win a contract. Policymakers can reduce the risk of overbidding, by adopting the uniform pricing format, but this results in increased subsidy payments to developers.

7.6 Conclusion

This chapter has analysed the effect of strategic bidding under two different pricing rules, uniform and pay-as-bid, on the subsidy utilisation of a CfD auction. The analysis has been conducted based on AR3 and AR4 offshore wind case studies, this is to ensure a realistic depiction of competition. A GA algorithm has been used to identify an equilibrium bidding strategy which maximises the auction pay-off for a set number of players. As the number of players who do not bid at cost and so bid strategically is unknown in the auction, varying degrees of strategic bidding have been tested. The analysis has also demonstrated how the bidding behaviour of individual strategic players varies between the two pricing rules.

The results show that under limited strategic bidding, the static auction efficiency is higher in pay-as-bid auctions. This is demonstrated as the utilisation of the subsidy budget is lower when compared to uniform-priced auctions, when there are few strategic bidders. However, there is no difference in results when the majority of players bid strategically and shade their bid. It can be seen from the results that one strategic player, under a uniform pricing auction, can significantly increase the subsidy payments from the results.

Analysis of the strategic bidding behaviour under the two pricing rules, shows that players under the pay-as-bid mechanism may lead actors to guess the level of competition and not bid lowest possible price. Players are encouraged to bid closer together. This can lead to speculative bidding and overbidding, resulting in governments failing to procure the targeted amount of capacity. Although players are incentivised to bid strategically in uniform price auctions, the incentive is reduced. However, payments made to developers are greater.

Chapter 8

Discussion

8.1 Findings and Contribution to Knowledge

8.1.1 Academia

A number of recommendations have been drawn from this work to benefit continued research in this field. Firstly, auction simulation models should incorporate uncertainty associated with players' bid prices, as, in reality, players are faced with incomplete information and significant uncertainty. A number of models approach renewable energy auction simulation as a deterministic problem, which is suitable for simplifying complex problems. Still, the auction can be better represented as a stochastic auction with incomplete information. The model presented in this work has added this functionality when compared to other models used to analyse renewable energy auctions, and so better represents the auctions from a developers perspective. This allows for academic researchers to model auction dynamics more accurately, and then therefore make more relevant policy recommendations.

Secondly, to depict a realistic set of competitors and, therefore, simulate a representative set of dynamics, real-life case studies comprised of existing offshore wind projects should be considered where possible. This is important as it increases the industrial relevance of academic papers and allows for more specific conclusions relating to players to be drawn from the work. The majority of current research in this field assumes fictitious projects and a bid price which is proportional to the LCOE of the technology. This work has shown that this is a crude estimation and that bid prices can be estimated through analysis of cash flows over the lifetime of a project, which follows industrial practice. Incorporating financial analysis models into an auction simulation tool has the additional benefit of assessing how changes to the subsidy mechanism can affect the profitability of developments, as demonstrated in Chapter 5.

Finally, the work presented in this thesis has demonstrated that auction simulation can incorporate elements of multiple academic fields, such as probability theory, financial analysis, game theory, Monte Carlo modelling, and ABMs, for the simulation of the intended problem. As explained in Chapter 3, the complexity of the model has increased while introducing a number of these different academic fields onto the model. Therefore, this work has demonstrated how academia can leverage theory from other academic fields to simulate renewable energy auctions.

8.1.2 Industry

Industry should employ more time and resources to develop auction simulation tools which can characterise the uncertainty, identify optimum bidding strategies, and make predictions of auction outcomes. This auction simulation tool has demonstrated a methodology which can be replicated or adapted by industry and has equipped management with methods to arrive at optimum solutions to complex investment decision-making problems. The work has shown how factoring in uncertainty is non-negligible and should be considered. For example, the model has demonstrated methodologies to investigate the incentive for different players to deviate from their minimum CfD bid price and analysed how this may affect auction dynamics. The work has also highlighted the key inputs required to determine a bid price and recommended how uncertainty associated with these inputs can be reduced. Building a detailed auction simulation tool requires specific knowledge and significant resources, but auctions are fundamental to developers' offshore wind growth. Therefore, the methods shown are important as they can help inform the selection of an optimal bid price, which prevents the winners' curse and mitigates the non-realisation of projects.

8.1.3 Policy

This work has demonstrated that policymakers should carefully consider the auction framework and design rules of a specific auction, as they can significantly affect auction dynamics and the profitability of developments. Auction design is not a "one-size-fits-all" solution, but rather the auction design rules should be tailored for the specific auction, competitor landscape, and policy targets. Policymakers can use simulation as a tool to empirically test auction design rules and monitor the effect on auction dynamics and outcomes. For example, this work has investigated the effect of uniform versus pay-as-bid pricing and subsidy contract length on allocation effectiveness. This work has then assessed how these rule changes affect offshore wind projects' profitability and total subsidy payments issued. The policy implication is that the work has demonstrated how policymakers face a trade-off between minimising subsidy payments to developers and increasing the risk of non-realisation. For example, the work has explored how by having a pay-as-bid auction could result in lower prices, but that it may be deterimental to the deployment of projects and therefore government meeting their targets.

Therefore, policymakers should remain weary of designing auctions which promote excessive competition and award subsidy support schemes at unfeasible prices. Furthermore, an application of the model has analysed what effect subsidy contract length has on auction dynamics, support payments, and profitability of developments. All three of these factors should be considered by policy makers while designing an auction, and this work has demonstrated how these important factors can be considered in Chapter 5. The policy outcome of this application is that governments can increase CfD contract length to reduce uncertainty experienced by bidders, but face larger support payments (based on their forecast of future electricity prices).

In addition to the specific application worked on in this thesis, this work demonstrates how policymakers can disseminate evidence collected through simulations to support their policy decisions and align industrial partners to their strategic goals. Simulation is important for analysis auction design changes on outcomes before implementation or stakeholder engagement.

8.2 Industrial Impact

This work has also demonstrated real life implications beyond theoretical research. The work has and has demonstrated a range of commercial benefits to the sponsoring company, EDF Energy R&D. Firstly, the methodologies developed as part of the auction simulation tool have developed the internal competencies regarding auction preparation work. For example, the modelling work and analysis presented have given an indication of how uncertainty associated with costs is propagated into auction outcomes. The auction simulation tool samples from individual cost distributions to estimate a distribution of possible bid prices for a project. Simulating the auction thousands of times, using different points on the bid distribution, allows for predicting probabilistic auction outcomes. Not only can this application be applied to the subsidy or off-take auctions, but it can also be applied to leasing auctions. As a result of this work, stakeholders within the EDF group are investigating incorporating similar techniques to quantify their main sources of uncertainty. Furthermore, this work has provided context to a number of different bid strategies (e.g. bid shading), and has explored methods for how optimum bids can be determined. This can inform EDF's future auction work in other markets.

Secondly, analysing past auctions has provided strategic context to auction results. This has benefited the sponsoring company. Simulating past auctions is useful as it allows for developer return rates to be estimated and contributes to verifying auction assumptions. Analysing past auctions can also be used to characterise past bidding behaviour by specific developers, which can be used to understand the short to medium plans of competitors, and can be used in preparation for future auctions.

Thirdly, the model has been used to predict the outcome of future auctions. A comparison of the estimated and actual auction results showed that the estimated results replicated the auction results well. Therefore, this prediction work, which was presented prior to auction results, increased stakeholders' confidence in the auction modelling capabilities of the EDF Energy R&D UK Centre.

Over the course of this Engineering Doctorate, the tool has been applied to a wide range of auction design questions, which have been presented in a quarterly market scope and issued to stakeholders throughout the EDF group. For example, a market scope issue included comparing the strategic bidding behaviour under uniform and pay-as-bid priced auctions. Not only has this advertised the capabilities and competencies of the R&D Centre, but this has also informed stakeholders operating in various markets of how different auction design rules may affect auction dynamics and thus their strategies, as the reports recommended how their bidding behaviour should alter between different auction designs.

Besides the sponsoring company, other players in the offshore wind sector have benefited from the different publications, presentations, and insights provided over the course of this research.

8.3 Limitations and Further Work

As with all simulation models, the auction simulation tool has a number of limitations. That is, the auction simulation tool can not model the real world perfectly.

A number of limitations have been identified throughout this thesis and are presented and discussed below:

Strategic Bidding and Irrational Bidding

The model uses assumptions used throughout auction theoretic literature to simplify the possible actions of each player. Game theory assumes that rational players would not accept a negative auction pay-off. A negative auction pay-off results if developers achieve a cost below their minimum CfD bid price. However, in reality, developers may accept a negative pay-off for wider strategic reasons (e.g. gaining a share in a new market). This type of strategic bidding is difficult to quantify without a detailed competitive landscape assessment, which has not been the focus of this work. To better approximate reality, the model should be expanded to investigate bidding strategies that consider wider forms of strategic bidding, such as reducing bid price to below the calculated minimum CfD threshold. A set framework which utilises existing corporate finance theory could be used to determine how individual projects expected returns may vary given a developer's wider strategic goals. This may increase the uncertainty associated with the model, but a scenario-based approach can provide different possibilities to help inform decision-making.

Furthermore, bidders may behave irrationally for a number of reasons such as emotional attachment to their projects, sunk cost fallacy where they continue to bid a poor project because they have already invested time and effort or because they possess limited information. This model does not factor in deviations from rational behaviour. Behavioral economics provides a framework for understanding and incorporating such deviations from perfect rationality into economic models, but it often involves more complex and nuanced analyses than traditional game theory, and is beyond the scope of this work. Therefore, a limitation of the model is that irrational behaviour is not accounted for, which affects auction dynamics. Expansion of this work would look to include bahvioural dynamics (which is expanded below).

Computational power

To incorporate more elements of uncertainty associated with the different inputs and increase the assumptions associated with strategic bidding, a greater number of auction runs are required to ensure that Monte Carlo analysis can propagate fully over the uncertainties. Throughout this work, a trade-off has appeared between incorporating more elements of uncertainty while reducing computational times. A high-performance computer cluster or a parallel computing architecture should be utilised to expand the model's assumptions and incorporate wider sets of uncertainty.

For example, a key source of uncertainty in estimating bid prices and depicting a realistic set of competitors is estimating the different wholesale electricity price curves that developers use. As stated previously, the various techniques to forecast future power prices vary significantly; therefore, separate developers may use different curves, which may differ significantly from the forecasts used throughout this curve. Therefore, a wider set of forecasts can be used, and additional computational power can be used to explore various uncertainty management techniques for factoring in varying forecasts.

Additional case studies or technology types

This thesis has focused on applications associated with offshore wind and the UK CfD auction. This has been done, in parts, due to the industrial requirements of the sponsoring company and the resources available. Further work is required to explore the applications of the auction simulation methodology to other offshore wind-related auctions (e.g. leasing or offtake auction in other markets) or to different technologies, such as floating offshore wind. This will help inform policy in different geographies and assist developers in preparing bid strategies in new and different markets. For example, the model could be applied to the Irish subsidy offtake auctions, O-RESS (Offshore-Renewable Electricity Support Scheme). It is more challenging to adapt the methodology to leasing rounds. However, some of the fundamental elements that underpin the model, such as sampling from cost contributions to produce probabilistic outputs, could be replicated in these types of auctions. Applying the methodology to other auctions can inform future iterations of the model to create a more generalisable version which enables a standard and repeatable approach to specific projects and auctions in the future.

Cost modelling assumptions

Fundamental to the outputs from the model and the analysis provided in this thesis is the cost modelling tool, which provides the cost data used to estimate the bid prices for each project. As stated in previous chapters, predicting costs for a project yet to be constructed without proprietary information relating to the project is challenging. Therefore, the cost modelling tool used gives a good indication of costs for early-stage projects without requiring significant resources from engineering or procurement teams for a bottom-up cost assessment of each individual project. However, the outputs generated from the cost model need to be considered, and the errors associated with the estimates should be explored to understand how they may propagate into estimated auction outcomes.

The cost assessment tool has been benchmarked against existing offshore wind project costs; however, providing an extended cost data validated phase is extremely challenging due to the limited cost data available. As the offshore wind market matures and further technological innovations begin to accelerate, the discrepancies between modelling and reality will likely be exacerbated. Therefore, it is vital that this tool is kept up to date to ensure consistency with technological and market trends. The tool should be kept up-to-date through conversations with experts and procurement teams as well as assessment of publicly available information.

Bidding behaviour in competitive auctions

The methodology developed as part of this work aims to model projects using quantitative methods, such as utilising cost data to determine the merit order. However, the model does not have the capability to simulate a competitor's behaviour at the auction. Separate competitors can be categorised into different "auction types" by assessing their likely behaviour. For example, the analysis may determine that new entrants into auctions may be less familiar with the dynamics and so are more likely to adopt a risk-averse bidding approach. Additionally, there may be a cultural difference between different groups of developers; for example, oil and gas majors may bid more aggressively compared to utility companies. This type of behavioural information can be used to alter the risk aversion parameter, which modifies the required return rates required by developers, and the forecast power price curves used. As a result, instead of using a generic investment return rate and wholesale power price curve for each player, each player has their own, which is informed by the work from the competitor behaviour analysis.

Bid preparation module

While the Bid Simulation tool uses a detailed approach to estimate bid prices for players, the cash flow model lacks the granularity of commercially used discounted project-finance cash flow models. For example, the cost differences between equity and debt finance are not considered, although, Companies often finance capital-intensive infrastructure projects through a combination of debt and equity because debt is a cheaper source of capital than equity. These simplifications are necessary as financial parameters are difficult to assume and often commercially sensitive, so they cannot be published. Furthermore, an overly detailed cash flow model is computationally expensive to run. If the model is run in stochastic mode (explained in Section 3.2.5, there is a trade-off between granularity and computational times. Therefore, only key elements are included to ensure that bid price estimations are realistic, and outputs from the model have been benchmarked against an internal detailed cash flow model as demonstrated in Section 3.2.8.

Sensitivity analysis of inputs

The sensitivity analysis conducted in this thesis explored how the input variations affect the auction outcomes. However, further work could include a more detailed sensitivity analysis, looking at how more granular inputs (e.g. wind turbine cost, steel price etc.) affect CfD bid price. This will give developers a greater understanding of where they must reduce their uncertainty.

Chapter 9

Conclusion

9.1 The Approach to the Problem

Offshore Wind is expected to contribute significantly to the decarbonisation of global energy systems due to its rapid cost reduction, which now makes it one of the cheapest forms of clean energy generation. An overview of the current state of the offshore wind industry has been given in Section 1. As discussed, CfD subsidy payments, awarded in competitive auction processes are one of the UK's main policy mechanisms for supporting the deployment of low-carbon renewable energy technologies. This Engineering Doctorate thesis aims to develop novel methodologies for simulating CfD auctions, which developers can use to prepare optimum bidding strategies and policymakers to better design the auction process to meet their policy targets. The methodology has been demonstrated through various applications, which include analysing past auctions, predicting auction results, testing auction design rule changes and conducting sensitivity analysis studies. A series of recommendations are made based on the auction simulation results. While the methodology has been designed specifically for UK CfD auctions, the theory underpinning the methodology readily applies to auctions in other markets. This is because many auctions for renewable subsidy auctions contain many common features such as high levels of competition, bidder uncertainty, and complex auction design rules. This Chapter draws on individual chapters throughout the thesis to provide a set of conclusions and recommendations for academia, industry and policy.

The first phase of research consisted of developing a framework for CfD auction simulation, which could simulate real-life case studies and consider game theoretical and uncertainty quantification. To achieve this, an auction simulation framework was designed that could estimate bid prices for specific projects and then simulate the allocation framework to determine the allocation of subsidies. A critical literature review identified the state-of-the-art in auction simulation and how this work could build on existing methods. The literature review demonstrated that existing methodologies did not consider the cashflows of projects when determining a bid price for players, considered fictitious projects, and could not characterise the uncertainty inherent in auctions. Therefore, to refine assumptions made by existing literature, a bid preparation model was designed, which utilised financial analysis to estimate bid prices for each player based on input cost and revenue data. The bid preparation model uses a forecast of grid and electricity charges to predict cash flow up to 40 years in the future. This meant that the required inputs for each player were carefully considered to ensure that the model was detailed enough to incorporate all key inputs. However, it did not have the granularity that would result in excessive computational times, particularly during repeat Monte Carlo simulations. The key inputs were selected through conversations with stakeholders within the sponsoring company and through a survey of sensitivity analysis literature conducted on offshore wind. To model the intended problem, a modelling approach had to be selected. ABMs were selected as the most suitable method, as it is useful for simulating the actions and interactions of autonomous agents to understand the behaviour of a system and what governs its outcomes. Additionally, it allows for agents with varying intelligence to be modelled. An allocation mechanism was incorporated into the auction simulation model to determine auction outcomes. To ensure the accuracy of the results, the model went through a systematic verification process. This involved the design of fictitious auctions, with increasing complexity, to ensure that there was the required confidence in the model's outputs.

The second phase consisted of demonstrating the methodology through a number of applications which would have implications and use cases for policymakers and developers alike. Analysing past auctions highlighted how the model can be utilised to characterise uncertainty, provide strategic context to auction outcomes, and identify which inputs are most critical in bid preparation. It also ensured an initial base case which proved that the model could be used to provide useful recommendations. Predicting future auctions demonstrated methodologies for developers to prepare future bidding strategies and for policymakers to test the effect of design rule changes on the level of subsidy payments and static auction efficiency. The results from both AR case studies demonstrate that developers can predict the results of CfD auctions with reasonable confidence, and if required, adjust their bidding strategies accordingly. This work shows how uncertainty surrounding future costs and revenue streams can be quantified and visualised in terms of bid prices. Furthermore, a number of applications have demonstrated how auction simulation can be used to inform policy through the design of the auctions. An investigation into CfD contract length identified how changes in the support mechanism would affect the uncertainty experienced by developers, the profitability of developments, and the net support payments made to developers. The work finds that an increase in CfD contract length decreases the uncertainty experienced by bidders, and so reduces the probability of bidders experiencing the winners' curse. The effect that different pricing rules have on strategic bidding and total subsidy payments has also been investigated. The results show that policymakers face a trade-off between reducing net subsidy payments and increasing the risk of the non-realisation of projects.

Bibliography

[1] Parliament of the United Kingdom, "Climate change act," 2008.

[2] P. Żuk and P. Żuk, "National energy security or acceleration of transition? energy policy after the war in ukraine," *Joule*, vol. 6, no. 4, pp. 709–712, 2022.

[3] B. Gilland, "World population, economic growth, and energy demand, 1990-2100: A review of projections," *Population and Development Review*, pp. 507–539, 1995.

[4] EU Commission, "Directive of the european parliament and of the council," 2021.

[5] IRENA, "Renewable energy auctions - status and trends beyond price.," 2019.

[6] IEA, "Renewables," 2022.

[7] P. Moriarty and D. Honnery, "What is the global potential for renewable energy?," *Renewable and Sustainable Energy Reviews*, vol. 16, no. 1, pp. 244–252, 2012.

[8] M. D. Esteban, J. J. Diez, J. S. López, and V. Negro, "Why offshore wind energy?," *Renewable energy*, vol. 36, no. 2, pp. 444–450, 2011.

[9] J. K. Kaldellis and D. Zafirakis, "The wind energy (r) evolution: A short review of a long history," *Renewable energy*, vol. 36, no. 7, pp. 1887–1901, 2011.

[10] P. A. Lynn, *Onshore and offshore wind energy: an introduction*. John Wiley & Sons, 2011.

[11] 4C Offshore, "Global offshore wind farm database," 2022.

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

[13] BVG Associates, "Future renewable energy costs: Offshore wind - 57 technology innovations that will have greater impact on reducing the cost of electricity from european offshore wind farms," 12 2020.

[14] M. Dukan and L. Kitzing, "Support cost savings from de-risking renewable energy projects in europe," *Available at SSRN 3903262*.

[15] T. C. Estate, "Information memorandum - introducing offshore wind leasing round 4," 2019.

[16] F. Kern, P. Kivimaa, and M. Martiskainen, "Policy packaging or policy patching? the development of complex energy efficiency policy mixes," *Energy Research and Social Science*, vol. 23, pp. 11–25, 1 2017.

[17] J. Shao, H. Chen, J. Li, and G. Liu, "An evaluation of the consumer-funded renewable obligation scheme in the uk for wind power generation," *Renewable and Sustainable Energy Reviews*, vol. 153, p. 111788, 2022.

[18] M. Welisch and R. Poudineh, "Auctions for allocation of offshore wind contracts for difference in the uk," *Renewable Energy*, vol. 147, pp. 1266–1274, 3 2020.

[19] M. Đukan and L. Kitzing, "The impact of auctions on financing conditions and cost of capital for wind energy projects," *Energy Policy*, vol. 152, p. 112197, 2021.

[20] P. Del Río and P. Linares, "Back to the future? rethinking auctions for renewable electricity support," *Renewable and Sustainable Energy Reviews*, vol. 35, pp. 42–56, 2014.

[21] M. Keay and D. Robinson, "The limits of auctions: reflections on the role of central purchaser auctions for long-term commitments in electricity systems," 2019.

[22] V. Anatolitis, A. Azanbayev, and A.-K. Fleck, "How to design efficient renewable energy auctions? empirical insights from europe," *Energy Policy*, vol. 166, p. 112982, 2022.

[23] J. Kreiss, K.-M. Ehrhart, and M.-C. Haufe, "Appropriate design of auctions for renewable energy support – prequalifications and penalties," *Energy Policy*, vol. 101, pp. 512–520, 2017.

[24] A. Amazo, A. Dertinger, M. Jakob, and F. Wigand, "Auction design and renewable energy financing," 2021.

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

[26] N. P. Kell, E. Santibanez-Borda, T. Morstyn, I. Lazakis, and A. C. Pillai, "Dealing with uncertainty while developing bid strategy for cfd auctions," in *43rd IAEE International Conference*, 2022.

[27] European Commission, "Communication from the commission — guidelines on state aid for environmental protection and energy.," 02 2014.

[28] A. Bose and S. Sarkar, "India's e-reverse auctions (2017–2018) for allocating renewable energy capacity: An evaluation," *Renewable and Sustainable Energy Reviews*, vol. 112, pp. 762–774, 2019.

[29] Z. Ngadiron and N. Radzi, "Feed-in-tariff and competitive auctions as support mechanism for renewable energy: a review," *ARPN Journal of Engineering and Applied Sciences*, vol. 11, no. 14, pp. 8938–8946, 2016.

