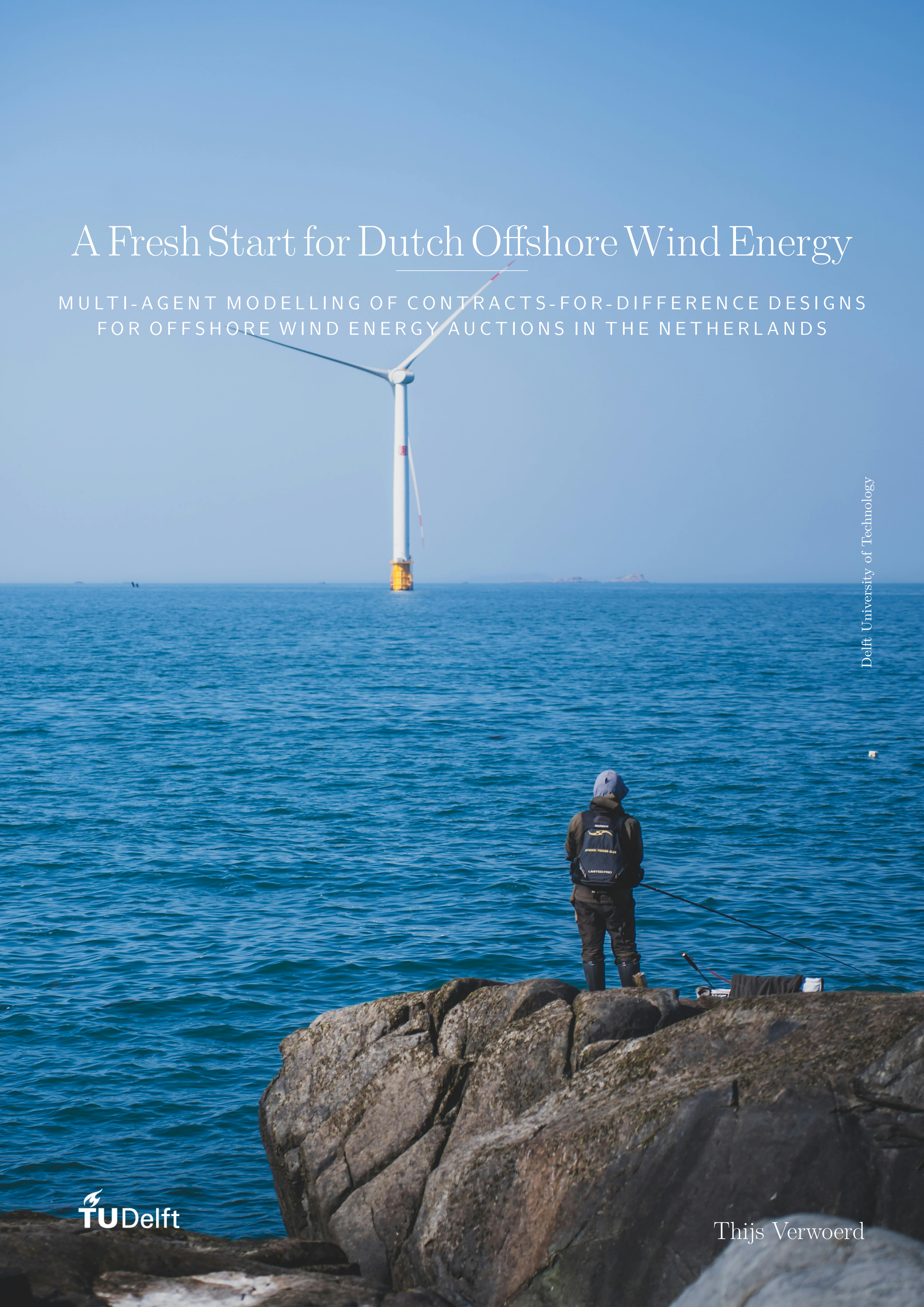

A Fresh Start for Dutch Offshore Wind Energy

MULTI-AGENT MODELLING OF CONTRACTS-FOR-DIFFERENCE DESIGNS FOR OFFSHORE WIND ENERGY AUCTIONS IN THE NETHERLANDS

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"A Fresh Start for Dutch Offshore Wind Energy"

Multi-Agent Modelling of Contracts-for-Difference Designs for Offshore Wind Energy Auctions in the Netherlands.

by

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Executive Summary

The Dutch offshore wind sector has come to a crossroads as recent tenders, IJmuiden Ver Gamma A and B and Nederwiek, have either attracted no bids or been postponed. This happened due to rising development costs, subsidy-free tender designs by the government and uncertain electricity prices. In the past, the Netherlands utilised a one-sided Contract-for-Difference mechanism before moving to tender without financial support. This led to zero-subsidy bids by offshore wind developers, who gambled on favourable electricity prices. In response to the failure of the recent tenders, a coalition of market parties called for the introduction of two-sided CfDs. This thesis studies which CfD design will actually best enable the Dutch Government to reach its target of 40 GW by 2040, whilst balancing the trade-off between minimising the public support costs and maximising developer participation under uncertain electricity prices and costs.

To address this complex issue, this research builds a multi-agent model in Python using the Mesa library, which enables the simulation of Dutch offshore wind tender auctions whilst incorporating bidding behaviour and strategy. The previous literature provides three different CfD designs: the one-sided CfD, the two-sided CfD and the Financial CfD. Each CfD is simulated in the model under a single-unit, pay-as-bid pricing tender format, with auctions being held twice a year until 2040. Each developer calculates a break-even strike price based on an NPV = 0 strategy, using individual beliefs about future electricity prices spread across three price levels and individual cost parameters, adjusting their risk appetite after each round based on the auction outcome. The model is then subjected to Monte Carlo Simulations, a sensitivity analysis and scenario analysis. The performance of each CfD is determined by the following metrics: deployment success rate, total subsidy cost, mean total number of exited agents per run, mean number of participating agents per tender, mean number of distinct winners per run, ceiling price rejection rate, and mean winning strike price.

The research yields the following insights. From a developer's perspective, CAPEX and capacity factor have the greatest impact on the strike price bid, more than OPEX or electricity price expectations. Furthermore, the ceiling price is the primary constraint on successful deployment. Under baseline conditions, the ceiling price rarely constrains developers. From the results of the ceiling price experiment, it is clear that the ceiling price acts as a market participation constraint, and its influence becomes apparent once the ceiling price level is lowered, leading to more unsuccessful simulations that fail to reach the 40GW target. Under high-cost scenarios, the two-sided CfD collapses almost entirely, succeeding in only 1.3% of the simulations. The one-sided CfD meets the target in only 19.2% of runs, whereas the financial CfD is the most robust, achieving a deployment success rate of 61.2%. This resilience is directly caused by the reference-generator bidding approach, in which the developer's bid is partially decoupled from their costs, allowing lower bids below the ceiling price. The designs

also produce very different fiscal effects. The financial CfD swings the most in fiscal results, from roughly €119bn in support costs under a low-price, high-cost scenario to a clawback of approximately €265bn under high realised electricity market prices. The two-sided CfD offers the largest recovery when electricity prices are high and costs are low, but it is easily disrupted when costs rise. The one-sided CfD results confirm the worries of market parties, where market competition forces zero-subsidy bids and the CfD offers no protection against rising costs. It exposes the government to subsidy costs when realised prices are low, whilst generating no revenue when prices rise.

This thesis contributes to the CfD literature by developing a model that compares all three designs within a single multi-agent framework with repeated auctions. No single design performs best on both deployment success rate and cost, so the choice depends on the government's preference, the first important finding of this thesis. A government prioritising the 40 GW target amid cost uncertainty should favour the financial CfD, which offers the most reliable path to the target but carries the risk of high subsidy costs or a substantial clawback. A government prioritising fiscal certainty in a stable cost environment may prefer the two-sided design, which delivers the largest net recovery, but collapses the hardest and provides the least competition. For both cases, the ceiling price policy plays a crucial role, with the current fixed price of 104€/MWh diminishing the viability of deployment under rising costs. This leads to the second significant finding of this thesis: a fixed ceiling price set above expected bids under normal conditions is rarely active but becomes the decisive constraint on achieving the target when costs rise. The ceiling price acts by excluding participants rather than by changing prices, making its calibration as important as the choice of CfD design itself.

Offshore wind is the largest component of the Netherlands' plan to decarbonise its electricity and industrial sector, and the design choices made for the future offshore wind tender auctions will play an important role in whether the target of 40GW is reached. CfDs offer several possible pathways towards the desired target, but the Dutch government must also take into account the potential subsidy costs relative to deployment success and the ceiling-price policy that creates their desired market. Otherwise, it could lead to a repeat of the past failed tenders. Whether the Dutch government heeds that warning and reignites the offshore wind sector will be seen in the upcoming tenders.

Preface

You are going to read the thesis 'A Fresh Start for Dutch Offshore Wind Energy: A Multi-Agent Modelling Research Towards Contracts-for-Difference Designs in the Dutch Offshore Wind Tender Market', which has been written for the Master Thesis Project of the programme Complex Systems Engineering and Management at the TU Delft. During my time as a TU Delft student, I have developed an affinity for the offshore wind sector. It was the reason I chose to do the minor Offshore Wind energy at the Aerospace Engineering faculty of the TU Delft during my bachelor's degree, and why I chose to do my thesis in a relevant topic for this sector.

During the process, I have received valuable feedback from my supervisors, Petra Heijnen and Martijn Warnier of TU Delft, whom I would like to thank for meeting with me so often and for providing very helpful guidance when I lost myself in my tunnel vision. I would also like to thank Quintijn Broshuis from Capgemini for supporting me in developing my research and model.

A special thanks goes out to my fellow COSEM students who joined me in the faculty's silent study hall whilst it was 30 degrees outside. I would also like to thank my parents for their support. My mother, who provided mental support like no other and made sure that I was always in reach of a Granny Smith apple during the final weeks of writing this thesis. My father, who, after working for 30 years in the energy industry, gave me valuable advice and provided a very safe environment to chat and brainstorm about my thesis. During the writing of this thesis, my father lost his own dad. Even through this period of grief, my dad would make himself available to help me, even if it was for a brief period. I will never be able to thank him enough for moments like that, as I know how tough the last two years have been during the illness of my grandfather. My grandfather came from an academic background, as he would one day become dean of Erasmus MC in Rotterdam, and I would have loved to share my first research with him. I like to think that I have always been able to channel some sort of academic skill set because of him.

I hope that you enjoy reading my thesis,

Thijs Verwoerd

List of Abbreviations

Abbreviation	Definition
ABM	Agent-Based Model(ling)
ASP	Administrative Strike Price
CAPEX	Capital Expenditure
CF	Capacity Factor
CfD	Contract-for-Difference
CV	Coefficient of Variation
FID	Final Investment Decision
GW	Gigawatt
IEA	International Energy Agency
KPI	Key Performance Indicator
LCOE	Levelised Cost of Energy
LNG	Liquefied Natural Gas
MW	Megawatt
MWh	Megawatt-hour
NPV	Net Present Value
OPEX	Operational Expenditure
PAB	Pay-as-Bid
PBL	Netherlands Environmental Assessment Agency (*Planbureau voor de Leefomgeving*)
PVA	Present Value Annuity (factor)
RVO	Netherlands Enterprise Agency (*Rijksdienst voor Ondernemend Nederland*)
SDE++	*Stimulering Duurzame Energieproductie en Klimaattransitie* (Dutch renewable energy subsidy scheme)
TOWOZ	Tender Offshore Wind Operating Zone framework
WACC	Weighted Average Cost of Capital

Keywords: offshore wind; Contracts-for-Difference; agent-based modelling; auction design; bidding behaviour; energy policy; Dutch energy transition.

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1. Introduction

1.1 Problem Context

The past few decades have seen dramatic changes to the landscape of the North Sea. Resembling a new vegetable garden, new wind farms are planted throughout its ocean each year. This rapid expansion has made offshore wind a cornerstone of the Dutch energy transition. Dutch wind farms produced almost 5 GW in 2024 and are a major contributor to reducing CO2 emissions in the Netherlands (Statista, 2025).

However, in the past year, several tenders from the Dutch government have gone without receiving a bid. IJmuiden Ver Gamma – A and B have been put back in their respective boxes and postponed because of the lack of interest ((Memija, 2025)). The Nederwiek tenders have also been moved to 2027 by Minister Hermans of Climate and Green Growth (NOS Nieuws, 2025). The unwillingness to produce abundant renewable energy sources has been caused by the reduced subsidies provided by the Dutch Government, the rising installation costs and the slow electrification of the industrial sector (Eneco, 2025). This has been accompanied by an increase in offshore wind costs. The past Dutch support mechanism, a one-sided Contract for Difference (CfD) under the SDE++ scheme, provides a revenue floor but allows developers to retain all upside when market prices exceed the strike price (Jansen et al., 2022). In competitive conditions, this CfD has historically produced zero-subsidy bids in the Dutch market, as developers gambled on rising electricity prices to finance their projects (Welisch and Poudineh, 2019; Ason and Dal Poz, 2024). Under today's more uncertain price environment, however, the same mechanism leaves developers exposed to downside risk without adequate compensation, discouraging participation (Đukan et al., 2025).

In an attempt to revive the installation of wind farms in the Dutch North Sea, a coalition of 21 organisations, operating in and around the production of offshore wind energy, has signed a letter calling for a restructuring of the subsidy framework. The companies have argued that the Dutch government should introduce two-sided Contracts for Differences (CfD's) in the offshore wind sector (Eneco, 2025). They also call for a backup plan, such as SDE++ and policies, to incentivise the electrification of the industrial sector. In response, the government has reintroduced subsidised support for the upcoming tenders through the temporary TOWOZ support mechanism, which, at the back end, follows the existing SDE++ scheme, with a PBL-advised maximum tender amount of 104 €/MWh acting as the ceiling price (Lensink and Henriquez, 2026; Ministry of Climate Policy and Green Growth, 2026). Two-sided CfDs would be a new mechanism for the offshore wind market in the Netherlands (De Vries et al., 2026). However, the design of the support mechanism for the longer term remains undecided, and the ceiling price policy has already proven contentious as the level set for the IJmuiden Ver Gamma tenders has since been raised from 104 €/MWh to 117€/MWh (van Economische

Zaken en Klimaat, 2026).

CfDs use a guaranteed minimum electricity price for the producer, which reduces the investment risks by protecting the producer's income. On the other hand, if the market price is higher than the agreed-upon maximum price, the government benefits financially. The policy has already been introduced in other European countries producing wind energy at sea. For example, Belgium, the United Kingdom and recently Denmark have all introduced CfDs to encourage the installation of offshore windfarms (Jenkinson, 2024; Ason and Dal Poz, 2024). Belgium switched from a one-sided CfD to a two-sided CfD in 2024, and Denmark will introduce the same mechanism in 2025, but definitive results on its effectiveness are not yet available (Jenkinson, 2024; Ason and Dal Poz, 2024). The UK implemented a one-sided CfD in 2013 with multiple rearrangements since, which was successful in increasing offshore wind installation but has also run into issues with increasing installation costs (Ason and Dal Poz, 2024).

Although Dutch organisations want a similar mechanism, there is still a lot of uncertainty about whether the introduction of CfDs will solve the issues the government is facing. There is uncertainty about which design will increase the number of bids for tenders and whether the strike prices will be affordable for the government. This thesis aims to analyse the performance of different CfD designs within the Dutch offshore wind market. Using a multi-agent model, this thesis will conduct sensitivity and scenario analyses to provide insights into how developer bidding behaviour and market outcomes differ across the three designs under varying electricity price and cost scenarios.

1.2 Research Question

Based on the identified problem in the current Dutch offshore wind energy sector, this thesis has determined the following main research question it will aim to answer:

Which Contract-for-Difference policy best enables the Dutch government to achieve its 40 GW offshore wind target by 2040, whilst balancing the trade-off between minimising public support costs and maximising developer participation under uncertain electricity market prices and development costs?

To answer the main research question properly, other sub-questions also need to be addressed to provide sufficient insights into the problem and the main research question. Knowledge of how CfD auctions work and how developers approach them is needed to properly model and replicate them, especially over time when multiple auctions follow one another. An understanding needs to be created of how developers approach these CfDs differently, and, if so, what changes in their bidding approach. This leads to the first sub-question:

- *How do wind developers change their bidding strategies based on previous auction rounds?*

Once this behaviour is understood, the research can turn to the designs themselves. With the uncertainties surrounding the sector and the concerns that the market parties have voiced, it is also important to understand how the CfD's change market results under an uncertain electricity market and cost supply chain. As each design distributes risk differently, the second sub-question examines how this shapes bidding and the resulting strike prices:

- *How do different Contract-for-Difference designs influence bidding strategies and strike-price outcomes?*

These designs must also hold up under the uncertainty of volatile prices and costs in today's markets and remain within the government-set ceiling price. The final sub-question therefore asks which design, and at which ceiling price level, remains robust when these conditions shift:

- *Which CfD auction design, and at which ceiling price level, is the most robust to uncertain electricity prices and cost levels?*

2. Literature Review

2.1 Literature Selection

To provide an extensive foundation of knowledge, the relevant literature has to be identified. The search process, described in Table 2.1, demonstrates how this thesis identified the literature supporting the research. The keywords and search queries enabled targeted searches for literature on CfD designs and offshore wind auctions in Scopus (Table 2.2). But it also allowed this research to broaden the understanding of tender auctions by also using keywords such as RES and renewable energy sources. Furthermore, this thesis also searched for studies and reports from governmental institutions to provide more background information on past- and future policy. CORDIS of the European Union and the RVO of the Dutch government provided databases of policy literature that contributed to this thesis. Some articles found also snowballed into additional literature. For example, Kell et al. (2023) led to the finding of Anatolitis and Welisch (2017), Welisch and Poudineh (2019) & Woodman and Fitch-Roy (2019). The final set of relevant literature identified for this review comprised 31 references, of which 9 were found through snowballing.

Table 2.1: Literature selection process

Step	**Description**
Search date	01-02-2026 – 01-05-2026
Database	Scopus, CORDIS (EU) & RVO (NL)
Keywords	Contract for differences, Offshore wind, Auctions
Language	English
Time frame	2011 – 2026
Context criteria	Studies focusing on contract for differences, particularly those applied to the offshore wind energy sector or other renewables in the Netherlands
Screening process	Title → Abstract → Conclusion → Sub-headings → Full Text
Articles found by snowballing	9 articles
Final articles selected	31 articles

Table 2.2: Literature search strings

#	Search string
1	(“Offshore wind”) AND (“Contracts for differences” OR “CfD”)
2	(“Netherlands”) AND (“Contracts for differences” OR “CfD”) AND (“Offshore wind”)
3	(“Offshore wind”) AND (“Contracts for differences” OR “CfD”) AND (“Auctions”)
4	(“Contracts for differences”) AND (“Renewable energy sources” OR “RES”) AND (“Auctions”) AND (“Design”)
5	(“Offshore wind”) AND (“Auctions”) AND (“Netherlands”)
6	(“Offshore wind”) AND (“Auctions”) AND (“Design”)
7	(’Auction’) AND (’Design’) AND (’Modelling’)

2.2 Contract-for-Difference Designs

A Contract for Difference (CfD) is a financial support instrument which can be used as a market-based policy. Its purpose is to protect renewable energy generators against volatile market prices and encourage investments for low-carbon technologies (Dai et al., 2025; Ason and Dal Poz, 2024). The core principle of a CfD is to provide a certainty of revenue against a specific agreed-upon strike price, which is determined through an auction (Kell et al., 2023). The increased certainty of revenue then reduces the weighted average cost of capital (WACC), making it easier to receive financing for projects (Helistö et al., 2025). Unlike support schemes like feed-in tariffs or premiums, CfDs feel less unfair during times of high electricity prices (Ason and Dal Poz, 2024).

One-sided CfD

Previous literature has provided insights into the different possible designs of CfDs, two of which are used for tenders throughout the offshore wind energy sector in Europe. Firstly, there is the one-sided contract for difference (Figure 2.1). The government accepts a strike price that acts as a floor: the difference between the market price of electricity and the strike price is compensated if the market price is below the strike price (Đukan et al., 2025). If the market price rises above the strike price, then the profits remain with the generator (Đukan et al., 2025). The Netherlands currently uses a similar mechanism in their SDE++ policy. One-sided CfDs are known to allow full profit retention for the generator, resulting in zero-subsidy strike prices in Dutch auctions. Generators take on the risk by gambling that the electricity price itself will be sufficient to finance their investment, saving the government a lot of money (Đukan et al., 2025).

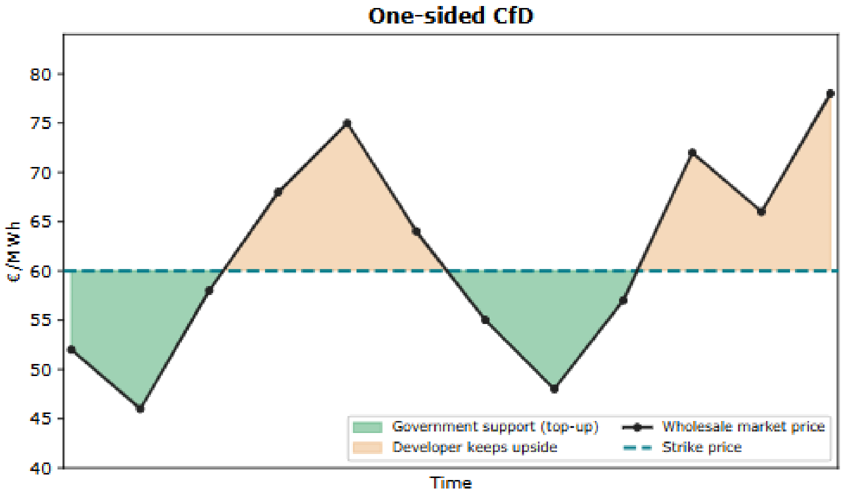

Figure 2.1: Framework of a One-sided CfD, based on the work by Đukan et al. (2025)

Two-sided CfD

The other mechanism is a two-sided CfD, used by, e.g., Denmark and the UK. As with the one-sided CfD, an auction takes place in which developers can bid a strike price to win the tender. Again, the government will compensate for the lost revenue if the market price falls below the strike price. However, the owner of the farm must return any profit earned if the market price is higher than the strike price (Figure 2.2). Two-sided CfDs provide long-term stability for the developer and government as the revenue is split (Đukan et al., 2025). However, two-sided CfDs provide little incentive for the developers to base their generation on the market. As they get a guaranteed price for producing electricity, they will still produce whether the price is low or when the electricity grid is congested, or as Schlecht et al. (2024) call it "Produce-and-Forget".

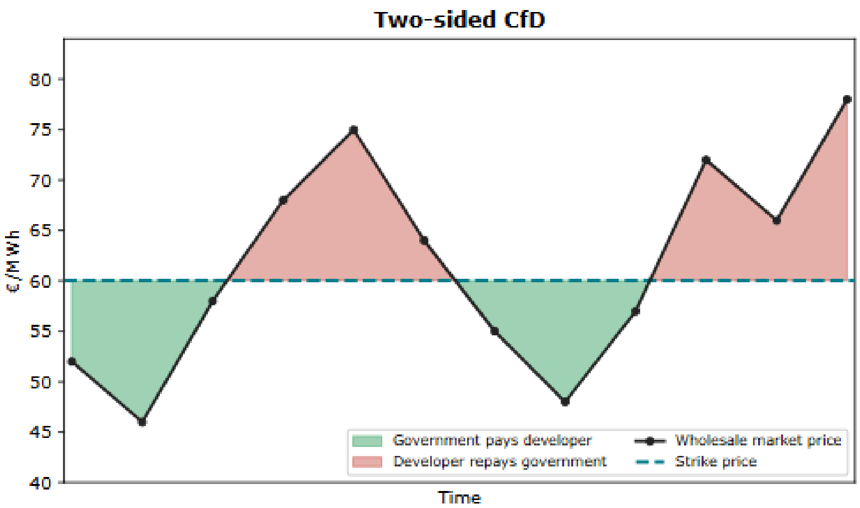

Figure 2.2: Framework of a Two-sided CfD, based on the work by Đukan et al. (2025)

Financial CfD

There is also a third type of CfD that is not implemented within a country's policy framework. Schlecht et al. (2024) discuss a contract for difference where the government pays the generator a fixed hourly rate. In return, the generator pays the government the revenue a 'standard' reference generator would have made during that hour (Figure 2.3). The government determines the output for the reference generator by judging the weather conditions of the tender's location. If the generator's output is more efficient than the reference benchmark, then they are rewarded for their innovation and can keep the profit. This also means that if their wind farm does not perform as well as they had expected, they owe the government the difference. This follows the principle of asset independence, where generators aren't incentivised to just keep producing electricity, even when the grid is full, like they would with two-sided CfD's.

Schlecht et al. (2024) recommend an independent reference generator derived from meteorological data combined with a representative wind farm. Because no developer's own production enters the calculation for reference generator parameters, none can influence it through strategic dispatch, securing asset independence. The implementation of the independent reference generator is complex, as it requires a credible weather-based reference and precise wind speed data to translate it into market revenue. A different approach uses a zonal aggregate reference: the average revenue per MW from all wind farms operating in a bidding zone over the CfD period. Johanndeiter et al. (2025) adopt this method for their research. The zonal aggregate is simpler than a weather-based reference and reflects the actual operating environment of nearby offshore wind farms. Its weakness is that each developer's output contributes to the average, which means that the reference can be influenced by the developer's own dispatch. Gupte (2025) shows that under a zonal-aggregate, strategic curtailment during low-price periods can shift the average upward and increase a developer's net profit. Furthermore, A financial CfD can create more risk for a developer if their windfarm is not able to deliver the required capacity and its output falls below the reference generator, as they will still owe the government the difference. This adds more complexity to the bidding process for developers, in addition to the already complex capacity bidding (Johanndeiter et al., 2025). However, Financial CfDs can provide both stability for the developer and efficiency for the government because of this decoupling mechanism.

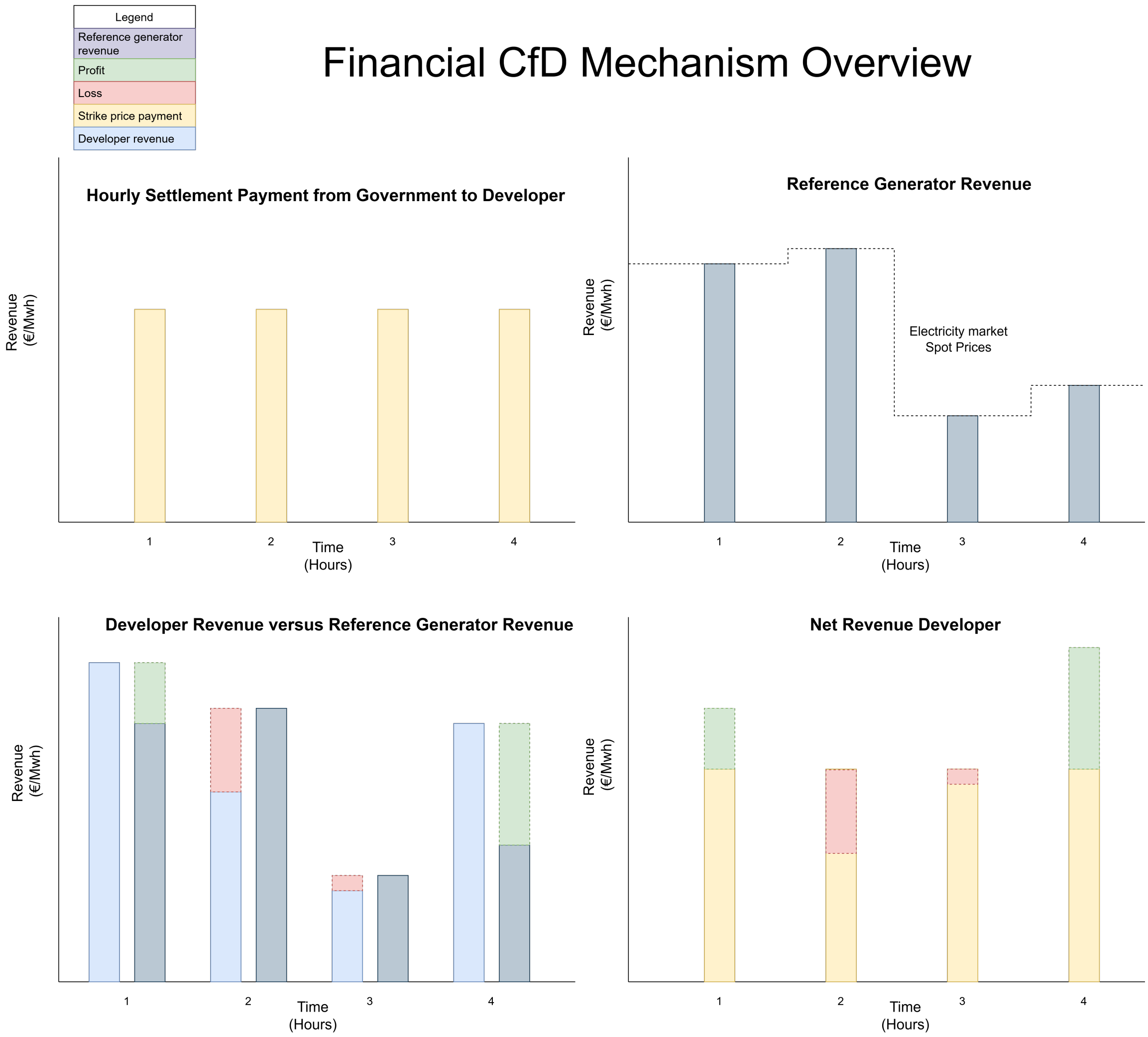

Figure 2.3: Illustration of the Financial CfD framework, based on the work by Schlecht et al. (2024)

Gupte (2025) also conducts further research on different CfD designs for the offshore wind sector in the North Sea region and examines how each design is affected by hourly electricity prices after the auction has been won. It finds that production-based CfDs relieve pressure from price risks but increase the volume risk. It also finds financial CfDs to be the most effective design. The research is limited by fixed, predictable electricity prices, whilst in reality these are uncertain. Van Delzen (2023) also studies CfD designs in the North Sea for offshore bidding zones. He identifies the volume risk offshore as a major issue because of low electricity prices, caused by wind energy. The study also shows that the optimal CfD design depends on the context of the system it is used in. It recommends that for all systems, CfDs must be two-sided, have a long lifetime and be auction-based. However, the research doesn't specify the design of the auctions in which the CfDs are awarded.

2.3 Contract-for-Difference Case Studies

When implementing a contract-for-difference policy, the auction design differs per nation. The Auctions for Renewable Energy Support II (European Commission, 2018), published by the European Commission, analyses multiple case studies. The UK uses an auction format that allows multiple bids to be accepted, according to the latest AR3 auction round (Woodman and Fitch-Roy, 2019). The government sets an Administrative Strike Price (ASP), which serves as the ceiling price for each technology and caps the maximum support that any developer can receive (Kell et al., 2023). The design determines the strike price by placing bids in a merit order and accepting bids until the capacity cap is reached. Each bid must be placed at the same time as the rest, meaning the UK applies a static multi-unit auction. Under a uniform pricing system, the highest bid sets the strike price for the remaining bidders. Because of this system, the UK achieved a high realisation rate (Woodman and Fitch-Roy, 2019). The UK design is complex, making it hard for smaller developers (Woodman and Fitch-Roy, 2019).

For offshore wind tenders, Denmark used a static single-unit tender with a two-sided CfD design (Larsen et al., 2020). Unlike the UK, Denmark applies a pay-as-bid pricing rule in tenders, meaning wind farm developers receive the exact strike price they bid in the auction. The “Thor” tender in Denmark is even more complex. It doesn’t use the current market price; instead, it determines cash flow based on a reference price set at the average price from the year before. This mechanism should further encourage the developer to generate efficiently and to follow market behaviour (Larsen et al., 2020). Rather than capping the per-MWh strike price directly, Denmark applies a lifetime cap on total CfD payments in both directions: a ceiling on how much support the state pays out and a ceiling on how much the developer repays when market prices exceed the strike price (Jansen et al., 2022). In the Thor auction, this payment-capped, two-sided design produced near-zero bids, as the cap left developers largely exposed to wholesale prices, effectively turning the tender into a seabed-lease mechanism (Jansen et al., 2022).

France uses a single-unit tender with pay-as-bid pricing, offered by the national regulatory agency CRE (Jansen et al., 2022). The first offshore wind tenders, held in 2011 and 2013, awarded feed-in tariffs with 20 years of support, judging each bid based on socio-economic contribution, the environmental assessment, and strike price. France is the only country that had a tender auction policy that included both a floor and a ceiling price per round: the first two tenders operated with floor prices in the range of €115–140/MWh and ceiling prices of €175–220/MWh (Jansen et al., 2022). The third tender, held in 2017 for the Dunkirk site, introduced a two-sided CfD with a ceiling price of €90/MWh but no floor (Jansen et al., 2022). The approach of bounding competition from both above and below sets France apart from other CfD auction policies, which typically use only a ceiling price. Looking ahead, the French energy plan foresees gradually declining ceiling prices across future rounds, from €60/MWh in the 2020–2021 tender to €50/MWh in the 2023 tender round. (Jansen et al., 2022).

Greece also uses a pay-as-bid format for a two-sided CfD, but in a 30-minute dynamic auction. They have used this format in multi-unit auctions, awarding the last bid to the developer whose project fits the remaining capacity. Poland applies a two-sided CfD and differentiates between projects above and below 1 MW (Diallo et al., 2019). Polish tenders are a multi-unit format with a static bidding moment and pay-as-bid pricing. However, due to the complex auction design, which combines different renewable energy sources and places offshore wind in the third category, offshore wind has had only limited success. In Portugal, the system offers multiple tenders at a given time, whilst prohibiting developers from winning more than 50% of the available capacity (Del Rio et al., 2019). This prevents a single developer from becoming a monopolist.

The Netherlands uses a single-unit tender in which the government provides the site characteristics and has TenneT deliver the grid connection (Jansen et al., 2022). Under the SDE++ framework, the auction selected the lowest bid, with the government setting a ceiling price calibrated by the Netherlands Environmental Assessment Agency (PBL) (Lensink and Henriquez, 2026). This ceiling was defined as sufficient for the majority of developers to expect a positive business case, and in the past, the winning strike prices have consistently fallen below. The first two Borssele tenders cleared at €72.7/MWh and €54.5/MWh, respectively, almost 50% below the maximum agreed in the energy action plan (Jansen et al., 2022). As costs continued to fall, the Netherlands became the first country to offer zero-subsidy offshore wind tenders, in which developers competed on ecological performance and system integration rather than on the strike price to win the tender (Jansen et al., 2022). This shift made the ceiling price concept irrelevant, although the government has since returned to subsidised procurement. A PBL-advised ceiling price of €104/MWh will be implemented for the 2026 IJmuiden Ver Gamma tender, following the 2025 Nederwiek round that attracted no bids (Lensink and Henriquez, 2026).

2.4 Auction Design and Modelling

This section reviews how bidding behaviour within auctions is modelled in the literature, establishing the behavioural rules the model requires to capture how developers change their bidding strategies across successive auction rounds, the focus of the first sub-question. It also analyses the modelling processes of prior literature to support the production of the model and cost modelling for this research.

2.4.1 Wind energy

Kell et al. (2023) use an ABM model to simulate two-auction rounds with one smart agent who predicts the bids of the other agents for UK auctions. The agents calculate their bids with the Net Present Value (NPV) to achieve a strike price bid necessary to make their project financially viable. Their CAPEX and OPEX are modelled stochastically to provide different uncertainties for the agents. In the UK, CfDs are offered in a multi-unit uniform-price auction once every few years. The auctions are capped by a maximum budget that can be allocated across multiple tenders. Their simulation demonstrates that a 1200 MW project could gain £135 million in additional profit over the CfD contract by bidding above cost, at the expense of a 25 percentage point reduction in the probability of winning. The study finds that if bidders submit large bids relative to the budget, their influence on the price increases. The study also finds that developers can see massive gains in profit against a small deficit in the probability. Anatolitis and Welisch (2017) also use an ABM approach to study onshore wind auctions in Germany and compare pay-as-bid and uniform pricing. It begins by differentiating the agents by size and capital. The model runs 14 auction rounds, in which the cost decreases if an agent wins the auction, and agents adjust their bidding strategy based on the outcome of the previous auction. In this model, the agents calculate their possible profit whilst accounting for the bid-shading behaviour of other agents. The research finds that pay-as-bid pricing requires lower support funding, but works inefficiently as it incentivises bid shading.

Welisch and Poudineh (2019) also studied the UK, using auction results from 2014 to 2017. They also use an ABM model and assign agents different risk appetites and views on their cost reductions over the tender's lifetime. The research compares auctions where bidding agents learn from the past and auctions where they have to do all the bidding at once. It also implements a possible penalty in some auctions to study truthful bidding and the realisation of the projects. They show through simulation that implementing a stringent non-delivery penalty restores truthful bidding, and that holding regularly scheduled annual auctions, rather than the UK's one-shot format, allows bidders to incorporate better information about technology cost trajectories, further pushing bids closer to true costs. These studies show that similar pricing formats can cause different strategic incentives and that bidding behaviour is an emergent property. Anatolitis and Welisch (2017) establish that uniform pricing induces truthful bidding when projects are small, single-unit, and penalties are irrelevant. Kell et al. (2023) show that when projects are large relative to the budget, the multi-unit structure creates market power that incentivises overbidding. However, their ABM simulations largely ignore risk heterogeneity. Anatolitis and Welisch (2017) assume risk-neutral agents, and Kell et al. (2023) have one 'smart' agent which bases its bid on profitability optimisation, therefore ignoring risk aversion.

Malleret et al. (2024) aim to analyse whether offshore wind developers achieve the profitability they calculated when placing their initial winning bid. They find that the electricity price is the most uncertain factor, more than CAPEX and OPEX, thus bringing the most risk to the development. Therefore, the duration of the support CfD is important as longer contract durations subject the developers to shorter open market merchant revenues, protecting them from unpredictable electricity prices. Kotsiki (2025) also studies the effects of CfDs after the auction. He applies the NPV for strike price calculation in the electricity market. Over the lifetime of the windfarm, the strike price is solved for NPV = 0. In their model, the CfD only lasts for 15 years, after which there are 15 more years where the developer finds revenue in the open market. The bid calculation also includes a mark-up or risk premium. His model shows that exposure to merchant revenue can be a major risk for developers and that bidders' expectations of the long-term electricity prices directly affect their bids. Van Delzen (2023) similarly identifies volume risk as a concern for offshore wind energy, where low electricity prices caused by wind energy cannibalisation can erode future revenues. These studies collectively demonstrate that auction bidding is not just about project costs but about developers' views on the future evolution of the entire electricity market, an element that causes the winner's curse at a systemic level. Radov et al. (2016) provides an analysis of offshore wind auctions with insights towards the bidding strategy wind farm developers apply when entering these auctions. Radov et al. (2016) state that "More risk-averse bidders, or bidders with wider strategic objectives such as market share, may tend to bid lower, closer to their break-even price". In doing so, these developers do take on the risk that their bid might end up being too low, resulting in the so-called winner's curse. Therefore, bidding higher than the minimum LCOE not only means more profits but also protection against the cost uncertainty of wind farm development. The trade-off between winning the auction or enduring potentially harmful losses is the core of the bidding strategy for offshore wind developers.

2.4.2 Other auction models

Other studies that focus on auction design discuss other renewable energy sources, construction tenders and licenses and use Agent-Based Modelling as a research method. In their model, Danielsson and Özaras (2022) study solar PV auctions in Sweden. The research attributes specific agents with a waiting period for bidding to reflect the limited time and resources these companies have in reality. A uniform distribution is used to define the LCOE, project capacity and cost reductions for each agent. The model has 32 auction rounds, with a fixed capacity for each round based on the average capacity required to reach Sweden's solar PV target. This study finds that the cost per kWh decreases over time as more auction rounds are completed, although they argue that the allocation is not as efficient as pay-as-pricing incentivises bids above true cost. In the agent-based model designed by Torres et al. (2017), the regulator, responsible for distributing ATC licenses under a single-unit auction design, implements a maximum market share for the bidding agents. The agents in this model are also issued with a minimum profitability threshold between 7% and 12%. Elsayegh et al. (2020) model construction tenders where agents can handle different types of capacity sizes, meaning they can only bid on projects within their capacity range. The capacity range is determined by financial boundaries, where agents might find projects too expensive or too small/cheap. The study also constrains the agents from handling more than one bid at a time. After losing a bid, agents increase estimation accuracy and decrease their markup to improve future winning chances. Hailu et al. (2011) discusses how landholders will increase their strike price after winning a tender as they seek to increase their profitability. On the other hand, if an agent loses, they become more desperate to win the next auction. They also implement agents leaving their model if they lose multiple times in a row. In auction design, Hailu et al. (2011) state that uniform pricing formats encourage bids closer to the true cost as the marginal winner sets the price.

Furthermore, according to general auction theory, Jeitschko (1998) theorises that bidders who have not yet won an auction may become more aggressive in their bids over time. It also addresses different strategies for bidders based on risk and learning. The research uses pay-as-bid pricing for single-unit rounds and uniform pricing for multi-unit auctions. It finds that bidders use information from earlier rounds to update their beliefs about opponents and adjust their bids, knowing their actions will reveal information to their competitors. Other studies analyse the bidding behaviour more rigorously. Ioannou (2021) provides a framework for understanding the interaction between risk aversion and cost uncertainty in competitive bidding. He shows that the direction in which risk aversion shifts the optimal bid depends on which risk dominates: when the main risk is losing the competition, a risk-averse bidder bids lower to increase the win probability; when the main risk is losing money on the project, a risk-averse bidder bids higher to build a safety margin. In offshore wind CfD auctions, both risks are present simultaneously, and their relative importance shifts with market conditions, the CfD design, and the developer's financial position. No existing simulation model captures this dual-risk dynamic.

2.4.3 Cost modelling

In offshore wind studies that employ cost modelling, various approaches to stochastic distributions are presented to introduce heterogeneity in developer costs. The choice of distribution reflects the assumptions a study makes about what is known regarding the underlying cost structure and varies across the literature depending on data availability and modelling context. The literature identifies three distributions used to model cost parameters: uniform, normal, and triangular.

As mentioned before, Danielsson and Özaras (2022) uses a uniform distribution to define the LCOE and project capacity. The study discusses how the unavailability of cost data requires them to use a uniform distribution. Further use of uniform distributions in research on offshore wind costs is fairly limited.

The normal distribution is a more common approach in offshore wind studies. Ioannou et al. (2017) aim to replace deterministic offshore wind LCOE models with probabilistic variables. This allows the model to produce an output that is a distribution of possible cost values. For this research, Ioannou et al. (2017) chose a normal distribution because the ranges of values reported in the literature follow a similar distribution. They find that deterministic models severely underestimate investment risk compared with models that include stochastic variables. Similar to Ioannou et al. (2017), Amlashi and Baniotopoulos (2024) aim to study the LCOE for offshore floating wind farms using a probabilistic approach, rather than traditional deterministic methods. Due to a lack of reliable data, this research uses a normal distribution for its input parameters. They find that the LCOE outputs resemble a lognormal distribution.

Jåstad and Bolkesjø (2022) aim to quantify the expected market value of offshore wind farms whilst accounting for future uncertainties. They use two different distributions in their study. For various cost, demand, and efficiency parameters, a triangular distribution is used. The research uses only a normal distribution for fuel prices. The reasoning for these modelling choices is not supported by argumentation, but only applied as an assumption. Another study that discusses triangular and normal distributions is Kanyako and Baker (2021). This paper examines the uncertainty in future wind energy costs and its impact on global electricity generation. They fit a triangular distribution to 140 cost estimates and then pool the resulting distributions by averaging their probability densities, creating a single empirical distribution. After that, the study tests which theoretical distribution best represents the shape of the created empirical distribution. They find that a lognormal distribution is the most accurate, which aligns with the finding of Amlashi and Baniotopoulos (2024).

2.5 Knowledge Gaps

The literature extensively covers research towards different Contract-for-Difference designs and the practical uses of these subsidy mechanisms, as well as analysis of CfD auction outcomes using ABM models. Some studies focus on analysing the design properties of different CfD contract types without simulating their effect on auction outcomes, or simulating renewable energy auction dynamics under a single CfD design without varying the contract type itself. However, the review also clearly identifies a lack of research surrounding the implementation of different CfDs under auctions specific for the Dutch offshore wind sector. None of the sources recommends the use of uniform pricing or PAB pricing and multi-unit tenders as an alternative to the single-unit PAB pricing format the Netherlands currently uses. To my knowledge, there is no existing study that combines the effect of bidding behaviour and different CfD designs for market outcome simulations specific to the Dutch offshore wind energy sector.

Furthermore, according to the literature, the bidding strategy is determined by the trade-off between securing revenue certainty and winning the tender, yet existing simulation models do not examine this trade-off in depth. Anatolitis and Welisch (2017) assume risk-neutral agents, while Kell et al. (2023) model a single profit-optimising agent rather than all the agents, so neither captures heterogeneity in risk appetite across developers. As Ioannou (2021) examine, the direction in which risk appetite can move for a developer depends on the developer's trade-off approach, and given the uncertainty of the offshore wind sector, developers' approaches can differ. No existing simulation model captures this dual-risk dynamic across different CfD designs.

Electricity prices play an important role in research towards offshore wind auctions and CfD designs. Gupte (2025) studies how CfDs affect wind farm developers after the auction, and uses flow-based market coupling to determine endogenous electricity prices. These developers do have perfect foresight into future prices, creating a market in which they can easily change their strategy. Whilst Malleret et al. (2024) and Kotsiki (2025) show that electricity prices are the most uncertain factor facing developers and that bids depend on long-term electricity price expectations, they analyse whether developers earn the profit they initially expected when they won the auction, given uncertain electricity prices. What the literature does not study is the performance of different CfD designs in auctions when developers must determine their bids based on uncertain electricity price expectations. Since the expectations are uncertain and can differ, it remains unclear which CfD design performs best under varying prices.

The final gap identified in this literature review is the design of the ceiling price policy. Across the case studies, countries use different implementation methods. The UK sets a ceiling price per technology, France lowers its ceiling price each round and in the Netherlands, the PBL calibrates a fixed ceiling price to sit above the expected bids. However, this approach is flawed because the Dutch ceiling price assumes more favourable cost and market conditions than the market expects, resulting in most bids falling below the ceiling price (Lensink and Henriquez, 2026). The literature fails to study whether the fixed ceiling price policy actually hampers the auction viability, as Anatolitis and Welisch (2017) let the ceiling adjust dynamically above the winning strike prices so that it rarely constrains the market, while Kell et al. (2023) hold it fixed but simulate only a single auction round, so the effect of repeated bidding against a binding ceiling is unknown. How the level of a fixed ceiling price affects auction viability across different CfD designs remains a gap in the literature.

2.6 Performance criteria

The sources provide a variety of performance metrics for comparing results. The criteria can be grouped into three different categories: price outcomes, allocation effectiveness and market participation.

For the first group, this model will rely upon the average winning strike price and the total subsidy costs. The average winning strike price is a metric used by Kell et al. (2023), Jansen et al. (2022) & Welisch and Poudineh (2019) in their research on offshore wind energy auctions to compare different simulations. Kell et al. (2023) also uses the total subsidy cost to analyse how the government can meet its deployment target at the lowest possible cost. Further research by Schlecht et al. (2024) & Johanndeiter et al. (2025) also uses the total subsidy costs to measure the necessary net support costs for the financial CfD.

In the second category, allocation effectiveness, the model's results will be measured by the deployment success rate and the ceiling price rejection rate. The deployment success rate is defined as the share of runs that reach the 40 GW target within the allocated number of tenders. This metric is inspired by the project realisation rate Kell et al. (2023) use. In their research on energy auctions, Anatolitis and Welisch (2017) measure how often bidders are excluded from auctions because their costs are too high, leading them to place bids above the ceiling price. As the ceiling price is a key policy in the Dutch offshore wind sector, this model will also use the ceiling price rejection rate as a performance metric (Lensink and Henriquez, 2026).

The last group concerns market structure and participation. To determine the performance of a CfD auction design, we need to know whether the CfD can create a competitive market. Torres et al. (2017) study the winning concentration as an auction outcome in their agent-based model, showing that different designs lead to a diverse market or a market dominated by a few agents. Jansen et al. (2022) emphasises that lack of competition is an auction risk in the offshore wind sector, which is why this model uses the number of distinct winners as a performance metric. Further metrics on market participation are the number of exited agents at the end of each simulation and the mean number of participating bidders per round, inspired by the work of Hailu et al. (2011) & Elsayegh et al. (2020). The complete list of the performance criteria is the following:

- Average winning strike price bid
- Total subsidy costs
- The success rate: share of target-reached runs
- Ceiling price rejection rate
- Average number of exited developers
- Average number of distinct winners
- Average number of participating developers

2.7 Literature Findings

The literature review has provided background information on Contracts-for-Difference, auction designs and bidding behaviour and auction modelling based on literature as well as practical application. The review identifies three CfDs: One-sided CfD, Two-sided CfD and Financial CfD as possible Contract-for-Difference designs which can possibly be implemented by the Dutch Government. The one-sided CfD, which compensates developers only when the market price falls below the strike and allows full upside retention. The two-sided CfD returns that upside to the government in exchange for revenue stability, using the same compensation method as the one-sided CfD if the market price falls below the strike price. Finally, the financial CfD settles against a reference generator, thereby decoupling a developer's payment from their own output and rewarding those who outperform the benchmark. These three designs and their bidding strategies will be carried on to the modelling process described in the next chapter.

Secondly, the case studies show how CfD designs are implemented in practice in each country and which policies are included in each country's CfD auction design. The UK, Denmark, France, and the Netherlands each take a different approach, with the Netherlands using a single-unit pay-as-bid tender under a fixed, PBL-calibrated ceiling price set above expected bids. These case studies will allow the modelling approach to recreate a more realistic model.

Furthermore, the literature acknowledges that developers use different methods to determine their strike price for each CfD. Each developer has to make a trade-off between revenue certainty and a high enough bid and winning the tender with a low enough bid. The literature also discusses how agents may adjust their approach to an auction after winning or losing a previous one. Next to behaviour, the literature also provided insights to how costs are modelled stochastically in previous offshore wind research, with the normal distribution being the most common. These findings provide insight into bidding behavioural rules, electricity price expectations, and parameter distributions, which provide answers to the first sub-question.

Finally, the review identified several gaps in the literature which this thesis aims to address. Starting of, no existing study combines bidding behaviour with different CfD designs for the Dutch offshore wind sector. Existing simulations also do not capture possible differences in risk appetites across multiple agents or in future electricity price expectations. It also remains unknown how a fixed ceiling price affects the market after repeated auction rounds. To compare these designs with the model that addresses these knowledge gaps, the review has identified a list of performance criteria. The knowledge gained from the literature review will be carried over to the next chapter, where the research methodology will be discussed.

3. Methodology

The Dutch offshore wind sector is an extremely complex socio-technical system in which wind farm developers interact indirectly with one another by participating directly in government tender auctions. In this chapter, the model design and framework will be explained. Once the model has been designed, it will be subjected to Monte Carlo simulations, sensitivity analysis, ceiling price experiment and scenario analysis.

3.1 Modelling approach

This thesis aims to address these knowledge gaps identified in Chapter 2 by using a Multi-Agent model to simulate CfD auctions. The model will be built in Python with the Mesa library (version 3.3.1). This framework supports the implementation of agent-based systems and allows the implementation of behavioural traits and limitations. In the literature, Agent-based modelling is an important approach for simulating agents' bidding behaviour. It allows agents to handle heterogeneous inputs and behave differently. It also allows agents to change their behavioural traits during model execution. The differing behaviour can be studied, allowing the researcher to understand levels of auction participation, competition, and design. These emergent properties operate at a higher level than the individual level, which, e.g., system dynamic modelling would not be able to analyse Dam et al. (2012). The Multi-Agent model will also allow for this research to test different policy approaches towards auction design. By experimenting with different CfD mechanisms by altering the input parameters and auction framework, this study can compare the results. Furthermore, the model will be subjected to Monte Carlo simulations and followed by a sensitivity analysis. ABM can also reduce uncertainty through its modelling approach. By creating a transparent model that can check its plausibility against specific rules, this approach helps validate the resulting system behaviour (Dam et al., 2012). When modelling offshore wind developers and their behaviour within different auction designs, an ABM model can attempt to replicate real-world decisions.

3.2 Model design

The model this study has created aims to replicate Dutch offshore wind tenders. In the model, there are two classes of agents. A single government agent that produces a tender at each time step. There will also be a population of offshore wind farm developer agents. The latter will be able to bid on the tender issued by the government. The government will then choose a winner and award the developer for winning the tender. The government and all offshore wind developer agents will store the auction results and adjust their strategies for the next auction, creating a competitive, dynamic market. In this design, the three different contract-for-difference mechanisms will be simulated. This chapter will describe the model design, agent characteristics, bid calculation, and how behaviour changes over time.

3.2.1 Model framework

Number of agents

In addition to the single government agent, the model will include 15 wind farm developer agents. The number of agents is fixed for the start of every simulation. The offshore wind market is small and has few participants (Jansen et al., 2022). There have not been many offshore wind tenders in the Netherlands compared with neighbouring countries such as the UK and Germany, so the exact number of participants in the Netherlands is unknown. However, for example, the research by Anatolitis and Welisch (2017) uses roughly 30 agents in their model to study onshore wind auctions in Germany. Since the market of the Netherlands is significantly smaller than that of Germany and the UK, this model chooses to estimate that 15 agents represent Dutch offshore wind farm developers in the model

Timesteps

In the model, a single auction takes place at each time step, resembling the single-unit auction format used in the Netherlands. The run ends if either the target of 40 GW is reached or all tenders are completed. The number of timesteps (T) per model run will depend on the average number of tenders ($\bar{a}$) auctioned per year until 2040 (Equation 3.1).

$$T = \min\left(\bar{a} \cdot (2040 - y_0 + 1),\ t^*\right) \tag{3.1}$$

- $\bar{a}$ is the total number of tenders available
- $t^* = \min\left\{ t : \sum_{k=1}^{t} C_k \geq C^* \right\}$ is the first timestep at which the summed awarded capacity $\sum_{k=1}^{t} C_k$ reaches the target C^*, with C_k the capacity awarded in tender k

For the model, we need to determine what each timestep represents. The Netherlands had a total offshore wind energy capacity of 4.7 GW in 2025 (RVO, 2025). To reach this total, the Dutch government has auctioned 10 tenders since the first one took place in 2016 (table A.1). This averages 1.11 tenders per year. However, it does include the latest tender, Nederwiek Zuid I-A, which received no bids. To reach the target of 40 GW by 2040, with a current capacity of 4.7 GW, the Netherlands depends on the amount of capacity tendered per round. In the past, the average tendered capacity has been ≈ 1011 MW. Thus, this trend will require ≈ 35 tenders to reach the 40 GW, which is slightly less than 2.5 tenders per year. Looking ahead, the policy is far more ambitious, aiming to auction 8 tenders in 2027 (table A.2). However, two of these tenders, both IJmuiden projects, were originally planned in 2026. Due to the Nederwiek I-A tender receiving zero bids, the government decided to postpone the auctions to 2027 (NOS Nieuws, 2025). The fact remains that without the postponement, 6 tenders were going to take place in 2027. This is a significant increase, given the sector's historical progress. Not only will there be more tenders, but capacity will also increase. The average capacity of the planned tenders ≈ 1300 MW, almost 300 MW more than the current average. If we compare the progress of the Netherlands to the other countries that are building offshore wind parks in the North sea. Denmark has a total capacity of 2.65 GW in 2025 and has averaged 2.8 tenders per year since 2005. The smallest tender auctioned in Denmark has a capacity of 200 MW Wind Europe (2025). The UK has a total capacity of 17 GW in 2025 and averages 11.8 tenders per year since 2014 Wind Europe (2025). However, the UK auction system works very differently from those of Denmark and the Netherlands. The UK has budgeted for auction rounds every few years, using a multi-unit format as described in Chapter 2.2. This means that some bids are only awarded a small amount of MW. For example, the “Forthwind” project was awarded 12 MW in 2019, so the average is slightly inflated. Based on the progress in the Netherlands history and their neighbouring countries, this model will assume that 2 tenders are auctioned per year.