[30] P. del Río and C. Kiefer, "Analysing patterns and trends in auctions for renewable electricity," *Energy for Sustainable Development*, vol. 62, pp. 195–213, 2021.

[31] P. Bajari, R. McMillan, and S. Tadelis, "Auctions versus negotiations in procurement: an empirical analysis," *The Journal of Law, Economics, & Organization*, vol. 25, no. 2, pp. 372–399, 2009.

[32] O. Ashenfelter and K. Graddy, "Auctions and the price of art," *Journal of Economic Literature*, vol. 41, no. 3, pp. 763–787, 2003.

[33] M. Gephart, C. Klessmann, and F. Wigand, "Renewable energy auctions–when are they (cost-) effective?," *Energy & Environment*, vol. 28, no. 1-2, pp. 145–165, 2017.

[34] M.-C. Haufe and K.-M. Ehrhart, "Auctions for renewable energy support–suitability, design, and first lessons learned," *Energy Policy*, vol. 121, pp. 217–224, 2018.

[35] B. Bayer, D. Schäuble, and M. Ferrari, "International experiences with tender procedures for renewable energy–a comparison of current developments in brazil, france, italy and south africa," *Renewable and Sustainable Energy Reviews*, vol. 95, pp. 305–327, 2018.

[36] K. Grashof, "Are auctions likely to deter community wind projects? and would this be problematic?," *Energy Policy*, vol. 125, pp. 20–32, 2019.

[37] R. H. Thaler, "Anomalies: The winner's curse," *Journal of economic perspectives*, vol. 2, no. 1, pp. 191–202, 1988.

[38] N. May, K. Neuhoff, and J. C. Richstein, "Affordable electricity supply via contracts for difference for renewable energy," *DIW Weekly Report*, vol. 8, no. 28, pp. 251–259, 2018.

[39] W. Europe, "Sustaining a cost efficient energy transition in europe," 2018.

[40] M. Klobasa, J. Winkler, F. Sensfuß, and M. Ragwitz, "Market integration of renewable electricity generation—the german market premium model," *Energy & Environment*, vol. 24, no. 1-2, pp. 127–146, 2013.

[41] C. Bader, D. Hübler, and M. Boemke, "Germany's latest offshore wind auction–a sign of things to come," *Legal and economic perspectives*, 2021.

[42] 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.

[43] A. Held, M. Ragwitz, M. Gephart, E. De Visser, and C. Klessmann, "Design features of support schemes for renewable electricity," *A report within the European project "Cooperation between EU MS under the Renewable Energy Directive and interaction with support schemes". Ecofys Netherlands, Utrecht*, 2014.

[44] Aures, “Auctions for the support of renewable energy in germany,” 2019.

[45] E. Cassetta, U. Monarca, C. R. Nava, and L. Meleo, “Is the answer blowin’in the wind (auctions)? an assessment of the italian support scheme,” *Energy Policy*, vol. 110, pp. 662–674, 2017.

[46] B. Probst, V. Anatolitis, A. Kontoleon, and L. D. Anadón, “The short-term costs of local content requirements in the indian solar auctions,” *Nature Energy*, vol. 5, no. 11, pp. 842–850, 2020.

[47] D. Matthäus, “Designing effective auctions for renewable energy support,” *Energy Policy*, vol. 142, p. 111462, 2020.

[48] G. Shrimali, C. Konda, and A. A. Farooquee, “Designing renewable energy auctions for india: Managing risks to maximize deployment and cost-effectiveness,” *Renewable Energy*, vol. 97, pp. 656–670, 2016.

[49] J. Winkler, M. Magosch, and M. Ragwitz, “Effectiveness and efficiency of auctions for supporting renewable electricity–what can we learn from recent experiences?,” *Renewable Energy*, vol. 119, pp. 473–489, 2018.

[50] S. Ye and R. L. Tiong, “Npv-at-risk method in infrastructure project investment evaluation,” *Journal of construction engineering and management*, vol. 126, no. 3, pp. 227–233, 2000.

[51] F. Ueckerdt, L. Hirth, G. Luderer, and O. Edenhofer, “System lcoe: What are the costs of variable renewables?,” *Energy*, vol. 63, pp. 61–75, 2013.

[52] Z. Dobrotkova, K. Surana, and P. Audinet, “The price of solar energy: Comparing competitive auctions for utility-scale solar pv in developing countries,” *Energy Policy*, vol. 118, pp. 133–148, 2018.

[53] L. Butler and K. Neuhoff, “Comparison of feed-in tariff, quota and auction mechanisms to support wind power development,” *Renewable Energy*, vol. 33, no. 8, pp. 1854–1867, 2008.

[54] H. Apostoleris, S. Sgouridis, M. Stefancich, and M. Chiesa, “Evaluating the factors that led to low-priced solar electricity projects in the middle east,” *Nature Energy*, vol. 3, 12 2018.

[55] BEIS, “Contracts for difference and capacity market scheme update 2022,” vol. ISBN 978-1-5286-2332-2.

[56] IEA, “Is renewable energy capacity in the european union making windfall profits from high wholesale prices?,” 2022.

[57] I. Schlecht, L. Hirth, and C. Maurer, "Financial wind cfds," tech. rep., Kiel, Hamburg, 2022.

[58] U. Gov, "Contracts for difference allocation round 4 results journal = BEIS,," 02 2022.

[59] 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.

[60] BEIS, "Contracts for difference allocation round 1 results," 2015.

[61] BEIS, "Contracts for difference allocation round 2 results," 2017.

[62] BEIS, "Contracts for difference allocation round 3 results," 2019.

[63] B. Woodman, O. Fitch-Roy, B.-L. Mária, B. Dézsi, L. Szabó, F. V. Bluecher, C. Klessmann, and F. Wigand, "Auctions for the support of renewable energy in the uk," 2019.

[64] R. B. Myerson, "Optimal auction design," 1981.

[65] Wind Europe, "Financing, and investment trends, the european wind industry in 2019," 2016.

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

[67] BEIS, "Contracts for difference scheme for renewable electricity generation," 2019.

[68] BEIS, "Contracts for difference scheme for renewable electricity generation allocation round 4: Allocation framework.," 2021.

[69] N. G. ESO, "Contracts for difference allocation round 4: Pre-application activities guidance," 2022.

[70] 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.

[71] S. Gatti, *Project finance in theory and practice: designing, structuring, and financing private and public projects*. Elsevier, 2023.

[72] R. Brückmann, "What is the development of wacc for wind power in the 28 eu member states-and why?," *Retrieved June 24th*, 2019.

[73] P. Noothout, D. de Jager, L. Tesnière, S. van Rooijen, N. Karypidis, R. Brückmann, F. Jirouš, B. Breitschopf, D. Angelopoulos, H. Doukas, *et al.*, "The impact of risks in renewable energy investments and the role of smart policies," *DiaCore report*, 2016.

[74] L. Tesniere, D. de Jager, P. Noothout, S. Boutsikoudi, R. Brückmann, F. Borek, I. Naydenova, S. Nicola, B. Valach, M. Dukan, *et al.*, "Mapping the cost of capital for wind and solar energy in south eastern european member states," *ECOFYS Netherlands BV, Utrecht available at: https://www. ecofys. com/files/files/ecofys-eclareon-2016-wacc-wind-pv-south-east-europe. pdf*, 2017.

[75] S. P. Pratt and R. J. Grabowski, *Cost of capital*. John Wiley & Sons, 2008.

[76] R. A. Brealey and S. C. Myers, *Capital investment and valuation*. McGraw Hill Professional, 2003.

[77] C. Hürlimann and D. S. Bengoa, "Corporate finance in renewable energy investments-a review about theory and practice," *Global Business and Economics Review*, vol. 19, no. 5, pp. 592–631, 2017.

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

[79] Oxera, "Cfd auctions, bidding strategies, and insights from auction theory," *Agenda*, 2014.

[80] F. James, "Monte carlo theory and practice," *Reports on progress in Physics*, vol. 43, no. 9, p. 1145, 1980.

[81] A. M. González, A. S. Roque, and J. García-González, "Modeling and forecasting electricity prices with input/output hidden markov models," *IEEE Transactions on Power Systems*, vol. 20, no. 1, pp. 13–24, 2005.

[82] D. Ozkan, *Financial analysis and cost optimization of offshore wind energy under uncertainty and in deregulated power markets*. PhD thesis, The George Washington University, 2011.

[83] UK Department of Energy and Climate Change (DECC), "DECC offshore wind programme simple levelised cost of energy model shore wind programme velised cost of energy model.," 2014.

[84] A. Ioannou, A. Angus, and F. Brennan, "Stochastic prediction of offshore wind farm lcoe through an integrated cost model," *Energy Procedia*, vol. 107, pp. 383–389, 2017.

[85] M. Shafiee, F. Brennan, and I. A. Espinosa, "A parametric whole life cost model for offshore wind farms," *The International Journal of Life Cycle Assessment*, vol. 21, no. 7, pp. 961–975, 2016.

[86] A. Ioannou, A. Angus, and F. Brennan, "Stochastic financial appraisal of offshore wind farms," *Renewable Energy*, vol. 145, pp. 1176–1191, 2020.

[87] DNV GL, “Value chain asssessment - the power of seeing the bigger picture,” 2014.

[88] B. Associates, “Future renewable energy costs: offshore wind: 57 technology innovations that will have greater impact on reducing the cost of electricity from european offshore wind farms,” 2017.

[89] E. Borràs Mora, “Cost and uncertainty in the design of offshore wind farms,” *University of Edinburgh*, 2019.

[90] 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.

[91] M. J. Kaiser and B. Snyder, “Modeling the decommissioning cost of offshore wind development on the us outer continental shelf,” *Marine Policy*, vol. 36, no. 1, pp. 153–164, 2012.

[92] A. Saltelli, “Sensitivity analysis: Could better methods be used?,” *Journal of Geophysical Research: Atmospheres*, vol. 104, no. D3, pp. 3789–3793, 1999.

[93] W. Tian, “A review of sensitivity analysis methods in building energy analysis,” *Renewable and sustainable energy reviews*, vol. 20, pp. 411–419, 2013.

[94] R. Martin, I. Lazakis, S. Barbouchi, and L. Johanning, “Sensitivity analysis of offshore wind farm operation and maintenance cost and availability,” *Renewable Energy*, vol. 85, pp. 1226–1236, 2016.

[95] E. Borràs Mora, J. Spelling, and A. H. van der Weijde, “Global sensitivity analysis for offshore wind cost modelling,” *Wind Energy*, vol. 24, no. 9, pp. 974–990, 2021.

[96] L. Castro-Santos and V. Diaz-Casas, “Sensitivity analysis of floating offshore wind farms,” *Energy Conversion and Management*, vol. 101, pp. 271–277, 2015.

[97] A. Ciarreta, B. Martinez, and S. Nasirov, “Forecasting electricity prices using bid data,” *International Journal of Forecasting*, 2022.

[98] O. A. Karabiber and G. Xydis, “Electricity price forecasting in the danish day-ahead market using the tbats, ann and arima methods,” *Energies*, vol. 12, no. 5, 2019.

[99] BEIS, “Department of energy & climate change - dynamic dispatch model,” 2021.

[100] M. Ventosa, Álvaro Baıllo, A. Ramos, and M. Rivier, “Electricity market modeling trends,” *Energy Policy*, vol. 33, no. 7, pp. 897–913, 2005.

[101] C. J. Day, B. F. Hobbs, and J.-S. Pang, “Oligopolistic competition in power networks: a conjectured supply function approach,” *IEEE Transactions on power systems*, vol. 17, no. 3, pp. 597–607, 2002.

[102] E. Guerci, M. A. Rastegar, and S. Cincotti, "Agent-based modeling and simulation of competitive wholesale electricity markets," in *Handbook of power systems II*, pp. 241–286, Springer, 2010.

[103] M. Shahidehpour, H. Yamin, and Z. Li, *Market operations in electric power systems: forecasting, scheduling, and risk management*. John Wiley & Sons, 2003.

[104] H. Yamin, S. Shahidehpour, and Z. Li, "Adaptive short-term electricity price forecasting using artificial neural networks in the restructured power markets," *International journal of electrical power & energy systems*, vol. 26, no. 8, pp. 571–581, 2004.

[105] S. K. Aggarwal, L. M. Saini, and A. Kumar, "Electricity price forecasting in deregulated markets: A review and evaluation," *International Journal of Electrical Power & Energy Systems*, vol. 31, no. 1, pp. 13–22, 2009.

[106] R. Weron, A. Misiorek, *et al.*, "Short-term electricity price forecasting with time series models: A review and evaluation," *HSC Research Reports*, no. HSC/06/01, 2006.

[107] 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.

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

[109] H. Schandl, S. Hatfield-Dodds, T. Wiedmann, A. Geschke, Y. Cai, J. West, D. Newth, T. Baynes, M. Lenzen, and A. Owen, "Decoupling global environmental pressure and economic growth: scenarios for energy use, materials use and carbon emissions," *Journal of cleaner production*, vol. 132, pp. 45–56, 2016.

[110] R. Bajo-Buenestado, "A survey on auctions in electricity markets: The challenges of recent advances in auction theory," 2014.

[111] H. J. Wu C, Mohsenian-Rad H, "Demand side management for wind power integration in microgrid using dynamic potential game theory," *IEEE Globecom Workshops*, 2011.

[112] A. M.-R. C. Wu and J. Huang, "Wind power integrationwith user participation: A game theoretic approach," *Second IEEEInternational Conference*, 2011.

[113] J. Mei, C. Chen, J. Wang, and J. L. Kirtley, "Coalitional game theory based local power exchange algorithm for networked microgrids," *Applied Energy*, vol. 239, pp. 133–141, 4 2019.

[114] J. Lin, M. Pipattanasomporn, and S. Rahman, "Comparative analysis of auction mechanisms and bidding strategies for p2p solar transactive energy markets," *Applied Energy*, vol. 255, 12 2019.

[115] Z. Liu, X. Zhang, and J. Lieu, "Design of the incentive mechanism in electricity auction market based on the signaling game theory," *Energy*, vol. 35, pp. 1813–1819, 2010.

[116] M. Plum, "Characterization and computation of nash-equilibria for auctions with incomplete information," *International Journal of Game Theory*, vol. 20, no. 4, pp. 393–418, 1992.

[117] N. S. Costa Filho, F. O. Saraiva, and V. L. Paucar, "Comparative analysis of game theory application to various types of auctions in electric markets," in *IEEE CACIDI 2016-IEEE Conference on Computer Sciences*, pp. 1–5, IEEE, 2016.

[118] D.-J. Kang, B. H. Kim, and D. Hur, "Supplier bidding strategy based on non-cooperative game theory concepts in single auction power pools," *Electric Power Systems Research*, vol. 77, no. 5, pp. 630–636, 2007.

[119] N.-I. L. Z. Dam, K.H. van, "Agent-based modelling of socio-technical systems, agent-based social systems," *Springer*, vol. 69, 2013.

[120] P. Klemperer, "Auction theory: A guide to the literature," *Journal of economic surveys*, vol. 13, no. 3, pp. 227–286, 1999.

[121] S. S. Oren, "Application of auction theory in electricity markets," *University of California at Berkeley*, 04 2006.

[122] R. Engelbrecht-Wiggans and C. Kahn, "Multi-unit auctions with uniform prices," *Economic Theory*, vol. 12, p. 227–58, 1998.

[123] R. Wilson, "Auctions of shares," *Source: The Quarterly Journal of Economics*, vol. 93, pp. 675–689, 1979.

[124] J. K. Goeree and T. Offerman, "Competitive Bidding in Auctions with Private and Common Values," *The Economic Journal*, vol. 113, pp. 598–613, 07 2003.

[125] L. Ausubel and P. Cramton, "Demand reduction and inefficiency in multi-unit auctions," *Digital Repository at the University of Maryland*, vol. 12, p. 227–58, 2002.

[126] C. D. Wolfram, "Strategic bidding in a multi-unit auction: An empirical analysis of bids to supply electricity," Working Paper 6269, National Bureau of Economic Research, November 1997.

[127] D. Trifunović and B. Ristić, "Multi-unit auctions in the procurement of electricity," *Economic annals*, vol. 58, no. 197, pp. 47–77, 2013.

[128] D. Nautz and E. Wolfstetter, "Bid shading and risk aversion in multi-unit auctions with many bidders," *Economics Letters*, vol. 56, no. 2, pp. 195–200, 1997.

[129] B. Baisa and J. Burkett, “Large multi-unit auctions with a large bidder,” *Journal of Economic Theory*, vol. 174, pp. 1–15, 2018.

[130] B. Lind and C. R. Plott, “The winners curse: Experiments with buyers and with sellers.,” *American Economic Review*, 1991.

[131] J. H. Kagel and D. Levin., “The winner’s curse and public information in common value auctions.,” *American Economic Review*, 1986.

[132] P. Cozzi, “Assessing reverse auctions as a policy tool for renewable energy deployment,” *Center for International Environment & Resource Policy (CIERP), zuletzt geprüft am*, vol. 20, p. 2014, 2012.

[133] D. Mathieu, “Commission staff working document european commission guidance for the design of renewables support schemes,” 2013.

[134] G. Buckman, J. Sibley, and R. Bourne, “The large-scale solar feed-in tariff reverse auction in the australian capital territory, australia,” *Energy Policy*, vol. 72, pp. 14–22, 2014.

[135] G. C.-L. A. Barroso and B. Bezerra, “Lessons learned from the auction-based approach to integrate wind generation in the brazilian electricity market,”

[136] A. Verbruggen and V. Lauber, “Assessing the performance of renewable electricity support instruments,” *Energy Policy*, vol. 45, pp. 635–644, 2012.

[137] J. Winkler, M. Magosch, and M. Ragwitz, “Effectiveness and efficiency of auctions for supporting renewable electricity – what can we learn from recent experiences?,” *Renewable Energy*, vol. 119, pp. 473–489, 2018.

[138] M. G. Pollitt, “Uk renewable energy policy since privatization,” *Harnessing Renewable Energy in Electric Power Systems*, pp. 253–282, 2010.

[139] L. Butler and K. Neuhoff, “Comparison of feed-in tariff, quota and auction mechanisms to support wind power development,” *Renewable energy*, vol. 33, no. 8, pp. 1854–1867, 2008.

[140] T. Grau, “Comparison of feed-in tariffs and tenders to remunerate solar power generation,” 2014.

[141] B. Becker and D. Fischer, “Promoting renewable electricity generation in emerging economies,” *Energy Policy*, vol. 56, pp. 446–455, 2013.

[142] S. M. Ross, *Simulation.* academic press, 2022.

[143] P. Bratley, B. L. Fox, and L. E. Schrage, *A guide to simulation*. Springer Science & Business Media, 2011.

[144] G. Li and J. Shi, “Agent-based modeling for trading wind power with uncertainty in the day-ahead whole-sale electricity markets of single-sided auctions.,” *Applied Energy 99*, 2012.

[145] E. J. Chappin, L. J. de Vries, J. C. Richstein, P. Bhagwat, K. Iychettira, and S. Khan, “Simulating climate and energy policy with agent-based modelling: The energy modelling laboratory (emlab),” *Environmental modelling & software*, vol. 96, pp. 421–431, 2017.

[146] F. Sensfuß, M. Ragwitz, and M. Genoese, “The merit-order effect: A detailed analysis of the price effect of renewable electricity generation on spot market prices in germany,” *Energy policy*, vol. 36, no. 8, pp. 3086–3094, 2008.

[147] D. Kiose and V. Voudouris, “The acewem framework: An integrated agent-based and statistical modelling laboratory for repeated power auctions,” *Expert Systems with Applications*, vol. 42, no. 5, pp. 2731–2748, 2015.

[148] S. Widergren, J. Sun, and L. Tesfatsion, “Market design test environments,” in *2006 IEEE Power Engineering Society General Meeting*, pp. 6–pp, IEEE, 2006.

[149] U. Schweizer and T. von Ungern-Sternberg, “Sealed bid auctions and the search for better information,” *Economica*, vol. 50, no. 197, pp. 79–85, 1983.

[150] D. K. Gode and S. Sunder, “Allocative efficiency of markets with zero-intelligence traders: Market as a partial substitute for individual rationality,” *Journal of Political Economy*, vol. 101, no. 1, pp. 119–137, 1993.

[151] G. Cai and P. R. Wurman, “Monte carlo approximation in incomplete information, sequential auction games,” *Decision Support Systems*, vol. 39, no. 2, pp. 153–168, 2005.

[152] Q. Wu and J. Guo, “Optimal bidding strategies in electricity markets using reinforcement learning,” *Electric Power Components and Systems*, vol. 32, no. 2, pp. 175–192, 2004.

[153] J. Liang, M. Ma, and X. Tan, “Gadqn-ids: A novel self-adaptive ids for vanets based on bayesian game theory and deep reinforcement learning,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 8, pp. 12724–12737, 2021.

[154] R. Poli, “Analysis of the publications on the applications of particle swarm optimisation,” *Journal of Artificial Evolution and Applications*, vol. 2008, 2008.

[155] Y.-H. Song and M. R. Irving, “Optimisation techniques for electrical power systems. ii. heuristic optimisation methods,” *Power Engineering Journal*, vol. 15, no. 3, pp. 151–160, 2001.

[156] C. Darwin, “On the origin of species by means of natural selection, or the preservation of favoured races in the struggle for life,” *London: J. Murray*, vol. 502, 1859.

[157] J. H. Holland, “Genetic algorithms,” *Scientific american*, vol. 267, no. 1, pp. 66–73, 1992.

[158] W. Paszkowicz, “Genetic algorithms, a nature-inspired tool: a survey of applications in materials science and related fields: part ii,” *Materials and Manufacturing Processes*, vol. 28, no. 7, pp. 708–725, 2013.

[159] T. Gentils, L. Wang, and A. Kolios, “Integrated structural optimisation of offshore wind turbine support structures based on finite element analysis and genetic algorithm,” *Applied energy*, vol. 199, pp. 187–204, 2017.

[160] S. Grady, M. Hussaini, and M. M. Abdullah, “Placement of wind turbines using genetic algorithms,” *Renewable energy*, vol. 30, no. 2, pp. 259–270, 2005.