CfD duration

The estimated total lifetime of an offshore wind farm is 30 years, of which 15 years are supported by a CfD subsidy policy (Kotsiki, 2025). In the past, tenders that included subsidy support in the Netherlands also had a 15-year lifetime (Wind Europe, 2025; Lensink and Henriquez, 2026; Jansen et al., 2022). This means that the merchant tail, when the wind farm is exposed to the electricity market, spans from year 16 tot year 30.

Electricity price series

The model also generates an electricity market price series that continues until the final auctioned CfD’s lifetime ends to calculate the government’s total subsidy costs. The electricity price (λ) is calculated for each timestep t and is drawn around the average electricity price μ_P, with a stochastic disturbance (ε_t). To prevent extreme values, any draw falling outside two standard deviations of the mean is rejected and redrawn until it lies within these bounds, so that the price follows a truncated normal distribution (Equation 3.3). The average electricity price is based on the mean hourly Dutch market price retrieved from the European Wholesale Electricity Price dataset in the Appendix (Table A.5). The post-crisis average electricity price from 2023 to 2026 is 91.88 €/MWh and is the mean used in the model (Ember, 2025). The standard deviation is derived using a method described in (Malleret et al., 2024). Malleret et al. (2024) uses a coefficient-of-variation method, which this model applies to the pre-crisis period of 2015 to 2019, to replicate a relatively stabilised price level (Equation 3.2). This method uses the relative volatility rather than the absolute standard deviation to ensure consistency with the mean electricity price level. The standard deviation σ_P therefore has a value of 27.44 €/MWh. This is close to the observed standard deviation of 29.50 €/MWh in the 2026 Dutch electricity market (Ember, 2025). Choosing 29.50€/MWh on its own would be unreliable, as the sample size is too small. However, it can serve as a confirmation that the final standard deviation is within a realistic range.

$$\sigma_P = CV \times \mu_P = 0.2987 \cdot 91.88 = 27.44 \text{ €/MWh} \tag{3.2}$$

$$\lambda_t \sim \mathcal{N}(\mu_P, \sigma_P^2) \quad \text{subject to} \quad \mu_P - 2\sigma_P \ \leq \ \lambda_t \ \leq \ \mu_P + 2\sigma_P, \qquad t = 0, \ldots, N_P - 1 \tag{3.3}$$

Each yearly price is therefore drawn from the normal distribution and accepted only if it falls within the bounds. Draws outside the range are discarded and redrawn. This sampling approach preserves the shape of the distribution without accumulating values at the boundaries, which a hard clamp to the bounds would otherwise produce. The price series must be long enough to cover the final contract right up to the end of its support period, so its length N_P must be at least the number of auction rounds plus the length of a CfD contract (3.4).

$$N_P \geq N_{\text{auctions}} + N_{\text{CfD}} - 1 \tag{3.4}$$

This price series is consistent for each CfD and each model run. This modelling choice has been made to allow for a sensitivity analysis of wind farm developer parameters. This provides insights into the effect of the bidding behaviour and auction design separately from the electricity market. In a further scenario analysis, the price series is deliberately changed to analyse the effect of the developers' expectations not aligning with the eventual future.

3.2.2 Government agents

Tender capacity

The role of the government agent is to provide tenders through an auction mechanism to expand offshore wind capacity. The capacity of the tenders can vary depending on the location, the amount of available space, and the grid connection capability (Jansen et al., 2022). At each time step, the government issues a single tender for auction. The government agent produces the capacity of these tenders using a uniform distribution between an upper and lower bound meant to resemble the current offshore wind market (Equation 3.5). Since the sizes of these tenders vary widely and the size of future tenders is unknown, the model uses a uniform distribution. The range of tender capacity distribution is based on current and projected offshore wind farm sizes. The bounds are set symmetrically around the average planned tender size of 1300 MW, which results in a 600 MW lower bound and a 2000 MW upper bound.

$$C_{tender} \sim \mathcal{U}(C_{\min}, C_{\max}), \quad C_{\min} = 600 \text{ MW}, \quad C_{\max} = 2{,}000 \text{ MW} \tag{3.5}$$

Ceiling Price

When a ceiling price is in place, the government will accept bids only from wind farm developers priced below the ceiling. All bids above the ceiling price are disregarded and cannot take part in the auction. In this research, the purpose of the ceiling price is to protect the government from astronomically high strike-price bids and prevent extremely high support budgets. It also incentivises developers who are above the ceiling price to innovate and improve their technology to drop below. The ceiling price level is crucial to the auction, as it affects the number of potential competitors. Based on the literature, the government can either adjust the ceiling price based on previous results or set a fixed ceiling price. The Netherlands has also chosen a fixed ceiling price of 104 €/MWh for the upcoming 2027 tenders as its base level, following the PBL recommendation (Lensink and Henriquez, 2026). This model will implement the second approach, as it is similar to the Netherlands' policy framework Lensink and Henriquez (2026). The ceiling price p_{ceiling} is held constant across all timesteps, in contrast to a dynamic ceiling that would adjust to the outcomes of previous auction rounds. However, the literature review also made it clear that the ceiling price level affects auction viability and has yet to be studied. Therefore, an experiment at different ceiling price levels will be conducted, as further explained in section 3.7.

Reference generator

Another important parameter of the government agent is the reference generator they provide for the financial CfD, based on the work of Schlecht et al. (2024), as explained in section 2. The reference generator is attributed its own capacity factor. This capacity factor stays constant throughout the model, just as the capacity factors of the developers (Schlecht et al., 2024). The capacity factor of the reference generator does not change over time because the framework of a financial CfD already encourages developers to follow market behaviour. So, further incentivization of innovation by increasing the reference generators' capacity factor is unnecessary. This approach of an independent reference generator is favourable because it is unsusceptible to market interference, whereas a bidding zone average could be subject to self-curtailment (Gupte, 2025). Introducing a weather-driven reference revenue variation that Schlecht et al. (2024) discusses would add complexity specific to the financial CfD, which is absent from the other two designs, breaking the symmetrical design and making comparative analysis unreliable. Therefore, the full-weather implementation is simplified into a capacity factor in this model.

The capacity factor for the reference generator is 41.8%, which is lower than the developers' mean of 46%. This modelling decision is based on the reported capacity factors in Lensink and Henriquez (2026). Choosing the lowest projected capacity factor among the wind farms resembles a competitive capacity factor with room for competition. This allows offshore wind farm developers to produce turbines that can outperform the reference generator and ensures that the tender is accessible to the average developer.

Subsidy costs

In each simulation, the model calculates what expenditure the government has made to support the offshore wind tenders. Once tender k has been awarded, the government supports the offshore wind developer for the duration of the CfD. For the one-sided CfD, the annual payment $G_{k,t}$ is the difference between the strike price S_k and realised electricity market price λ_t if the λ_t is lower than the strike price S_k, multiplied by the developer's annual generation $g_{\text{own},k}$ (Equation 3.6).

$$\mathrm{G}_{k,t} = \max(0,\ S_k - \lambda_t) \cdot g_{\text{own},k} \tag{3.6}$$

For the two-sided CfD, payments go both ways: the government supports the developer when λ_t is below the strike price, and the developer repays the profit when λ_t is above the strike price (Equation 3.7).

$$\mathrm{G}_{k,t} = (S_k - \lambda_t) \cdot g_{\text{own},k} \tag{3.7}$$

Since the financial CfD mechanism works differently from the other CfDs, the calculation process is more elaborate (Equation 3.8). The government pays an annual support cost based on the developer's strike price bid S_k. The developer returns a payment equal to the revenue that the reference generator, $\lambda_t \cdot g_{\text{ref},k}$, would have produced during that time span. The total subsidy costs G_{tot} for the government are equal to the sum of all the expenditures during the support period for each CfD (Equation 3.9). A negative net total indicates a recovery for the government, and a positive net total means that the government paid more in support costs.

$$G_{k,t} = S_k^{\text{fin}} \cdot g_{\text{own},k} - \lambda_t \cdot g_{\text{ref},k} \tag{3.8}$$

$$G_{\text{tot}} = \sum_k \sum_{j=0}^{N_{\text{CfD}}-1} G_{k,\,t_k+j} \tag{3.9}$$

3.2.3 Wind farm developer agents

The developer agents represent an offshore wind farm developer in the Dutch offshore wind energy sector. These developers participate in auctions and bring out bids for certain tender projects. The developers calculate their strike price using a set of parameters and change their behaviour throughout the simulation depending on auction results. The specific behavioural characteristics and parameters will be discussed in the upcoming section.

CAPEX & OPEX

Each developer is assigned a set of starting parameters. Based on prior literature, a normal distribution will be used to model the stochasticity of CAPEX and OPEX. To prevent unrealistic low cost levels, the distribution is bounded symmetrically at ±15% of the mean. Bounding the distribution in this way keeps the sampled costs within a realistic range, as is done in other offshore wind cost models such as Kell et al. (2023). The standard deviation σ_{CAPEX} has been set to 2% of the mean to attempt to shape the cost distribution similarly to Ioannou et al. (2017); Amlashi and Baniotopoulos (2024), who apply this distribution when data is limited. The valuation is also based on the findings of Malleret et al. (2024) where the reported LCOE standard deviations for European projects are around 1-2%. The valuation is further supported by the assumption that Dutch offshore wind farms are not responsible for transmission costs, since these are borne by TenneT, thereby narrowing the range. As discussed in chapter 2, some offshore wind cost studies find that LCOE outcomes follow a lognormal or triangular shape. However, these describe the distribution of a computed LCOE across many combined cost components. Therefore, this model uses a single input cost parameter created with a normal distribution. The same shape and standard deviation apply for the OPEX and the capacity factor to retain consistency throughout the model (Equation 3.10 & Equation 3.11).

If we compare the CAPEX of the Netherlands and Germany with those of the other European countries, the CAPEX value is much lower (Table A.3). The biggest reason for the decrease in CAPEX is that the connection of the transmission grid is not included in their tenders, as TenneT is responsible for providing these services (Jansen et al., 2022). The reported CAPEX for the realised Hollandse Kust West VI and VII projects was 2.24-2.26 M€ /MW respectively. In the report by Lensink and Henriquez (2026), the projected CAPEX for the upcoming tenders was estimated to be around 2.54-2.60 M€ /MW. However, in this report, there was significant pushback from offshore wind organisations in the market, who stated that the costs had been underestimated. Based on these sources, the model makes a rough assumption of 3.2 M€/MW as the mean CAPEX μ_{CAPEX} that will be used in the distribution.

$$\text{CAPEX}_i \sim \mathcal{N}(\mu_{\text{CAPEX}},\, \sigma^2_{\text{CAPEX}}), \quad \text{CAPEX}_i \in [0.85\,\mu_{\text{CAPEX}},\ 1.15\,\mu_{\text{CAPEX}}] \tag{3.10}$$

Similar to the CAPEX, the input value for the OPEX is based on data from previous wind farms (table A.4). Malleret et al. (2024) reports values of 10.4€/MWh for Hollandse Kust Zuid I-II and 16.8€/MWh for Borssele III-IV. Lensink and Henriquez (2026) projects OPEX costs of approximately 42–47 €/kW/year, which, at the planned full-load hours of 3,659–3,852 h/yr, correspond to roughly 11–13 €/MWh. Under the same school of thought that these costs have been underestimated, the model assumes a mean OPEX μ_{OPEX} value of 15 €/MWh.

$$\text{OPEX}_i \sim \mathcal{N}(\mu_{\text{OPEX}},\, \sigma^2_{\text{OPEX}}), \quad \text{OPEX}_i \in [0.85\,\mu_{\text{OPEX}},\ 1.15\,\mu_{\text{OPEX}}] \tag{3.11}$$

Electricity price forecasts

To calculate their bid, a developer needs to know electricity prices to estimate their revenue. Electricity prices are highly unpredictable, and it is unreliable to assume a single price over the lifetime of a wind farm. Therefore, the model has three electricity price levels: a low electricity price, a medium electricity price and a high electricity price. Each level resembles a possible future electricity price and is the same for all the developers. The three price levels are derived from the baseline electricity price and its standard deviation, as established in Equation 3.2. The medium level p_{mid} is set equal to the mean electricity price μ_P of 91.88€/MWh. The low and high levels are calculated by one standard deviation σ_P below and above the mean, giving $p_{\text{low}} = \mu_P - \sigma_P = 64.44$€/MWh and $p_{\text{high}} = \mu_P + \sigma_P = 119.32$€/MWh. This spread represents a plausible band of future price outcomes around the expected level, with each developer assigning their own belief weights to the three levels. These price levels remain constant throughout the entire simulation run. As this thesis will discuss later, the price levels will undergo a sensitivity analysis to assess their effect on the model outcomes.

Each developer has their own perception of what electricity prices will be in the future. To reflect this perception each electricity price level is attributed with a certain "weight"(Equation 3.13, Equation 3.14 & Equation 3.15). Here u_1 and u_2 are two independent draws from a uniform distribution, and $u_{(1)}$ and $u_{(2)}$ are those two values ordered from smallest to largest (Equation 3.12). The weight represents the likelihood that the electricity price level will occur in the future, in the developer's view. The weights for the electricity price all have the same lower bounds δ, where $\delta = 0.05$ (Equation 3.13), to ensure that every developer considers every price level as a futuristic possibility. This is a modelling choice to ensure that every developer recognises that each electricity price level is a future possibility. $(1 - 3\delta) = 0.85$, guaranteeing that the rest of the weight is divided randomly over the three price levels (Equation 3.16). Each weight is then multiplied by its respective electricity price to form a calibrated electricity price for each developer (Equation 3.17).

This approach is based on a method used by Kell et al. (2023). This research uses three distinct electricity price curves and each agent is his model chooses a single curve at the start of the simulation. However, Kell's model only runs two auctions. If our model were to apply the same school of thought, the agents' differences would be greatly reduced because they are committed to the same curve over a large number of timesteps. Therefore, this model uses the same three-curve approach as Kell et al. (2023) but allows developers to account for all three possible electricity price futures rather than choosing a single curve.

$$u_1, u_2 \sim U(0,1), \quad u_{(1)} = \min(u_1, u_2), \quad u_{(2)} = \max(u_1, u_2) \tag{3.12}$$

$$w_{\text{low}} = \delta + (1 - 3\delta)\, u_{(1)} \tag{3.13}$$

$$w_{\text{mid}} = \delta + (1 - 3\delta)\left(u_{(2)} - u_{(1)}\right) \tag{3.14}$$

$$w_{\text{high}} = \delta + (1 - 3\delta)\left(1 - u_{(2)}\right) \tag{3.15}$$

$$w_{\text{low}} + w_{\text{mid}} + w_{\text{high}} = 1 \tag{3.16}$$

δ is the probability floor applied to each scenario.

$$\hat{p} = w_{\text{low}} \cdot p_{\text{low}} + w_{\text{mid}} \cdot p_{\text{mid}} + w_{\text{high}} \cdot p_{\text{high}} \tag{3.17}$$

Starting capacity

As mentioned before, the current Dutch offshore wind sector has a capacity of 4.7 GW. To use this number as a starting point for the model, the capacity needs to be divided among the developers. This also means it counts as GW obtained while working toward the 40 GW target. Since every simulation is random, the capacity is distributed equally over every developer, dividing the total capacity C_{total} of 4.7 GW over the N developers. This results in a starting capacity C_{init} of $\approx$ 313 MW per agent (Equation 3.18). The initial capacity serves only as a baseline and does not affect auction behaviour at the start.

$$C_{\text{init}} = \frac{C_{\text{total}}}{N} = \frac{4700 \text{ MW}}{15} \approx 313 \text{ MW} \tag{3.18}$$

Capacity range

Each wind farm developer agent has their own range of tender capacity they are interested in. The agents will only produce bids for tenders that fall within their range, or their "interests". This assumption is based on research by Welisch and Poudineh (2019), which finds that bidders in UK auctions have varying project sizes. The UK does use a multi-unit tender auction format, which is different to the Netherlands. However, for the Borssele I & II tenders, both worth 350 MW, some parties bid on both tenders while others bid on just one (Jansen et al., 2022). To simulate these preferences in project size, each developer is assigned a minimum and maximum capacity representing an interval of tender sizes within which the agent is willing to bid (Equation 3.21). The range is constructed from two independently drawn parameters.

First, a preferred capacity $c_{\text{pref},i}$ is drawn from a normal distribution centred on the average offshore wind tender size of planned Dutch offshore wind tender, μ_c = 1,300 MW, with a standard deviation of σ_c = 200 MW chosen to produce a plausible spread of preferred capacities across the developer population (Equation 3.19). The normal distribution represents the scale of project size, which is most appealing to the developers. The lower/higher the preferred capacity, the more niche the projects become, thus decreasing the chance of a project with your preference coming along. Since most developers want to be involved in the market, the likelihood that the preferred capacity is closer to the average offshore wind tender size is greater.

Second, a half-width Δ_i is determined for each developer, defining a symmetrical window around the preferred capacity to create the range. This window is drawn with a uniform distribution with bounds of $\Delta_{\min} = 300$ MW and $\Delta_{\max} = 700$ MW (Equation 3.20). It showcases a developer as a specialist in a narrow range of capacities, or perhaps a generalist open to a variety of project sizes. Due to the lack of data in Dutch offshore wind tenders and developer insights, a uniform distribution is chosen to give every possible range the same chance. For Dutch tenders, the number of participants is unknown, making it impossible to assess how the capacity ranges might be affected. Agents whose capacity range does not overlap with the auctioned tender capacity C_t at that time will not participate in the auction(Equation 3.22). The resulting capacity range for each developer remains unchanged throughout the simulation.

$$c_{\mathrm{pref},i} \sim \mathcal{N}(\mu_c,\ \sigma_c^2), \qquad \mu_c = 1300 \text{ MW},\ \sigma_c = 200 \text{ MW} \tag{3.19}$$

$$\Delta_i \sim \mathcal{U}(\Delta_{\min},\ \Delta_{\max}), \qquad \Delta_{\min} = 300 \text{ MW},\ \Delta_{\max} = 700 \text{ MW} \tag{3.20}$$

$$\underline{c}_i,\ \overline{c}_i = \max(600,\ c_{\mathrm{pref},i} - \Delta_i),\ \min(2000,\ c_{\mathrm{pref},i} + \Delta_i) \tag{3.21}$$

$$\underline{c}_i \leq C_t \leq \overline{c}_i \tag{3.22}$$

Capacity factor

Every developer has their own capacity factor. This capacity factor represents the fraction of their annual production relative to their capacity. The capacity factor directly impacts the developer's bidding process, as it determines their annual generation. The capacity factor is modelled using a normal distribution, similar to CAPEX and OPEX, to replicate the probable capacity factor range in the actual market (Equation 3.23). The range of the distribution on which this capacity factor is based is derived from reports on Dutch offshore wind farms. Malleret et al. (2024) reports that the Hollandse Kust Zuid I-II and Borssele III-IV wind farms have capacity factors of 46.1% and 42.9%, respectively. The RVO reports an estimated capacity of 49.6% for the Borssele III-IV wind farm, based on its projected output and a capacity factor of 46.8% (Netherlands Enterprise Agency (RVO), 2022). In Table A.6, the projected load hours of 3,659-3,852 per year correspond with a capacity factor range of roughly 0.42-0.44. Based on these sources, this model chooses a capacity factor mean of 0.46 (46%) and a standard deviation of 0.02, with a cap at ±15% of the mean to prevent unrealistic outliers, consistent with the CAPEX and OPEX distributions.

$$cf_i \sim \mathcal{N}(\mu_{cf},\ \sigma_{cf}^2), \quad cf_i \in [0.85\,\mu_{cf},\ 1.15\,\mu_{cf}] \tag{3.23}$$

Discount rate

The discount rate is a variable that allows developers to express their risk preferences. This metric is often used in the previous literature on offshore wind auctions, as described in chapter 2. This research uses the same discount rate distribution for all CfDs to facilitate comparison across them (Equation 3.24). However, there is also literature that supports the implementation of different risk premiums against different CfD's. To assess the impact, the model will also include different risk approaches for each CfD framework in the sensitivity analysis.

$$r_{i,t} \sim \mathcal{U}(r_{\min},\ r_{\max}), \qquad i = 1, \ldots, N \tag{3.24}$$

The research by Jansen et al. (2022) focuses on one-sided and two-sided CfD and use a range of 6.2-7.9%. with a 7.3% mean. Breitschopf and Alexander-Haw (2022) study renewable technologies and apply a range of 1-12%, with a cut-off at 9% as higher values are treated as outliers. The report by Lensink and Henriquez (2026) assumes a 4.5% return on debt and 10% return on equity at a 70/30 split. This results in a discount rate of roughly $0.7 \times 4.5\% + 0.3 \times 10\% \approx 6.5\%$. However, the report consulted market participants, who said the discount rate was underestimated. Based on the sources, this research will use a range from 7-10%. According to Schlecht et al. (2024) the risk level of a financial CfD lies somewhere between a one-sided and two-sided CfD, so the model assumes the range of the discount rate is sufficient as it's based on one-sided and two-sided CfDs. The range will mirror the uncertainty and divided-risk approaches of the current offshore wind sector and will be the same for each CfD for comparison. Further, it will also allow the sensitivity analysis to differentiate the discount rates of the different CfD models.

The discount rate is also a dynamic variable that changes at each time step. This adjustment mechanism is central to how developers change their bidding strategy based on previous auction rounds, the behaviour identified in chapter 2 contributing to the first sub-question. As discussed in chapter 2, when a wind farm developer loses an auction, they discover that their bid was too high. This means they will have to take more risks at the next auction to secure the winning bid. This means they will reduce their discount rate at the next auction and bid lower. The adjustment mechanism is described in Equations 3.25 and 3.26. In offshore wind auctions, the details of the auction always remain unknown. The only information which is publicly presented is the winning strike price. Therefore, the amount of risk that a losing agent is willing to take depends on how large the difference was between their bid $S_{i,t}$ and the winning strike price $S_{\text{win},t}$. A modelling choice has been made to limit the discount rate drop to 0.2, on the grounds that if the difference between the winning bid and the loser's market position is larger, their discount rate would drop at such a rate that the swing in bidding behaviour would be dramatic. By capping the behavioural adjustment at 0.2, the developer gradually takes on more risk if they keep losing an auction, thereby replicating a more careful approach. Secondly, there is a fallback if the winning bid is zero-subsidy. If a 0€/MWh bid occurs, then the discount rate decreases by 0.005. This fallback preserves the mechanism whereby developers increase their risk if they lose an auction, even when the winning bid might be a zero-subsidy bid. Lastly, if a developer keeps losing, they will keep decreasing their strike price. To prevent a developer from reducing their discount rate to an extremely low value, the minimum discount rate has been capped at 4%.

On the other hand, when a developer wins an auction, they realise there might have been a higher bid they could have made and still won. This leads the developer to increase their discount rate, thereby increasing their bid in the next auction (Equation 3.27). Whilst the literature in chapter 2 supports the direction of the discount rate adjustment for winning developers, it does not identify the level of the increase. The factor of 1.015 is therefore a modelling assumption, chosen to keep the upward adjustment small and to reflect the realistic, gradual increase a developer would apply to their strike price.

$$\beta_{i,t} = \begin{cases} \min\left(\dfrac{S_{i,t} - S_{\text{win},t}}{S_{i,t}}\, r_{i,t},\ 0.2\right) & \text{if } S_{i,t} > 0 \text{ and } S_{\text{win},t} > 0, \\ 0.005 & \text{otherwise,} \end{cases} \tag{3.25}$$

$$r_{i,t+1} = \max(0.04,\ r_{i,t}\,(1 - \beta_{i,t})) \tag{3.26}$$

$$r_{\text{win},i,\,t+1} = r_{\text{win},i,\,t} \cdot 1.015 \tag{3.27}$$

Cost reduction

If a wind farm developer wins an auction and is permitted to execute the tender, they will be credited with a possible cost reduction (Equation 3.28). Anatolitis and Welisch (2017) use a similar mechanism that comes from the idea of "learning-by-doing" with the reduction spanning a range from 0-1.5% uniform distribution. Welisch and Poudineh (2019) use a 4% linear cost degression factor. This model assumes a uniform distribution, with a slightly broader range of 0-2.5% based on the sources (Equation 3.29). In the model, $C_{i,t}$ represents the CAPEX as well as the OPEX, both of which are reduced when agent i wins a tender.

$$C_{i,t+1} = C_{i,t}\,(1 - cr_{i,t}) \tag{3.28}$$

$$cr_{i,t} \sim U(cr_{\min}, cr_{\max}) \tag{3.29}$$

3.2.4 Strike prices

In each auction, the developers must determine what bid to submit to the government. The bidding approach for a developer depends on the support mechanism the government is offering them. Deriving a separate bidding formulation for each design will allow this thesis to address the second sub-question within a single model. In this model, the government can offer the three different contract-for-difference support designs discussed in the previous section. The developers will alter their calculation strategy based on the provided CfD. Based on the literature discussed in Section 2, this model will also choose to set all the bids to an NPV = 0 framework for the developers (Kell et al., 2023; Johanndeiter et al., 2025). Once the developer calculates their strike price S_i, and if they win tender k, the submitted strike price becomes the awarded strike S_k. The possible incoming revenue per MWh for a given electricity price is represented by Equation 3.30.

$$R = \max(p,\, S_i) \tag{3.30}$$

where S_i is the strike price of the developer and p is the predicted electricity price. This calculation process will require the developer to determine the expected revenue during the CfD support using the weighted future electricity forecasts (Equation 3.31).

$$\mathbb{E}[R \mid S_i] = w_{\text{low}} \cdot \max(p_{\text{low}}, S_i) + w_{\text{mid}} \cdot \max(p_{\text{mid}}, S_i) + w_{\text{high}} \cdot \max(p_{\text{high}}, S_i) \tag{3.31}$$

Following the NPV = 0 framework, the developer will then calculate the minimum required revenue T for the CfD years. By calculating the present value annuity factors for the CfD support years PVA_{cfd} (Equation 3.32) and the entire project lifetime PVA_{life} (Equation 3.33), the annuity factor for the merchant tail PVA_{tail} can also be determined (Equation 3.34). The present value converts future cash flows into their present value at the time of investment. Using their capacity factor, developers can determine their generation g_{own} and calculate their required revenue (T) (Equation 3.35). Once the developer has calculated T, they can find their break-even strike price. The capital expenditure enters the numerator undiscounted because it is a lump sum incurred at the start of the project (t = 0) and is therefore already in present value terms, whereas the operational expenditure and merchant-tail revenue are future cash-flow streams converted to present value using their annuity factors. The net present value of all lifetime costs and tail revenues is then annualised over the CfD support period rather than the full project life, reflecting that the strike price is only active during the 15-year window and that the merchant-tail revenue is accounted for as a revenue offset in the numerator rather than recovered through the strike. T is therefore expressed in €/MWh and represents the per-MWh revenue the contract must deliver during the support period for the developer to break even across the full 30-year asset life, after accounting for the expected merchant-tail revenues in years 16 to 30.

$$\text{PVA}_{\text{cfd}} = \frac{1 - (1 + r_{i,t})^{-N_{\text{CfD}}}}{r_{i,t}} \tag{3.32}$$

$$\text{PVA}_{\text{life}} = \frac{1 - (1 + r_{i,t})^{-N_{\text{life}}}}{r_{i,t}} \tag{3.33}$$

$$\text{PVA}_{\text{tail}} = \text{PVA}_{\text{life}} - \text{PVA}_{\text{cfd}} \tag{3.34}$$

$$g_{\text{own}} = 8760 \cdot cf_{\text{own}} \tag{3.35}$$

$$T = \frac{\text{CAPEX} + \text{OPEX} \cdot g_{\text{own}} \cdot \text{PVA}_{\text{life}} - \hat{p} \cdot g_{\text{own}} \cdot \text{PVA}_{\text{tail}}}{g_{\text{own}} \cdot \text{PVA}_{\text{cfd}}} \tag{3.36}$$

$$\mathbb{E}[R \mid S_i] = T \tag{3.37}$$

Once a developer has determined their strike price S_i under the respective CfD design, the bid is only admitted to the auction if it does not exceed the ceiling price p_{ceiling} set by the government. If the calculated strike price is higher than the ceiling, the bid is rejected, and the developer is excluded from that auction (Equation 3.38). A rejected bid also raises the developer's exit probability by α_{breach}, as described in the exit mechanism (Equation 3.49).

$$\text{bid}_i = \begin{cases} S_i & \text{if } S_i \leq p_{\text{ceiling}} \\ \text{rejected} & \text{if } S_i > p_{\text{ceiling}} \end{cases} \tag{3.38}$$

One-sided CfD

In the previous section, it became clear that research has been done on one-sided CfD in an analytical capacity, using Monte Carlo simulation and optimisation algorithms. However, these models were not applied in an agent-based environment. Other studies using agents mainly focus on two-sided CfDs and auction dynamics; when they include one-sided CfDs, they use a single electricity price curve with no real uncertainty about future prices. These assumptions mean that agents know exactly when the price will be above or below the strike price in the future. The problem with this approach is that the calculated strike price is identical to that of a two-sided CfD. The method this model will use attempts to integrate the agent-based environment with a closed-form approach that encapsulates uncertainty in upside revenue. Since the upside revenue is unknown, it creates an asymmetric payoff. For a one-sided CfD, this asymmetric payoff can make it quite complex to calculate the bid strike price. During the CfD support years, developers may retain the upside revenue generated. In Equation 3.31, it depends on the relationship between S and the price level, whose value is chosen by the max. For each price level, the max function returns S if the strike price is higher than the electricity price level, or returns the price level if S is equal to or less than p_k. As the expected revenue function $\mathbb{E}[R \mid S]$ is a sum of three potential revenue streams, which change per scenario depending on the value of S, the output of the equation is non-linear. Across the full trajectory of $\mathbb{E}[R \mid S]$, there can be kinks in the function at each scenario.