[161] A. Azadeh, S. Ghaderi, B. Pourvalikhan Nokhandan, and M. Sheikhalishahi, “A new genetic algorithm approach for optimizing bidding strategy viewpoint of profit maximization of a generation company,” *Expert Systems with Applications*, vol. 39, no. 1, pp. 1565–1574, 2012.

[162] F. Meng, X.-J. Zeng, Y. Zhang, C. J. Dent, and D. Gong, “An integrated optimization+ learning approach to optimal dynamic pricing for the retailer with multi-type customers in smart grids,” *Information Sciences*, vol. 448, pp. 215–232, 2018.

[163] T. N. Bao, Q.-T. Huynh, X.-T. Nguyen, G. N. Nguyen, and D.-N. Le, “A novel particle swarm optimization approach to support decision-making in the multi-round of an auction by game theory,” *International Journal of Computational Intelligence Systems*, vol. 13, no. 1, pp. 1447–1463, 2020.

[164] A. D. Yucekaya, J. Valenzuela, and G. Dozier, “Strategic bidding in electricity markets using particle swarm optimization,” *Electric Power Systems Research*, vol. 79, no. 2, pp. 335–345, 2009.

[165] J. V. Kumar, S. J. Pasha, and D. V. Kumar, “Strategic bidding in deregulated market using particle swarm optimization,” in *2010 Annual IEEE India Conference (INDICON)*, pp. 1–6, IEEE, 2010.

[166] K. V. Price, “Differential evolution,” in *Handbook of optimization*, pp. 187–214, Springer, 2013.

[167] V. V. S. Angatha, K. Chandram, A. J. Laxmi, *et al.*, “Bidding strategy in deregulated power market using differential evolution algorithm,” *Journal of Power and Energy Engineering*, vol. 3, no. 11, p. 37, 2015.

[168] I. O. Essiet, Y. Sun, and Z. Wang, “Optimized energy consumption model for smart home using improved differential evolution algorithm,” *Energy*, vol. 172, pp. 354–365, 2019.

[169] V. Anatolitis and M. Welisch, “Putting renewable energy auctions into action – an agent-based model of onshore wind power auctions in germany,” *Energy Policy*, vol. 110, pp. 394–402, 2017.

[170] M. Welisch and R. Poudineh, “Auctions for allocation of offshore wind contracts for difference in the uk,” *Renewable Energy*, vol. 147, pp. 1266–1274, 2020.

[171] L. Lundberg, “Auctions for all? reviewing the german wind power auctions in 2017,” *Energy Policy*, vol. 128, pp. 449–458, 2019.

[172] Mesa, “Agent-based modeling in python 3+,” 2016.

[173] PINS, “National infrastructure planning,” 2022.

[174] BEIS, “Electricity generation costs,” 2020.

[175] The Crown Estate, “Modelling 2050: Electricity system analysis,” 2019.

[176] E.On, “Transmission network use of system recovering the cost of running and maintaining the national grid,” 2014.

[177] NationalGridESO, “Final TNUoS tariffs for 2021/22 - final grid electricity system operator,” 2019.

[178] The Crown Estate, “Information memorandum - introducing offshore wind leasing round 4,” 2021.

[179] R. Zhang, A. Shu, S. Han, J. Zhang, D. Wang, and X. Liao, “Neta approach of power transmission pricing and its tryout in northeastern power grid of china,” in *2005 IEEE/PES Transmission & Distribution Conference & Exposition: Asia and Pacific*, pp. 1–6, IEEE, 2005.

[180] Gov.uk, “Rates and allowances for corporation tax,” 2021.

[181] S. Titman and J. Martin, *Valuation: The Art and Science of Corporate Investment Decisions*. Addison-Wesley series in finance, Pearson Addison Wesley, 2008.

[182] S. Ross, “Introduction to probability models,” vol. Twelfth edition of 1972 original ed, 2019.

[183] F.-A. Fortin, F.-M. De Rainville, M.-A. G. Gardner, M. Parizeau, and C. Gagné, "Deap: Evolutionary algorithms made easy," *The Journal of Machine Learning Research*, vol. 13, no. 1, pp. 2171–2175, 2012.

[184] S. H. Fischer, J. A. A. De Oliveira, J. D. Mumford, and L. T. Kell, "Using a genetic algorithm to optimize a data-limited catch rule," *ICES Journal of Marine Science*, vol. 78, pp. 1311–1323, 03 2021.

[185] H. Penman, "Sse renewables launches consultation on seagreen grid connection plans," 2021.

[186] BEIS, "Contracts for difference methodology used to set administrative strike prices for cfd allocation round 3," 2019.

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

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

[189] ONS, "Consumer price inflation."

[190] M. Jones and F. Rothenberg, "The renewable cannibalisation problem: Why full merchant risk will become increasingly challenging," *Market Insight*, 2019.

[191] 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."

[192] R. Zeithammer, "Strategic bid-shading and sequential auctioning with learning from past prices," *Management Science*, vol. 53, pp. 1510–1519, 9 2007.

[193] V. Anatolitis and M. Welisch, "Putting renewable energy auctions into action – an agent-based model of onshore wind power auctions in germany," *Energy Policy*, vol. 110, pp. 394–402, 2017.

[194] reNEWS, "Ocean winds lands off-take deal for moray west," 2022.

[195] J. N. Wooldridge, M., "Intelligent agents: Theory and practice.," *The Knowledge Engineering Review*, 2002.

[196] G. Federico and D. Rahman, "Bidding in an electricity pay-as-bid auction," *Journal of Regulatory Economics*, vol. 24, no. 2, pp. 175–211, 2003.

[197] M. E. Oren and A. C. Williams, "On competitive bidding," *Operations Research*, vol. 23, no. 6, pp. 1072–1079, 1975.

[198] P. R. Milgrom and R. J. Weber, "A theory of auctions and competitive bidding," *Econometrica*, vol. 50, no. 5, pp. 1089–1122, 1982.

Applied Energy 334 (2023) 120645

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Simulating offshore wind contract for difference auctions to prepare bid strategies

Nicholas P. Kell [a,b,*], Adriaan Hendrik van der Weijde [c], Liang Li [d], Ernesto Santibanez-Borda [b], 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] TNO, The Hague, The Netherlands
[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

ARTICLE INFO

Keywords:
Contract for difference
Renewable energy auctions
Game theory
Bid Strategy
Offshore wind
Agent-based modelling

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.

* Corresponding author at: Industrial Doctorate Centre for Offshore Renewable Energy, The University of Edinburgh, Edinburgh, UK.
E-mail address: n.kell@ed.ac.uk (N.P. Kell).

https://doi.org/10.1016/j.apenergy.2023.120645
Received 26 January 2022; Received in revised form 25 November 2022; Accepted 4 January 2023
Available online 17 January 2023

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

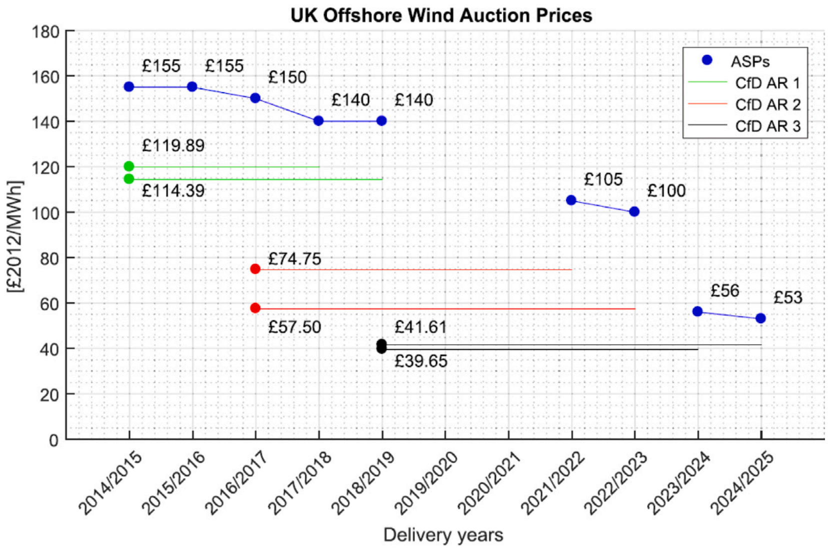


Fig. 1. UK contract for difference allocation round results for offshore wind [13].

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 $[-\bar{s}, \bar{s}]$. 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

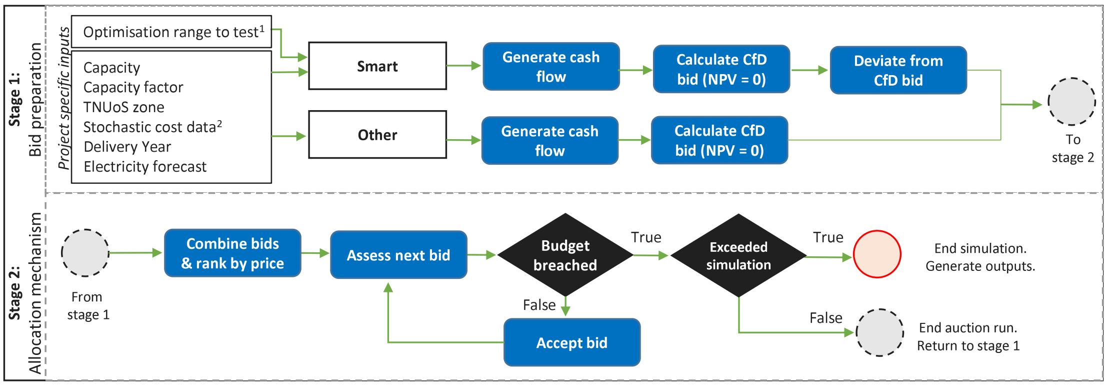


Fig. 2. High-level flow diagram illustrating one auction run process.[1] Highlights the optimum bid price range to test, which is user input and gives the *smart* agent added flexibility to deviate from the calculated CfD bid price. The range provided allows the *smart* player to test the success of 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

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	–

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.

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

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

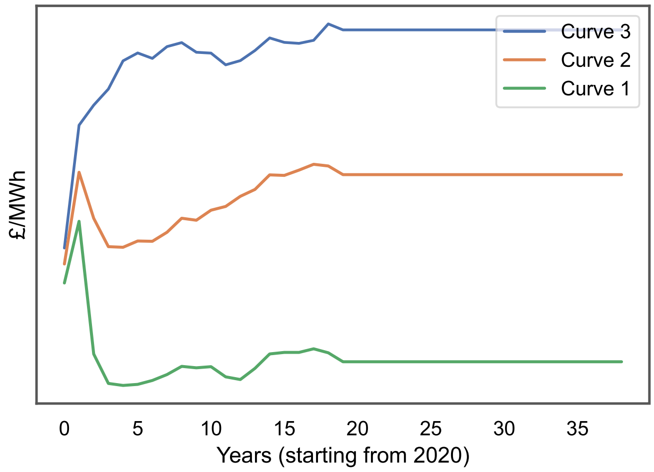


Fig. 3. Illustration of the three wholesale electricity market price curves used in the model. The curves are proprietary, so some information has been redacted.

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

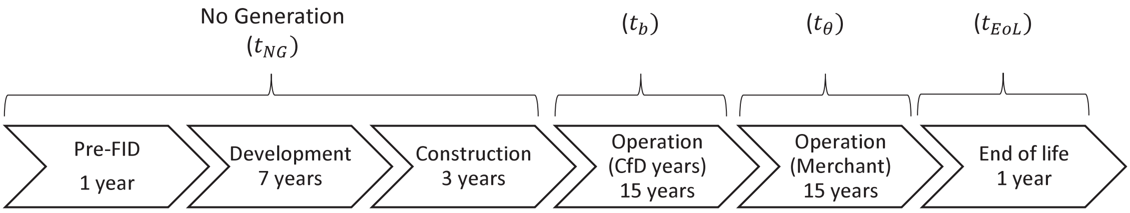


Fig. 4. Life stages and respective years t_x, of each project modelled [39].

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.

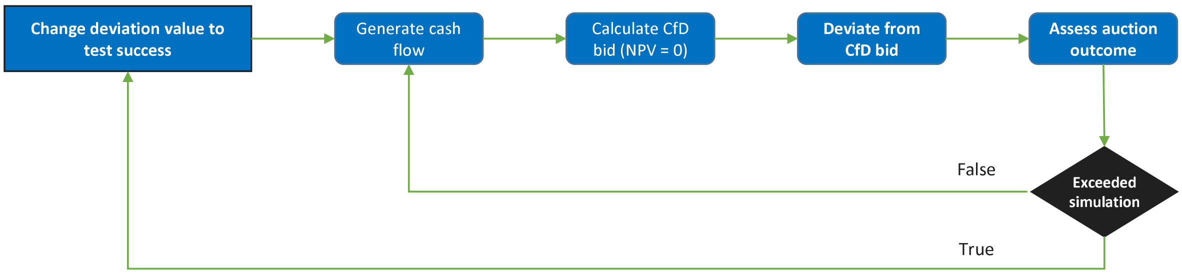


Fig. 5. Simplified flow diagram illustrating simulation for the *smart* player.

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.

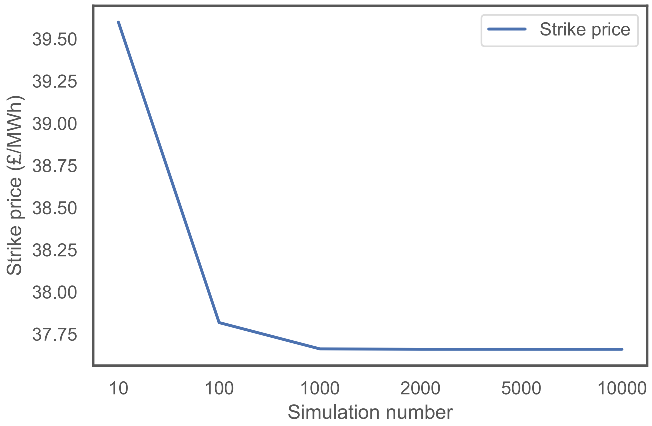


Fig. 6. Convergence of strike price results for the first delivery year, with varying simulation numbers.

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

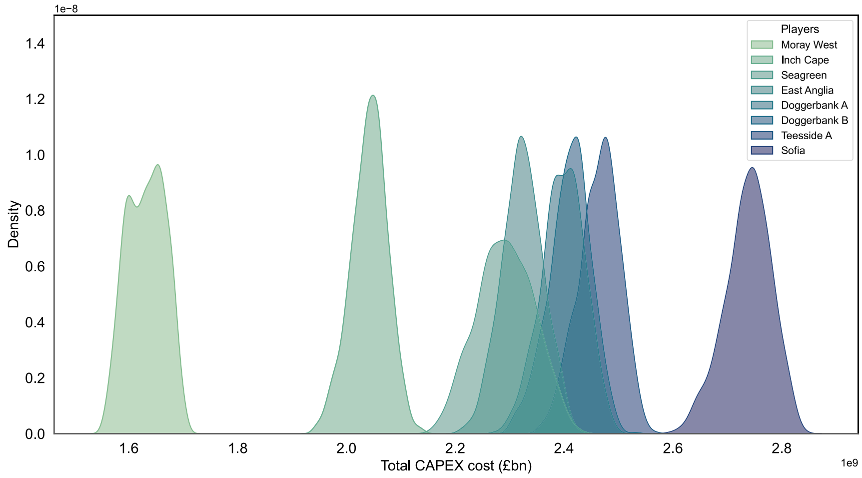
Fig. 8 illustrates the most likely clearing prices predicted by the stochastic simulations. The figures show the most likely clearing price for the 23/24 delivery year, with a 22.5% probability of occurrence is £38/MWh. The most likely clearing price for the 24/25 delivery year with a 22.5% probability 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.

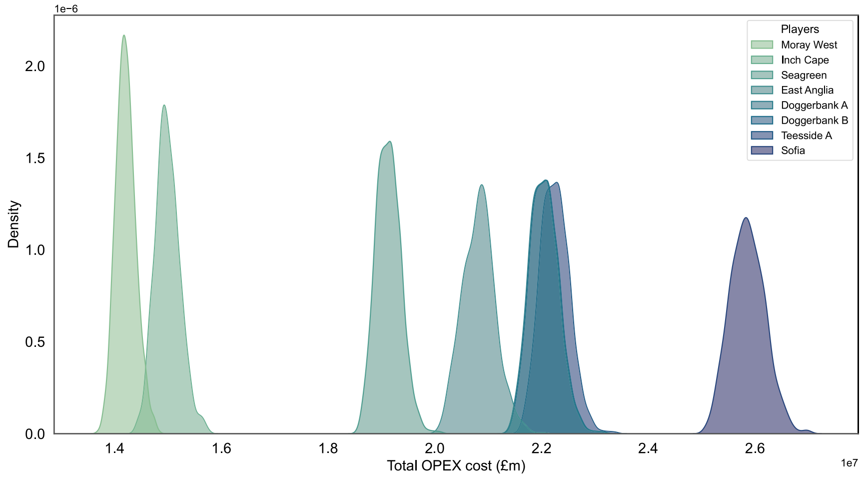
Fig. 9 illustrates the spread of bid prices submitted by each project. The figures are in ascending order, sorted by the median bid price; this demonstrates the merit order of projects. In both cases, the Doggerbank projects have the lowest bid prices. Conversely, the three Scottish projects have a significantly 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.

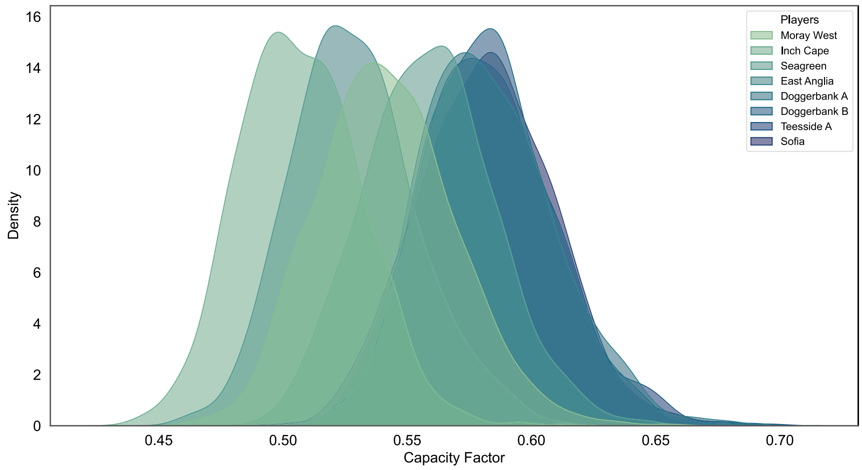
The translation of median bid prices into the probability of being awarded a subsidy is seen in Fig. 10. Sofia, Doggerbank A and Doggerbank B are predicted to be successful with high certainty (>92%). On the other hand, the three Scottish-based projects with the highest bid prices have a very low chance 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.



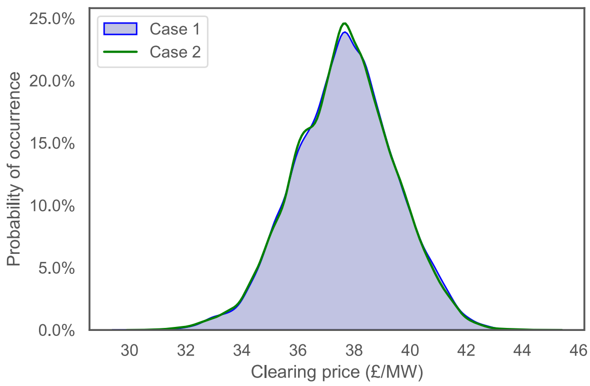
(b) Empirical distribution of generated OPEX costs.



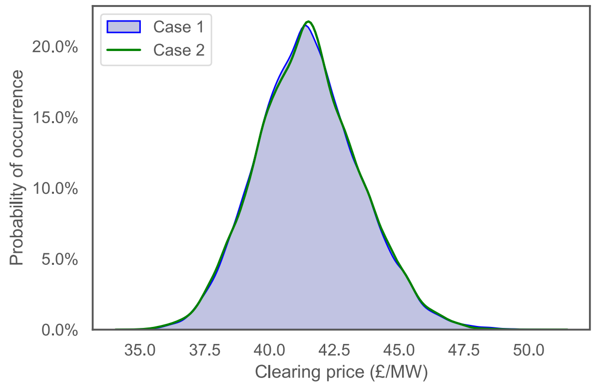
(c) Empirical distribution of generated Capacity Factors.

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.

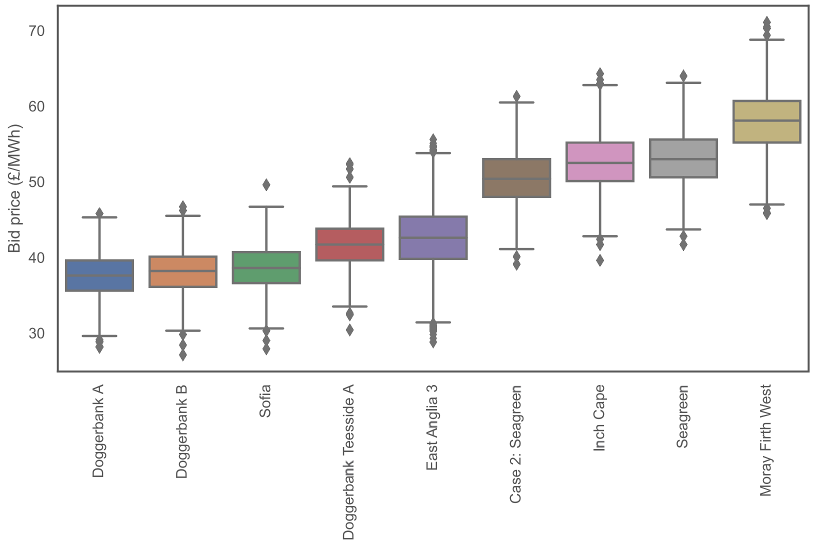


Fig. 9. Box diagram illustrating the merit order of projects which bid into the offshore wind AR3 pot, in ascending order. For Case 2: Seagreen, the project is based on the Seagreen project, but modelled with a 10% increase in forecast electricity market price.

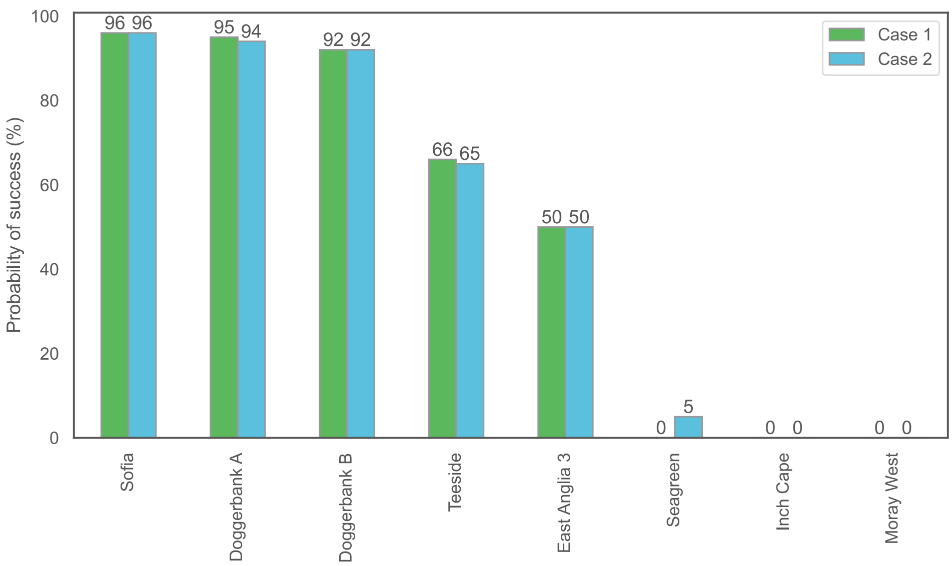
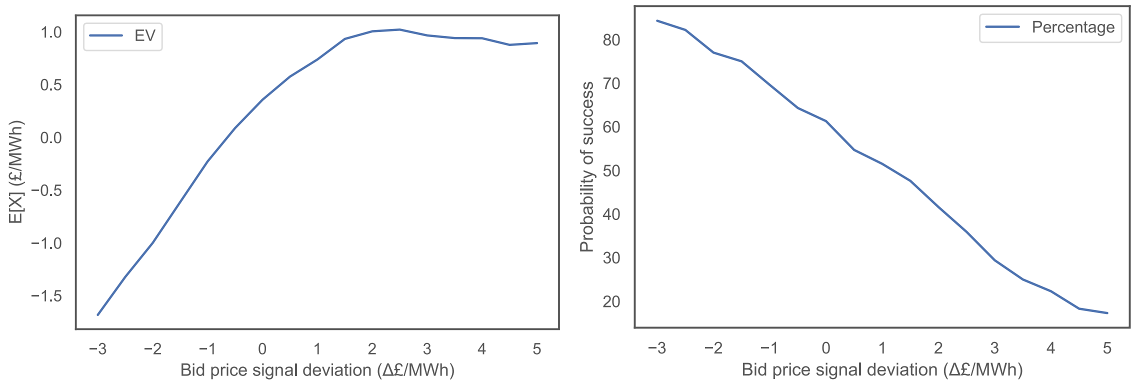


Fig. 10. Percentage win rate of different projects estimated by the stochastic simulations.



(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

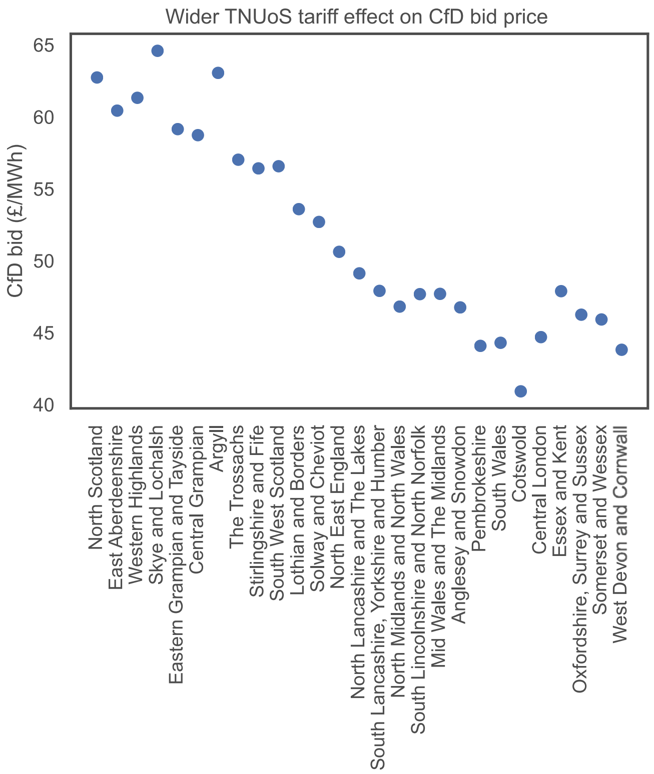


Fig. 12. Effect of geography on CfD bid as a result of transmission charges, which vary significantly by geography.

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.

Acknowledgements

The authors wish to acknowledge funding for this work from the EPSRC, United Kingdom and NERC, United Kingdom for the Industrial CDT for Offshore Renewable Energy (EP/S023933/1).
A.C. Pillai acknowledges support from the Royal Academy of Engineering, United Kingdom under the Research Fellowship scheme (2021–2026) award number: RF\202021\20\175.

References

[1] BEIS. United Kingdom enshrines new target in law to slash emissions by 78% by 2035. 2021.
[2] EUFramework. Long-term low greenhouse gas emission development strategy of the European Union and its Member States. 2020.
[3] Kern F, Kivimaa P, Martiskainen M. Policy packaging or policy patching? The development of complex energy efficiency policy mixes. Energy Res Soc Sci 2017;23:11–25.
[4] BEIS. Contracts for Difference and Capacity Market scheme update 2020. 2020.
[5] Amazo A, Dertinger A, Jakob M, Wigand F. Auction design and Renewable Energy Financing. Aures II 2021;2–15.
[6] Welisch M. The importance of penalties and pre-qualifications: A model-based assessment of the UK renewables auction scheme. Econ Energy Environ Policy 2018;7:15–30.
[7] Bowman EH, Moskowitz GT. Real options analysis and strategic decision making. Organ Sci 2001;12(6):772–7.
[8] Ausubel L, Cramton P. Demand reduction and inefficiency in multi-unit auctions. Digit Repos Univ Maryl 2002;12:227–58.
[9] NERA. Gale force competition auctions and bidding strategy for offshore wind. 2018.
[10] Anatolitis V, Welisch M. Putting renewable energy auctions into action – An agent-based model of onshore wind power auctions in Germany. Energy Policy 2017;110:394–402.
[11] Woodman B, Fitch-Roy O, Mária B-L, Dézsi B, Szabó L, Bluecher FV, Klessmann C, Wigand F. Auctions for the support of renewable energy in the UK. Aures I 2019;2–20.
[12] BEIS. Contracts for difference and capacity market scheme update. 2022.
[13] Mora EB, Spelling J, van der Weijde AH. Global sensitivity analysis for offshore wind cost modelling. Wind Energy 2021;24:974–90.
[14] DECC. Contract for difference: Final allocation framework for the october 2014 allocation round. 2014.
[15] BEIS. Contracts for difference allocation round 1 results. 2015.
[16] BEIS. Contracts for difference allocation round 2 results. 2017.
[17] BEIS. Contracts for difference allocation round 3 results. 2019.
[18] BEIS. Contracts for Difference scheme for renewable electricity generation. 2019.
[19] BEIS. Contracts for Difference Scheme for renewable electricity generation Allocation Round 4. 2021.
[20] BEIS. Contracts for difference - methodology used to set administrative strike prices. 2021.
[21] Myerson RB. Optimal auction design. Math Oper Res 1981;6(1):58–73.
[22] Kreiss J, Ehrhart KM, Haufe MC. Appropriate design of auctions for renewable energy support – Prequalifications and penalties. Energy Policy 2017;101:512–20.
[23] Kagel JH, Levin D. The winner's curse and public information in common value auctions. Am Econ Rev 1986;894–920.
[24] Bajo-Buenestado R. A survey on auctions in electricity markets: The challenges of recent advances in auction theory. USAEE working paper, 2014.
[25] Wu C HJ. Demand side management for wind power integration in microgrid using dynamic potential game theory. In: IEEE globecom workshops. 2011.
[26] Wu AM-RC, Huang J. Wind power integration with user participation: A game theoretic approach. In: IEEE international conference. 2011.
[27] Mei J, Chen C, Wang J, Kirtley JL. Coalitional game theory based local power exchange algorithm for networked microgrids. Appl Energy 2019;239:133–41.
[28] Lin J, Pipattanasomporn M, Rahman S. Comparative analysis of auction mechanisms and bidding strategies for P2P solar transactive energy markets. Appl Energy 2019;255.
[29] Liu Z, Zhang X, Lieu J. Design of the incentive mechanism in electricity auction market based on the signaling game theory. Energy 2010;35:1813–9.
[30] Wilson R. Auctions of shares. Q J Econ 1979;93:675–89.
[31] Welisch M, Poudineh R. Auctions for allocation of offshore wind Contracts for Difference in the UK. Renew Energy 2020;147:1266–74.
[32] Welisch M, Kreiss J. Uncovering bidder behaviour in the German PV auction pilot Insights from agent-based modellings. IAEE 2019.
[33] MESA. Agent-based modeling in Python 3+. 2016.
[34] BEIS. Contract length analysis for Feed-in Tariff. 2013.
[35] The Crown Estate. Modelling 2050: electricity system analysis. 2019.
[36] E On. Transmission Network Use of System Recovering the cost of running and maintaining the National Grid. 2014.
[37] NationalgridESO. Final TNUoS Tariffs for 2021/22 - Final Grid Electricity System Operator.
[38] ONS. Inflation and price indices. 2021.
[39] The Crown Estate. Information memorandum - introducing offshore wind leasing round 4. 2019.
[40] Govuk. Rates and allowances for Corporation Tax. 2021.
[41] Hürlimann C, Bengoa DS. Corporate finance in renewable energy investments-a review about theory and practice. Glob Bus Econ Rev 2017;19(5):592–631.
[42] Titman S, Martin J. Valuation: The art and science of corporate investment decisions. Addison-Wesley series in finance, Pearson Addison Wesley; 2008.
[43] Penman H. SSE renewables launches consultation on Seagreen grid connection plans. 2021.
[44] Ross SM. Introduction to probability models. Academic Press; 2014.
[45] BEIS. Electricity generation costs. 2020.

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-

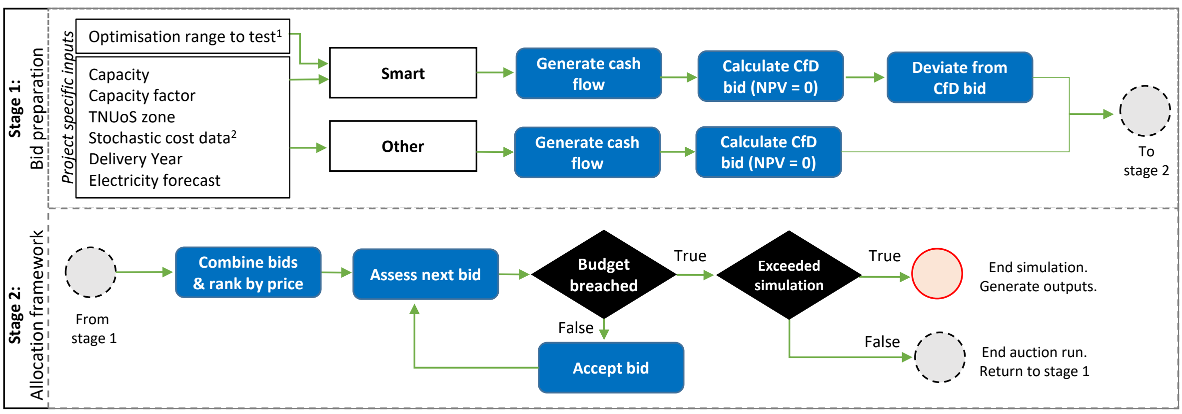


Figure 1: High-level flow diagram illustrating simulation process.
[1] This is the optimum bid price range to test.
[2] Stochastic cost data includes the DEVEX, CAPEX, OPEX and DECEX.

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

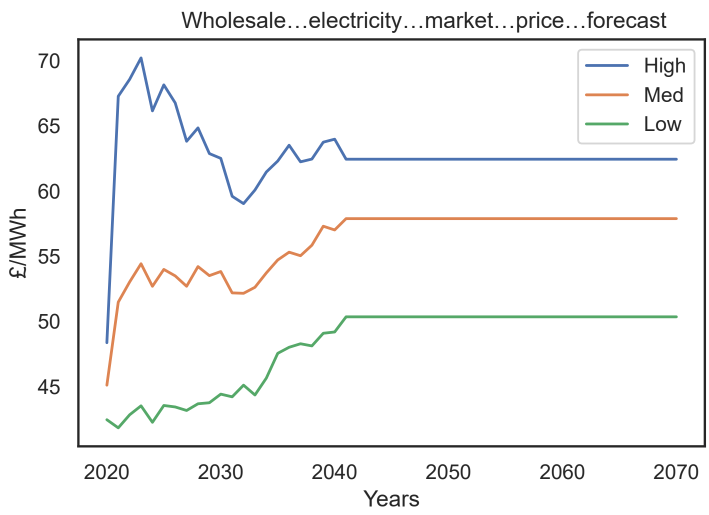


Figure 2: Illustration of the three wholesale electricity price curves used in the model. BEIS forecast data is up until the year 2040, with data beyond predicted using an inflation multiplier

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

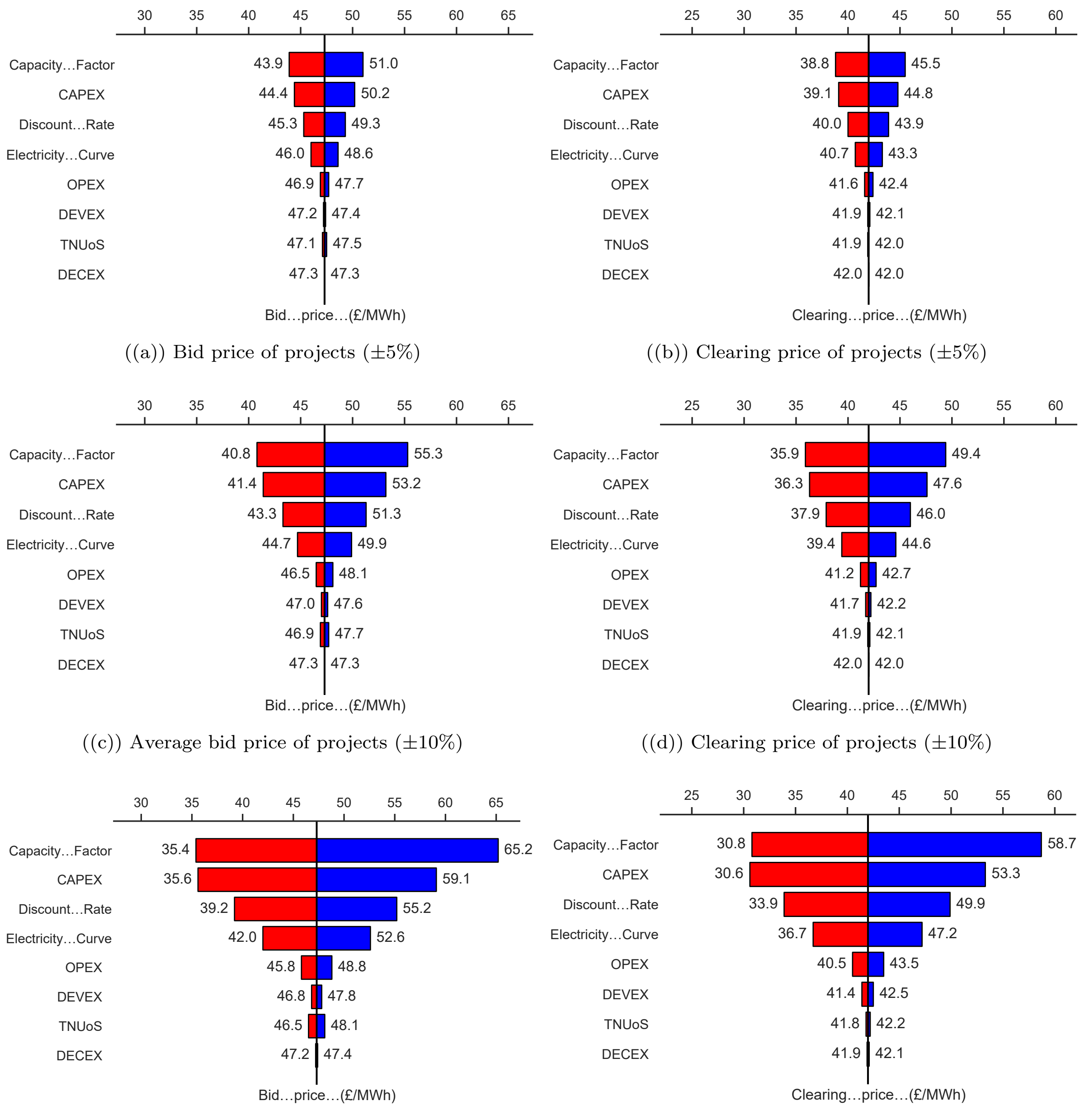
The results in this subsection show which inputs have the most impact, and thus where resources should be allocated to reduce uncertainty. Figure 3 demonstrates how the main outputs of the model change with varying inputs.

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%)

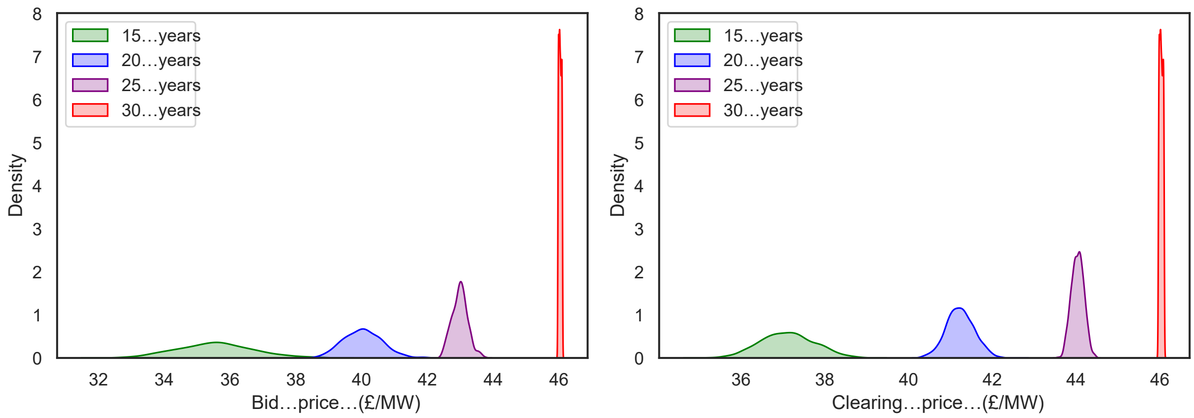
((c)) Average bid price of projects (±10%)

((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.

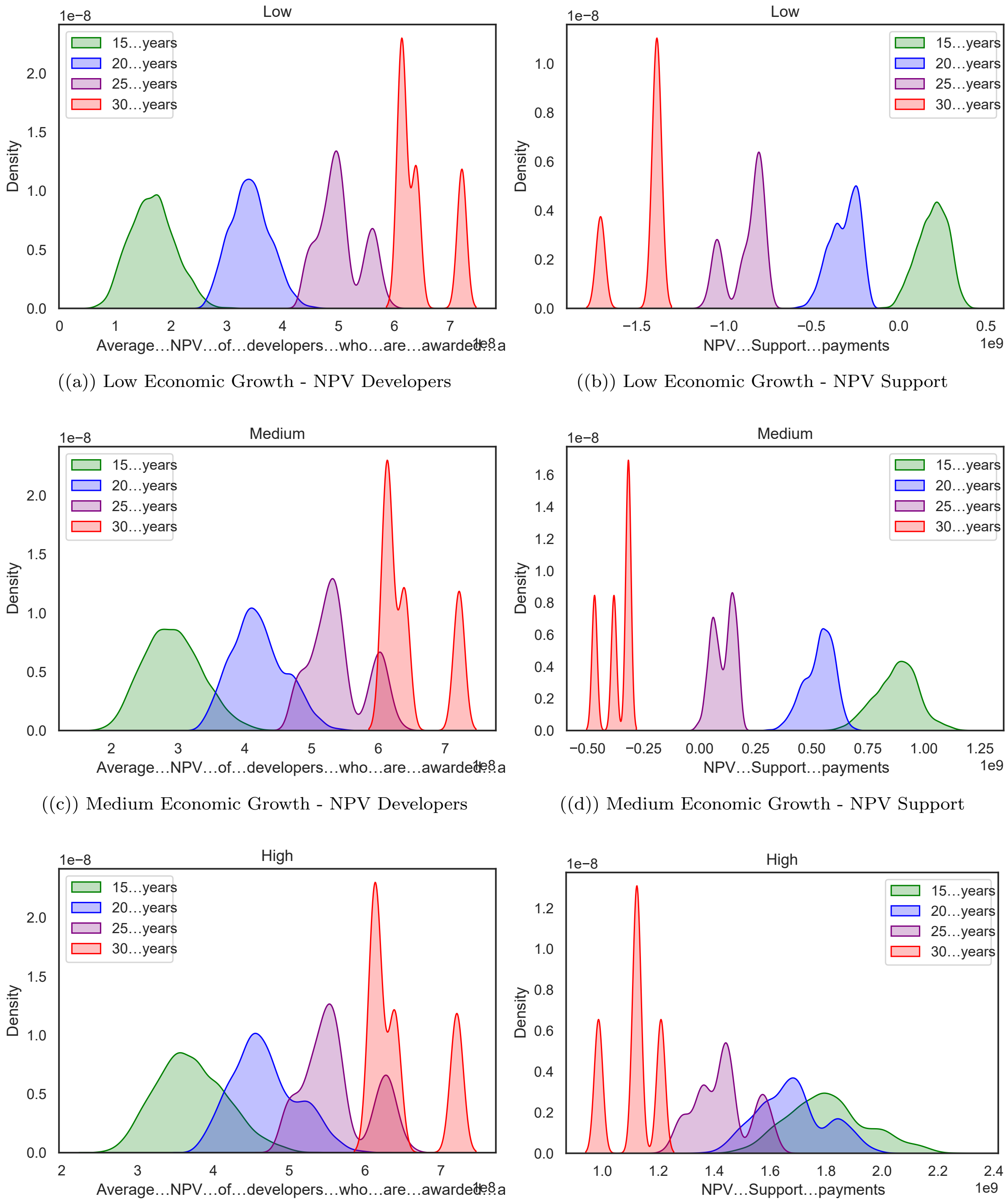
Figure 5 demonstrates the effect of an increased CfD contract length on net payments to developers and the NPV of wind farm projects. From the results, it can be seen that the general trend is that for an increase in contract length, there is an increase in expected NPV for developers and an increase 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.