With these three different price levels, the strike price can be determined under four different cases (Table 3.1). In case 1, the required revenue (T) is lower than the lowest electricity price level, which, in the developer's view, means their costs can be fully recovered by the electricity market. Therefore, as we see in practice, developers will submit bids of 0 €/MWh and assume the risk of exposure to market prices. In case 4, the required revenue (T) exceeds the highest electricity price, so the developer needs full support and submits a bid similar to a two-sided CfD.

For cases 2 & 3, there is variation in the outputs of the max function. If the required revenue (T) falls between the lowest expected price level and the highest expected price level ($p_{\text{low}} < T \leq p_{\text{high}}$) then the developer will need some support, but that is not clear at first glance, so the exact strike price needs to be calculated. The developer calculates the strike price for cases 2 and 3 and checks which condition is true, meaning the calculated strike price falls within that case's price band. In both equations, the market price contribution is subtracted from the required revenue and divided by the total weight of the electricity price levels, with the strike price providing the revenue stream.

Table 3.1: Strike price under the four cases for a one-sided CfD.

Cases	**Condition**	$\mathbb{E}[R \mid S]$	**Strike** S
1	$T \leq p_{\text{low}}$	$w_{\text{low}} \cdot p_{\text{low}} + w_{\text{mid}} \cdot p_{\text{mid}} + w_{\text{high}} \cdot p_{\text{high}}$	$S = 0$
2	$p_{\text{low}} < S \leq p_{\text{mid}}$	$w_{\text{low}} \cdot S + w_{\text{mid}} \cdot p_{\text{mid}} + w_{\text{high}} \cdot p_{\text{high}}$	$S = \dfrac{T - w_{\text{mid}} \cdot p_{\text{mid}} - w_{\text{high}} \cdot p_{\text{high}}}{w_{\text{low}}}$
3	$p_{\text{mid}} < S \leq p_{\text{high}}$	$(w_{\text{low}} + w_{\text{mid}}) \cdot S + w_{\text{high}} \cdot p_{\text{high}}$	$S = \dfrac{T - w_{\text{high}} \cdot p_{\text{high}}}{w_{\text{low}} + w_{\text{mid}}}$
4	$T > p_{\text{high}}$	$(w_{\text{low}} + w_{\text{mid}} + w_{\text{high}}) \cdot S$	$S = T$

These equations will find the eventual strike price by validating which region statement is true. This approach allows each agent to be heterogeneous because they all have their own weight factors for the same electricity price levels. The payoff function in this model also allows the one-sided CfD structure to remain intact without it becoming deterministic as in previous literature. The closed-form equation also allows this model to be submitted to Monte Carlo simulations. The calculations draw on established literature for each component: the NPV = 0 break-even condition from Kell et al. (2023) and Johanndeiter et al. (2025), and the payoff revenue function from Anaya and Pollitt (2020).

Two-sided CfD

For a two-sided CfD, the calculation process is less complex. Since the developers do not retain their upside revenue but instead return it to the government, they are incentivised to bid at their required revenue level due to the merit order effect. If they bid above their required revenue, they risk being under-bid by another developer and losing the auction. Therefore, under a two-sided CfD, the developers will always bid $S = T$. The developers perform the same calculations with Equations 3.32, 3.33, and 3.34 and calculate T.

Financial CfD

For the bidding approach under a financial CfD, additional calculations are required due to the reference generator. As described in the government agent section, the reference generator is characterised by a fixed capacity factor that remains constant throughout the model run. Once the developer has calculated their required revenue T, they will need to perform additional calculations beyond those for a two-sided CfD to determine their NPV = 0 strike price. Johanndeiter et al. (2025) use the following equation in their research to determine the break-even strike price for financial CfD (3.39).

$$S_i^{\text{fin,MW}} = \frac{A}{Q} + R_{\text{ref}} - R_{\text{own}} \tag{3.39}$$

However, in financial CfD research, the strike price is expressed in €/MW, not €/MWh, and this applies to both one-sided and two-sided CfDs. This means that the T calculated in Equation 3.36 cannot provide the exact strike price as it does for the two-sided CfD. A/Q represents the annualised cost in the equation by Johanndeiter et al. (2025) in a full-life support financial CfD. Multiplying T by the CfD annuity factor gives the present value of the required revenue. Adding the present value of the expected price during the merchant tail recovers the total present value of revenues required per MWh. Multiplying this by the developer's generation yields a per-MW conversion, which can then be divided by the lifetime PVA_{life} to obtain the €/MW strike price, similar to the research by Johanndeiter et al. (2025). By dividing the strike price we would retrieve in equation 3.39 by the developer's g_{own}, a strike price per MWh is calculated (Equation 3.41).

$$\frac{A}{Q} = \frac{g_{\text{own}}\left(T \cdot \text{PVA}_{\text{cfd}} + \hat{p} \cdot \text{PVA}_{\text{tail}}\right)}{\text{PVA}_{\text{life}}} \tag{3.40}$$

$$S_i = \frac{S_i^{\text{fin,MW}}}{g_{\text{own}}} \tag{3.41}$$

T now represents the present value of the annual costs and can be used to find the strike price under the NPV = 0 condition. The break-even price is calculated by adding the reference generator revenue and subtracting the developer's revenue, which serves the function of a volume correction, adjusting the strike price based on how the developer performs relative to the reference generator (Equation 3.42, 3.43, 3.35, & 3.44). This is a key difference from the two-sided CfD. In a two-sided CfD, this correction happens through the price gap between the strike price and the market price, applied to the developer's own generation. In a financial CfD, the correction happens through the volume gap between the reference generator and the developer, applied at the expected price. A developer whose capacity factor exceeds the reference generator earns surplus market revenues beyond what the reference assumes, so $(R_{\text{ref}} - R_{\text{own}})$ is negative and the required strike falls below A/Q. A developer whose site underperforms the reference generator faces the reverse and must bid above A/Q to remain viable.

$$g_{\text{ref}} = 8760 \cdot cf_{\text{ref}} \tag{3.42}$$

$$R_{\text{ref}} = g_{\text{ref}} \cdot \hat{p} \tag{3.43}$$

$$R_{\text{own}} = g_{\text{own}} \cdot \hat{p} \tag{3.44}$$

$$G_{k,t} = \underbrace{S_k^{\text{fin}} \cdot g_{\text{own},k}}_{\text{annuity leg}} - \underbrace{\lambda_t \cdot g_{\text{ref},k}}_{\text{clawback leg}} \tag{3.45}$$

$$G_{\text{tot}} = \sum_k \sum_{j=0}^{N_{\text{CfD}}-1} \left[S_k^{\text{fin}} \cdot g_{\text{own},k} - \lambda_{t_k+j} \cdot g_{\text{ref},k} \right] \tag{3.46}$$

Exit chance

Each developer has the option to exit the market if they feel that they cannot compete in the auctions. For $t = 0$, the chance of every developer exiting the market is zero, as they have supposedly just entered the market. After the first auction, the exit chance is activated and increases if the developer loses an auction or can't participate, $p_{\text{exit}} \in [0, 1]$, inspired by the work of Hailu et al. (2011) & Elsayegh et al. (2020). At the start of each round, before bid submission, each developer draws a uniform random variate. If ξ_i is less than e_i, the developer exits permanently and is removed from all future rounds (Equation 3.47). It is important to note that this also applies if the developer did not participate in the auction, not only after a loss. So, a developer who does not submit a bid because the tender capacity is outside their range still experiences an increase in their exit probability (Equation 3.49). The same rule applies if the calculated strike price for a developer is higher than the ceiling price set by the government (3.49). However, there are different weights applied for each type of exclusion.

α_{loss} is a small positive increment and $\alpha_{\text{win}} \gg \alpha_{\text{loss}}$. The increment α_{loss} is small by design: $\alpha_{\text{loss}} = 0.0025$. A losing developer is unlikely to exit after a single unsuccessful bid, but repeated exclusion from contract awards gradually increases the probability of a permanent market exit, as seen in Dutch tender rounds, where developers persist in participating (Jansen et al., 2022). The ceiling price breach α_{breach} has the same value of 0.0025 because this model treats losing to a winning bid and bidding above the ceiling price as equivalent effects, since both indicate that the developers' strike price is too high. The capacity misalignment has a smaller effect on the exit chance, set to half the value of the previous increments, $\alpha_{\text{mismatch}} = 0.00125$ (Equation 3.48). This modelling decision has been made because a developer who does not participate in an auction, due to the tender capacity not being interesting or viable, is less discouraged than a developer who loses the auction.

If a developer wins the auction, their exit probability decreases by a larger margin (Equation 3.49); $\alpha_{\text{win}} = 0.05$. The competitive success and financial security of winning a single contract result in a strong trust in the market position from the developer's perspective. The resulting mechanism of winning and losing ensures that competitive participants have a higher probability of staying active in the market, whilst persistent losers will gradually exit.

$$\xi_i \sim \mathcal{U}(0,1), \quad \text{agent } i \text{ exits permanently if } \xi_i < e_i \tag{3.47}$$

$$\alpha_{\text{loss}} = \alpha_{\text{breach}} > \alpha_{\text{mismatch}} \tag{3.48}$$

$$e_i \leftarrow \begin{cases} \max(0,\ e_i - \alpha_{\text{win}}) & \text{if agent } i \text{ wins} \\ \min(1,\ e_i + \alpha_{\text{loss}}) & \text{if agent } i \text{ loses} \\ \min(1,\ e_i + \alpha_{\text{breach}}) & \text{if bid exceeds ceiling} \\ \min(1,\ e_i + \alpha_{\text{mismatch}}) & \text{if capacity mismatch} \end{cases} \tag{3.49}$$

Table B.1 in the Appendix provides an overview of all variables, including their symbols, short descriptions, and corresponding units.

3.3 Process diagram

Figure 3.1 shows a process diagram of how the model runs per timestep for each CfD. The auction design is pre-determined at the start of the simulation. It shows the loop that the model finds itself in, as after each auction, processes happen for the government agent and the developer agents to prepare for the next auction. At the start of each round, the government (GovAgent) announces a tender and its capacity. The developers (WFAgent) then process the tender, first checking whether the tender falls within their preferred capacity window before proceeding to calculate a break-even strike price. The strike price calculation draws on each agent's individually held beliefs about future electricity prices, represented as a weighted distribution across optimistic, neutral, and pessimistic scenarios, combined with agent-specific cost, capacity factor, and discount rate parameters. Bids are submitted under pay-as-bid rules, and the government agent selects the winner based on the lowest bid(s). The auction outcome then feeds back into agent behaviour through two channels. First, winning reduces an agent's perceived project risk and triggers learning-by-doing cost reductions. Second, losing agents observe the gap between their own bid and the winner's and adjust their discount rate downward accordingly, observing that the market is more competitive than they assumed. Simultaneously, their exit chance increases, and the developer decides whether they leave the model. The simulation continues until either the deployment target is reached or the round limit is exhausted.

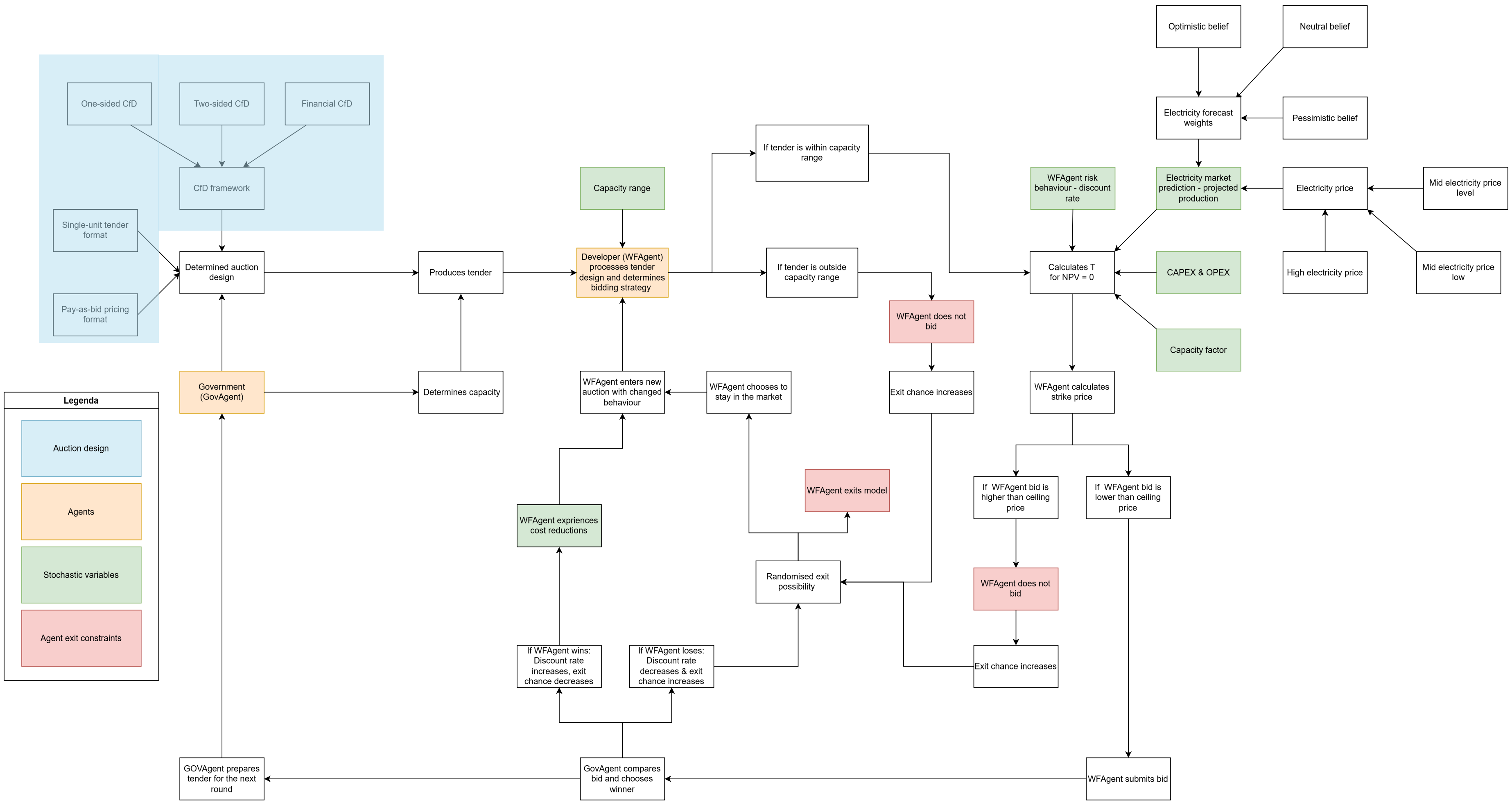

Figure 3.1: Process diagram of a single model timestep across all three CfD designs.

3.4 Modelling Approach Limitations

Multi-Agent models often suffer from simplification, in which a socio-technical system is reduced to a set of rules for agents to follow (Liu et al., 2025). The simplification can fail to capture real-world behaviour and human irrationality (Kell et al., 2023). This happens because human behaviour and irrationality can be incredibly difficult and complex to replicate, creating a notorious bottleneck for multi-agent models. Anatolitis and Welisch (2017) illustrate this in their research, noting that their auction model sacrifices realism for tractability. To prevent oversimplification, this model focuses on only CfD auctions and the bid preparation phase, rather than attempting to represent the entire offshore wind sector.

The results of agent models can be highly sensitive to initial assumptions. Changes to the input parameters can give inaccurate results (Anatolitis and Welisch, 2017). Models can also suffer from excluded parameters that are forgotten or lost in complexity. To mitigate this, the extensive literature review provides a substantial, well-grounded basis for the model's input parameters. Furthermore, this model uses stochastic input parameters, allowing the agents to fall within a range of starting values rather than choosing a single, potentially incorrect value. By then subjecting the agents in the model to Monte Carlo simulations, the results will illustrate probabilistic outcomes.

Another significant limitation is the inability of agent models to provide precise forecasts of a complex system's future state. Complex systems often inhabit chaotic elements, meaning that small differences are magnified through iteration, the so-called "butterfly effect" Dam et al. (2012). By applying the Monte Carlo simulations that were mentioned before, and running a scenario analysis with the model, different future possibilities can be analysed and provide insights into the possible behaviour of the system. The next section will discuss the setup for the sensitivity and scenario analysis.

3.5 KPI's

Table 3.2 shows the KPI's that will be used to evaluate the CfD designs and describes how each is computed for the model. As established in section 2.6 of chapter 2, these metrics are categorised in three dimensions to align with the components of the main research question: price outcomes, market participation and allocation effectiveness. The first dimension captures the cost of support to the government, the second whether the 40 GW target is reached, and the third whether the design sustains a competitive market. Each indicator is recorded during or after a simulation run and then averaged across the 1,000 Monte Carlo runs, allowing the designs to be assessed consistently across the results.

Table 3.2: KPI definitions and recording location, grouped by the three performance dimensions. Each KPI is computed per run and averaged across the 1,000 Monte Carlo runs.

KPI	**Description**	**Recorded by**
Price outcomes		
Winning strike price	Mean of the awarded strike prices S_k across all tenders won in a run, indicating the support level developers require.	Government
Total subsidy cost	Net government expenditure G_{tot} summed over all awarded contracts and their support years (Equation 3.9); negative values denote a net clawback.	Government
Allocation effectiveness		
Success rate	Fraction of runs in which the cumulative awarded capacity reaches the 40 GW target C^* within the round limit T.	Model
Ceiling rejection rate	Share of submitted strike prices S_i that exceed the ceiling price p_{ceiling} and are rejected (Equation 3.38).	Government
Market participation		
Distinct winners	Number of unique developer agents awarded at least one tender per run.	Government
Participating developers	Mean number of agents submitting a valid bid per tender round.	Model
Exited developers	Number of agents that permanently leave the market per run (Equation 3.47).	Model

3.6 Sensitivity analysis

As part of the model analysis, a sensitivity analysis will be performed. The role of the sensitivity analysis is to show which input parameters have the largest effect on the model outputs when their values are increased or decreased by the same relative margin. Table B.2 shows an overview of the starting values for all the parameters. Based on this table, the starting parameters for the developer agents, which are assumed ranges provided with either probabilistic distributions or different weighted levels, are CAPEX, OPEX, the base electricity price, the standard deviation of the electricity price, the capacity factor, and the discount rate. The discount rate, however, is held identical across each CfD design as discussed earlier in this chapter, because otherwise it would have to take on different values and ranges for each CfD design. Each of these other parameters will be tested and compared to ±10 % of their original input value, which will be determined in a later chapter. These are selected because they are the uncertain inputs that a developer must estimate when forming a bid and that the literature identifies as the main cost and revenue drivers, so analysing each parameter by an equal margin isolates their influence on the model outcomes. The remaining parameters in Table B.2, such as the tender capacity bounds, the number of developers and the behavioural adjustments, define the auction structure rather than representing uncertain developer inputs, and therefore remain fixed.

Table 3.3: Sensitivity analysis input parameters. Each parameter is perturbed ±10% around its baseline value, with 1000 Monte Carlo runs per sweep point.

Parameter	**Low** (−10%)	**Baseline**	**High** (+10%)	**Unit**
Electricity price (mean)	82.69	91.88	101.07	€/MWh
Electricity price (std. dev.)	24.70	27.44	30.18	€/MWh
CAPEX (mean)	2,880,000	3,200,000	3,520,000	€/MW
OPEX (mean)	13.50	15.00	16.50	€/MWh
Capacity factor (mean)	0.414	0.46	0.506	%

3.7 Ceiling price level experimentation

In half a year's time since the advised ceiling price of 104 €/MWh, the government has already increased the ceiling price for the Ijmuiden-Gamma tenders to 117 €/MWh and 116 €/MWh, respectively (van Economische Zaken en Klimaat, 2026), a difference of 13 €/MWh. The Dutch government is still searching for an appropriate level for the ceiling price, which is why this model will also be tested with different ceiling price levels. The ceiling price has been omitted from the sensitivity analysis because the previously discussed parameters are uncertain variables that a developer must estimate; therefore, changing them by the same margin allows their influence on the outcomes to be compared equally. The ceiling price levels are less an uncertain input and more a policy value set by the Dutch government. For this reason, it varies based on real margins. The upper level of the ceiling price level is based on the recent announcement by the Dutch Government to increase the ceiling price (Table 3.4). Since there is no known lower price level, the experiment will remain consistent with the symmetric approach of the previous sensitivity analysis. Therefore, the lower level is set to 13 €/MWh below the baseline, at 91 €/MWh (Table 3.4). This lower level is an assumption the model chooses, as there is no known lower ceiling price level for future Dutch offshore wind tenders.

Table 3.4: Ceiling price levels tested in the sensitivity analysis

Ceiling level	Value (€/MWh)
Low	91
Baseline	104
High	117

3.8 Scenario analysis

In reality, prices and costs fluctuate, and some forecasts can be more plausible than others. To further analyse the behaviour of the contracts for differences, the CfD models will be subjected to a scenario analysis along two dimensions. The ceiling price, which the government sets and has proven to change over time, and the future cost and price environment, which impacts the CfD designs externally.

The ceiling price is treated as a policy choice by the Dutch government. In the scenario analysis, it uses two different levels: the baseline of 104 €/MWh advised by the PBL in Lensink and Henriquez (2026), and 117 €/MWh, the level to which the government recently raised the ceiling price for the IJmuiden Gamma tenders (van Economische Zaken en Klimaat, 2026). The lower ceiling price level of the sensitivity analysis is omitted as it does not represent a current policy level in the Dutch offshore wind sector. Comparing the two real ceiling price levels with the scenarios isolates how the CfD designs perform under the ceiling price policy options which are actually being used, across differing cost and price conditions. The scenarios are based on the 2025 World Energy Outlook report by the International Energy Agency, which presents multiple possible futures (International Energy Agency, 2025). Each scenario is run for both ceiling price levels and for each CfD design, using the same 1000 Monte Carlo simulation runs as the sensitivity analysis,

First of all, this scenario resembles a possible situation such as the energy crisis caused by the war in the Middle East. The closing of the Strait of Hormuz led to a disruption in the global oil & gas supply, resulting in high energy prices. The closure of the waterway also disrupts the global supply chain, hampering not only the export of energy sources but also the transportation of materials necessary for offshore wind development. Combined with the reported financial distress offshore wind developers have been experiencing, with severely diminished profits, the costs of offshore wind farm development have reached high levels (International Energy Agency, 2025).

Secondly, electricity prices may decrease as supply increases. Since the war in the Middle East in 2026, the European Union has made it clear that it needs to become more independent of imported energy sources. Therefore, it starts expanding its renewable energy supply continent-wide, which in turn lowers the electricity price as they push fossil fuels out the merit order. Simultaneously, global knowledge and the learning curve surrounding offshore wind increase and spread across the world. This dramatically increases turbine efficiency and decreases offshore wind development costs (International Energy Agency, 2025).

In the third scenario, LNG establishes itself as the new major energy source because it's cheaper than oil, gas, and coal. It pushes through the merit-order, driving down electricity prices in the EU, as the IEA reports a possible 50% increase in LNG supply by 2030 (International Energy Agency, 2025). Lower gas prices reduce the electricity prices offshore wind developers need to generate revenue during their merchant tail periods, or, if the developer has a zero-subsidy tender contract, provide general revenue (International Energy Agency, 2025). At the same time, the geopolitical tensions the world has grown accustomed to over the last decade continue, disrupting supply chains and further increasing offshore wind investment costs. Countries with a majority stake in key energy materials increase their market share, leaving offshore wind farm developers even more vulnerable to higher costs (International Energy Agency, 2025). Globally, the implementation of offshore wind is becoming more expensive, whilst LNG asserts its dominance amid low electricity prices, driving out other fossil fuels.

Lastly, a future the model takes into account is the "AI-Boom", where demand for artificial intelligence increases drastically, raising electricity demand and resulting in very high electricity prices. The IEA predicts massive growth in AI usage by 2030, surpassing the total global oil-supply investment budget (International Energy Agency, 2025). Since the demand is so high, fossil fuels are still needed to supply enough electricity, as offshore wind, being a zero-marginal-cost energy source, does not set the market price. To meet electricity demand, EU policy connects North Sea wind farms to one another and to their respective countries to create a massive North Sea grid, lowering infrastructure costs for offshore wind. Furthermore, China's projected over-manufacturing of offshore wind technology drives down CAPEX for offshore wind developers (International Energy Agency, 2025). Table 3.5 shows the values and an overview of the input parameters for the scenarios. The values for the CAPEX and OPEX are based on the offshore wind farm data in tables A.3 & A.4 in the Appendix.