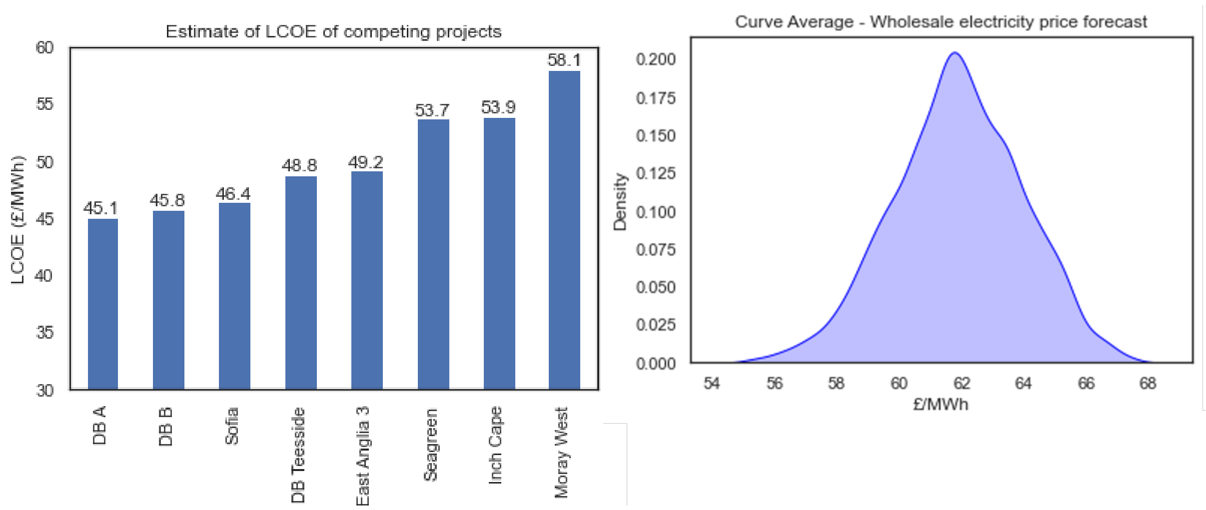
OPEX is commonly referred to in the literature as making up 33% of total wind farm costs (27). However, it can be seen from Figure 3 that the outputs of the auction are not sensitive to a change in OPEX. This is because although the total nominal value of OPEX costs over the lifetime of a project is 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.

Applied Energy 336 (2023) 120844

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Methodology to prepare for UK's offshore wind Contract for Difference auctions

Nicholas P. Kell [a,b,*], Ernesto Santibanez-Borda [b], Thomas Morstyn [c], Iraklis Lazakis [d], Ajit C. Pillai [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, Department of Engineering, Faculty of Environment, Science, and Economy, University of Exeter, Penryn, UK*

ARTICLE INFO

Keywords:
Contract for Difference
Stochastic
Renewable energy auctions
Bid strategy
Offshore wind
Auction efficiency

ABSTRACT

In the UK, the Contract for Difference (CfD) subsidies for renewable energy generation are awarded through a competitive auction process. This paper simulates the most recent CfD auction for offshore wind, using a novel methodology to assist developers in preparing their bid strategy and for policymakers to test auction efficiency. The simulation's results show developer's leading strategy is to shade their bid to increase auction pay-off. A developer's incentive to shade their bid depends on the project's capacity and minimum bid price; the offshore wind farm Hornsea 3 has the greatest incentive to shade its bid as its optimum bid price is further from its cost price, and results in the highest expected value of additional auction pay-off. The median strike price estimated by the model is £39.23/MWh, and the most likely winners, as predicted from the simulations, are Hornsea 3, Inch Cape, East Anglia 3 and Norfolk Boreas. Published auction results show that the estimated strike price from the simulation is 5% higher than the £37.35/MWh awarded strike price; however, the model successfully predicted the winners. Further analysis of results demonstrates that developers adopted a risk-averse bidding strategy, bidding at a pre-determined floor (coexist) price, guaranteeing subsidy. As a result, £38 million of the subsidy budget was unused.

1. Introduction

Many governments worldwide have announced ambitious renewable energy generation targets due to anthropogenic global warming, energy security and volatility of fossil fuels prices [1]. For example, the EU has mandated that 43% of energy generation must come from renewable energy sources by 2030 [2]. Governments have introduced a series of policy tools to accelerate the deployment of these renewable energy technologies, including offshore wind. In the UK, the primary subsidy mechanism to help achieve these targets is the Contracts for Difference (CfD), awarded in competitive auction processes [3]. The CfD guarantees renewable energy asset owners a fixed price (£/MWh) for the electricity generated for the 15-year contract length [4].

The subsidy award heavily incentivises investment in renewable energy projects by protecting developers from volatile wholesale prices. Providing revenue certainty helps de-risk renewable projects, thus reducing the cost of raising capital and increasing the economic viability of renewable projects [5]. For many developers in offshore wind, the CfD is the only viable route to market [5]. Failure to win a CfD contract can result in significant project delays as developers await the next auction or attempt to secure alternative financing. There are several risks to consider while bidding at auction. Bid too high and risk not being awarded a contract, or bid too low and then risk experiencing the winner's curse, potentially leading to unprofitable sites and the non-realisation of projects [6].

Renewable energy developers must perform financial and strategic analyses to formulate a bidding strategy. Financial analysis is related to all known factors (e.g. seabed rental cost). Strategic analysis is associated with assessing uncertainties (e.g. level of competition, competition costs, future wholesale electricity market prices). This strategic element is crucial and is considered non-negligible [7]. Therefore, to determine a bid price, bidders must characterise the uncertainty to understand the auction dynamics and make predictions of the auction outcome. One way of achieving this is through auction simulation, which helps test the existence of dominant strategies in the presence of different bidder configurations, valuations and uncertainty [8].

* Corresponding author at: Industrial Doctorate Centre for Offshore Renewable Energy, The University of Edinburgh, Edinburgh, UK.
E-mail address: N.Kell@ed.ac.uk (N.P. Kell).

https://doi.org/10.1016/j.apenergy.2023.120844
Received 7 December 2022; Received in revised form 18 January 2023; Accepted 10 February 2023

Table 1
Budget (million £), in monetary terms [2012 prices], for the fourth CfD Allocation Round. Illustrating pot structure for the auction [15–18].

	Delivery and valuation years					
	2023/4	2024/5	2025/6	2026/7	2027/8	2028/9
Pot 1 - Wind & Solar (M£)	10	10	10	10	–	–
Pot 2 - including: (M£)	–	–	75	75	75	75
Minimum for floating wind (M£)	–	–	24	24	24	24
Minimum for tidal stream (M£)	–	–	20	20	20	20
Pot 3 - Fixed offshore wind (M£)	–	–	210	210	210	210

Developer's incentive to bid strategically and deviate from marginal cost further complicates the CfD auction process. From an auctioneer's standpoint, strategic bidding, whereby developers do not reveal their true cost, is an example of auction inefficiency [9]. In auction-theoretic literature, when the auction concerns several homogeneous items (i.e. multi-unit auction), the dominant strategy is not to bid at cost, as seen in a perfectly efficient allocation process [10]. The design features of the CfD auction incentivise varying strategies. For example, the uniform pricing auction format means that all accepted bids receive the same price. One form of strategic bidding is shading, where players increase their bid above cost to increase their expected pay-off [11]. Bid-shading is explained further in Section 2.2. Simulation routed in game-theoretic principles can help quantify the likelihood of each player engaging in this form of strategic behaviour. In the context of CfD auctions, players participating in the auction are developers.

Simulation can test auction design and its effect on allocation efficiency, allowing empirical testing of several different rule configurations, which helps inform policymakers on auction design. Renewable energy subsidy (RES) auctions have not yet converged onto one design; therefore, further research is warranted to explore rule design changes for policy recommendations [3]. Additionally, simulating the auction can be useful to test any rule changes or parameters set (e.g. budget impact) [12].

This paper introduces a novel methodology for studying CfD auctions dynamics, building on the model methodology outlined in [13], and enables for detailed analysis of real-world Renewable Energy Subsidy auctions. Several novel elements associated with the methodology 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. [14]. However, this work differs from the presented model for a number of reasons. Firstly, previous work considers fictitious case studies. This work couples an auction simulation with an offshore wind cost assessment tool that allows CfD auctions to be simulated by depicting real auction players characterised by real offshore wind projects. Basing case studies on real auctions allows for a realistic depiction of competition, allowing for auction dynamics to be analysed. Additionally, introducing stochastic simulation allows for better characterisation of the uncertainty experienced by auction participants. Secondly, this work incorporates game theory and probability theory elements to allow auction participants to test various bidding strategies. Previous work assumed that developers reveal their true value and bid at cost. Finally, the presented methodology uses auction simulation to analyse past auction results, which can be used to understand auction behaviour and inform future bidding strategies. It also enables policymakers to make conclusions on the auction's effectiveness at allocating resources.

The simulation results obtained in this paper have not been calibrated against the actual auction results and are based solely on information available before the auction. The results are then compared against the actual auction results to help inform future bidding strategies. Developers can use the methodology to prepare better auction strategies, which prevents the winner's curse and mitigates project non-realisation. Policymakers can also use the methods described to test new auction formats and ensure allocation efficiency. The remainder of this paper is structured as follows: Section 2 introduces the theoretical background underpinning the methodology and the relevant literature. Section 3 outlines the novel methodology for simulating CfD offshore wind allocation rounds. In Section 4, the methodology is applied to an actual Case Study designed to replicate the most recent auction. Finally, Section 5 presents the results before concluding.

2. Theoretical background and literature review

2.1. CfD auction design

The UK CfD auctions have a multi-unit, sealed-bid, uniform price (pay-as-cleared) format. A multi-unit auction is where several homogeneous items are sold [19]. 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 receive either the highest accepted bid (their own) or zero.

The total CfD subsidy budget is divided into different technology pots. Pot definitions are modified according to policy targets at the time of the auction [20]. The CfD subsidy is awarded in different allocation rounds; previously, each round occurred every two years. However, CfD auctions are now set to occur every year. The most recent CfD auction, the fourth auction to occur, is known as Allocation Round 4 (AR4) [21], which is the focus of the Case Study presented in this work. Table 1 illustrates the AR4 pot structure and allocated budgets. Pot allocation is dependent on the UK Government's renewable energy policy. For example, a lack of government support for solar and onshore wind saw the withdrawal of funding for these technologies in previous auction rounds [22]. Support for these technologies has been reinstated for AR4. The government can also ring-fence budget for particular technologies, this guarantees that support is awarded to those technologies and is frequently done to support the deployment of less mature technologies. In AR4, only floating wind and tidal technologies received ring-fenced support.

The allocation process for CfD contracts is as follows: The process begins with National Grid Electricity System Operator (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. For example, developers must obtain all the necessary consent for their site and a grid connection agreement. Additionally, for projects exceeding 300 MW, a *supply chain plan* which outlines how the project will promote competition, innovation, and skills in the supply chain must be submitted and approved. Other important considerations, such as local content, will also play a part in the eligibility of projects [23].

Prior to the auction, a budget notice is issued, which declares a capacity minima, capacity maxima, or total budget for the auction. Any singular project exceeding the capacity maximum is rejected. A minimum capacity results in projects with the lowest bids automatically accepted up to the minimum, providing the bid price is equal to or below the ceiling price. Finally, the budget dictates how many projects are accepted by assessing the budget impact of each project using the Valuation Formula (described in Section 3.1.3). Typically, the capacity maximum or budget notice is the limiting factor in determining the

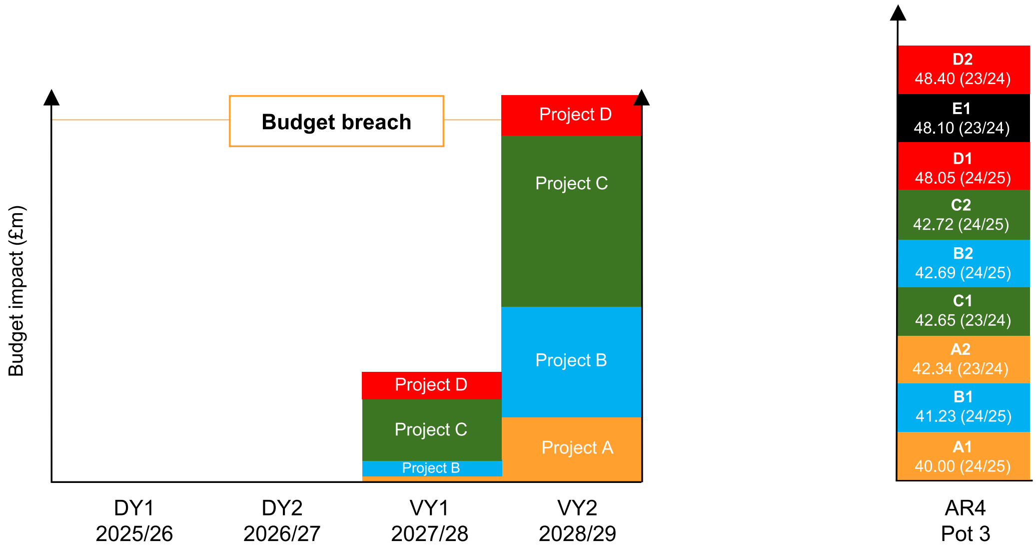


Fig. 1. Illustration of how the stack of bids is assessed against a budget, resulting in a budget breach.

volume of capacity procured. The UK government did not apply a maxima or minima to Pot 3 in AR4, so an auction determined by the budget will occur. Therefore, this type of auction will be the focus of this paper. Not imposing a capacity cap on the auction is frequently done to drive competition between developers. Six months prior to the auction the government issued a revised budget revision for Pot 3, increasing the budget by £10 m to £210 m. This budget revision's effect on auction dynamics is analysed in Section 4.2.

Developers in the UK CfD auction submit up to four flexible bids. The flexibility applies to the bid's capacity, price, and delivery year. Developers can only submit a maximum of two bids into each delivery year. The flexible bids allow developers to submit a number of different capacities into the auction. Developers can, therefore, choose to submit multiple bids for varying proportions of their total consented capacity, reducing the bid's total budget impact and increasing the probability of being awarded a contract.

After receiving all sealed bids from all developers, National Grid ESO combines all bids arranged in ascending order based on the bid price to create a bid stack. The bids are then considered in the order of the bid stack, starting with the cheapest bid. If accepted, the auctioneer assesses the budget impact of the next bid. A bid is rejected if the addition of the bid results in a budget breach (as seen from Fig. 1). If this occurs, the next flexible bid of this project is considered under the interleaving rule. For more detail on the UK CfD allocation mechanism, refer to the CfD allocation framework [24].

The interleaving rule allows the auctioneer to consider the flexible bids of developers. Under the interleaving mechanism, a participant's next flexible bid is considered after the original bid is rejected. In the illustrative example shown in Fig. 1, Project D results in a budget breach, resulting in an interleaving loop forming which includes all bids between the first rejected bid and the next flexible bid of that project. Therefore, in this example, Project E1 and D2 are considered together, as E1's bid price is between D1 and D2, so it forms part of the interleaving loop. For D2 to be accepted, both E1 and D2 must fit into the budget and not result in a budget breach of VY2 (Valuation Year 2). If either E1 or D2 results in a budget breach of either VY, then both bids are rejected, and the auction is closed. This is an example of unsuccessful interleaving. In this example, as Project C is the last accepted bid, it is the project which sets the strike price for both delivery years of the auction. However, if neither E1 nor D2 results in a budget breach, interleaving is successful, so both bids are accepted, and D2 becomes the strike price for both delivery years. If two bids are submitted with an equal bid price, and accepting both bids results in a budget breach, then the accepted bid is decided by a tiebreaker. During a tiebreaker, the Delivery Body must choose one of the Qualifying Applications at random [24].

One significant change from previous CfD auction rounds is simplifying the role of delivery years. In AR4, the whole auction closes if the monetary budget is breached in one delivery year. Therefore, a single strike price will apply across the auction, which is subject to the Administrative Strike Price (ASP). The auctioneer sets the ASP, the ceiling price awarded to a technology. For further information on determining the ASP, refer to the UK Government website [25]. However, qualifying applicants will still bid into individual delivery years as before. In previous ARs, typically, there were separate strike prices for each delivery year; this is unlikely to happen in AR4. The two strike prices in previous auction rounds occurred because a budget breach would result in delivery year closure instead of entire auction closure. This meant that in the case of a budget breach, the auctioneer could continue allocating capacity to the other delivery year until a second breach occurred, resulting in auction closure [22]. The effect of this rule change on the auction dynamics has been analysed in Section 4.2.4.

2.2. Background to bidding into CfD auctions

An awarded CfD strike price can significantly affect the profitability of offshore wind developments. Therefore, CfD bids must be carefully considered, allowing developers to cover costs and give investors the required return on their investment. Determining a CfD bid price requires an analysis of costs and revenues throughout the entire lifetime of the wind farm. This is necessary to estimate the project's cash flow and then calculate a minimum CfD bid price which satisfies the investment criteria. However, estimating cash flows accurately is challenging, as significant uncertainty exists. For example, there is uncertainty associated with one's cost of components, such as foundation, cables and steel costs [7]. Therefore, Monte Carlo sampling from cost distributions produces stochastic outputs, which better characterises the uncertainty associated with each cost component [26].

The relevant corporate finance theory can explain developers' motives for bidding in a CfD auction. Offshore Wind developments are large capital-intensive projects where developers must raise significant capital before reaching a final investment decision on a project. Recent surveys on costs of capital of onshore wind energy projects across the EU have found shares of debt of between 55% and 80% [27–29], largely because debt is cheaper than equity, and so minimises project costs.

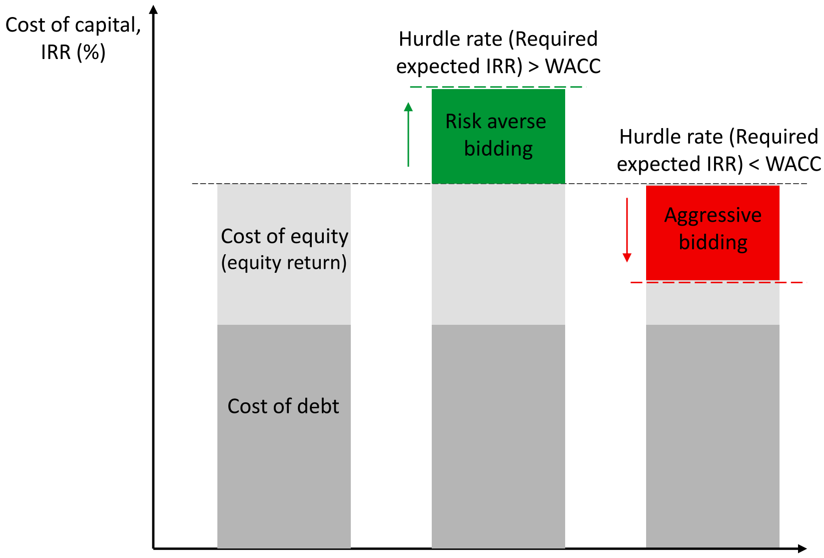


Fig. 2. Developers may differentiate their hurdle rate (required IRR for project execution) from the calculated WACC as part of their bid strategy. *Source:* Adapted from [33].

Moreover, to raise a high proportion of debt at preferred lending rates, banks typically require that projects have revenue certainty and are protected from merchant risk [30].

The cost of capital is the costs under which lenders invest debt or equity into a company or project [31]. The overall cost of capital is weighted by the shares and cost of debt, which forms the weighted average cost of capital (WACC) [32]. Developers use the WACC to discount cash flows and calculate the Net Present Value (NPV). A positive NPV indicates that the project creates value and should be undertaken. However, in practice, companies only undertake projects which meet or surpass an internal hurdle rate (required IRR). The hurdle rate is typically based on the WACC and is usually higher but, in some instances, can be lower depending on the strategic motivation of a company. For example, in project finance, hurdle rates can be lower than WACC if trying to gain a strategic advantage in a new market [33]. Therefore, in simulating auctions, it is the internal hurdle rates which can be set by developers and varied according to risk appetite [34]. This dynamic can be seen in Fig. 2. The risk appetite represented by the hurdle rate can vastly impact a developer's CfD bid value. As a result, developers can alter their risk profiles and significantly alter their CfD bid price (discussed further in Section 4.3.1).

2.3. Auction simulations review

Bidding behaviour in auctions is a well-studied area of research. Wilson et al. [35] were the first to formalise the multi-unit auction. They noted that an offer is made according to a private value. Goeree et al. [36] used an auction theoretical model to demonstrate how uncertainty experienced by bidders harms allocation efficiency and efforts to reduce uncertainty by the auctioneer results in increased efficiency and sellers' revenue. There is substantial literature which utilises auction theory to describe expected auction outcomes and optimum strategies for multi-unit auctions for electricity spot markets [37–39]. For example, Wolfram et al. [40] demonstrate that in multi-unit auctions, such as in electricity spot markets, developers typically strategically bid to increase their auction pay-off. The above examples have focused on varying auction formats, which are related but not equivalent to the auction dynamics, design rules, or behaviour of players in Renewable Energy Subsidy (RES) auctions. Therefore, further research is required on RES auctions specifically, to draw recommendations which is useful for auction preparation and design.

RES auctions, such as the CfD auction, are a widely studied area of research. Significant literature has addressed auction design to optimise allocation efficiency to ensure policy targets are met. For example, Matthaus et al. [41] used empirical data from previous auction rounds to determine the effect of penalties and pre-qualification criteria on the realisation rates of projects. Kreiss et al. [42] used auction theory to assess the impact of uncertainty on bidders and the implications of this on the non-realisation of projects. This work builds on both examples, by not only focusing on making recommendations for policymakers, but also developing a methodology for developers to better prepare a bid price, which mitigates against the non-realisation of their project.