Table 3.5: Per-scenario input parameters

	Baseline	**Geopolitical Energy Crisis** *(High λ / High C)*	**Accelerated Energy Transition** *(Low λ / Low C)*	**LNG Dominance & Supply Strain** *(Low λ / High C)*	**AI Surge** *(High λ / Low C)*
Mean market price (€/MWh)	91.88	172.44	39.59	39.59	172.44
Market price SD (€/MWh)	27.44	51.50	11.82	11.82	51.50
CAPEX (€M/MW)	3.20	4.25	2.25	4.25	2.25
OPEX (€/MWh)	15	20	10	20	10

4. Results

This chapter discusses the model's results by first reviewing the base model's dynamics and outcomes. After that, the model will be subjected to Monte Carlo simulations, a sensitivity analysis, a ceiling-price experiment, and scenario analysis. In both analyses, the criteria determined in chapter 2 will be used as a benchmark to compare the results:

- Average winning strike price bid (€/MWh)
- Total subsidy costs (€bn)
- The success rate: share of target-reached runs (%)
- Ceiling price rejection rate (dimensionless)
- Average number of exited developers (#)
- Average number of distinct winners (#)
- Average number of participating developers (#)

4.1 Base Model

Firstly, a single run of the model presents figures that showcase the dynamics among developers in the market under different CfD designs. Only a single run of the model provides these figures, as multiple simulations create a distribution clouding individual agent dynamics. The model produces figures that follow each agent's strike-price bid trajectories, showcasing the bidding behaviour. The model also follows the number of agents in the market and the cumulative capacity to measure market performance. The last figure for the one-sided CfD represents the percentage of zero-subsidy bids in the market. For the other CfD designs, the last figure shows the bid spread to show how close the auction results are.

4.1.1 Model Dynamics

One-sided Contract-for-Difference

The dynamics of the one-sided model in this simulation showcase what the past Dutch offshore wind market might have looked like. There are a number of developers who accept taking on the risk of receiving no subsidy and place a bid of 0 €/MWh. In this run, some developers are unsure about the risk, such as agent 2, who bounces up and down between strike price bids and zero-subsidy bids, or agent 14, who at some point decides that it is worth the risk of bidding for no support after bidding for 70€/MWh for a number of rounds. Another dynamic showcased in Figure 4.1 is agent 13, who, after realising their required strike price is far too high to compete, exits the market. These trajectories exemplify the bidding adjustments discussed earlier in this thesis and provide insights into the first sub-question.

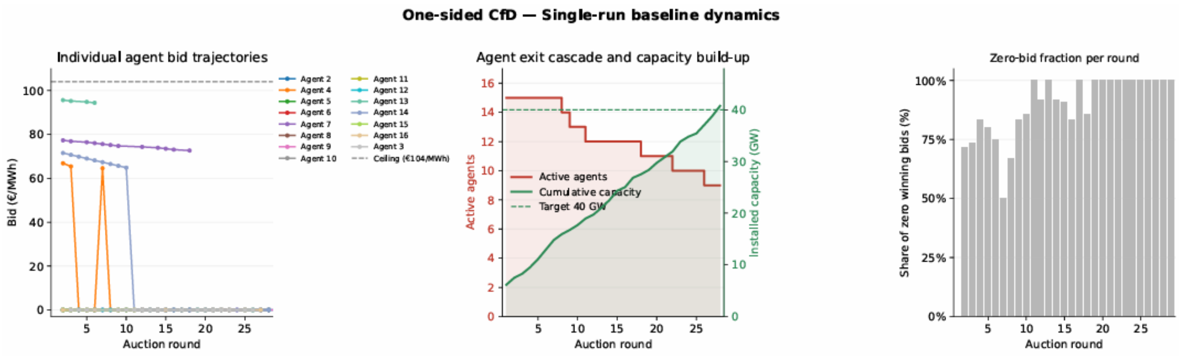

Figure 4.1: Panel of the one-sided CfD single simulation figures

(a) Agent 1 is the government agent, which is why it is not represented in the figure

Two-sided Contract-for-Difference

In the two-sided CfD, the developers bid honestly against their required revenue. Over a single run, the bid spread is quite large, as the difference in required revenue between the agents can be substantial, as seen in the spread of bids across the individual bid trajectories (Figure 4.2). Over the model, the bid trajectories come closer to together as winning developers will increase their bids after wins and losing developers lower their bids to become more competitive. The trend of the winning strike price also trends downwards in this single run. As more agents exit the model, the chances of the same developer winning increase, leading to cost reductions and other developers taking on more risk, resulting in lower bids.

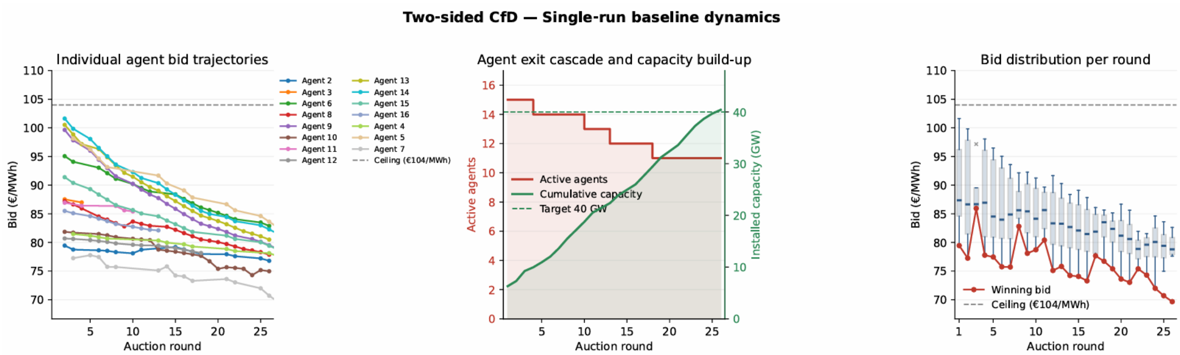

Figure 4.2: Panel of the two-sided CfD single simulation figures

Financial Contract-for-Difference

The dynamics of the financial CfD look similar to the two-sided CfD in a single simulation run (Figure 4.3). A wide spread in bids early on by the developers as they discover their position in the market. The losers keep lowering their bids in hopes of winning an auction, whilst the winners can carefully increase theirs to see if more profit is available. The winning strike price does have a flatter trajectory than the two-sided CfD. That is because the developers are bidding not only against each other but also against the reference generator.

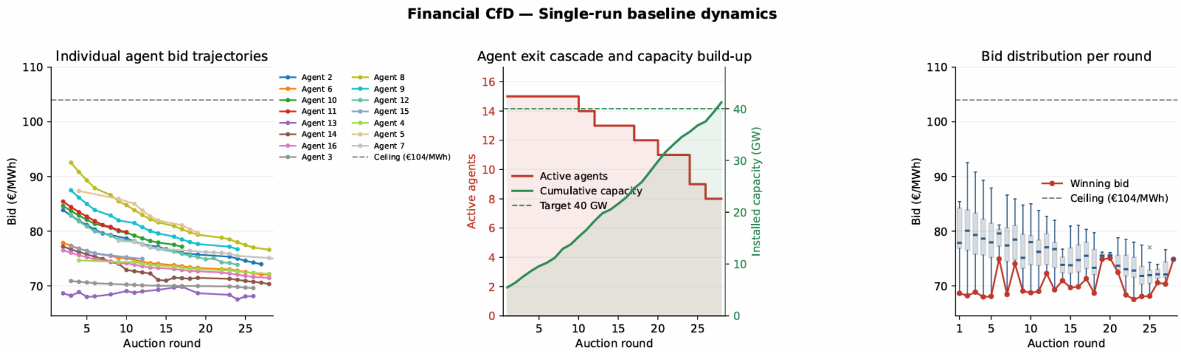

Figure 4.3: Panel of the Financial CfD single simulation figures

The figures of the different CfD dynamics during a simulation run also indicate a start-up phase in the model. The effects of this phase will be further elaborated on in the discussion in chapter 5.

4.1.2 Base Model Monte Carlo Simulations

Before presenting the CfD auction results, this section describes the probability distributions of the cost and price environments in which the auctions take place. The probability distributions illustrate how market parameters assumptions described in chapter 3 are represented in auction simulations.

Cost Distributions

The MC results provide insights into the distributions of the developers' input parameters. In Figure 4.4, the distributions of all 15 developers in the 1000 runs are showcased. It resembles the normal distribution the model tried to replicate based on other literature. The figure also shows that the generated CAPEX and OPEX for the developers do not reach the bounds, as expected given the standard deviation. These results indicate that the model creates a diverse market in which developers have different costs but are not so far apart that they can never compete.

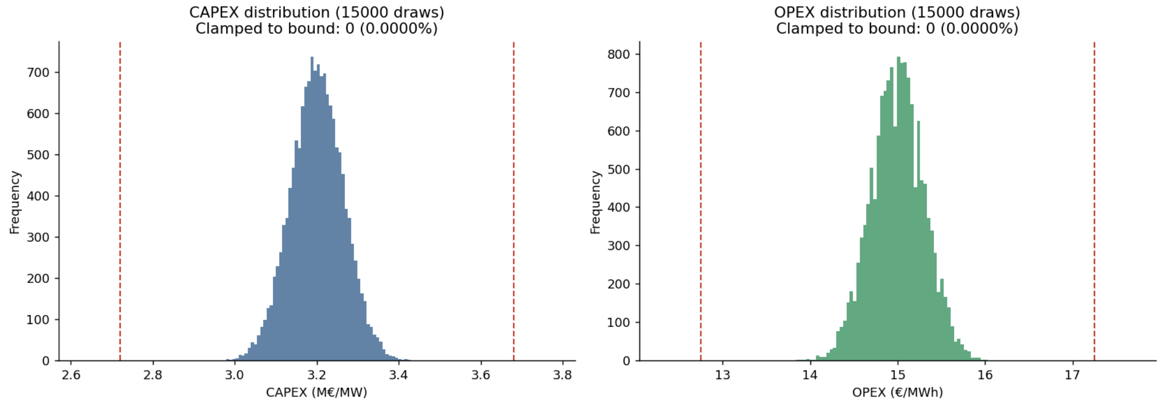

Figure 4.4: Cost distributions for the offshore wind farm developers

Capacity Factor

Similar to the CAPEX and OPEX parameters, the capacity factor is drawn with a normal distribution. The resulting distribution resembles that expected for a normal distribution and shows that capacity factors are spread across developers within a realistic, calibrated range because developers have different production efficiencies (Figure 4.5).

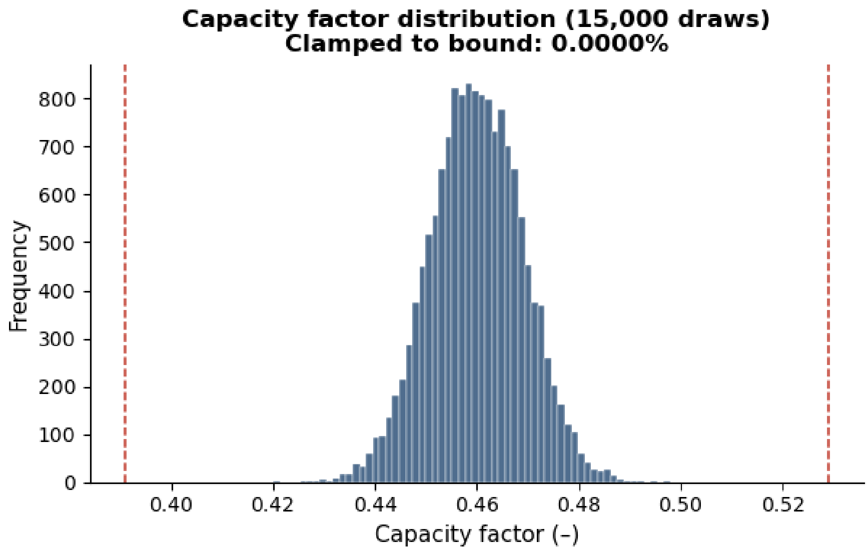

Figure 4.5: Capacity factor distributions of the developer agents over 1000 Monte Carlo simulation runs

Electricity prices

The expected price distribution was centred on a mid-level price of 91.88 €/MWh, with symmetrical ranges at the upper and lower levels. This has produced an expected electricity price distribution with a triangular shape (Figure 4.6). The shape comes from the weighted-beliefs equations, where each developer's expected price is a weighted sum of electricity price levels calibrated by their beliefs. An expected price near either extreme level would require almost all the weight to fall on a single level, which cannot happen because of the minimum belief constraint. The distribution ensures that the model produces a realistic distribution of expected price beliefs for individual developers.

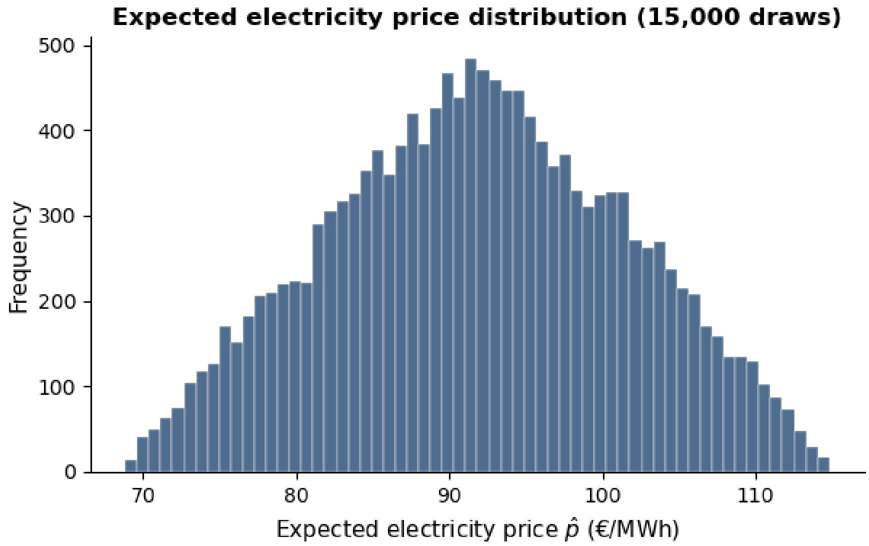

Figure 4.6: Expected electricity price distribution of the offshore wind developers over the 1000 runs of Monte Carlo simulations

The realised electricity market price series, shown in Figure 4.7, behaves independently of the beliefs of the agents. It is a volatile market price moving around the mean of €91.88/. It also shows that the market price has rare extreme values in the light blue strips, resembling extreme moving electricity prices observed in real electricity markets. This means the model can produce a realistic market price series, allowing it to calculate a realistic eventual subsidy expenditure for the government agent.

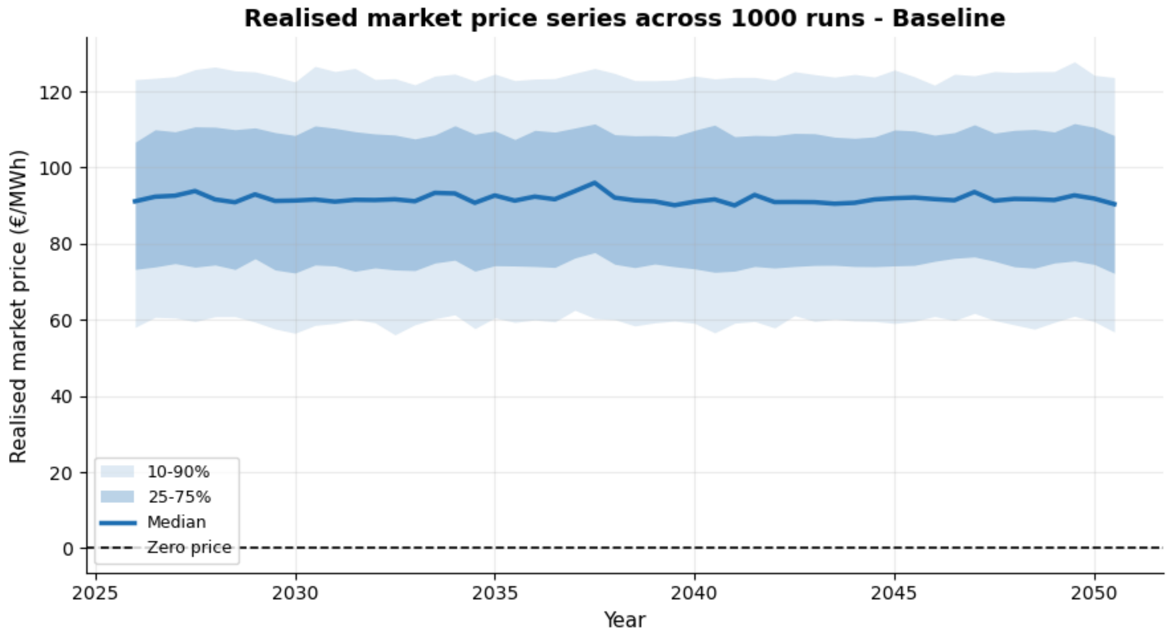

Figure 4.7: Realised electricity market price series over the 1000 runs of Monte Carlo simulations

Base model KPI performance

Each CfD is subjected to Monte Carlo simulations under the assumed baseline input parameters. After the simulations, the results show that the two-sided CfD yields the highest average strike price among the designs and the highest clawback for the Dutch government (Table 4.1). The standard deviation of the two-sided CfD also indicates that the design is close to the average winning strike price of the Financial CfD, but it is small enough to distinguish the two CfD designs. (Table 4.1). The CfD designs all share nearly the same success rate. However, the one-sided CfD has by far the most distinct winners, as a lot of agents are bidding for a zero-subsidy tender, as the average strike price is nearly zero for the one-sided CfD with a small standard deviation (Table 4.1). This results in the government choosing a random winner, diversifying the market. It creates such a diverse market that the average number of distinct winners exceeds the average number of participating developers, indicating that, because bids are zero-subsidy, almost any developer can win if they participate. Although the number of winners is far lower for the financial and two-sided CfD, they do create a market where developers are willing to participate, with an average almost as high as that of the one-sided CfD. In fact, accounting for the standard deviation, the average number of participating developers per auction is almost identical across CfD designs, given the observed spread of 0.96. The averages are therefore a reliable indication for comparing the price and cost metrics of the CfD designs. The participation averages all have the same standard deviation, indicating that the CfD design does not necessarily affect developers' willingness to participate. However, the average total number of exited developers is lowest for the one-sided CfD at 5.32, compared with 6.81 and 6.87 for the financial and two-sided designs, which follows from its far higher number of distinct winners. Because winning reduces a developer's exit probability, the many zero-subsidy winners in the one-sided market keep more developers active. This means that the CfD design can affect the developer's ability to compete in the market whilst it does not affect their willingness to participate.

Table 4.1: Baseline KPI summary across CfD designs. Values show the mean with standard deviation across 1000 Monte Carlo runs in brackets. Subsidy cost sign convention: negative values denote a net clawback (recovery) to the government.

KPI (§2.4 criterion)	One-sided	Financial	Two-sided
Avg. winning strike price (€/MWh)	0.67 (2.20)	68.66 (2.83)	72.72 (3.46)
Total subsidy cost (€ B)	+0.09 (0.44)	−29.95 (11.84)	−41.76 (13.55)
Success rate (% reaching 40 GW)	93.4	93.3	93.3
Ceiling price rejection rate	0.00	0.00	0.02
Avg. number of distinct winners	8.90 (1.46)	3.43 (1.46)	3.43 (1.16)
Avg. participating developers	8.33 (0.96)	8.03 (0.96)	7.90 (0.95)
Avg. number of exited developers	5.32 (1.74)	6.81 (1.93)	6.87 (1.95)

4.2 Model Sensitivity

Success rate

The results of the sensitivity analysis highlight key differences among the different CfDs. First, by studying the effect of the input parameters on the success rate of reaching the target 40 GW, we notice some differences among the CfDs (figure 4.8). The two-sided CfD is sensitive to reaching the target when the CAPEX and capacity factor change. This CfD seems to clash with the ceiling price more often when the CAPEX and capacity factor increase, resulting in more invalid bids. This results in fewer participants and fewer tenders being auctioned. The one-sided CfD is also sensitive to changes in the same parameters. The effects on the one-sided CfD are somewhat smaller because the strike prices overall sit further from the ceiling price than with the two-sided CfD.

However, the financial CfD is barely affected, showing only differences in success rates as the capacity factor changes (Figure 4.8). The reason the capacity factor has the greatest impact on the success rate of a financial CfD is that it closes the gap relative to the reference generator. The larger the gap, the more additional profit the developer is allowed to keep. For the other parameters, the financial CfD seems fairly robust. Across all three designs, OPEX and electricity prices have a much smaller effect, and price volatility seems entirely ineffective on the success rate of the CfD mechanisms.

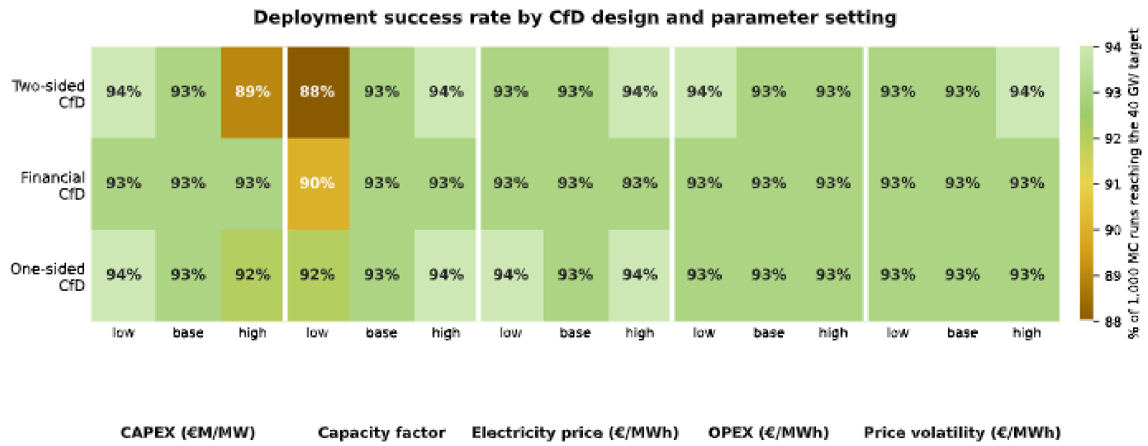

Figure 4.8: Success rate - sensitivity analysis

Total subsidy costs

The total subsidy costs are an important indicator for the government, given that the government does not have an unlimited budget. In figure 4.9, the sensitivity of the total subsidy costs per input parameter is shown. The subsidy cost responds most strongly to changes in CAPEX and capacity factor. OPEX and electricity prices have a small effect on costs, and price volatility is ineffective. For every parameter, the two-sided CfD yields a negative cost, implying a net recovery for the government. The one-sided CfD remains close to zero or slightly above, reflecting the zero-subsidy bids the CfD is known to produce. The financial CfD follows a similar pattern to the two-sided CfD, but it does cost the government money when CAPEX is high or the capacity factor is low. The two-sided CfD offers the most potential for a net positive return for the government; the one-sided CfD never generates any income, which is the core working of the CfD mechanism, and the financial CfD sits in the middle with a smaller net recovery for the government than the two-sided CfD.

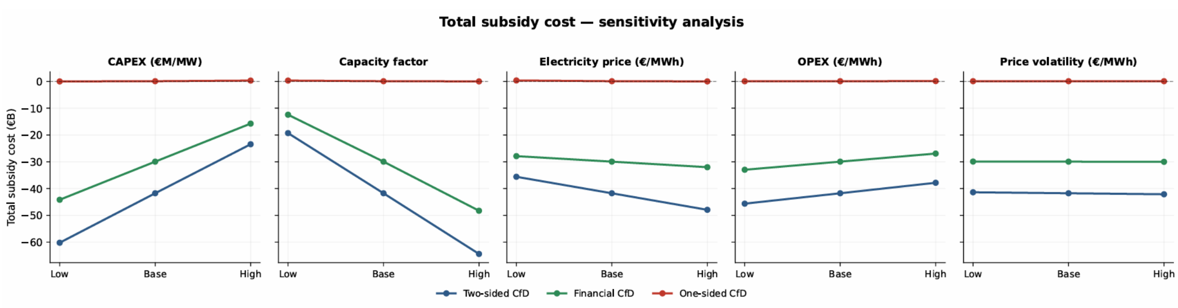

Figure 4.9: Subsidy costs - sensitivity analysis

Strike price

The trajectory of the average winning strike price over the sensitivity analysis says a lot about how the developers respond to market changes in their bids, addressing the second sub-question directly (figure 4.10). CAPEX and capacity factor have the largest effects on developers' bidding, whilst the other parameters have only marginal effects. The higher the costs, the more bids increase, and the lower the production and electricity prices, the more bids decrease. Depending on the input parameters, the one-sided CfD can reach an average of nearly 0 €/MWh, meaning that under those parameters, there are almost always multiple developers who believe a zero-subsidy bid is worth it. The two-sided CfD and financial CfD move slightly parallel to one another, except for when the capacity factor changes. This is because, in the financial CfD mechanism, where the capacity factor affects the residual profit the developer is allowed to keep, bids decrease more rapidly as the capacity factor declines.

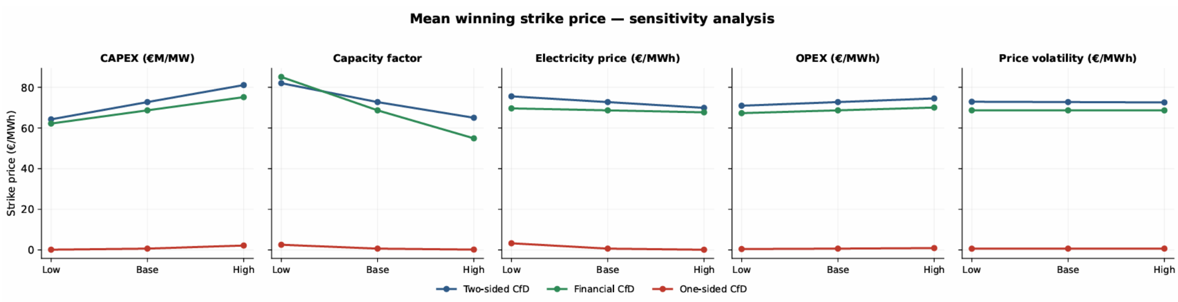

Figure 4.10: Strike price - sensitivity analysis

Bidding participation

As the offshore wind sector is a somewhat niche sector, the last thing you want happening as a government is a single organisation becoming a monopolist in the market. The results of the diverse number of winners and the amount of ceiling rejected bids for each CfD provide some insights into the market movements (figure 4.11,

Looking at the metric per CfD, the one-sided CfD shows a large difference in the number of distinct winners when CAPEX, capacity factor, and electricity price change (Figure 4.11). On the other hand, the financial CfD and the two-sided CfD show little to no change. Compared with the ceiling price rejection rate, the results show differences across markets. Under favourable input values, such as low CAPEX and a high capacity factor, all three CfDs have almost no bids rejected due to the ceiling price. However, when the CAPEX shifts, the number of rejected bids increases at different rates (Figure 4.12). The two-sided CfD has the largest swings, with more than a quarter of the bids placed above the ceiling price. The one-sided CfD also sees an increase in bids placed above the ceiling price, whilst the financial CfD bids remain mostly viable. The financial CfD reacts very differently when the capacity factor decreases, as this brings the developers closer to the reference generator in terms of revenue, meaning they need to bid a higher strike price to earn back their investment. Further, a low capacity factor also results in an even slightly higher ceiling price rejection rate for the one-sided and two-sided CfD, but the curves remain fairly similar to the CAPEX results. Electricity prices and OPEX also affect the number of rejected bids, following similar trajectories but with much less impact than CAPEX and capacity factor.

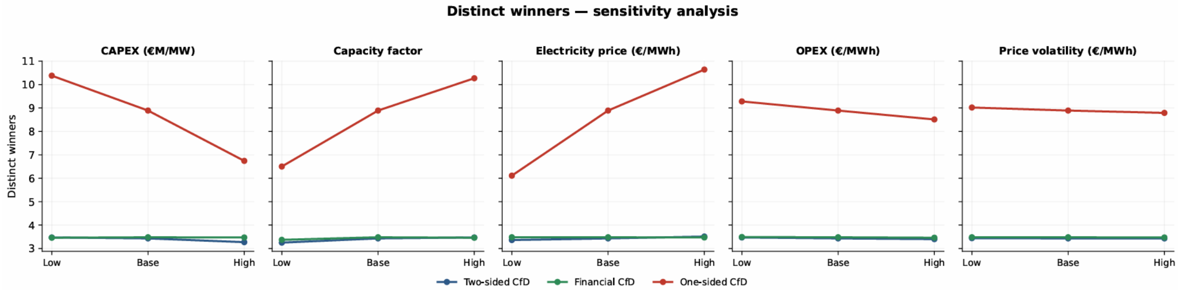

Figure 4.11: Distinct winners - sensitivity analysis

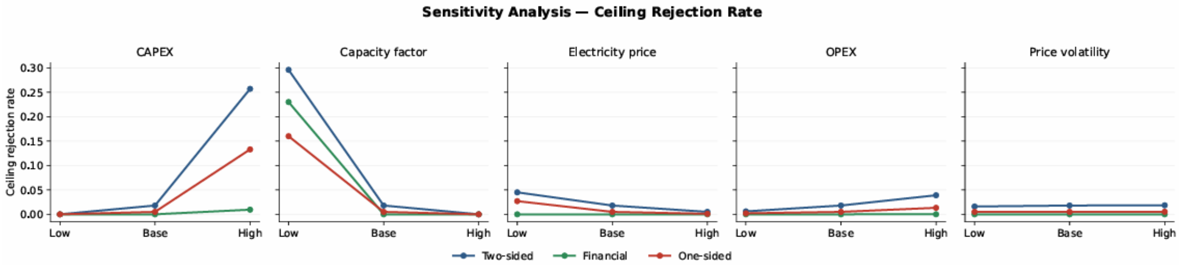

Figure 4.12: Ceiling price rejection rate - sensitivity analysis

What is interesting to see is that the increase in bids being rejected by the ceiling price does not lead to more agents exiting the model for the two-sided and financial CfD (Figure 4.13). For the financial CfD, the mean number of valid bidders also remains consistent (Figure 4.14), only decreasing as the capacity factor increases, as more bidders bid above the ceiling price. For two-sided CfD, the amount of valid bidders is clearly impacted by the ceiling price as the number of bidders decreases under a high CAPEX and low capacity factor, similar to the input parameters when the ceiling price rejection rate is higher. The expected electricity price also swings the number of bidders, but the ceiling price rejection rate is not very high under the different expected electricity prices. Due to the uncertainty of the electricity market, the bidders still consider the possibility of high electricity prices which is why they still often choose to bid for zero-subsidy.

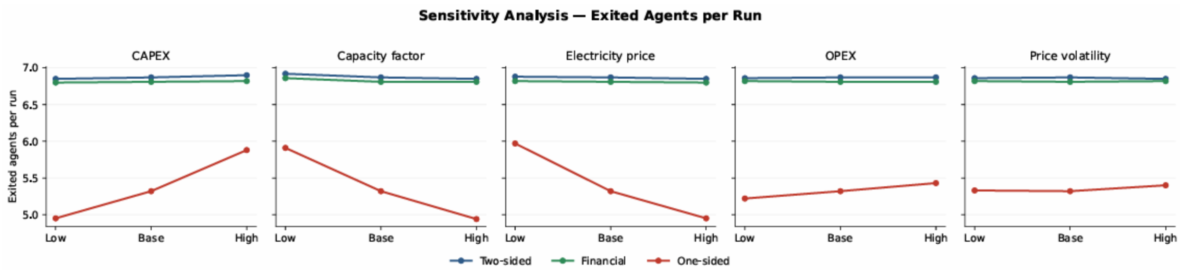

Figure 4.13: Exited agents - sensitivity analysis

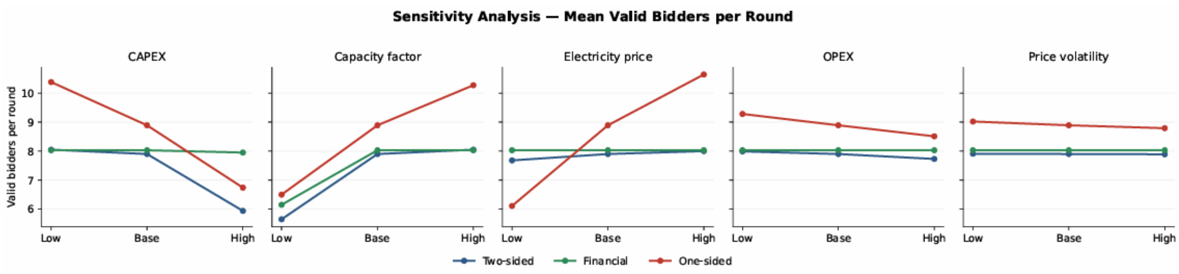

Figure 4.14: Mean valid bidders per round - sensitivity analysis

Based on the sensitivity analysis, the developers' expected electricity price volatility has barely any effect on any of the CfD mechanisms. CAPEX and capacity factor have the greatest impact on auction outcomes and market behaviour. This finding supports the results of Malleret et al. (2024), whose sensitivity analysis identifies the capacity factor, WACC, and CAPEX as the main factors driving strike-price bid variation. The strike price bid must at least provide a break-even revenue stream, covering not only the CfD lifetime but also protecting against a volatile merchant tail. The OPEX exerts a smaller effect but similar influence on the strike price bids. These findings show that the project economics are the primary factor for a developer when determining the necessary subsidy support. The electricity price expectation has a small effect on the two-sided and financial CfD, similar to OPEX. It has a larger effect on one-sided CfD market outcomes, as it provides greater upside for developers under the merchant tail, which is why developers take on the risk of zero-subsidy bids, or forces them to bid higher strike prices when the expected price is low. The OPEX having a smaller effect actually corresponds with the real project economics of an offshore wind farm, as wind energy is known to have very low marginal costs. The price volatility range parameter produces an even smaller effect, effectively not affecting the developer's position within the auctions. Malleret et al. (2024) also found that electricity price plays a smaller role in strike price determination but has a large effect on post-auction profits, similar to what this study finds with swings in subsidy costs.

However, Malleret et al. (2024) distinguishes between the moment of the auction and the moment of the final investment decision (FID), which will be elaborated on in chapter 5. An insight that previous studies on offshore wind CfD auctions do not provide is the market disruption caused by the ceiling price. In Anatolitis and Welisch (2017), the ceiling price follows a dynamic pattern, always leaving room for the market to submit bids and allowing tenders to be awarded. Kell et al. (2023) implements a fixed ceiling price, but their model is a single-tender round and focuses more on game theory. The repeated-auction structure of our model reveals insights that a single-round analysis by Kell et al. (2023) does not capture: when the ceiling consistently binds due to increasing costs, it creates a potential exit incentive that reduces future competition, further concentrating the remaining bidder pool and increasing the likelihood of deployment failure across future rounds.

4.3 Ceiling Price Policy Levels

To study the effect of different ceiling price policy levels, a standalone experiment was performed varying the ceiling price from 91 €/MWh to the baseline value of 104 €/MWh to the increased value for the upcoming IJmuiden Gamma tenders of 117 €/MWh. This experiment addresses the ceiling-price component of the third sub-question by identifying how different ceiling levels affect system robustness, while the sensitivity and scenario analyses add to these findings by focussing on the cost and price levels. Each level is evaluated over 1000 Monte Carlo simulation runs, just as the sensitivity analysis parameters are. The ceiling price policy results in Table 4.2 provide insights towards possible ceiling price levels the Dutch government could implement.

Table 4.2: Ceiling price experiment on the base model. Each KPI is the mean across 1,000 Monte Carlo runs for ceiling price levels of €91, €104 and €117. Standard deviations across runs are shown in brackets for the averaged KPIs.

KPI	CfD design	Ceiling price level		
		91 €/MWh	104 €/MWh	117 €/MWh
Success rate (%)	One-sided	92.5	93.4	93.4
	Financial	92.7	93.2	93.2
	Two-sided	87.3	93.3	93.3
Total subsidy (€bn)	One-sided	0.0 (0.3)	0.1 (0.4)	0.1 (0.4)
	Financial	-30.0 (11.8)	-29.9 (11.8)	-29.9 (11.8)
	Two-sided	-41.9 (13.5)	-41.8 (13.6)	-41.7 (13.6)
Avg. strike price (€/MWh)	One-sided	0.5 (1.9)	0.7 (2.2)	0.7 (2.2)
	Financial	68.6 (2.8)	68.7 (2.8)	68.7 (2.8)
	Two-sided	72.5 (3.4)	72.7 (3.5)	72.7 (3.5)
Ceiling rejection rate (–)	One-sided	0.131	0.005	0.000
	Financial	0.068	0.000	0.000
	Two-sided	0.373	0.018	0.000
Avg. distinct winners (#)	One-sided	8.78 (1.49)	8.89 (1.46)	8.89 (1.46)
	Financial	3.44 (1.25)	3.48 (1.26)	3.48 (1.26)
	Two-sided	3.19 (1.07)	3.43 (1.16)	3.44 (1.16)
Avg. exited developers (#)	One-sided	5.36 (1.75)	5.32 (1.74)	5.32 (1.74)
	Financial	6.83 (1.94)	6.81 (1.93)	6.81 (1.93)
	Two-sided	6.97 (1.97)	6.87 (1.95)	6.86 (1.95)
Avg. valid bidders per round (#)	One-sided	7.27 (1.13)	8.33 (0.96)	8.37 (0.95)
	Financial	7.48 (1.01)	8.03 (0.91)	8.03 (0.91)
	Two-sided	5.03 (1.18)	7.90 (0.95)	8.04 (0.94)

The first indication of the baseline policy of 104 €/MWh is that it rarely excludes developers from bidding, as the ceiling rejection rate is very low. This also leads to high deployment success rates, with percentages of 93.4% for the one-sided, 93.3% for the two-sided, and 93.2% for the financial CfD. A similar result is observed when the ceiling price is increased to 117 €/MWh, with success rates remaining largely unchanged, as do the mean winning strike price, subsidy costs, and bidder participation. The ceiling price rejection rate falls to zero for all CfD designs, where it was still at 1.8% for the two-sided CfD and 0.5% for the one-sided CfD under the baseline level. This shows that all the developers' bids fall within the ceiling price range. At these ceiling price levels, 104 €/MWh and 117 €/MWh, the policy acts more as a participation controller and does not influence the developers' bidding strategy, as it does not lower the mean winning strike price bid or subsidy costs. This is expected as the subsidy costs are settled against the realised market electricity price relative to the awarded strike price, neither of which the ceiling price directly alters.

Under the lowest level, the constraining impact of the ceiling price becomes more visible. The two-sided CfD is the most vulnerable as the ceiling price rejection rate rises from 1.8% to 37.3%, resulting in the success rate falling to 87.3% (Figure 4.15). The one-sided and financial CfD have milder results with the rejection rate rising to 13.1% and 6.8%, and the success rate dropping to 92.5% and 92.7%, respectively. The ordering of rejection rate is directly correlated with the bidding strategy for each CfD design. The two-sided CfD has the highest average strike price of 72.5 €/MWh, bidding at break-even with no potential upside, resulting in the highest rejection rate. The financial CfD and one-sided CfD are more interesting, as their rejection rates are relatively close, but the mean winning strike prices are widely spread out. The financial CfD average sits at 68.7 €/MWh, whilst the one-sided CfD sits at 0.5 €/MWh. The standard deviations of these strike prices, at 2.8 and 1.9 €/MWh, respectively, are small relative to the gap between them, confirming that the two designs occupy distinct strike-price levels despite their similar rejection rates. This suggests that when developers are unwilling to take on the risk of zero-subsidy bids under the one-sided CfD mechanism, their strike-price bids are higher than those they would place under a financial CfD design, because the rejection rate under the one-sided CfD is higher.

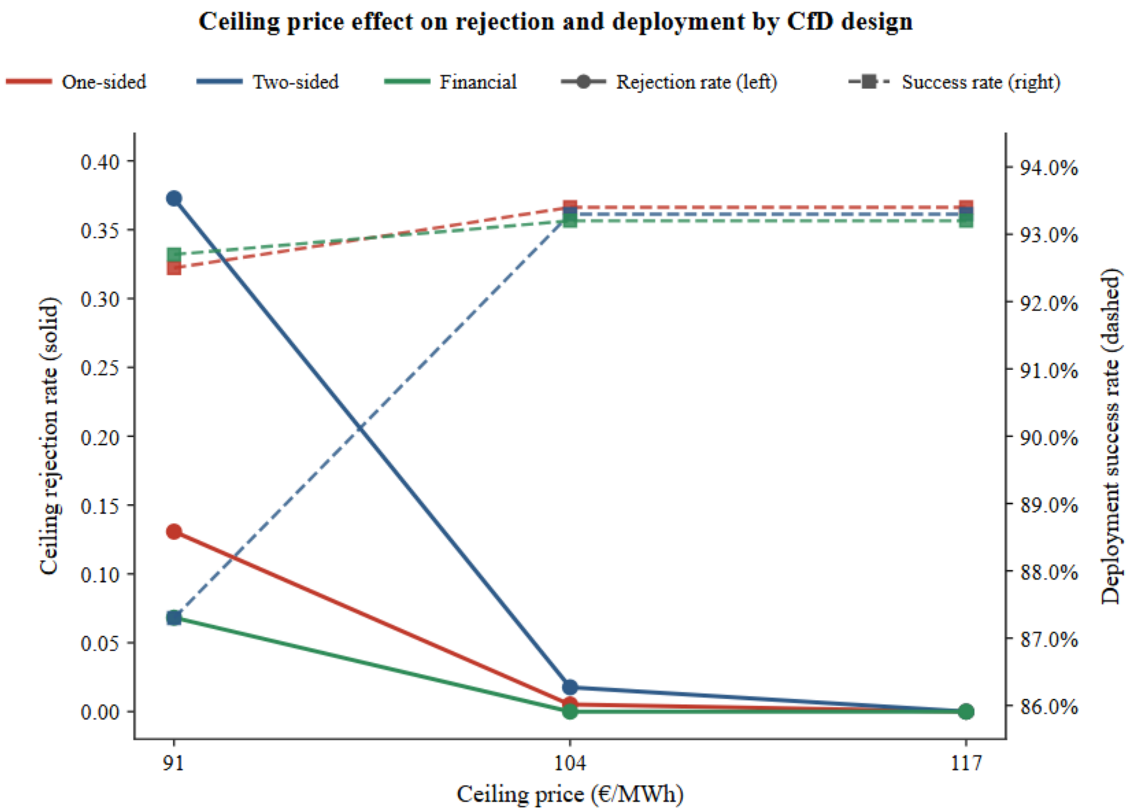

Figure 4.15: Ceiling price experiment results of deployment success rate versus ceiling rejection rate on a dual-axis graph

These results show that as long as auction bids remain below the ceiling price, the market has room to operate freely. In the baseline and upper level of the ceiling price, this is often the case, as evidenced by the low rejection rates. At the lower ceiling price level, more bids are rejected by the ceiling price, leading to more developers leaving the market and more simulations failing to reach the 40 GW target. The two-sided CfD suffers the most, whilst the financial CfD and one-sided CfD are more robust. To study the effects of the baseline ceiling price under uncertainty in costs and electricity prices, a scenario analysis has been conducted.

4.4 Future Scenarios

The future will always remain uncertain and unpredictable. The offshore wind sector in the Netherlands finds itself at a crossroads. The possible scenarios identified in the previous chapter may provide insights into the behaviour of contract-for-difference policies and the Dutch offshore wind market under future scenarios (3.5). These insights can help answer part of the third sub-question regarding the robustness of CfD designs to uncertainty in electricity prices and cost levels.

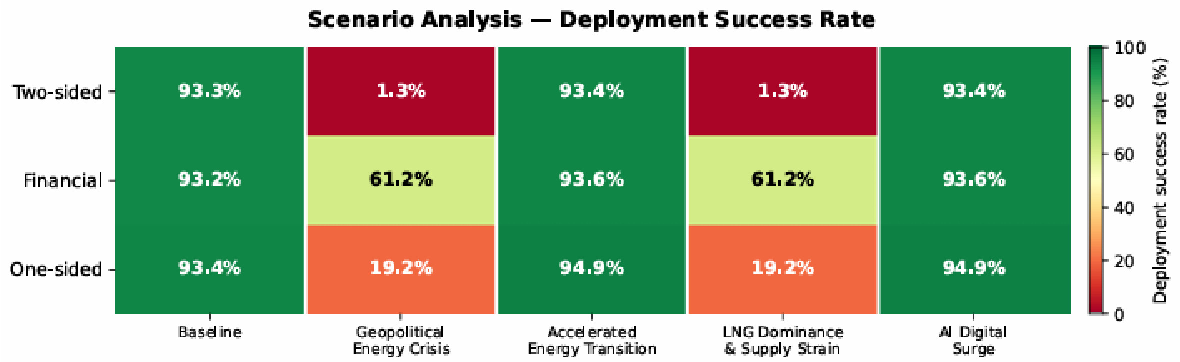

Figure 4.16: Success rate - scenario analysis

It is clear that under the energy crisis scenario, characterised by high electricity prices and high costs, the CfDs endure the most stress. The two-sided CfD collapses completely and practically never reaches the target with 1.3% success (Figure 4.16). The increased costs push the developers over the ceiling price, as the rejection rate is 1.0 (Figure 4.17). The one-sided CfD also shows a high rejection rate of ≈ 0.90, reducing the percentage of successful simulations; only 19% of runs reach the target (Figure 4.16). On the other hand, the financial CfD proves somewhat robust against the energy crisis. It has a deployment rate of 61.2%, a testament to the financial CfD mechanism, in which the developer can recoup their costs by outperforming the reference generator. This corresponds to the strike price levels: the two-sided CfD has a higher mean strike price than the financial CfD, and when developers choose not to bid for zero-subsidy, they reach the ceiling price faster than developers under the financial CfD (Figure 4.17). That being said, it is clear that the financial CfD suffers from a lack of competition under this scenario, as many competitors are unwilling to take on more risk and are otherwise unable to bid below the ceiling price. The subsidy cost implications for the two- and one-sided CfD are very low, as very few contracts are awarded. The financial

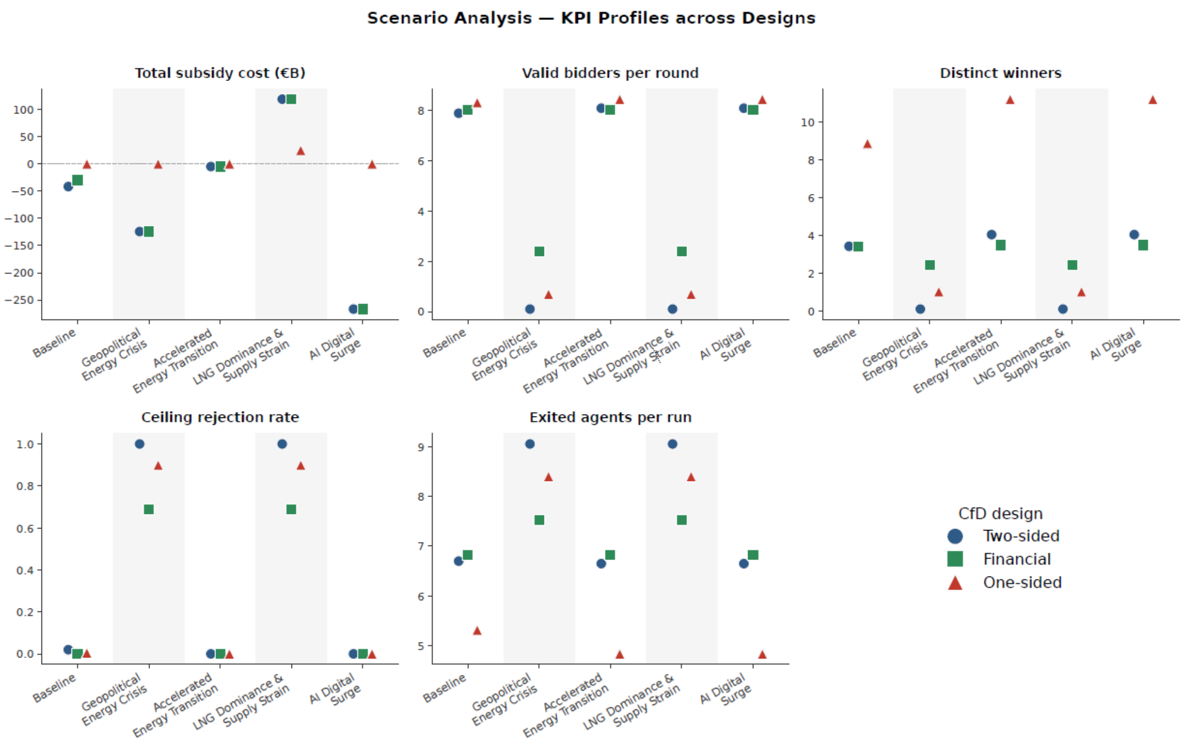

Figure 4.17: Overview of KPI results -scenario analysis

CfD produces a large clawback of ≈ €125bn as the high energy prices force the developers to return a large part of their revenue.

In the accelerated energy transition scenario, the difference in deployment rate is much smaller. The one-sided CfD sees a minor increase, and the other two CfDs have a similar success rate to the baseline scenario (Figure 4.16). The low-cost environment allows developers to place bids well below the ceiling price, with mean winning strike prices of 34.36 €/MWh for the two-sided CfD, 29.35 €/MWh for the financial CfD, and effectively 0 €/MWh for the one-sided CfD (Figure 4.18). For the developers under the financial CfD, the gap between the reference generator and their own capacity factor has increased, thereby supporting the developers' ability to lower their strike-price bids. Due to the low market prices, the subsidy clawbacks are relatively low, €5.01bn for the financial CfD and €12.85bn for the two-sided CfD. The one-sided approach produces zero subsidy costs, as the environment has driven competition among developers to zero-subsidy bids. All three CfD's see an increase in competition relative to the baseline, reflecting that low costs allow more developers to compete.

The third scenario, "LNG Dominance & Supply Strain", has costs similar to the energy crisis scenario but experiences low electricity prices. The scenario produces a success rate similar to that of the energy crisis scenario because high costs push a majority of developers above the ceiling price, resulting in a similar collapse for the two-sided CfD (Figure 4.17). The major difference in the energy crisis scenario is the government's subsidy expenditure. Since electricity prices are very low, the government has to provide far more support to developers.

The awarded contracts have high strike prices due to high costs (Figure 4.18). Due to the low electricity prices, the awarded contracts rely on CfD support to achieve sufficient revenue. This leads to a subsidy of roughly €25 bn for the one-sided CfD and €115 bn for the financial CfD, a massive swing compared to the energy crisis. The "LNG Dominance & Supply Strain" and "Geopolitical Energy Crisis" scenarios provide a clear example of the swing in support costs that can occur under the CfD mechanisms.

Finally, the "AI-Boom" scenario, where electricity prices are high and developer costs are low, is somewhat ideal for developers. The deployment rate is similar to the accelerated energy transition, confirming that cost conditions largely determine deployment outcomes. The meaning: winning strike prices are similar as well, as bid determination depends on costs and capacity factor, not the eventual realised electricity prices Figure 4.18. However, due to high electricity prices, the government receives a much larger subsidy income than in the energy transition scenario. The two-sided CfD generates a clawback of ≈€340B, the largest clawback in the entire scenario analysis, as the large difference between the high realised price (172 €/MWh) and the low strike price (34.36 €/MWh) accumulates over the first 15 years of all awarded contracts. The financial CfD generates a clawback of roughly €265B. The one-sided CfD produces zero subsidy and zero clawback, as it has no mechanism to recover value if the market price exceeds the strike price. The comparison of the Accelerated Transition and AI Surge scenarios also illustrates the large difference in fiscal outcomes between low-cost scenarios with different electricity price trajectories.

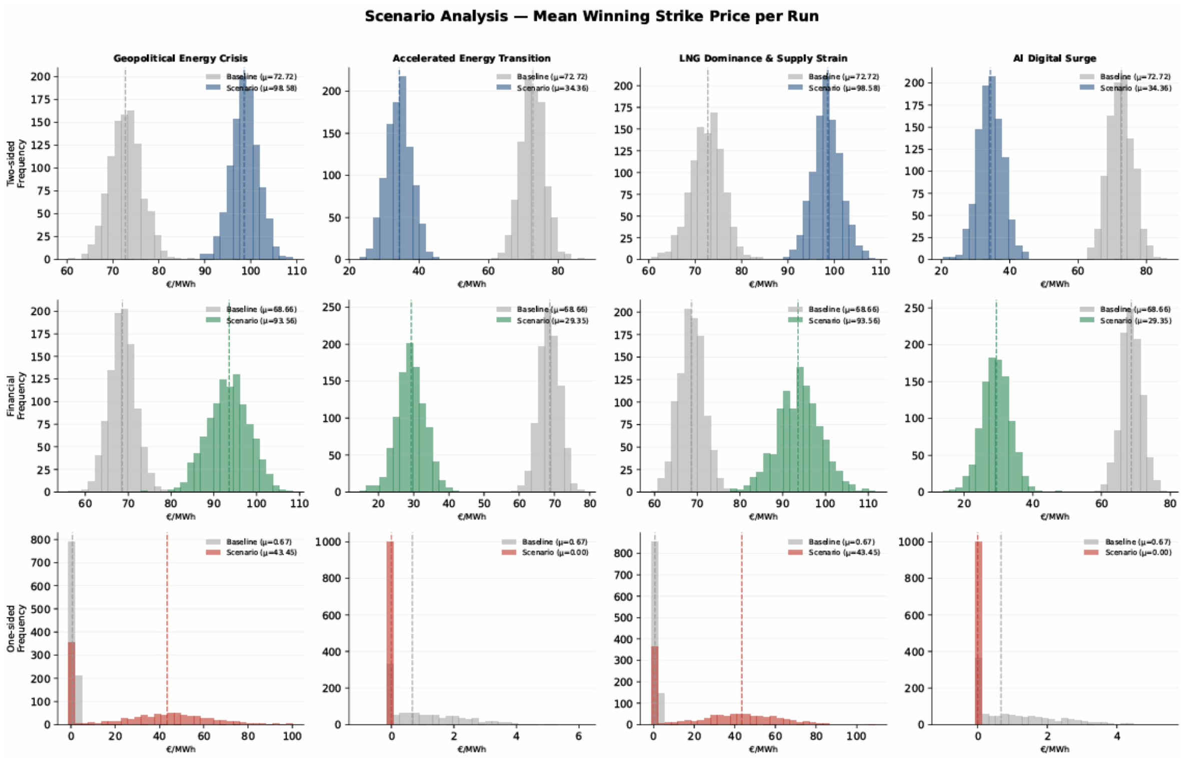

Figure 4.18: Mean strike prices overview - scenario analysis

The scenario analysis reveals that the deployment outcomes across all three CfD designs are determined primarily by the cost environment relative to the administrative ceiling of 104 €/MWh. This is clearly illustrated by scenarios with high costs that produce near-identical low deployment rates and high ceiling price rejection rates. Developers have their expected price fixed at 91.88 €/MWh because the future is uncertain, and they already spread their expectations across three levels. This means that, in the scenario analysis, costs and capacity factors govern the strike price calculations and determine the success rate entirely by the cost environment relative to the administrative ceiling. The financial CfD's partial resilience in high-cost scenarios, retaining 61.2% deployment, where the two-sided collapses to 1.3% and the one-sided to 19.2%. This is the sole deployment differentiator across designs and scenarios, and it is driven entirely by the structural mechanism of the financial CfD, which decouples costs from strike price formation.