Welisch et al. [43] used a previously developed agent-based model to empirically test the effect of non-realisation penalties on developers bidding truthfully and revealing their costs. However, this work was based on fictitious case studies, therefore it does not portray a realistic depiction of competition. Anatoloitis et al. [44] used the same agent-based model to test the allocation efficiency of two major auction formats, pay-as-bid versus pay-as-clear, for German onshore wind power auctions. In both these previous examples, the simulations assume that agents bid truthfully in uniform price auctions. However, several pieces of literature demonstrate that in multi-unit auctions with uniform pricing, players have the incentive to bid strategically [10], particularly if bidders hold estimations of the valuations of other players. Additionally, it is assumed that players bid according to an estimated LCOE (Levelised Cost of Energy). In reality, auction bid prices are related to but are not equal to the LCOE of the project, as LCOE does not take into account estimate future revenues [45].

The literature survey suggests that there have been recent attempts to simulate renewable energy subsidy (RES) auctions to understand auction dynamics better and ensure allocation efficiency. However, most published work focuses on fictitious case studies and does not make recommendations for auction participants. To the best of our knowledge, no published literature has used auction simulation and estimated project-specific costs to predict and analyse a CfD auction result and then make recommendations evidenced by simulation for auction participants. Simulating auctions is helpful for developers and policymakers; it allows to test whether the auction is efficient at allocating resources and will enable developers to test hypotheses used to prepare bidding strategies. A well-thought-out bidding strategy can help prevent the winner's curse, mitigating the non-realisation of renewable projects [45].

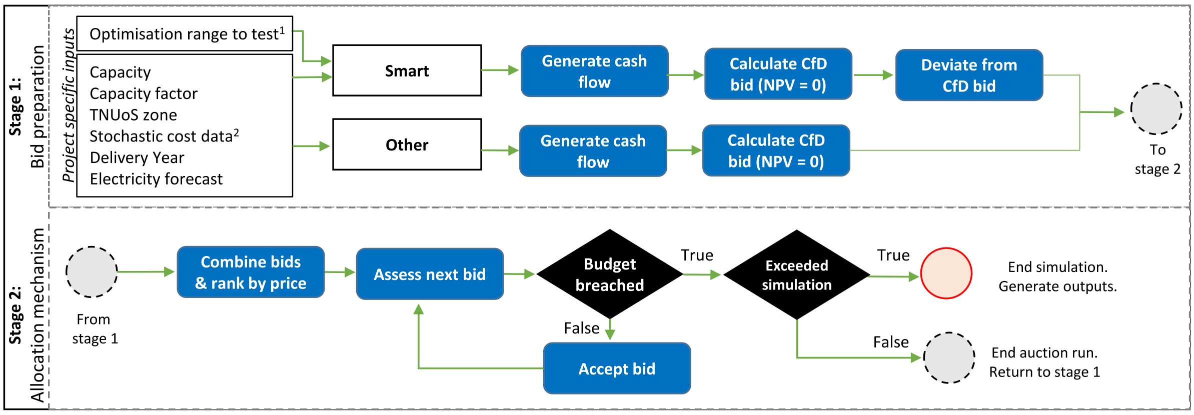


Fig. 3. High-level flow diagram illustrating one auction run process [13].[1] Highlights the optimum bid price range to test, which is user input and gives the *smart* agent added flexibility to deviate from the calculated CfD bid price. The range provided allows the *smart* player to test the success of a range of bids given the competition it expects.[2] Stochastic cost data includes the DEVEX, CAPEX, OPEX and DECEX.

3. Methodology

3.1. Model summary

The scope of work outlined in Section 1 uses a novel modelling approach for simulating CfD auctions. For a detailed presentation of the numerical framework used to carry out this analysis, refer to work produced by the authors in Kell et al. [13]. The auction modelling tool has been modified to allow for CfD auction rule changes made for AR4 and to enhance the pre-auction analysis; Section 3.1.3 outlines the modifications made to the tool.

The auction modelling tool is a stochastic, agent-based, modelling approach which utilises game-theoretic principles to generate bid strategies for generators attempting to win a CfD contract. The model utilises the Python framework for agent-based modelling: Mesa [46]. The model allocation mechanism is based on the CfD allocation framework; however, the theory underpinning the model applies to other RES auctions. The model uses Monte Carlo sampling from cost data to produce stochastic outputs that better characterise the uncertainty experienced by developers (as described in Section 2.2). Therefore, each complete simulation typically contains over 20,000 auction runs to average over stochastic inputs. There are two main stages of each auction run. These are defined as the *Bid Preparation* and *Allocation Mechanism* sections; further explained in this Section.

The game-theoretic aspect of the model is utilised to determine a bid price for a selected *smart* player based on the expected value E[X] of auction pay-off. This player differs from the others based on their knowledge and capabilities, as shown in Table 2. 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 will act. However, the smart player's added capability allows for optimising a bid price based on increasing the expected value E[X] of its auction pay-off in £/MWh. The uncertainty means many possible probabilistic outcomes are feasible, and given the uncertain outcome, E[X] gives a basis for selecting a bid price. An overall flow diagram illustrating the game-theoretic feature of the model is shown in Fig. 3.

The smart player can deviate from the calculated minimum CfD bid price b_i, for player i, calculated in the bid Preparation stage (see Section 3.1.1). In deviating from this bid price, by an amount known as x, it obtains a new bid price, $b_i + x$, which it tests many times to assess the success of this bid price. The smart player collects information on the strike price, P, and whether the project was successful for each auction run. The *smart* player can predict P using its additional capabilities as highlighted in Table 2; it is then used to determine the amount bid-shaded. The E[X] of additional auction profit for a particular bid price is calculated using Eq. (1). Where $W\%$ is the mean

Table 2
Demonstration of the knowledge and capabilities of each category of an agent in the model.

Capability/Knowledge	Smart	Other
Competitor cost and capacity	Yes	No
Number of competing projects	Yes	No
Total capacity auctioned	Yes	No
Deviate CfD bid price	Yes	No
Optimisation of E[X]	Yes	No

probability of winning for that bid deviation. $W\%$ and P are a function of the bid price submitted by the smart player. For a detailed theoretical derivation of Eq. (1), and for more detail on the theory relating to the model's game-theoretic element, refer to the work produced by Kell et al. [13].

$$E(b) = \sum_x ([P(b_i + x) - b_i] \cdot W\%(b_i + x)) \tag{1}$$

3.1.1. Bid preparation

The bid preparation stage converts input project data into a CfD bid price, b_i, for a player i. To generate a bid price for each player, it samples project data from a unique distribution for each player. For each auction run, a bid price is generated through independent samples of the same distribution. 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. Calculating cash flows of renewable generating projects to determine a bid price is consistent with previous analysis on this topic [4].

Cost streams include capital, operational, decommissioning, development, rent, interest payments, tax and TNUoS (transmission network use of system) charges. Revenue streams include CfD payments, contracted power, and wholesale revenues. An AEP (annual energy production) value calculated for each wind farm enables the model to estimate future revenues. AEP (MWh) is calculated by multiplying the wind farm's capacity, capacity factor and total hours in a year. The capacity factor is determined considering the mean wind speed, the power curve of a generic turbine, and estimated losses. The calculated bid price, b_i, is mapped to each player. The submitted bid of each player consists of the bid price, capacity and delivery year.

3.1.2. Allocation framework

After the bid preparation stage is completed, the allocation framework collects and then sorts in ascending order all bids from each player. Then, the budget impact of bids is assessed against the auction budget, using a Valuation Formula to decide which bids are accepted.

The model replicates the uniform price auction format (as described in Section 2), assessing bids one at a time. Bids are combined into a bid stack arranged in ascending order. If a bid is accepted, it elevates the auction's strike price to the price of the last accepted bid. Once a bid is accepted, all other flexible bids associated with this project are removed from the bid stack. All previously accepted bids will have their payment price elevated, which ensures that all successful bids receive the same price. Once the total budget is exceeded, then the bid which causes the capacity breach is rejected. An interleaving loop forms (as described in Section 2) between the rejected bid and the second flexible bid from that player. The auction closes if the second flexible bid also breaches the budget.

The model accepts up to four flexible bids for each project, of which a maximum of two bids can be submitted for each delivery year. Submitted bids must be of varying capacities. Therefore, the outputs from one auction run of the model are as follows: strike price, winning projects, all project bids and the total amount of capacity procured.

3.1.3. Modification of numerical framework

The auction modelling tool has been adapted to account for rule changes made in this allocation round, so it has been modified from the methodology outlined in Kell et al. [13]. The novelty of this paper is associated to the application of the model to study CfD auctions. The methodology is demonstrated through a case study designed to replicate a live auction process. The auction type has been changed from a maximum-only auction, where a maximum total capacity limit determines total accepted bids, to an auction concerning an overall budget. Previously, the auctioneer was set to procure a fixed amount of capacity (MW) from developers. This set amount of capacity was then used to assess the number of bids accepted and close the auction when this total amount of capacity was met or exceeded. This simplification of the auction procedure has been repeated in other published work in this research area, such as by Welisch et al. [47]. While it is reasonable to make this simplifying assumption for the AR3 Pot 2, it does not truly replicate the actual auction procedure outlined in the AR4 allocation framework [20]. In previous auctions (e.g. AR3), a capacity maxima of 6 GW of offshore wind was applied to the auction and this set the total amount of capacity procured [24].

Discussed in Section 2, the limiting factor in determining the volume of procured capacity is a monetary annually capped budget issued by BEIS. Therefore, one cannot accurately predict the capacity procured in pre-auction analysis without estimating the budget impact of each auction participant. For this reason, the auction model has been updated to procure capacity as a function of the stated budget. The model is updated to assess each bid and its impact on the budget before deciding whether to accept or reject it. The model considers the budget impact of each project as outlined in Section 2, and utilises the Valuation Formula (shown in Eq. (2)) as outlined in the Valuation Framework document produced by BEIS [20]. Where BI is the budget impact, SP is the strike price, RP is the reference price, LF is the given Load Factor for offshore wind, $YR1F$ is a factor applied to each project to account for partial year generation, C is the capacity, TLM is the Transmission Lost Multiplier, RQM is the Renewable Qualifying Multiplier and determines the payments made to generators based on the renewable content of their fuels, and $CHPQM$ is the CHP Qualifying Multiplier which ensures that developers are producing good quality Combined Heat and Power.

$$BI = (SP - RP) \cdot LF \cdot YR1F \cdot C \cdot (Days_{yr} \cdot 24) \cdot (1 - TLM) \cdot RQM \cdot CHPQM \tag{2}$$

The values for each term in the above equation are summarised in Table 3. The values for the constants are released along with the budget by BEIS, and are known parameters. The applicable BEIS reference price used in this analysis is £32.85/MWh, given for the valuation year 2028/29. As this is the lowest reference price for all valuation years, it is the price which will set the affordability.

Table 3
Values are constant for all developers and have been obtained from the Allocation Framework document produced by BEIS [20].

Term	Value	Unit
RP	32.85	£/MWh
LF	63.1	%
YR1F	1	
Days	365	
TLM	0.9	%
RQM	1	–
CHPQM	1	–

As mentioned in Section 3, the role of delivery years has been simplified. This change has, therefore, also been implemented in the numerical framework, meaning that the auction will close once the budget has been breached in any delivery year. This means that one strike price will be issued for all projects regardless of the delivery year they bid. This rule change will impact the auction dynamics and, thus, the potential bidding strategies of developers. A comparison of the effect this has on strike prices awarded can be seen in Section 4.2.4.

3.2. Modelling methodology

3.2.1. Affordable capacity

The monetary budget issued by BEIS gives an indication of affordable capacity if used alongside the Valuation Framework Formula (Eq. (2)) outlined in Section 3.1.3. Therefore, an affordable capacity analysis can be used to estimate the competitiveness of the auction based on the monetary budget and the expected eligible capacity competing. As mentioned in Section 2, a budget notice revision was issued by the Secretary State of BEIS to increase the budget by £10 m to £210 m. Therefore, the affordable capacity for the old and new budgets is analysed. Using the known budget and constants outlined in Table 3 it is possible to solve for C with a range of SP values using Eq. (3).

$$C = \frac{BI}{(SP - RP) \cdot LF \cdot YR1F \cdot (Days_{yr} \cdot 24) \cdot (1 - TLM) \cdot RQM \cdot CHPQM} \tag{3}$$

3.2.2. Game-theoretic methodology

The model has been used to demonstrate how the incentive to engage in strategic bidding (e.g. bid shading) depends on the player and its project. The model is run seven times (once for each player), altering the smart player for each simulation. This means that only one player at a time will have additional capabilities (seen in Table 2) and, therefore, knowledge of other competitors' bids. Therefore, only one player at a time uses its additional competence to test for the existence of a bid price that maximises E[X].

When running the model for each smart player, the smart player's costs are assumed to be deterministic. This is because the game-theoretic simulations are computationally expensive, and stochastic bid prices for the smart player would require many more thousand auction simulations for results to converge. If it can be assumed that the smart player's costs are known, then computational times are reduced significantly. Therefore, a deterministic cost modelling tool (OWCAT) [48] has been used to generate input data for the project, acting as the smart player. The *other* players will utilise stochastic cost data to generate bid prices. This cost modelling tool is described in Section 4.

Players are assumed to be unwilling to reduce their bid price below the minimum CfD bid price calculated, which gives them a minimum equity return. In doing so, the developer would risk not meeting the hurdle rates required for the project, which could result in non-realisation. For this reason, the players only consider increasing their

Table 4
High-level overview of some of the publicly available site/project specific input data which was used to generate cost estimations [49,50].

Project	Capacity	Average depth (m)	Mean wind speed @ hh (m/s)	Distance to port (km)	Foundation type	Export type	TNUoS zone
Hornsea 3	3000	38	10.47	250	Monopile	HVDC	18
Norfolk Boreas	1800	33	10.30	92	Monopile	HVDC	18
East Anglia 3	1480	39	10.23	80	Monopile	HVDC	18
Moray West	850	45.4	10.13	70	Monopile	HVAC	1
Inch Cape	1000	52	9.97	45	Monopile	HVAC	11
Seagreen 1A	500	54	10.55	65	Jacket	HVAC	4
Seagreen	1075	54	10.55	65	Jacket	HVAC	4

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]
Hornsea 3	3000	172.6	5752.6	83.2	232.0	0.480
Norfolk Boreas	1800	134.1	3634.2	52.6	132.4	0.477
East Anglia 3	1480	121.3	2839.4	44.4	106.8	0.475
Moray West	850	92.2	1524.3	29.3	72.1	0.479
Inch Cape	1000	99.9	1783.8	27.7	78.4	0.499
Seagreen 1A	500	71.2	939	19.4	56.8	0.507
Seagreen	1075	107.1	1953.1	40.4	91.9	0.507

[a]Inputs, show the median data for stochastic inputs, distribution of stochastic data is shown in Fig. 4.

bids beyond the minimum acceptable CfD bid price. Therefore, the players observe the effect of increasing their bid price by a maximum of £5/MWh, with an interval of £0.50/MWh. This range was chosen as it considers a wide possible bid range which also identifies a peak in the E[X] graphs produced in the results (see Fig. 11). Each player observes the success of 10 bid prices beyond their minimum calculated CfD bid price. For every bid price tested by the model, 1000 auction simulations are generated. This auction simulation number is chosen because there is a strong convergence of results after 1000 simulations per bid price [13].

3.2.3. Delivery year rule change

AR4 delivery year rules stipulate that if the monetary budget is breached in one delivery year, the whole auction closes. Therefore, a single strike price applies across the auction (subject to ASPs). This reduces the strategic complexity of the auction, as it means that the success of a bid is irrespective of what delivery year it bids into.

To model the effect the rule change has on the auction outcome, the case study described in Section 4 is modelled with AR3 delivery year rules and compared to the AR4 rules. To model the AR3 delivery year rules, a similar procedure as described in Section 3.1.3 is followed. The budget impact of each bid is assessed using the Valuation Formula; however, the delivery year that the bid is submitted determines which reference price is used to calculate the budget impact. For example, if the bid is submitted into the first delivery year, a reference price of £38.77/MWh applies. Similarly, if the bid is submitted into the second delivery year, a price of £32.85/MWh applies. Once the £210 m budget is breached in either of these delivery years, that delivery year is closed, and all other bids associated with that delivery year are removed from the bid stack. Allocation continues to the other delivery year until the £210 m budget for that year is breached; the last accepted bid into that delivery year sets the strike price. The auction then closes. As the reference price for the second delivery year is significantly lower, the budget impact is greater, meaning that the second delivery year is likely to close first. The results generated from the simulation using AR3 delivery year rules are then compared to the results from AR4.

4. Case study and results

4.1. Case study description

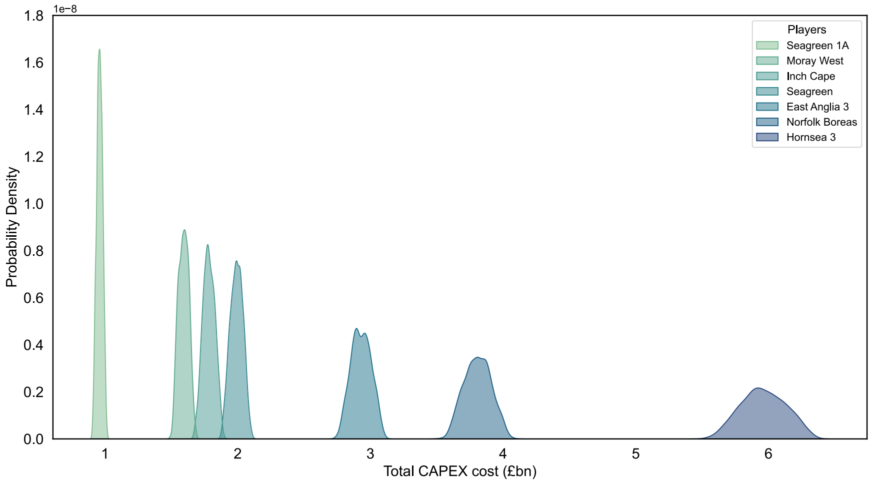
The eligible projects expected to compete in AR4 are first introduced in this Section. As projects must have obtained the necessary consent and approval from the UK government, details surrounding eligible projects are publicly available on the Planning Inspectorate (PINS) website [49]. The consenting documents outline a significant amount of information for each project, such as allowable build-out capacity, cable landfall point, export type and maximum turbine rating.

The project costs are modelled using publicly available site-specific and project-specific characteristics, which can be seen in Table 4. The data presented in this Table has been obtained from various sources such as PINS [49], and 4C Offshore's database [50]. Using this publicly available information, cost data is generated for each project using a previously validated proprietary stochastic cost modelling tool. The costs generated from this costing tool have been validated to an accuracy of ±15% [48]. Stochastic cost data is used to better characterise the uncertainty associated with projecting costs. The cost model 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. The cost distributions used for the AR4 prediction can be seen in Fig. 4 and the median cost data for each project is shown in Table 5).

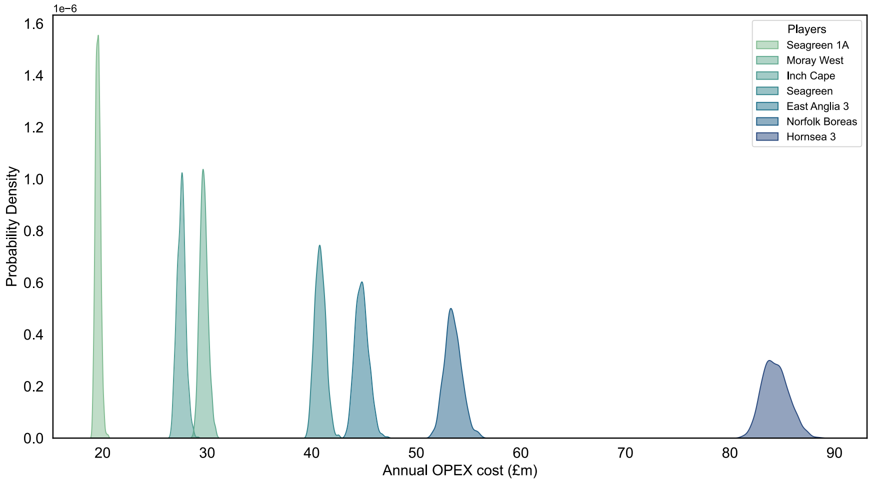
In addition to generating cost data for each project, several other inputs are required to estimate the CfD bid price of different projects. Financial assumptions such as WACC, IRR, and gearing ratios required for detailed financial modelling, are difficult to assume with any confidence for each player, so they are left generic for all developers. Hence, the site/project characteristic data is the key driver of differentiation between projects and determines the estimated bid price merit order of projects.

The following additional assumptions are the author's own and are made to simulate the AR4 auction. The assumptions are required to reduce the complexity surrounding unknowns of the auction process and do so without sacrificing the detail of the auction design.

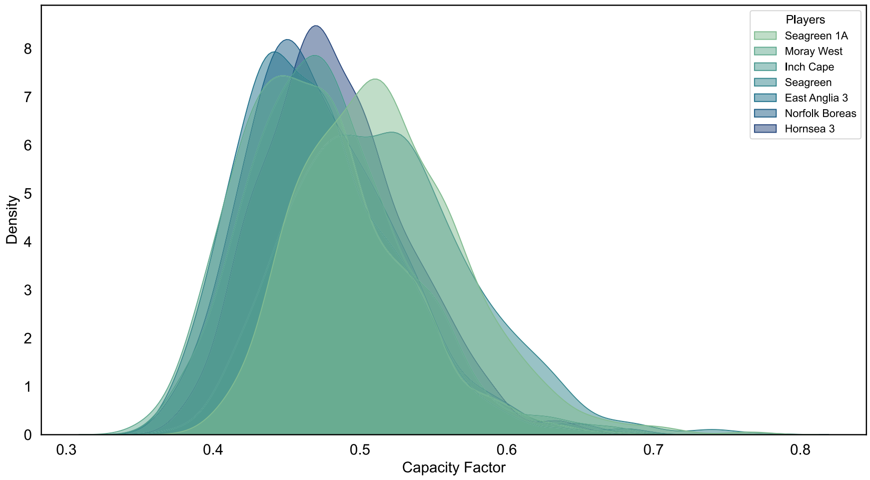
1. **Forecast wholesale electricity market price** - Future wholesale electricity prices 30 years into the future are extremely challenging to predict. Forecasts will differ between developers and can impact the calculated CfD bid. As it cannot be estimated which forecast each player may use, to keep calculations relative, all developers use the same curve, which has an average market price forecast of £55/MWh for the next 30 years. This is based on the medium economic growth forecast produced by BEIS [51].



(a) Empirical distribution of generated CAPEX costs.



(b) Empirical distribution of generated OPEX costs.



(c) Empirical distribution of generated Capacity Factors.

Fig. 4. Distributions of stochastic inputs for each player in the case study.

2. **TNUoS forecasts** - Transmission Network Use of System (TNUoS) charges over the operational lifetime of a wind farm are required to estimate total costs. TNUoS charges are levied on generators as a cost for transmitting electricity on the electricity grid. The charges reflect the cost of building and maintaining transmission infrastructure. National Grid ESO provides forecasts only up to 2027/28. Therefore, this final forecast is extrapolated from the last forecast in a straight line to provide

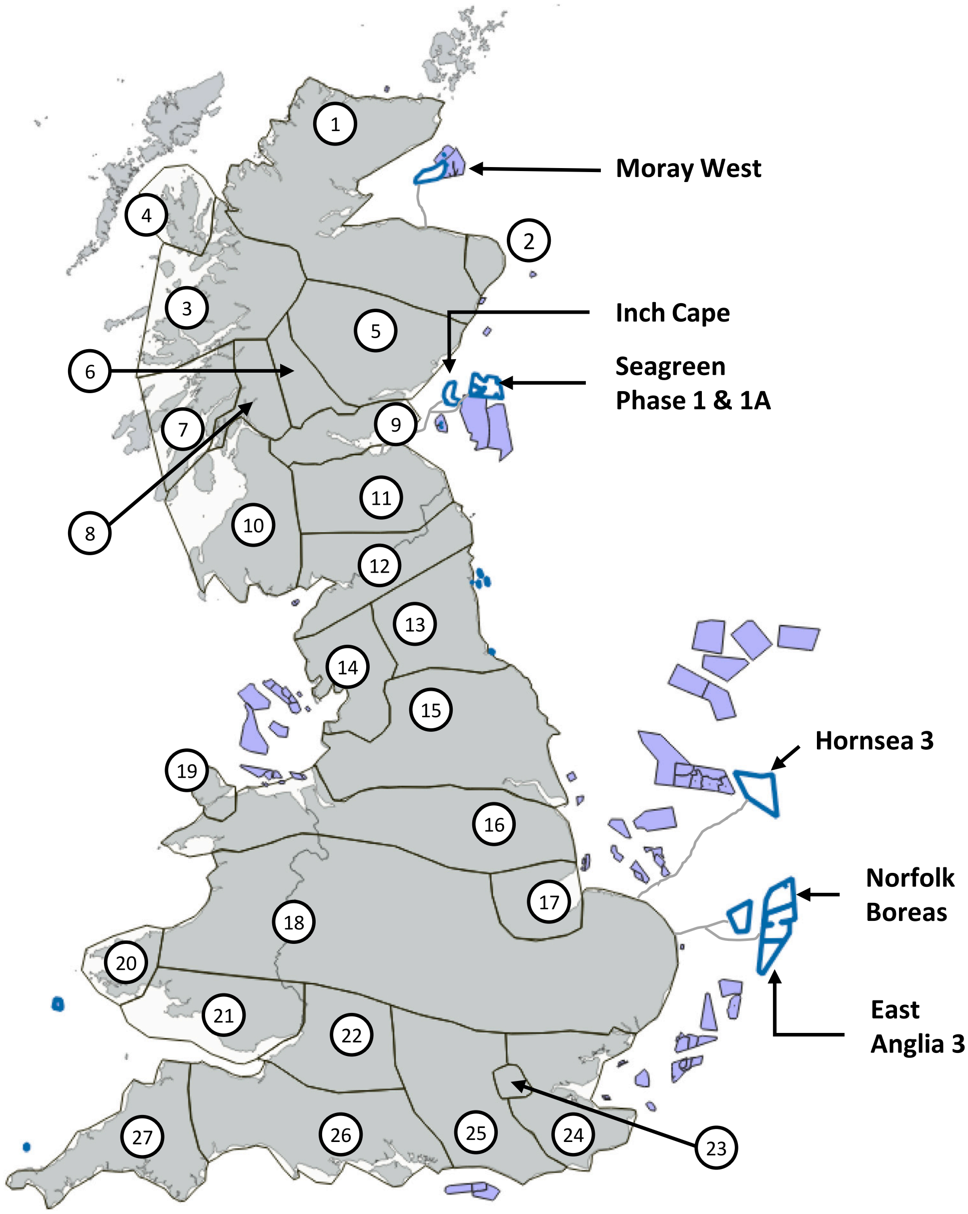


Fig. 5. Geographical location of offshore wind farms expected to compete in Pot 3 AR4. The 28 TNUoS zones, as outlined by National Grid ESO, are displayed on the map.

estimated charges for the entire 30-year wind farm period. All projects will derive their TNUoS charges from the same forecast.

3. **Discount rate** - Discount rates used by different developers are likely to vary based on risk appetite and business models. Variation between developers cannot be predicted; therefore, all developers are modelled using the same central discount rate of 6.3%, based on BEIS estimates [52].
4. **Flexible bids** - Developers can submit variations of their primary bid by varying the total amount of capacity of their bid. Flexible bids trigger the interleaving rule (as explained in Section 2). Flexible bids submitted by each player for each project are difficult to predict. However, as large eligible projects compete in AR4, the interleaving rule is expected to be of more importance (discussed in Section 2). For this reason, it is assumed that each player submits two bids, one at their total consented capacity and one at half this value.
5. **Real terms** - The auction modelling tool is set to analyse revenues and costs in 2012 in real terms, as this is the reference year used in the CfD auction.

4.2. Case study results and discussion

4.2.1. Affordable capacity results

Fig. 6 shows the relationship between affordable capacity against strike prices. The intersection between the vertical lines and the curve shows how much capacity will be afforded at different strike prices of interest. It can be seen by comparing the £210 m and £200 m budget lines that the budget revision has made a marginal difference to the expected outcome of the results. The first vertical line represents the strike price which would be achieved if all 9250 MW of eligible projects (as depicted in Table 4) receive a CfD. This strike price is £36.85/MWh and £36.80/MWh for the £210 m and £200 m budgets, respectively. This is the coexist price and acts as a bid floor, the minimum price developers bidding in the auction will achieve. The coexist strategy is possible in AR4 as there is no capacity maxima cap and because a monetary budget determines the allocation process (as discussed in Section 2). As the coexist price is a function of the total eligible capacity expected to bid into the auction, developers must accurately predict the capacities of other competing projects. This price

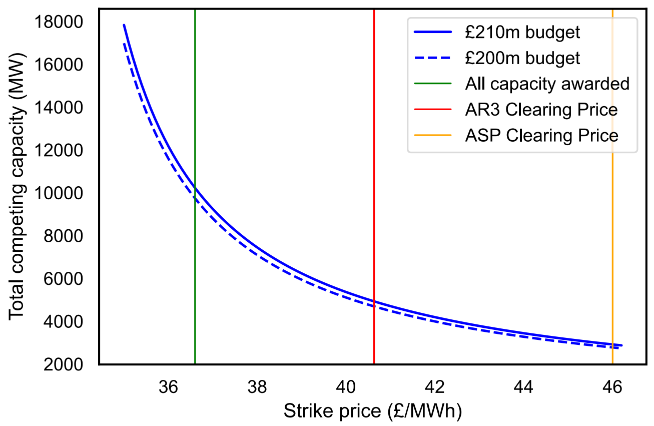


Fig. 6. Affordable capacity by the auctioneer due to the budget notice. The intersection of vertical lines and curves illustrates affordable capacity at three different strike prices.

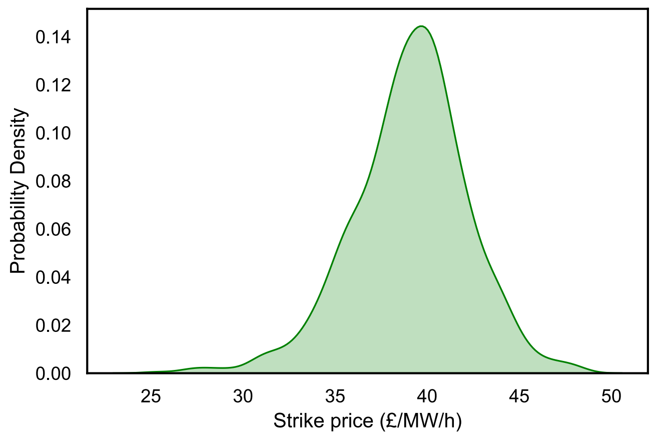


Fig. 7. Stochastic results indicating the estimated likely strike price for AR4.

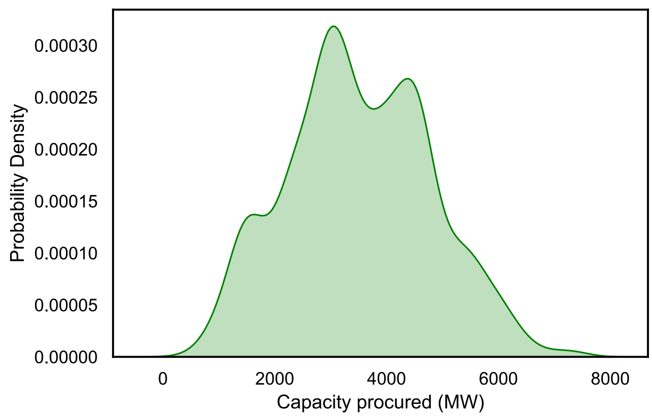


Fig. 8. Estimated total capacity procured by the auctioneer in AR4.

would remain true considering the assumptions based on the eligible projects and their build-out capacities are valid. The second vertical line depicts the total affordable capacity if the same average strike price of £40.63/MWh, achieved in AR3 (2019), occurs again in AR4. However, a repeat of the 2019 CfD strike price is unlikely, as historically, the price has decreased between auction rounds [15–18]. Under this scenario, 4950 GW of offshore wind capacity would be procured for the revised budget, compared to 4600 MW for the previous budget. The final vertical line on Fig. 6 shows the minimum amount of capacity that the auctioneer will procure. This represents the ASP set before the auction at £46/MWh and is the maximum strike price awarded to offshore wind generators. Under this scenario, a total of 2915 MW and 2800 MW will be procured for the revised and old budgets.

Fig. 6 also demonstrates to developers and the auctioneer the expected effect of increasing the budget by £10 m. It shows that the change in capacity procured and strike price is marginal. Therefore, it is unlikely that developers will aim to significantly change their bidding strategy due to the revised budget notice. However, suppose the government's intention by issuing the budget notice is to dramatically increase the amount of offshore wind capacity procured in line with their renewable targets. In that case, a larger increase in a budget revision is required.

Bidding at the coexist price depends on a developer's estimated costs, financial assumptions, risk appetite, outlook on future wholesale electricity prices, and eagerness to be awarded a CfD contract. If winning a CfD contract in AR4 is imperative to the project's viability, then there are several financial levers, such as sell-downs, project financing and hurdle rates that developers can adjust to reduce their CfD bid.

4.2.2. Stochastic results

Fig. 7 highlights the most likely strike price, which is the subsidy priced given to each successful developer and has been predicted by the stochastic simulations of AR4. The peak in the graph illustrates that the most likely strike price is between £37.50/MWh–£40.50/MWh. The most likely strike price, with a 14% probability of occurring, is £39.26/MWh. The simulated strike price range for AR4 is between £25.30/MWh and £48.24/MWh, with a standard deviation of £3.13/MWh.

A developer could use the predicted strike price probability density graph to determine where the strike price is most likely expected to fall and then bid below this value to increase the probability of being awarded a contract. It will also indicate to developers the competitiveness of their site and whether the hurdle rate should be altered (as described in Section 2.2) to increase/decrease profitability to alter their CfD bid price closer to the estimated strike price.

The results indicate that the estimated procured capacity ranges from 1500 to 8000 MW (Fig. 8). The median result from the simulation is that 3450 MW will be procured. This is considerably lower than the 9600 MW of eligible capacity. However, there is a 35% possibility that greater than 4000 MW of capacity will be procured and a 14% probability that greater than 5000 MW will be procured.

Fig. 9 illustrates the spread of bid prices submitted by each project. The figures are in ascending order, sorted by the median bid price for each project; this demonstrates the bid merit order of projects based on the assumptions outlined in Section 4.1. It can be seen that Hornsea 3 has the lowest expected bid price. Conversely, three Scottish projects have a significantly higher spread of bid prices. There is a spread of close to £10/MWh–£20/MWh in median bid prices between Hornsea and the three Scottish-based projects (Seagreen, Seagreen 1A and Moray West). This can be attributed mainly to the geographical spread of grid connection TNUoS charges (shown in Fig. 5), which are significantly higher in Scotland than in the rest of Great Britain. Based on analysis carried out on TNUoS charges [13], the differences in charges accounts for £14.30/MWh of the difference in CfD bid between the Hornsea 3 and Moray West project.

The translation of median bid prices into a probability of being awarded a subsidy can be seen in Fig. 10. It can be seen that Hornsea 3, Inch Cape and East Anglia 3 are predicted to be successful with a reasonable amount of certainty (>70%). On the other hand, Moray West and Seagreen 1A are predicted to win a low amount of certainty (<30%).

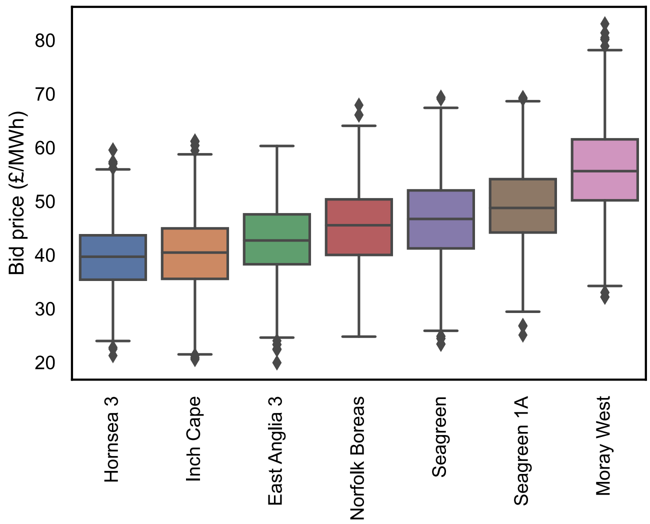


Fig. 9. Estimated merit order of projects competing in AR4. The bid spread for different projects due to stochastic cost data is also illustrated.

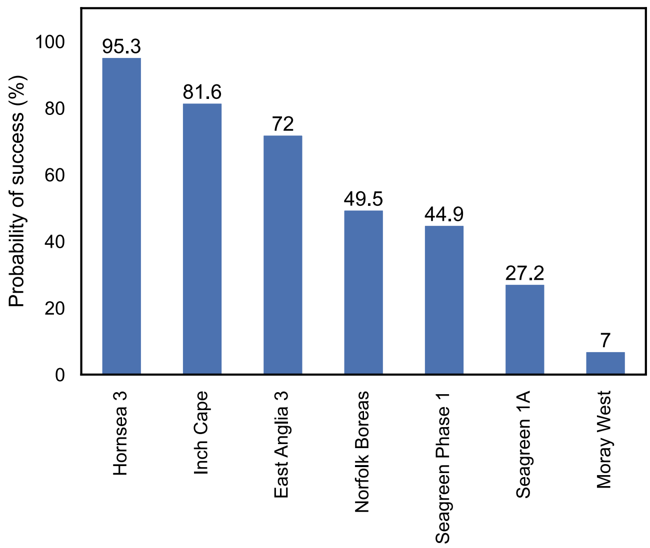


Fig. 10. Probability of each project successfully being awarded a subsidy.

4.2.3. Game-theoretic bidding behaviour results

The game-theoretic bid shading analysis has quantified the incentive for different developers to deviate from cost and shade their bids. Fig. 11 shows how the optimal bid with respect to the E[X] of auction pay-off and the incentive to engage in bid shading (described in Section 2.2) depends on the developer in the Case Study. The incentive is defined as how high developers can increase their expected E[X] of auction pay-off by increasing their bid beyond the minimum calculated CfD bid price (explained in Section 3.1.1. It can be seen from the results presented in Fig. 11 that the incentive to engage in strategic bidding varies for each player and their project. Results show that Hornsea 3 has the largest incentive to bid shade, as identified by having the largest E[X] peak. This is because the optimum bid price is not only the furthest away from the cost price at a bid price signal deviation of £3.00/MWh but also gives the player the highest E[X] of approximately £2.00/MWh. This is mainly due to its position of having the lowest minimum CfD bid price but also because it has the largest budget impact as it attempts to procure the most capacity from the auctioneer. This result is consistent with auction-theoretic literature, where in uniform price, multi-unit auctions, the incentive to shade depends on the units demanded and the bidders' market power [10]. Inch Cape, which also has a low median bid price (see Fig. 9), is incentivised to bid shade; this is because it can optimise its bid by increasing its bid price by £2.50/MWh and achieve an E[X] of auction pay-off of £1.70/MWh. Developers such as Moray West and Seagreen 1A, defined as unlikely to win by the model, have minimal incentive to engage in bid shading behaviour. Therefore, projects with a high estimated median bid price and, therefore, unlikely to win cannot increase their E[X] of auction pay-off by increasing their bid price further.

4.2.4. Delivery year rule change results

Fig. 12 demonstrates the effect changing the purpose of delivery years (this rule change is explained in Section 2) has on the auction outcome. The new rules for AR4 drastically reduce the volume of capacity procured and the expected strike price. The median strike price estimated if the old delivery year rules are applied is 4650 MW. This is a 1300 MW increase from what has been predicted using the new rules predicted by AR4. The median strike price predicted by the model is £43.78/MWh, compared to £39.26/MWh, which has been predicted using the new rules.

The results demonstrate that the delivery year rule change is likely to put further downward pressure on CfD bid prices, which will likely impact the profitability of offshore wind developments. Therefore, this rule change can be considered less preferential for developers as it increases the budget impact of projects and reduces the total amount of capacity procured. However, as one strike price is issued for both delivery years, there will be some reduction in the strategic complexity of the auction, as developers will now not need to consider which delivery year it is preferential to bid into.

The difference between estimated results for both rule formats can be explained due to how each bid's budget impact is assessed. As mentioned in Section 3.1.3, a reference price is used to calculate the budget impact of each bid. The reference price corresponds to the first and second delivery years, which are £38.77/MWh and £32.85/MWh, respectively. Applying AR3 rules, bids are assessed against the delivery year in which they are submitted. This means any bid accepted into the second delivery year will have a larger budget impact due to the first term of the Valuation Formula: *Budget Impact = (Strike price - reference price)*. Once there is a budget breach, this delivery year closes; however, bids can still be accepted into the first delivery year. Bids submitted into the first delivery year are then assessed using the higher £38.77/MWh reference price and are accepted until there is a second breach for that delivery year. As a result, far more capacity is procured as the reference price of £38.77/MWh now sets the affordable capacity.

4.3. Summary of AR4 results

Table 6 gives an overview of the CfD AR4 Offshore Wind auction results, issued by the UK Government after completion of the CfD auction round. A full list of results for AR4 can be found on the UK government CfD website [18]. The strike price of £37.35/MWh awarded at AR4 is an 8% further reduction in CfD strike price (demonstrated in Fig. 13). A total of 6994.34 MW of offshore wind capacity was procured. It can be seen that five out of seven of the eligible projects were successful in being awarded a contract at a strike price of £37.35/MWh. East Anglia 3, Inch Cape and Moray West, who were unsuccessful in being awarded a contract in AR3, were successful in this auction. SSE's Seagreen projects were the only successful projects and failed to win a subsidy for its 1120 MW of eligible build-out capacity.

Four out of five successful projects were awarded contracts for over ≥75% of their total build out-capacity. Moreover, three out of five projects were awarded a contract for their total build-out capacity. This demonstrates that hedging against volatile electricity prices through securing a CfD contract is still the preferred route to market for developers.