On the outcomes of the subsidy costs, the scenario analysis also provides some insights. Despite identical deployment, the energy crisis and LNG & supply strain scenarios produce opposite fiscal outcomes: the financial CfD swings from €124bn clawback to a +€119bn subsidy, a €243bn reversal driven by the realised price level. Across all scenarios, the financial CfD generates the largest swing, achieving a €265bn clawback in the AI Surge scenario and €118.66bn subsidy cost in the LNG Dominance scenario, followed by the two-sided CfD, which reaches a €340bn clawback and €8bn subsidy cost, respectively. The one-sided CfD is fiscally unresponsive under high prices but exposes the government to subsidy payments when low realised prices trigger the floor.

The scenario analysis provides two distinct findings that contribute towards the research questions of this study. Firstly, the scenario analysis finds that the success rate suffers significantly when project costs cause the strike prices to exceed the ceiling price. This is showcased by the similar deployment success rates achieved by the "Geopolitical Energy Crisis" and "LNG Dominance & Supply Strain" scenarios, where, despite producing different realised electricity prices, both scenarios impose the same CAPEX stress on developer strike-price bids. Since developer price expectations are fixed at the baseline mean value of 91.88 €/MWh across all scenarios, the bid formation process is identical in both cases, and the ceiling becomes binding for the same reason. Within the deployment success rate, the financial CfD consistently demonstrates the greatest resilience under cost stress, retaining 61.2% deployment in both high-cost scenarios, where the two-sided collapses to 1.3% and the one-sided to 19.2%. This resilience is attributable to the settlement structure described by Schlecht et al. (2024). By referencing a fixed external benchmark capacity factor rather than individual developers' output, the financial CfD partially decouples developers' strike-price bids from the full per-MWh cost burden, allowing above-average capacity-factor agents to clear the ceiling, even under extreme conditions such as these. The results of our model demonstrate that developers allow their break-even bid to sit below the ceiling even when CAPEX is elevated under the financial CfD mechanism.

Furthermore, the scenario analysis also reveals that the three CfD designs provide different risk profiles for the Dutch government. The contrast between the Geopolitical Energy Crisis and LNG Dominance & Supply Strain scenarios shows that despite similar deployment success rates, the financial CfD swings from €124bn clawback to €119bn subsidy support cost, a €243bn difference driven by the realised price level. If the LNG dominance & Supply Strain scenario is compared with the AI Surge, the government endures an even larger swing in expenditure as the government earns almost €340bn during the AI Surge scenario. This is a direct consequence of the settlement structure, where larger spreads between the realised market price and the strike price produce larger cash flows in either direction, an effect that Schlecht et al. (2024) identifies theoretically but does not quantify across multiple price scenarios in a repeated-auction setting. The one-sided CfD supports developers during periods of low electricity prices and generates no revenue for the Dutch government. Johanndeiter et al. (2025) identifies this asymmetry as a fundamental design property of one-sided CfDs, noting that one-way contracts only hedge risk in one direction. Our model confirms this property by showing that the one-sided CfD provides no deployment protection under increasing costs, resulting in a deployment collapse, whilst also exposing the government to high subsidy costs. The scenario with an increased capacity factor, "Accelerated Energy Transition" and "AI Surge", further supports this finding of the fiscal costs that previous studies have not addressed. Malleret et al. (2024) analyses the sensitivity of project profitability to capacity factor variation at the point of the auction bid and the final investment decision, without simulating the fiscal consequences of different price realisations across future possibilities. Schlecht et al. (2024) analyses the settlement properties of financial CfDs theoretically, focusing on the incentive effects of the reference generator design rather than quantifying fiscal outcomes across different price environments. Neither framework, therefore, provides a comparison of subsidy outcomes under identical cost and deployment conditions and alternate future electricity prices. As mentioned earlier, the differences in clawback and subsidy costs can be quite drastic for the CfD designs.

4.5 Synthesis of Results

The results of the scenario and sensitivity analyses provide insights that, taken collectively, distinguish each CfD design within the context of the Dutch offshore wind sector and clearly show the market outcomes and dynamics under each design. The first important finding is that, under each CfD design, the fixed ceiling price of 104 €/MWh is the primary constraint on the viability of the designs. The unreliability of CAPEX levels in the current market, combined with uncertain capacity factors, determines whether a developer can secure a strike price bid below the ceiling price, far more than other parameters. Displaying the CfD vulnerability to different future scenarios showcased that the ceiling price can cause a total collapse of the sector. With the current state of geopolitics, energy prices & transportation costs can differentiate by a wide margin in a short amount of time. This finding implies that the effectiveness of any CfD design depends on an accurately calibrated ceiling price that preserves auction viability.

Across the sensitivity and scenario analyses, the financial CfD demonstrates the greatest resilience and, overall, delivers a market that reaches the target of 40 GW. In the worst case, 61.2% of cases with a financial CfD still achieve a successful simulation. The intricate settlement structure of the financial CfD allows developers to determine their strike price based on the reference generator's output rather than their own production, allowing developers whose capacity factor exceeds the reference generator's to partially offset their cost burden and clear the ceiling even when CAPEX is elevated, a mechanism unique to the financial CfD. The trade-off the Dutch government would have to make if this CfD were implemented is the fiscal variance. The financial CfD generates the largest absolute swing from high subsidy costs to generating a large sum for the government. Our model quantifies the magnitude of that stabilisation and shows that the financial CfD reaches large values in both directions. Taken together with the ceiling-price experiment, this provides the combined answer to the third sub-question: the financial CfD is the most robust design to uncertain prices and costs, while the ceiling price level is the decisive policy condition determining whether any design remains viable at all.

Another finding worth mentioning is that the one-sided CfDs results correspond well with the current state of the market. The zero-subsidy bids, which made the CfD so attractive for the Dutch government, result in very little subsidy costs. However, based on the analyses, it is clear that market parties' warning that the one-sided CfD is too risky in the current situation is justified, as the CfD collapses under rising costs. One-sided CfDs compensate the producer only when the market price falls below the strike price, leaving the government with no claim on revenues when prices exceed it. The results show that zero-subsidy outcomes are due to competition, not to the efficient cost recovery the CfD offers. The takeaway is that the one-sided CfD does not balance support costs and deployment success; instead, it exposes the government to residual subsidy costs due to the settlement environment it creates, thereby forcing developers to submit zero-subsidy bids to win.

Taken together, the results do not point to a direct best auction design for the Dutch government, but they do support a conditional ranking rather than a simple "trade-off exists" framing (Figure 4.19). The financial CfD is the most resilient; it is the only design that sustains deployment under cost stress, retaining 61.2% success, whereas the two-sided collapses to 1.3% and the one-sided falls to 19.2%. The two-sided CfD dominates on expected fiscal return in high electricity price conditions, generating the largest net recovery for the government when costs sit comfortably below the ceiling. The one-sided CfD is dominated on both criteria; it doesn't protect deployment against rising costs or generate revenue when market prices rise, except when its zero-subsidy bids reflect the competitive nature of developers willing to take on the risk, saving the government from potential subsidy costs.

The choice of which design to implement depends on the government's risk preference. A government that prioritises hitting the 40 GW target under uncertain costs would favour the financial CfD and accept the potentially large subsidy costs that it might require, additionally hoping for some clawback as it swung from roughly €119bn in support under the LNG Dominance & Supply Strain scenario to a clawback of €265bn in the AI Surge scenario. A government that prioritises fiscal certainty in a stable cost environment would prefer the two-sided design, accepting that it is brittle when costs rise. What unifies both cases is that the fixed 104 €/MWh ceiling price, based on the advice from Lensink and Henriquez (2026), determines whether any design remains viable at all. If project costs push break-even bids above it, the design choice loses its impact and is constrained by the ceiling price.

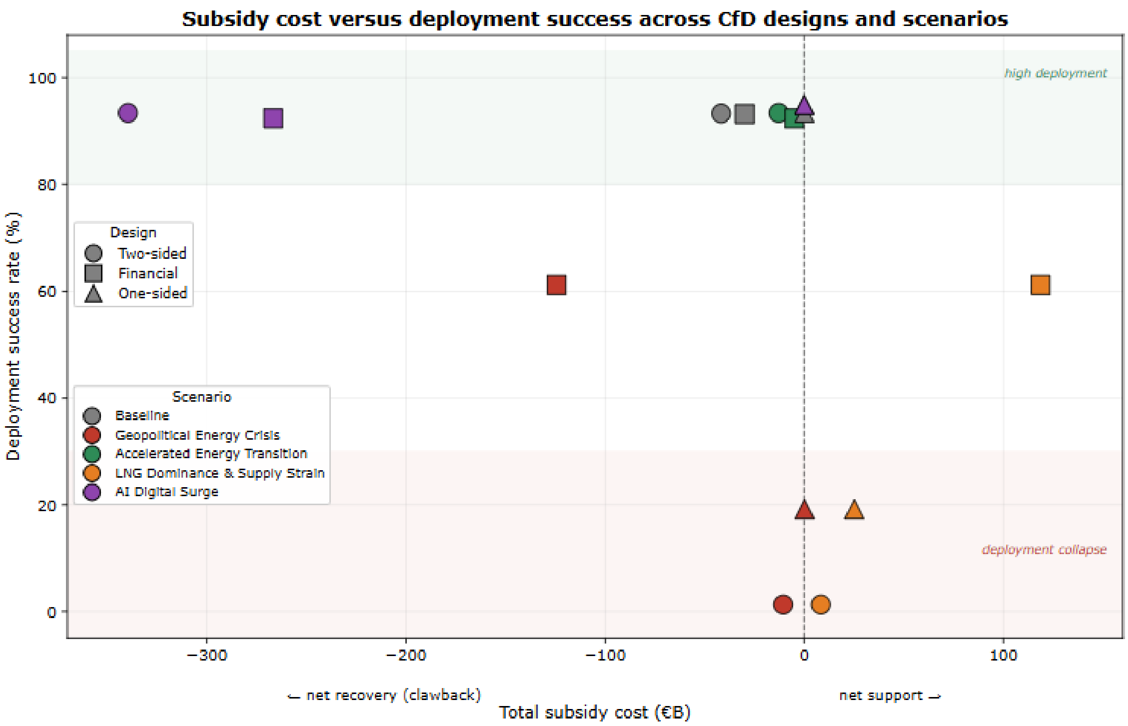

Figure 4.19: Comparison graph of subsidy cost versus deployment success rate under the scenario analysis

5. Discussion

This chapter of the thesis will go in-depth on the findings compared to other literature. It will also discuss certain limitations of the model and how these impact the results. Based on the findings and limitations, this thesis has also identified future research recommendations, which will be discussed at the end of this chapter.

5.1 Interpretation of the Findings

The results of this study confirm, extend, and in some cases challenge the findings of the existing literature on CfD auction design. This section discusses each of the main findings in turn.

Firstly, the addition of the ceiling price experiment addresses the knowledge gap identified in chapter 2 regarding how the level of a fixed ceiling price influences market performance under different CfD designs, speaking towards the ceilin-price component of the third subquestion. By varying the ceiling price across different levels for the baseline model, the effects of the ceiling price could be isolated. The results show that the fixed ceiling price regulates market participation but does not affect developers' bidding strategies, as the average winning strike prices remained fairly stagnant. The ceiling price also does not alter the subsidy costs or clawback that the government has to pay/receive. This happens because it is settled against the realised electricity market price relative to the awarded strike price, which the ceiling price does not directly affect in this model. The results do show that the ceiling price actually influences the system.

Under the baseline model, the increased ceiling price of 117 €/MWh yielded very similar results across all three CfD designs; for example, each achieved a success rate of roughly 93%. But if the ceiling price decreases to 91 €/MWh, the rejection rate rises sharply and the average number of valid bidders per round falls, as rejected bids push developers to exit the market. These effects differ across the CfD designs: the two-sided CfD shows the highest increase, with 37.3% of bids rejected, compared with 13.1% for the one-sided CfD and 6.8% for the financial CfD. The average number of valid bidders per round also follows a similar pattern, with the two-sided CfD seeing the largest drop, from 7.90 to 5.03. The reason for these results and the ordering of the CfD designs is the developer's bidding strategy for each design. The financial CfD bids the lowest average winning strike price of 68.6 €/MWh because the reference-generator settlement allows developers to earn part of their costs by outperforming the generator, giving them more headroom. Under the two-sided CfD, developers bid their full required break-even strike price, resulting in a higher average winning price of 72.5 €/MWh. As it offers no upside to absorb, it is closest to the ceiling price and is rejected most often. The one-sided sits between, its near-zero average bid masking the fact that if developers are unwilling to take the upside risk and bid for zero-subsidy, their bids are placed above the ceiling price more often than the financial CfD. Because rejected developers also accumulate exit probabilities, the effect is not a one-off rejection but cumulative, thinning competition in future rounds and resulting in fewer successful simulations that reach the target of 40 GW. These results show that the notion that the PBL-advised ceiling is set above the bids most developers are expected to submit, so that the majority of developers can create a positive business case (Lensink and Henriquez, 2026), is a fragile policy that requires extensive calibration.

The scenario analysis builds on this finding by showing that the fixed administrative ceiling price of 104 €/MWh is the primary determinant of auction viability, overriding the effect of CfD design under adverse cost conditions. This finding builds on Anatolitis and Welisch (2017) and Kell et al. (2023), both of whom implement ceiling prices in their models but do not study their exclusion effect across multiple auction rounds. Anatolitis and Welisch (2017) use a dynamic ceiling price that adjusts to the highest winning bids from the preceding three rounds, thereby preventing the ceiling price from becoming a binding constraint. Kell et al. (2023) implement a fixed ceiling but study only a single auction round, so developers do not have a chance to adjust their bidding behaviour for the next auction, and repeated ceiling-price rejections cannot occur. The repeated-model dynamic of ceiling price rejections captures that a fixed ceiling price, which consistently constrains developers, leads to developers exiting the market and reduces the chance of successfully reaching the government's target. In the energy crisis and LNG dominance & supply strain scenario, the ceiling price constraint determines whether the CfD collapses.

Furthermore, the behaviour of the one-sided CfD in the baseline model accurately reflects the zero-subsidy bidding observed in recent Dutch offshore wind auctions (Jansen et al., 2022). This contributes to the second sub-question, on how design shapes bidding. The zero-subsidy bids occur because developers competitively undercut one another, not because the CfD design is so efficient that they can afford extremely low bids. Developers gamble on future electricity prices to bail them out and provide enough upside.Johanndeiter et al. (2025) identify this asymmetry as a fundamental property of one-sided CfDs, noting that one-way contracts only compensate the producer when the market price falls below the strike, leaving the government with no claim on revenues when prices exceed it. So, in scenarios with high developer costs, we would expect developers to be forced to abandon this tactic and bid strike prices for actual support. But in these scenarios, the costs prove too high for developers, and bids are submitted above the ceiling price, as illustrated by a ceiling-price rejection rate of roughly 90%. The ceiling price experiment adds to this by presenting a low average winning strike price, whilst simultaneously showing that more developers need higher support coverage, who are exposed by the higher rejection rate. The increasing costs lead to bids above the ceiling price rather than within the support coverage range, meaning the one-sided CfD does not provide a smooth transition from zero-subsidy bidding to CfD-supported bids. In the LNG Dominance & Supply Strain scenario, the government incurs a subsidy cost of approximately €25B, indicating that with low realised electricity prices, it must provide support for the one-sided CfD.

Next, the financial CfD proves far more resilient than the other two CfDs, still reaching the target 61.2% of the simulations, where the two-sided collapses to 1.3% and the one-sided to 19.2%, providing answers to the robustness element of the third sub-question. By partially decoupling their costs from the break-even calculation and using the reference generator as a benchmark, the difference in capacity factor allows the developers to produce at a lower strike price, even under higher costs. This incentivises the developer to generate efficiently, something that the two-sided CfD misses due to its guaranteed per-MWh payment and "produce-and-forget" behaviour, as described by Schlecht et al. (2024). Schlecht et al. (2024) establishes this property theoretically but does not quantify it across multiple price scenarios in a repeated-auction setting. It must also be noted that this model captures this incentive only through the settlement process and does not simulate hourly dispatch once the wind farm is active, at which point the developer would eventually be paid out. Johanndeiter et al. (2025) similarly analyses the financial CfD's cost-recovery economics but focuses on a fully decarbonised European system rather than on an offshore wind auction context with a fixed ceiling price. The results of this model and the scenario analysis demonstrate that the decoupling mechanism of the financial CfD is highly robust to changes in market conditions. The ceiling experiment confirms that this robustness is structural rather than specific to the scenarios. At the binding 91 €/MWh ceiling, the financial CfD has the lowest ceiling rejection rate of the three designs at roughly 7%, compared to 13% for the one-sided and 37% for the two-sided CfD. However, it does come with a large swing in fiscal consequences as the CfD costs the government €119bn in the LNG dominance & Supply Strain scenario, whilst providing a payback of €265bn in the AI Surge scenario. This magnitude of fiscal variance has not been reported in the existing literature for a repeated-auction setting.

A notable finding relative to the previous literature is that this research reaches a different conclusion than Malleret et al. (2024) and Kotsiki (2025). They identify electricity price as the most uncertain factor for developers, whereas this model finds CAPEX and capacity factor to be the dominant drivers. This difference relates to what each study measures. Malleret et al. (2024) and Kotsiki (2025) study the realised profitability of CfD-supported offshore wind projects across their operating life after the auction, meaning the strike price is already agreed upon, and the return depends on the realised electricity market prices. However, this model examines the bid-formation phase, in which developers set a strike-price bid, partly based on their expected electricity prices rather than the realised prices. The capacity factor does create a slight exception: it affects both the strike-price bid and the developer's eventual revenue, so it's used alongside the expected price and the realised market price. The difference between this model and the findings of Malleret et al. (2024) and Kotsiki (2025) is therefore due to the two-price setup, which separates developer expectations from the realised market price to isolate bidding behaviour. These findings are complementary to each other and show that cost parameters dominate how developers bid within the CfD acutions, while the electricity price determines the eventual viability and profitability of the offshore wind projects.

Finally, combining the results of the three analyses reveals that the Dutch government faces a layered decision-making process. The sensitivity analysis shows that CAPEX and the capacity factor are the dominant drivers of every outcome, while electricity price volatility has little effect on bids, meaning a design's viability is governed far more by project cost levels than electricity price expectations. This is an interesting finding that is not in line with previous literature, which indicated that electricity prices are the most uncertain factor for developers. It is also a valuable contribution to clarifying which uncertainties drive robustness for the third sub-question. The scenario analysis then shows that once costs rise, the designs diverge sharply. The financial CfD is able to sustain deployment in cases of two-sided and one-sided collapse. The ceiling price experiment adds by demonstrating that the fixed ceiling price acts more as a market participation policy, determining whether any design can clear at all under stress, whilst retaining competition under baseline conditions. The Dutch government therefore faces a trade-off with three factors. The subsidy cost it is willing to spend whilst keeping the deployment success rate it needs to reach the 40 GW target, and setting a ceiling price level that creates a market environment where bids can clear competitively. Intuition might lean towards a lower ceiling price, leading to lower subsidy costs, but as the success rate decreases with a lower ceiling price, costs also decline because fewer tenders receive bids. For the Dutch government, it is therefore crucial that the decision-making process for future offshore wind tenders and CfD design include this trade-off and determine the risk balance they are willing to take to achieve their sustainability target of 40 GW, versus their total expenditure, with a ceiling-price policy that enforces this balance.

5.2 Start-up Agent Behaviour

At the start of each run, each agent in the model is assigned a set of starting parameters. However, in reality, these agents are already part of the market and might have been for quite some time. The developers would not have the existing capacity divided equally across all fifteen agents, but rather some developers with large amounts of offshore wind capacity and others with little or no offshore wind capacity. The costs and capacity factor are drawn from distributions, placing agents in a perhaps very unfortunate position in the market and potentially preventing them from entering it in the first place. The discount rates are also randomised, with no account taken of past investments or auction experience, which would alter their risk appetite. The agent also all start with a zero exit-chance, resembling the start of a model rather than already having a valued exit-chance based on the agent themselves. As a result, the early rounds of each simulation run resemble this starting point rather than the settled market we see later on in the model, also shown in the base model dynamic illustrations (Figure 4.3 & Figure 4.2). Therefore, the model cannot capture the path-dependent advantages or disadvantages that developers would have in reality. However, it does not hinder the results as the lowest-cost and most risk-tolerant developers still win the first few tenders, as they would in reality. It just takes the developers some time to calibrate their market position, which would have largely taken place before the first auction in reality. This is why the model runs Monte Carlo simulations to ensure that no single run yields the results for this research.

5.3 Model Limitations

The Dutch offshore wind sector is an extremely complex system with numerous variables and uncertainties. Therefore, the simulation developed in this research has incorporated simplifications and several modelling choices that constrain the interpretation of the results.

Discount Rates

An important modelling choice that led to a simplification was to use a constant discount rate across all three designs. This choice was made to isolate the effect of the CfDs and the impact of internal and external parameters. In reality, each design carries a different level of risk in the eyes of the offshore wind developers. Johanndeiter et al. (2025) states this in their research, noting that the revenue uncertainty of financial and two-sided CfDs could be applied with a specific risk premium per design. Đukan et al. (2025) also emphasises the difference in risk between two-sided CfDs and one-sided CfDs, as the one-sided leaves more price risk with the developer. Other sources, such as Kell et al. (2023) & Jansen et al. (2022), use a fixed discount rate, albeit that their research, although focused on offshore wind, applied a single design. The uniform distributed discount rate with a range of 3% was therefore a modelling choice. If the model had exhibited different discount rates, the two-sided CfD would have had the lowest discount rate, the one-sided CfD the highest, and the Financial CfD in between. This was recommended by Schlecht et al. (2024) as the financial CfD has not yet been implemented in practice. This would result in lower strike-price bids for the developers under the two-sided CfD design, making the results more similar to the financial CfD results. The one-sided CfD would have seen fewer zero-subsidy bids and fewer developers taking on that risk. However, this would have meant those developers would also sit closer to the ceiling price, making the market very tight. This would be an interesting dynamic to study in future research.

Electricity Price and the Price Expectations

Another simplification this model applies is how developers set their price expectations. To our knowledge, no literature provides an equation that can be applied to a one-sided CfD as well as a two-sided CfD without some alterations. This is because the approaches to the different CfDs differ. For the two-sided CfD, it is fairly simple because the developers have a guaranteed revenue or clawback on both sides of the strike price. The potential upside of the one-sided CfD makes this far more difficult to calculate. Other literature uses complex solvers or programs that enable developers to run their own Monte Carlo simulations, which would have been too elaborate for this study. Therefore, we simplified the price expectations, allowing us to combine the potential upside of a one-sided CfD into a closed equation we could use for all three CfD designs.

This required a fixed electricity price of 91.88 €/MWh, with the standard deviation calculation from Malleret et al. (2024) serving as the price range. The choice of method by Malleret et al. (2024) was made because the standard deviation of Dutch electricity prices over the past 3 years would have rendered the price extremely volatile. The model also had another limitation regarding electricity prices, as they could not be lower than zero. Negative electricity prices could lead to negative strike prices for the two-sided and financial CfD; for simplicity, this choice was made to keep the focus on the CfD designs. If we had included negative prices, the government's subsidy costs would have increased drastically under both the two-sided and one-sided CfD. For the financial CfD, negative prices mean the reference generator incurs negative revenue, which would result in the government effectively paying out a sum on top of the guaranteed strike-price compensation. Schlecht et al. (2024) actually proposes a mechanism for dealing with this: if the prices are negative, the hourly profit of the reference generator is set to zero. This means that the developer keeps the hourly subsidy sum and, at the same time, is incentivised to stop producing since the prices are negative. This mechanism should be tested in future research on financial CfD design to assess its performance relative to other designs.

The developers' electricity price expectations also remain fixed during the simulations. This was a deliberate simplification to study the effect of bidding behaviour purely in the auctions, isolated from changing electricity prices. In this model, a developer never fully commits to a specific price expectation, as they always account for the other levels with at least a 5% chance. This also explains why the developers don't react to the electricity prices in the scenarios. This was chosen to resemble the unpredictability of the electricity price market, and because CfD lifetimes are fixed contracts, it highlights how this impacts the results if the electricity market suddenly changes. If the model had included dynamic expectations, strike prices would have moved more erratically as expectations shifted after each auction round. It would also have allowed developers to bid even more aggressively if they expected higher prices. Developers would have been able to anticipate and respond to the electricity market, perhaps making it more competitive. It would also probably have changed the success rates across scenarios, with the higher-price scenario seeing more success and the lower-price scenario less, because lower prices mean a higher strike price is needed to cover the developers' costs. This would continue, with more developers seeing their bids rejected due to the ceiling price.

Tendering Process

In other literature, such as Malleret et al. (2024), the period between the auction closing and the Final Investment Decision (FID), which in practice may occur several years later, is an important part of the tender process. This may lead to tenders being postponed or cancelled if market conditions or supply chains worsen, rendering the project unviable. Malleret et al. (2024) show that the gap between auction and FID is where post-auction price and cost movements disrupt the initial projected profitability, and that developers who won with aggressive bids incur substantial losses. This model assumes that every developer who wins an auction at a given strike price accepts the tender and develops the offshore wind farm, as otherwise this would undermine the success rate of the CfD designs. Similarly, the model does not incorporate any post-auction behaviour towards exposing the two-sided CfD. Gupte (2025) notes that developers can use strategic curtailment to influence their revenue versus the government. For example, under a two-sided CfD, the developer can continue to overproduce in a congested electricity market, keeping prices low and guaranteeing government support.

Two other assumptions within the tendering process are the number of tenders auctioned per year and the length of the contracts. The first is the assumed pace of two tenders per year. This was based on historical progress data and future projections. Because the success rate measures whether the 40GW target is reached within the available rounds until 2040, the number of tenders per year directly limits the capacity that can be awarded before 2040. A faster auction pace would likely create more opportunities to reach the target, leading to a higher success rate. It would also intensify market dynamics, as developers face more auctions. The success rates should therefore be interpreted for the scope of the model rather than as absolute deployment probabilities. The second choice, a fixed 15-year CfD support period, was also based on the historical support periods provided by the Dutch government. The length of this tail enters the break-even calculation through the present value of expected merchant revenues, which offsets the required strike price. A shorter CfD lifetime reduces the developer's years of strike-price revenue guarantees, thereby increasing the merchant tail period and leaving the developer more exposed to market risk. This increases the risk the developer must take, resulting in higher strike-price bids. A longer CfD period has the opposite effect: more years with guaranteed income at the strike price, with fewer years exposed to the market. The discount rate for a single developer can influence the impact of gaining or losing CfD support years. However, the impact of CfD support itself is far greater and having longer contracts would probably result in lower strike prices.

Further Assumptions

The number of developers is fixed at 15, but modelling the CfDs under tighter and broader market conditions might yield interesting results. This research does not include the number of developers in the sensitivity analysis, which is a limitation of this model. In this model, adding more agents would probably only increase the number of exited agents and participating bidders, as there is still only one winner. A tighter market would be more interesting, as it might give the developers more room to elevate their bids if they win an auction, as they would face less competition. Another market replication was to distribute the current capacity of the Dutch offshore wind energy sector equally among all developers. In reality, there would be developers who have already installed a wind farm and some without any contribution to the sector. This was done for simplicity reasons to easily track the progression of the entire market.