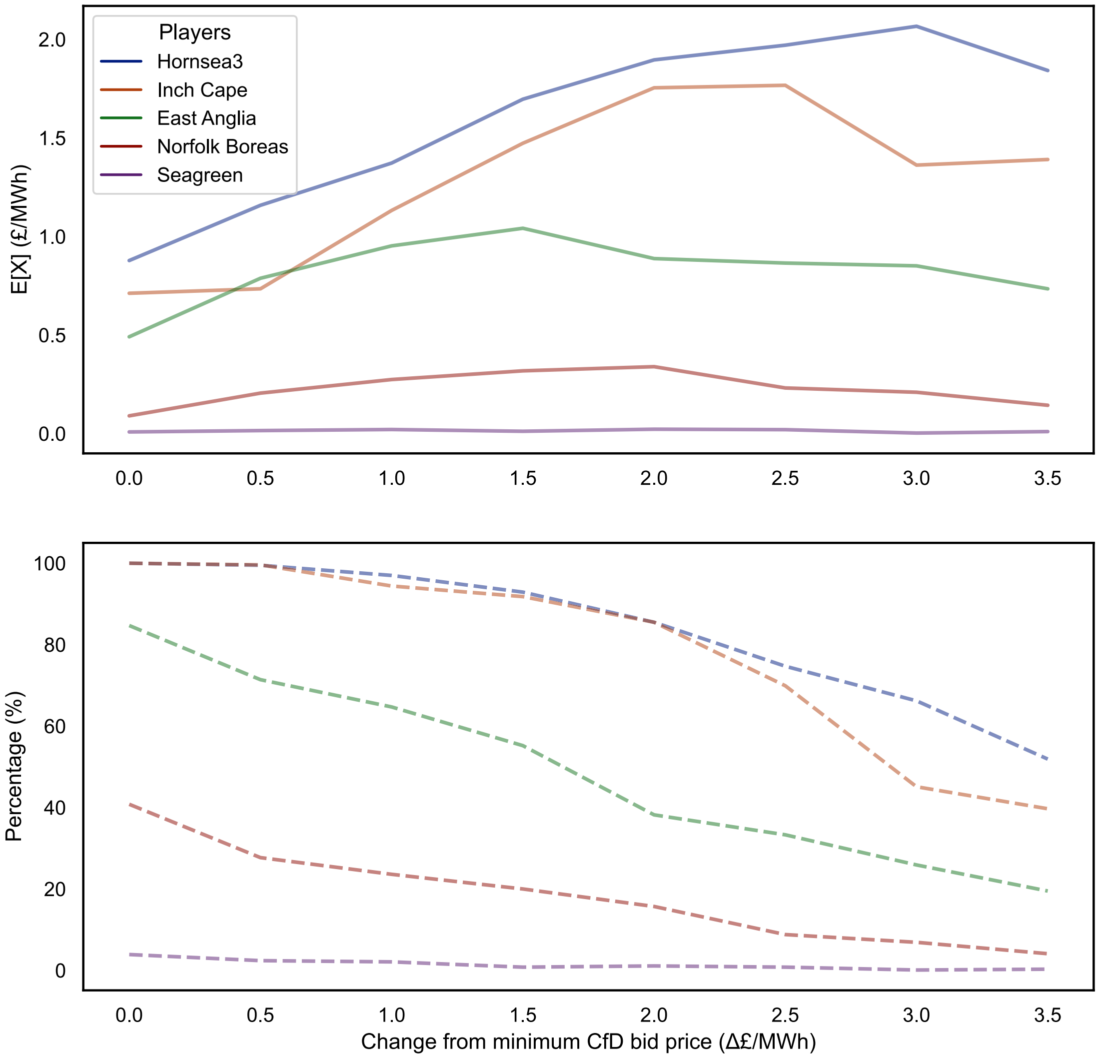
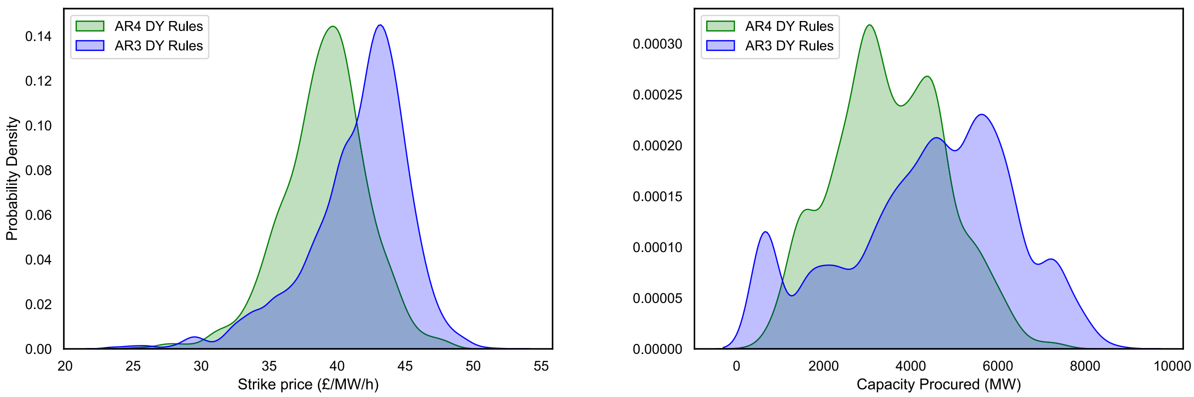


Fig. 11. Incentive for different players to engage in bid-shading is highlighted by the change in E[X]. The effect of bid-shading on the probability of winning is also shown.



(a) First delivery year

(b) Second delivery year

Fig. 12. Probability density function illustrating the effect of the delivery year rule change on the estimated strike price and capacity procured.

4.3.1. *Coexist price*

The estimated competing capacity used for the pre-auction analysis was estimated from the consenting documents available on the National Planning Inspectorate Website. The consenting documents stipulate the maximum build-out capacity of the wind farms. Typically, developers will build out to this maximum capacity but may differ slightly due to turbine power ratings and other limitations. As a result, the eligible capacities have been updated in Table 6. As developers typically aim to have a CfD cover the entirety of their site, the auction results represent the best estimate for the actual capacities of each of the consented sites. Additionally, Moray West signed a PPA (power purchase agreement) for 350 MW of its capacity at an undisclosed price [53]. This reduces

Table 6
Overview of AR4 Pot 3 auction results [18]. Successful projects are shown with a strike price.

Project	Owner(s)	Eligible capacity (MW)	Capacity (MW)	Strike price (£/MWh)
Inch Cape	Red rock power	1080	1080.00	37.35
East Anglia 3	Scottish power	1373.34	1373.34	37.35
Norfolk Boreas	Vattenfall	1800	1396.00	37.35
Hornsea 3	Ørsted	2852.00	2852.00	37.35
Moray West	Ocean winds	510	294.00	37.35
Seagreen 1A	SSE	1075	–	–
Seagreen	SSE	500	–	–
Total		**8735**	**6994.34**	

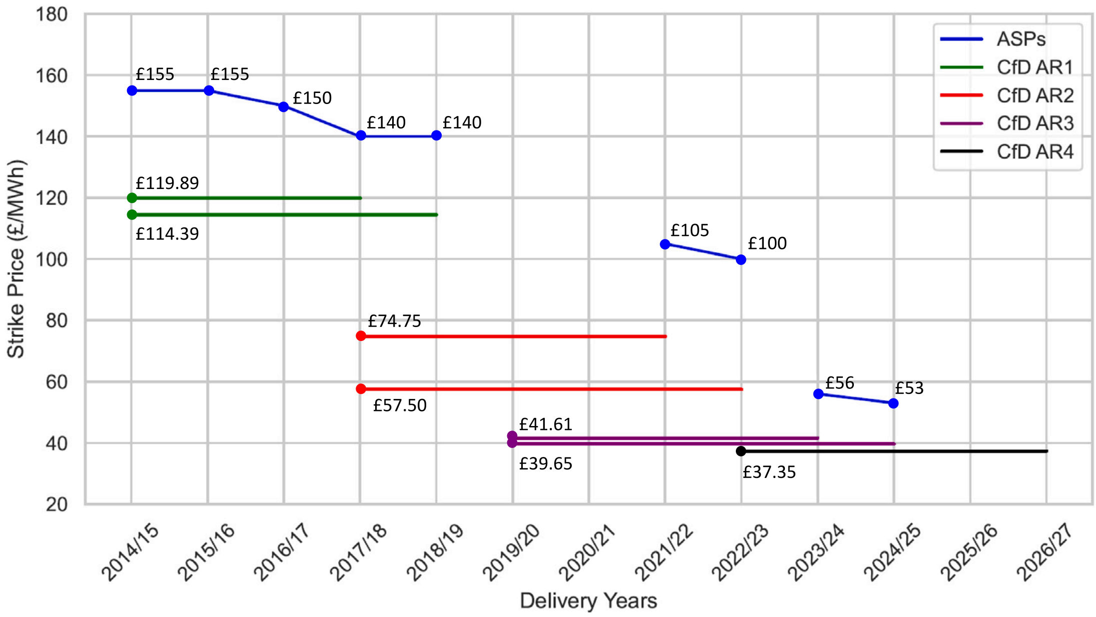


Fig. 13. Offshore Wind CfD strike price historical results [15–18], demonstrating sustained CfD strike price reduction.

the amount of capacity Moray West will likely bid from 850 MW to 510 MW. Therefore, the actual eligible capacity for each site has been updated post-auction and can be seen from Table 6.

Using the same methodology outlined in Section 3.2.1, the new coexist price is £37.23/MWh. As the coexist price is a function of total eligible capacity, developers can raise this price by reducing the total capacity submitted in their bid. For example, Moray West submitted a bid of 294 MW instead of the total 510 MW that they were eligible to submit. This means Moray West's view on total submitted capacity is reduced by 216 MW to 8520.34 MW. The new coexist price for this calculated amount of eligible capacity is £37.35/MWh, the same price as the auction results.

The budget impact of all successful bids is £172 million; approximately £38 million of additional subsidy budget was unused. This unused budget represents an extra £0.63/MWh possible increase in strike price, or a further 1524 MW of total capacity subsidised. The inefficient use of budget by developers is a disadvantage of adopting a risk-averse bidding strategy, such as bidding at the coexist price. This *optimum* price was not achieved as winning developers would have factored in Seagreen and Seagreen 1A bidding into the auction when calculating the coexist price. In reality, Seagreen and Seagreen 1A, the only unsuccessful projects, either did not adopt the coexist strategy or did not submit bids into the CfD auction. As the auction is sealed-bid, the successful developers would not have known the bid price of either Seagreen or Seagreen 1A (see Fig. 14).

The coexist analysis shows that developers are highly likely to have followed a risk-averse auction strategy and bid at a price which guarantee's them a CfD contract. The stochastic analysis has indicated that each project's median bid price (Fig. 9) is likely to be higher

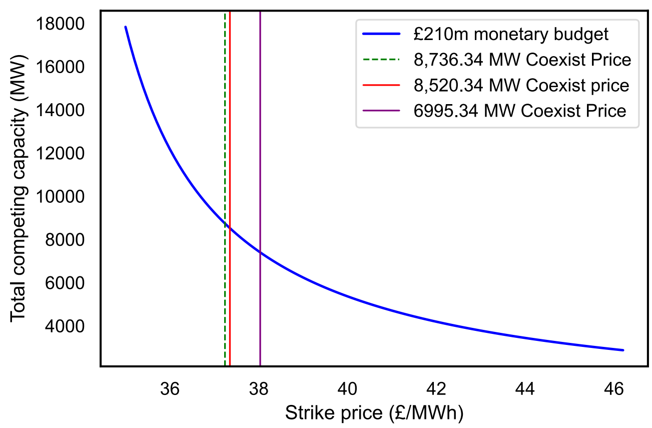


Fig. 14. Post-auction analysis of affordable capacity results and identification of coexist price.

than the coexist price obtained of £37.35/MWh. One possibility is that projects may have adjusted hurdle rates to ensure a CfD bid price at the coexist price and therefore accept a reduction in profitability of their developments. Results demonstrate that the CfD is still primarily the preferred route to market for large-scale offshore wind developments (as explained in Section 4.3). Risk-averse bidding in CfD auctions can be attributed partly to additional costs incurred by developers due to missing out on a CfD contract and delaying construction for a year as projects wait for the next CfD auction. From a policy standpoint, the auction is well designed and ensures allocation efficiency. The auction rules ensure competitiveness and, in light of increasing supply chain pressures, have resulted in further CfD cost reductions. However, the low prices are likely to increase the probability of developers experiencing the winner's curse, resulting in the non-realisation of projects [42]. Under continual pressure to accept decreasing CfD prices, developers may look at alternative route-to-markets, particularly in light of the maturation of the corporate PPA market [5].

4.4. Comparison of auction results and prediction

There is currently no published literature which has analysed using simulation the described Case Study. For this reason, a comparison with previously available work is not possible. Therefore, a direct comparison between the auction results and the simulation allows for the analysis of the methodology and the identification of any limitations.

The award of subsidy largely follows the estimated merit order of projects as shown in Fig. 9. The four cheapest projects, Hornsea 3, Inch Cape, East Anglia 3 and Norfolk Boreas, as predicted from the stochastic simulations, were all awarded a CfD contract. The three projects Hornsea 3, Inch Cape and East Anglia, which won a contract to cover the entirety of their build-out capacity, are the three projects estimated to win with the highest certainty (as demonstrated in Fig. 10. This demonstrates that the actual auction results well replicate the pre-auction prediction of the likely winners (demonstrated in Table 6. However, Moray West, which is predicted by the simulations to have a very low chance of winning, was awarded a contract. This can be explained in parts due to the project's hybrid financing approach. As the PPA price is unknown, it is difficult to model the CfD bid price required by the project. This introduces more uncertainty and further complexity associated with estimating auction outcomes.

The strike price AR4 result achieved of £37.35/MWh is 5% lower than the most likely estimate from the stochastic simulations. The AR4 result is obtained in approximately 11% of auction simulations. There are several possible explanations for this, owing to the limitations of the model. Firstly, the model relies on inputs from a cost assessment tool, which is used to generate cost data for each site. As the outputs from the auction simulation depend on the cost assessment tool, any inaccuracy in cost estimation for the offshore wind farms would lead to incorrect auction predictions. Secondly, the case study uses the same wholesale electricity price forecast for all developers. In reality, developers may use more or less optimistic forecasts than the one used in the simulation. Therefore, the simulation does not capture the effect of using different wholesale electricity price forecasts. Thirdly, developers bid according to their cost bid price in the stochastic simulations. In CfD auctions, developers can strategically bid lower than their estimated minimum CfD bid price to guarantee themselves an award of a contract. One form of strategic bidding is to vary the required IRR of the development to bid at the coexist price. This work does not consider lowering the bid price below the minimum CfD bid price.

5. Conclusion

This paper has introduced a novel methodology for developers and policymakers to analyse CfD auctions. The analysis is useful for developers to prepare a dominant bidding strategy, which mitigates the winner's curse and so reduces the risk of non-realisation, and is valuable for policymakers to test allocation efficiency. A previously validated stochastic cost modelling tool, which utilises the publicly available site and project-specific data, is used to generate stochastic cost estimates for the different competing projects in a Case Study. The Case Study replicates AR4 with information only available to developers before the auction. Cash flow analysis over the lifetime of the projects is used to estimate a distribution of CfD bid prices for each player. The auction is simulated thousands of times using the different estimates of CfD bids, which produce stochastic auction outputs, which characterise the significant uncertainty experienced by developers. Developers can use the outputs to determine a bid strategy in the context of the given probabilities. The paper has demonstrated how each developer's incentive to deviate from cost differs. The incentive to deviate from cost is achieved through identifying a bid price which maximises the expected value of auction pay-off for each player. Finally, the effect of a rule change on this auction has been investigated. This rule change simplifies the role of delivery years and is analysed by modelling the auction using AR3 rules and then comparing it to the results of the AR4 simulation. This gives developers and policymakers a deeper understanding of what effect this change will have on auction dynamics. Finally, the actual AR4 results are compared to the stochastic pre-auction simulations.

The simulation of this CfD auction has demonstrated that the most likely strike price, as predicted by the analysis, is £39.26/MW, 5% lower than the actual auction results. Post-auction analysis has demonstrated that the strike price was largely determined by a risk-averse coexist strategy, with projects bidding at a price which would ensure the award of a CfD. The analysis successfully identified the most likely winners of the auction. Estimated merit orders are useful to assess their projects' competitiveness and align their bidding strategy accordingly. The results of the game-theoretic simulations have found that player have an incentive engage in bid shading, where the level of incentive varies between projects. The projects lower down on the merit order (i.e. cheapest projects) have a larger incentive to deviate from cost in an attempt to increase pay-off. Shading ones bid decreases the allocation efficiency, and should be mitigated against policy makers, such as through the introduction of stringent pre-qualification criteria which result in significant sunken costs. Finally, an analysis of the delivery year rule changes demonstrates that it makes the auction more competitive for developers and puts further downward pressure on CfD bid prices. Excessive downward pressure on awarded CfD bid prices increases the risk of the non-realisation of projects. Therefore, policymakers face a trade-off between increased risk of non-realisation and minimising subsidy payments (i.e. minimising cost to tax-payer).

Interesting expansions of this work could be to increase the *smart* capabilities of all players in the game-theoretic analysis to investigate what effect it would have on the expected value if all players are attempting to optimise at once.

CRediT authorship contribution statement

Nicholas P. Kell: Conceptualization, Methodology, Software, Validation, Investigation, Data curation, Writing, Visualization. **Ernesto Santibanez-Borda:** Supervision, Writing – review & editing. **Thomas Morstyn:** Supervision, Writing – review & editing. **Iraklis Lazakis:** Supervision, Writing – review & editing. **Ajit C. Pillai:** Supervision, Writing – 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.

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: RF\202021\20\175.

References

[1] EU Framework. Long-term low greenhouse gas emission development strategy of the European union and its member states. 2020, p. 772–7.
[2] EU Commission. Directive of the European parliament and of the council. 2021.
[3] Amazo A, Dertinger A, Jakob M, Wigand F. Auction design and renewable energy financing. 2021.
[4] BEIS. Contract length analysis for feed-in tariff. 2013.
[5] PwC. Financing offshore wind: A study commissioned by invest-NL. 2020.
[6] Kreiss J, Ehrhart KM, Haufe MC. Appropriate design of auctions for renewable energy support – Prequalifications and penalties. Energy Policy 2017;101:512–20.
[7] Bowman EH, Moskowitz GT. Real options analysis and strategic decision making. Organ Sci 2001;12:772–7.
[8] Oxera. CfD auctions, bidding strategies, and insights from auction theory. Agenda 2014.
[9] Kreiss J, Ehrhart KM, Haufe MC. Appropriate design of auctions for renewable energy support – Prequalifications and penalties. 101, 2017, p. 512–20, Elsevier Ltd,
[10] Ausubel L, Cramton P. Demand reduction and inefficiency in multi-unit auctions. Digit Repos Univ Maryland 2002;12:227–58.
[11] Zeithammer R. Strategic bid-shading and sequential auctioning with learning from past prices. Manage Sci 2007;53:1510–9.
[12] NERA. Gale force competition auctions and bidding strategy for offshore wind. 2018.
[13] Kell NP, van der Weijde AH, Li L, Santibanez-Borda E, Pillai AC. Simulating offshore wind contract for difference auctions to prepare bid strategies. Appl Energy 2023;334:120645.
[14] Anatolitis V, Welisch M. Putting renewable energy auctions into action – An agent-based model of onshore wind power auctions in Germany. Energy Policy 2017;110:394–402.
[15] BEIS. Contracts for difference allocation round 1 results. 2015.
[16] BEIS. Contracts for difference allocation round 2 results. 2017.
[17] BEIS. Contracts for difference allocation round 3 results. 2019.
[18] BEIS. Contracts for difference allocation round 4 results. 2022.
[19] Myerson RB. Optimal auction design. 5, 1981,
[20] BEIS. Contracts for difference scheme for renewable electricity generation allocation round 4: Allocation framework. 2021.
[21] BEIS. Contracts for difference scheme for renewable electricity generation allocation round 5: Allocation framework. 2022.
[22] DECC. Contract for difference: Final allocation framework for the october 2014 allocation round. 2014.
[23] National Grid ESO. Contracts for difference allocation round 4: Pre-application activities guidance. 2022.
[24] BEIS. Contracts for difference scheme for renewable electricity generation. 2019.
[25] BEIS. Contracts for difference - methodology used to set administrative strike prices. 2021.
[26] Zakaria A, Ismail FB, Lipu MS, Hannan MA. Uncertainty models for stochastic optimization in renewable energy applications. Renew Energy 2020;145:1543–71.
[27] Brückmann R. What is the development of WACC for wind power in the 28 EU member states-and why? Strommarkttreffen 2019.
[28] Noothout P, de Jager D, Tesnière L, van Rooijen S, Karypidis N, Brückmann R, Jirouš F, Breitschopf B, Angelopoulos D, Doukas H, et al. The impact of risks in renewable energy investments and the role of smart policies. DiaCore Rep 2016.
[29] Tesniere L, de Jager D, Noothout P, Boutsikoudi S, Brückmann R, Borek F, Naydenova I, Nicola S, Valach B, Dukan M, et al. Mapping the cost of capital for wind and solar energy in south eastern European member states. In: ECOFYS Netherlands BV. 2017.
[30] Wind Europe. Financing, and investment trends, the European wind industry. 2019.
[31] Pratt SP, Grabowski RJ. Cost of capital. 2008.
[32] Brealey RA, Myers SC. Capital investment and valuation. 2003.
[33] Dukan M, Kitzing L. The impact of auctions on financing conditions and cost of capital for wind energy projects. Energy Policy 2021;152:112197.
[34] Hürlimann C, Bengoa DS. Corporate finance in renewable energy investments-a review about theory and practice. Glob Bus Econ Rev 2017;19(5):592–631.
[35] Wilson R. Auctions of shares. Q J Econ 1979;93:675–89.
[36] Goeree JK, Offerman T. Competitive bidding in auctions with private and common values. Econ J 2003;113(489):598–613.
[37] Li R, Svoboda AJ, Oren SS. Efficiency impact of convergence bidding in the california electricity market. J Regul Econ 2015;48(3):245–84.
[38] Engelbrecht-Wiggans R, Kahn C. Multi-unit auctions with uniform prices. Econom Theory 1998;12:227–58.
[39] Bajo-Buenestado R. A survey on auctions in electricity markets: The challenges of recent advances in auction Theory. USAEE working paper No. 14-185, 2014.
[40] Wolfram CD. Strategic bidding in a multi-unit auction: An empirical analysis of bids to supply electricity. Working paper 6269, National Bureau of Economic Research; 1997.
[41] Matthäus D. Designing effective auctions for renewable energy support. Energy Policy 2020;142:111462.
[42] Kreiss J, Ehrhart K-M, Haufe M-C. Appropriate design of auctions for renewable energy support – prequalifications and penalties. Energy Policy 2017;101:512–20.
[43] Welisch M, Poudineh R. Auctions for allocation of offshore wind contracts for difference in the UK. Renew Energy 2020;147:1266–74.
[44] Anatolitis V, Welisch M. Putting renewable energy auctions into action – An agent-based model of onshore wind power auctions in Germany. Energy Policy 2017;110:394–402.
[45] Kell NP, Santibanez-Borda E, Morstyn T, Lazakis I, Pillai AC. Dealing with uncertainty while developing bid strategy for CfD auctions. In: 43rd IAEE international conference. 2022.
[46] Mesa. Agent-based modeling in Python 3+. 2016.
[47] Welisch M, Kreiss J. Uncovering bidder behaviour in the German PV auction pilot insights from agent-based modellings. In: IAEE. 2019.
[48] Mora EB, Spelling J, van der Weijde AH. Global sensitivity analysis for offshore wind cost modelling. Wind Energy 2021;24:974–90.
[49] PINS. National infrastructure planning. 2022.
[50] 4C Offshore. Global offshore wind farm database. 2022.
[51] BEIS. Department of energy & climate change - dynamic dispatch model. 2021.
[52] BEIS. Electricity generation costs. 2020.
[53] reNEWS. Ocean winds lands off-take deal for moray west. 2022.