The fixed ceiling price was also a modelling choice. The Dutch government has not set a ceiling price for some time, as the last tenders were issued without any government support. The recent report by Lensink and Henriquez (2026) states that for all upcoming tenders in 2026 & 2027, there will be a fixed ceiling price of 104 €/MWh. This is an interesting choice because these wind farms all differ in location, average wind speeds and environmental requirements.

This might make the ceiling price very tight for one tender and lenient for the other, but that remains to be seen. Later in 2026, the Dutch government announced a higher ceiling price of 117 €/MWh for two of the 2027 tenders (van Economische Zaken en Klimaat, 2026). Therefore, the ceiling experiment in this thesis still treats the ceiling price as fixed but studies different levels of this policy. In addition to the earlier limitation of the FID, the Dutch government has determined the ceiling price some time in advance and for multiple auctions, as reported by Lensink and Henriquez (2026). If the markets swing during the bid preparation phase, it leaves the developers unable to produce a fair bid or unable to carry out the tender they had won.

If multiple developers submit the lowest bid, the government chooses the winner at random. This is an assumption the model has made to replicate the fact that tenders also include requirements beyond the lowest strike price. For example, that is why the one-sided CfD can produce the largest amount of distinct winners. When almost all developers bid for zero subsidy, and the government chooses randomly, it can lead to what seems like an extremely diverse market.

According to the Financial CfD mechanisms in Schlecht et al. (2024), the Financial CfD uses strike-price bidding in €/MW. However, this complicates comparing the financial CfD results with those of the other CfD designs. Therefore, this model assumed fixed generation by setting the capacity factor for each developer for the entire simulation, after the randomised distribution, so that the strike-price bid could be calculated in €/MWh for the financial CfD. This results in the Financial CfD mechanism being slightly muted, as a developer never underperforms relative to their expectations. If this were implemented, the developers might bid for a higher strike price under the financial CfD due to generation uncertainty.

5.4 Future Research Recommendations

Based on the findings of this research, the following recommendations have been identified for future studies on Contract-for-Difference designs in offshore wind auctions. Research on CfD auction design should examine the implementation of different discount rates across CfD designs, as this study applied the same discount rate range to all three designs to isolate the effect of the CfD design. The price expectations of developers should be elaborated on, as they are held fixed throughout the model. Allowing these expectations to change, so that developers can change their beliefs based on market behaviour, would show whether price uncertainty starts to influence bidding strategies of developers across multiple auction rounds,

Future research could combine the FID stage by Malleret et al. (2024) and strategic behaviour by Gupte (2025), together with the different CfD design approach in this research, to fully understand the bidding process under a financial CfD. Previous literature shows that overly aggressive developers suffer from the winner's curse and are unable to recoup their investment. If future research combines the approach of Malleret et al. (2024) and this thesis, the auction process and operating life can be integrated into a single model. This approach would let developers bid based on costs and adjust their bidding strategies in response to realised electricity prices and project profitability. A further extension should implement the multi-CfD design approach proposed in this thesis, since different CfD designs distribute price risk differently. This would provide more insight into the effectiveness of CfD designs and how the cost-based bidding phase compares with price-based project profitability. If this can be combined with a game-theory approach, as Kell et al. (2023) utilised, the realism of developers' bidding behaviour would increase, providing even more reliable findings.

Studies should also examine different ways to accurately determine a ceiling price that fits the market and accounts for various scenarios, ensuring that the CfD designs do not collapse under pressure. In addition, the finding that raising the ceiling price does not lead to higher bids, but does protect deployment success under stress, entails that more research can be done to compare dynamic ceiling prices versus fixed ceiling prices, as well as studying if higher ceiling prices also encourage or lead to higher strike price bids as developers feel the market offers more headroom. Because this model applies a single fixed ceiling uniformly across all tenders, future work could also examine tender-specific ceilings that account for different tender characteristics, as we have seen the Dutch government increase the strike price for two separate tenders in 2026.

A further addition to future research concerns the financial CfD itself. The financial CfD is still a concept which has only been studied in scientific literature and has not been used in practice. Therefore, this thesis makes several assumptions during the modelling process of the CfD design. For example, this research assumes each developer's capacity factor is fixed, whilst in reality it would fluctuate. While the risk of underperforming the reference generator is well documented (Schlecht et al., 2024; Gupte, 2025), existing studies examine it either in post-auction dispatch with perfect foresight (Gupte, 2025) or in cost-recovery terms (Johanndeiter et al., 2025), not in how it shapes competitive bidding. Future research could therefore let generation vary stochastically within the auction process of this model, testing whether developers bid a higher strike under the financial CfD to protect themselves against the risk of falling below the reference generator, a bidding strategy that the existing studies do not capture.

A very valid extension of this research would also be expanding research towards multi-unit tenders and uniform pricing in the Dutch offshore energy sector and the length of the support periods. For example, the Dutch government has multiple tenders planned for 2027. It is interesting to see whether an approach similar to the UK's might produce more competitive and attractive auctions for developers. Such an extension would address the single-unit pay-as-bid format assumed throughout this thesis, allowing a comparison of how the three CfD designs perform under different pricing and tender structures, rather than under the single-unit pay-as-bid format alone. I would also suggest incorporating negative electricity prices into future research to increase the realism of the results, and testing future models with different market sizes, as this study only looks at a market with 15 developers. Since the CfD support period was set at the 15-year level used in past Dutch tenders, varying it in future work would directly test how the length of guaranteed support shapes developers' bids.

All in all, the model provides a set of interesting findings, such as the role the ceiling price plays. It leaves bidding strategies and subsidy costs largely unchanged, but it does affect the success rate of development, as it can cause tenders to remain unauctioned. An effect that becomes clear under cost stress and across different scenarios, varying for each design. The financial CfD proves the most resilient design overall through its reference-generator decoupling, though at the cost of large fiscal swings. In contrast, the two-sided is the most exposed to the ceiling price. The analysis also showed that cost parameters, rather than the electricity price, dominate bid formation, a finding that complements the literature that focused on post-auction results and can now be used to combine bidding and post-auction stages. These findings are limited by the model's limitations, as described in this chapter. Although stochastically generated at the start of the simulation, the fixed discount rates, fixed electricity price expectations, realised market price series, and fixed capacity factor mainly leave room for future research. Together, the results indicate that the Dutch government's path to 40 GW of offshore wind energy does not depend on the choice of CfD design alone, but on the combination of CfD, ceiling price calibration, and the risk the government is willing to take to balance subsidy costs and deployment success.

6. Conclusion

This thesis examines how different CfD designs perform in Dutch offshore tender auctions under different market conditions and expectations. Based on market case studies and prior literature, the research identified the one-sided CfD, two-sided CfD, and Financial CfD as the three viable CfD designs for the Dutch offshore wind sector. Motivated by recent failed tenders in the Netherlands and market parties voicing concerns about zero-subsidy tenders, this thesis combined different CfD designs with uncertainty in electricity prices and investment costs using a Multi-Agent model to re-enact bidding behaviour in offshore wind auctions. The model assumed a fixed number of 2 tenders per year until 2040, which the Dutch government has set to reach the target of 40 GW. The model resembles the single-unit tender format and pay-as-bid pricing system the Dutch government has used for past tenders. The model was then subjected to Monte Carlo simulations, a sensitivity analysis and scenario analysis, with scenarios supported by the IEA 2025 World Energy Outlook (International Energy Agency, 2025). With the findings of this research, the main research question and corresponding sub-questions can be answered.

The literature review provided knowledge into how developer change their bidding strategies based on the results of previous auction rounds, answering the first sub-question. Bidding behaviour was identified as an emergent property within offshore wind auctions with CfD designs, as the design of these contracts and the sector itself requires developers to determine how much risk they are willing to take. Developers have to make a trade-off between bidding low enough to win the auction and bidding high enough to ensure sufficient income to recoup their initial investment. How a developer determines this trade-off varies from developer to developer. After the auction, the developers will be able to see how their initial position was compared to the rest of the market. If they win the auction, the developer would increase their bid to see if they left any profit on the table. In return, if a developer loses an auction and sees the winning strike price, they can calibrate by how much they lost and how much extra risk they are willing to take in future auction rounds.

Previous literature also contributed to the bidding strategy for each CfD design, thereby answering part of the second sub-question. Under the two-sided CfD, developers were required to bid their true break-even revenue, since there was no upside potential during the CfD lifetime, removing any incentive to bid above their cost. The one-sided CfD did introduce an upside for developers, as revenue generated when electricity prices exceeded the agreed-upon strike price was retained by the developers. However, the competitive nature of the model surrounding this potential drove developers down to zero-subsidy bids to win the auction. The mechanism of the financial CfD, in which the reference generator partially decouples the strike-price bidding calculation from the developer's break-even costs, allowed developers with a higher capacity factor than the benchmark to bid below what their costs alone would require. The model results showed that the financial CfD produced the lowest average winning strike price, and the two-sided CfD the highest. The one-sided fell in between because the average was lower than the financial CfD due to zero-subsidy bids, and when the developers did not risk a zero-subsidy bid, their returns were higher than those under the financial CfD.

In the model, the sensitivity and scenario analyses provided insights into the third sub-question by answering how the CfDs behave under changing costs and electricity prices for different ceiling price levels. The results showed that CAPEX and capacity factor have the greatest influence on strike price levels, more than OPEX and electricity price expectations, as they can cause the developer to breach the ceiling price more quickly. It also found that the range of price expectations did not affect the developers' bidding strategy under any of the CfD designs. The financial CfD showed the most robustness under extreme scenarios, with the CfD design still reaching the target of 40 GW 61.2% of the simulations in the high-costs scenarios, as the other two CfD designs collapsed, with the two-sided CfD achieving a success rate of 1.3% and the one-sided CfD achieving a success rate of 19.2% respectively. This resilience is directly caused by the reference generator bidding approach, which makes the Financial CfD unique. The model provided insights into the ceiling price policy by showing that ceiling prices have very little impact on the bidding strategy but play a large role in market participation. Especially under the low ceiling price level, the success rate of each CfD design fell as more developers were excluded from the tender auctions, making the proper calibration of the ceiling price level crucial to achieving the target of 40 GW.

This research also makes several contributions to the academic literature on CfD auction design whilst answering the research questions. First, to our knowledge, this research is the first study to compare the one-sided, two-sided, and financial CfD designs within a single Multi-Agent model of repeated offshore wind auctions, specific to the Dutch single-unit pay-as-bid tender format. Where existing literature either analyses CfD designs without auction simulation with agent dynamics, or analyses a single type of CfD design with auction simulation with agent dynamics, this thesis combines both. Secondly, this thesis develops a closed-form bidding equation for the one-sided CfD that includes the potential and uncertain upside revenue based on possible future electricity prices, allowing the asymmetric pay-off of a one-sided CfD to be modelled without a solver or a single deterministic price curve, simultaneously in the model with the other two CfD designs. Next, this thesis shows that the fixed ceiling price can constrain market participation across repeated auction rounds, as evidenced by the ceiling price experiment. This effect was not captured in previous literature, as the ceiling price either adjusted dynamically or was applied only in a single-round simulation. Finally, the research identifies how widely the government's financial CfD costs can swing across different scenarios, a feature that previous research on financial CfDs has not studied in a repeated-auction setting.

Reaching 40 GW by 2040 is an ambitious target, but an important one. Beyond its academic contribution, this thesis also contributes to the Dutch energy transition, as the offshore wind sector faces a challenging geopolitical position. The offshore wind sector is the largest component of the Netherlands' journey towards a decarbonised and sustainable energy sector. With so much uncertainty in the current offshore wind market, the existing tender system had too many flaws to convince developers to bid in past tenders. To restart the offshore wind energy sector, a change is needed. This research contributes to this change by examining how different CfD designs could offer solutions for the Dutch government. It also provides insights into how public expenditure depends on which CfD design the Dutch government chooses, which can affect the viability of offshore wind development. By also providing more insights into the workings of different CfD designs, such as providing Dutch policymakers in the offshore wind sector with more knowledge about the financial CfD design, this could help create a more balanced offshore wind sector. Taken together, this thesis will enable the Dutch government to advance its mission to provide clean energy for future society.

Recommendations

Combining all the findings, the answer to the main research question is that no single design performs best if the aim is to achieve the target as often as possible whilst keeping costs low for the government. It is up to the government's risk preference to determine how much they are willing to spend to achieve the highest chance of success. The financial CFD best enables the Dutch government to achieve their target. However, it comes with the risk of very high subsidy costs and the potential for a large clawback sum. The One-sided CfD offers the government a higher participation rate and a more competitive market, which drives down developers' strike prices to the point that they bid for zero subsidy. This means that the government doesn't have to pay anything to support the developers. However, the results show that as costs increase, the success rate of this design decreases dramatically, which corresponds with what is observed in the current Dutch offshore wind market. The two-sided CfD offers the government the largest net recovery under benign conditions but is brittle, collapsing entirely under cost stress. Another important finding applies to all three designs: the fixed ceiling price is the primary determinant of whether any CfD remains viable. For the Dutch government, this research recommends implementing the financial CFD design, as it offers the most reliable path to achieving the target of 40 gigawatts by 2040, assuming the government is willing to take on the risk of investing a large sum in the offshore wind energy sector. However, the government should also reconsider its approach to calculating the ceiling price, as it does not leave sufficient headroom for developers and markets to absorb rising costs.

7. Reflection

Looking back on this thesis, the process went very differently from what I first anticipated. My ambitious goal of replicating nine different auction designs and testing the three different CfDs in those designs was a mountain too high for me to climb, something I realised very early on. The process of writing this thesis was a continuous battle of steps forward and backwards. Secretly, I did anticipate this as previous courses involving modelling and coding have often been quite a challenge. Python had never really been a strength of mine, but because what I knew was possible with the software from earlier courses in my education and the potential fit it had with my topic, I was adamant that I would somehow make it work.

I'd say building the right scope for my thesis was quite challenging at the beginning of my process. The offshore wind sector is a complex system with many moving components. It is directly connected to the electricity grid and thus indirectly to other industrial sectors. Once I had the scope figured out, the hardest part of the thesis hit me straight in the face. Modelling the one-sided CfD with the other CfD designs. Since the one-sided CfD had the unknown upside during the CfD period, there was so much uncertainty and no literature that had studied this design within a closed equation. I had to get creative and, inspired by other work, came up with a small equation solver, along with corresponding electricity price belief levels, to create an equation that would allow me to compare the CfD designs.

For me, a crucial motivator was the mid-term meeting. Seeing my supervisors offer positive feedback alongside the fair share of justified criticism led me to believe that this thesis could really amount to something. As we discussed choosing between the financial CfD and one-sided CfD, it created a fire within me to include both designs as a comparison for the two-sided CfD. The fact that I was even able to create a model which included all three is something I am really proud of.

I have also learned a lot during the process of completing my master's thesis. As Mrs Heijnen will know, I have a hard knack for falling into tunnel vision if I feel like I have an idea that works. She often caught me in my own world during our meetings and really reminded me of the logical thinking processes I could use to better illustrate my thoughts. This is something I feel I have improved in, but I am still learning how to reduce the number of mistakes I make because of it. Another attribute that I have learned during this thesis is being specific about your modelling choices. Given the complexity of the offshore wind sector, I had to make quite a few assumptions. At first, I was pretty lost about how to determine the correct value or distribution that fit the model as well as reality. Now, I look at this process differently, and it is all right to make your own assumptions that others might not have made before, as long as you feel they are supported by the real world.

Beyond the thesis process itself, I am glad I got to finish my Master's thesis on a topic I am really passionate about. Early on in my TU Delft career, I knew that the offshore wind sector was an industry that I was very interested in. I am leaving the TU Delft with a much better understanding of complex socio-technical systems and especially how we approach these problems and find solutions for them. I have gained valuable experience working on difficult issues and have learned to be patient and confident in the process. I have a deep appreciation for everyone who has helped me on my journey and devoted their time and energy to my education.

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AI Statement

Artificial Intelligence was used with Claude software from Anthropic. AI played a role in increasing the efficiency of the modelling and writing process. Firstly, AI was used to fix errors in the code and find hidden bugs that did not produce errors when running in the model, which was created in PyCharm. It also helped with coding the thesis in Overleaf, resulting in a cleaner report and presentation by creating neater tables and page design.

Furthermore, Claude improved the thesis's academic and professional quality by identifying grammatical and spelling errors in the report. AI provided suggestions for cleaner sentences and more professional grammar, which improved readability towards an academic level. Grammarly was another piece of software consulted during this thesis's writing process to improve reading comfort. All analytical content, policy interpretations, market predictions and conclusions are the author's own work. The author takes full responsibility for the illustration, interpretation, and conclusions of this thesis.

A. Data Tables

Dutch Offshore wind auctions

Table A.1 presents the complete record of Dutch offshore wind tenders awarded between 2016 and 2025, listing the year, awarded capacity, support mechanism, awarded strike price, contract duration, and project name.

Year	Awarded Volume (MW)	Support	Awarded Strike Price (€/MWh)	Duration	Name
2025	1000	Zero-subsidy bid	€0.00	–	Nederwiek Zuid I-A
2024	2000	None	€0.00	40 years	IJmuiden Ver Beta
2024	2000	None	€0.00	40 years	IJmuiden Ver Alpha
2022	700	None	€0.00	–	Hollandse Kust West VI
2022	700	None	€0.00	–	Hollandse Kust West VII
2020	759	Zero-subsidy bid	€0.00	–	Hollandse Kust Noord
2019	760	Zero-subsidy bid	€0.00	–	Hollandse Kust Zuid III and IV
2018	700	Zero-subsidy bid	€0.00	–	Hollandse Kust Zuid I and II
2016	732	Feed-in-Premium	€54.50	15 years	Borssele 3 and 4
2016	752	Feed-in-Premium	€72.70	15 years	Borssele 1 and 2

Table A.1: Overview of Dutch Offshore Wind Auction Results History. Source: Wind Europe (2025).

Table A.2 lists the offshore wind tenders the Dutch government has planned for 2027, with their awarded volume, support mechanism, contract duration, and project name.

Year	Awarded Volume (MW)	Support	Duration	Name
2027	1000	Subsidy SDE++	15 years	IJmuiden ver Gamma-A
2027	1000	Subsidy SDE++	15 years	IJmuiden Ver Gamma-B
2027	2000	Zero-subsidy bid	–	Doordewind I
2027	700	Zero-subsidy bid	–	Ten noorden van de Waddeneilanden
2027	2000	Zero-subsidy bid	–	Nederwiek Noord II
2027	2000	Zero-subsidy bid	–	Nederwiek Noord III
2027	700	Zero-subsidy bid	–	Hollandse Kust WEST VIII
2027	1000	Zero-subsidy bid	–	Nederwiek Zuid I-B

Table A.2: Overview of Planned Offshore Wind Auction in the Netherlands. Source: Wind Europe (2025).

Offshore Wind Cost tables

Table A.3 compiles reported and projected capital expenditure (CAPEX) figures for recent offshore wind farms across Europe, listing the country, year, project name, capacity, total CAPEX in billions of euros, and the normalised CAPEX per megawatt. These figures inform the model's CAPEX calibration and the per-scenario cost assumptions.

Country	Year	Wind Farm	Capacity (MW)	CAPEX (€bn)	CAPEX (M€/MW)
Denmark	2023	Thor	1,000	3.3	3.30
France	2023	Dieppe	496	2.7	5.44
France	2023	Isles of Yeu	496	2.5	5.04
Germany	2025	Nordlicht 1	980	3.0	3.06
Germany	2024	Nordsee	225	0.7	3.11
Germany	2024	Nordsee	435	1.4	3.22
Germany	2024	Nordsee	420	1.4	3.33
Germany	2024	Nordsee	480	1.6	3.33
Germany	2024	Windanker	315	1.0	3.17
Germany	2023	EnBW	960	2.4	2.50
Netherlands	2024	Hollandse Kust West VII	795	1.8	2.26
Netherlands	2023	Hollandse Kust West VI	760	1.7	2.24
Poland	2025	Baltica 2	1,498	5.9	3.94
Poland	2025	BC-Wind	390	2.1	5.38
Poland	2025	Baltyk 2	760	3.6	4.74
Poland	2025	Baltyk III	760	3.6	4.74
Poland	2023	Baltic Power	1,140	4.7	4.12
UK	2025	Inch Cape	1,080	4.2	3.89
UK	2023	Moray West	882	3.0	3.40
UK	2023	East Anglia Hub	1,400	5.2	3.71
UK	2023	Hornsea Three	2,900	10.2	3.52

Table A.3: CAPEX overview of recent offshore wind farms in Europe. Frémaux (2026), Frémaux (2025) & Ramírez (2024)

Table A.4 lists operational expenditure (OPEX) figures for a set of European offshore wind farms, giving the project name, year, country, capacity, and OPEX per megawatt-hour. These values provide the empirical basis for the model's OPEX calibration.

Table A.4: Overview of OPEX costs from (Malleret et al., 2024).

Project	Year	Country	Capacity (MW)	OPEX (€/MWh)
Rødsand 2	2008	Denmark	207	26.1
Kriegers Flak	2016	Denmark	605	14.4
Hollandse Kust Zuid I-II	2018	Netherlands	760	10.4
Borssele III-IV	2016	Netherlands	732	16.8
Hornsea 2	2017	UK	1386	12.6
Moray East	2017	UK	950	12.3

Electricity price dataset

Table A.5 shows an overview of the mean electricity price, standard deviatio of the electricity prices, minimum and maximum price per year of the last 10 years. This table has been used for the calibration of the input parameters

Table A.5: Annual descriptive statistics of Dutch day-ahead electricity prices, 2015–2025 (NL bidding zone).

Year	Mean (€/MWh)	Std. Dev. (€/MWh)	Min (€/MWh)	Max (€/MWh)
2015	40.02	10.78	1.67	99.77
2016	32.25	11.32	2.79	135.00
2017	39.31	12.77	1.74	151.07
2018	52.54	15.18	0.55	175.00
2019	41.19	11.27	−9.02	121.46
2020	32.24	15.31	−79.19	200.04
2021	102.97	74.71	−66.18	620.00
2022	241.91	131.55	−222.36	871.00
2023	95.82	49.05	−500.00	463.77
2024	77.29	49.49	−200.00	872.96
2025	87.32	47.92	−350.00	523.47
2015–2025	**76.89**	**78.36**	**−500.00**	**872.96**

Note: Based on 96,432 hourly observations. Source: Ember (2025), retrieved from ENTSO-E Transparency Platform. Prices in nominal euros.

Projected Tender Data Dutch Government

In table A.6 the calculations by the Dutch government for the tenders in 2026 and 2027 have been reported. The table shows the estimated load hours and what strike price the expect the developers to require based on a specific electricity price. The table also provides the equation the Dutch Government used for the calculations.

Table A.6: Subsidy parameters for offshore wind energy in TOWOZ 2026

Wind farm	Tender amount [€/kWh]	Full load hours [h/yr]	Base electricity price [€/kWh]	Correction amount formula
IJV-A	0.101	3,729	0.0377	EPEX-NL × profile factor WOZ + GO
IJV-B	0.103	3,659	0.0377	
IJV-G (a)	0.104	3,703	0.0377	
IJV-G (b)	0.103	3,738	0.0377	
NW-1 (a)	0.104	3,756	0.0377	
NW-1 (b)	0.104	3,756	0.0377	
NW-2	0.099	3,852	0.0377	

B. Variables Overview

Table B.1 provides a complete reference of the symbols used throughout the model, grouped by category: the model framework, the electricity price series, the government agent, and the developer agent. For each symbol the table gives a short description and its corresponding value or unit.

Table B.1: Overview of model variables and parameters with corresponding symbols.

Symbol	Description	Value / Unit
Model framework		
N	Number of wind farm developer agents	#
$\bar{a}$	Tenders auctioned per year	tenders/yr
T	Number of timesteps (auction rounds) per run	rounds
y_0	Start year of simulation	year
C^*	Deployment capacity target	GW
C_k	Capacity awarded in tender k	MW
t^*	First timestep at which target is reached	round
D_{CfD}	CfD support duration	yr
N_{life}	Total project lifetime	yr
N_{CfD}	CfD support years	yr
N_P	Length of electricity price series	rounds
$N_{auctions}$	Number of auction rounds	rounds
C_{total}	Total starting capacity of the sector	MW
C_{init}	Initial capacity per developer	MW
Electricity price series		
λ_t	Realised market electricity price at timestep t	€/MWh
μ_P	Mean realised electricity price	€/MWh
σ_P	Standard deviation of realised price	€/MWh
ε_t	Stochastic price disturbance	€/MWh
CV	Coefficient of variation	dimensionless
Government agent		
C_{tender}	Tender capacity	MW
C_{min}	Lower bound tender capacity	MW
C_{max}	Upper bound tender capacity	MW
$p_{ceiling}$	Ceiling (administrative) price	€/MWh
cf_{ref}	Reference generator capacity factor	dimensionless
$g_{ref,k}$	Reference generator generation for contract k	MWh/MW
R_{ref}	Reference generator revenue	€/MW

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Table B.1 – *continued from previous page*

Symbol	Description	Value / Unit
$G_{k,t}$	Government payment for contract k at time t	€
G_{tot}	Total government subsidy cost	€
S_k	Awarded strike price of contract k	€/MWh
Developer agent — costs and production		
$CAPEX_i$	Capital expenditure of developer i	M€/MW
$OPEX_i$	Operational expenditure of developer i	€/MWh
μ_{CAPEX}, μ_{OPEX}	Mean CAPEX / OPEX	M€/MW, €/MWh
$\sigma_{CAPEX}, \sigma_{OPEX}$	Cost distribution std. dev.	dimensionless
cf_i	Capacity factor of developer i	dimensionless
μ_{cf}, σ_{cf}	Capacity factor mean / std. dev.	dimensionless
$g_{own,k}$	Developer annual generation for contract k	MWh/MW
R_{own}	Developer revenue	€/MW
$cr_{i,t}$	Learning-by-doing cost reduction	dimensionless
cr_{min}, cr_{max}	Cost reduction bounds	dimensionless
Developer agent — capacity range		
$c_{pref,i}$	Preferred tender capacity	MW
μ_c	Mean preferred capacity	MW
σ_c	Std. dev. of preferred capacity	MW
Δ_i	Half-width of capacity window	MW
$\Delta_{min}, \Delta_{max}$	Capacity window bounds	MW
$\underline{c}_i, \overline{c}_i$	Lower / upper capacity bound	MW
Developer agent — bidding and risk		
$r_{i,t}$	Discount rate of developer i at time t	dimensionless
r_{min}, r_{max}	Discount rate bounds	dimensionless
$\beta_{i,t}$	Discount rate adjustment factor (loss)	dimensionless
T	Required per-MWh revenue (break-even)	€/MWh
$\hat{p}$	Weighted expected electricity price	€/MWh
$p_{low}, p_{mid}, p_{high}$	Low / mid / high price levels	€/MWh
$w_{low}, w_{mid}, w_{high}$	Price level belief weights	dimensionless
u_1, u_2	Independent uniform draws for belief weights	dimensionless
$u_{(1)}, u_{(2)}$	Ordered uniform draws (min, max)	dimensionless
δ	Probability floor per price level	dimensionless
$E[R \mid S]$	Expected revenue given strike price S	€/MWh
PVA_{cfd}	Present value annuity factor, CfD period	dimensionless
PVA_{life}	Present value annuity factor, project life	dimensionless
PVA_{tail}	Present value annuity factor, merchant tail	dimensionless

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Table B.1 – *continued from previous page*

Symbol	Description	Value / Unit
$S_i^{fin,MW}$	Financial CfD strike price (per MW)	€/MW
Developer agent — exit mechanism		
e_i	Exit probability of developer i	dimensionless
ξ_i	Uniform random exit draw	dimensionless
α_{win}	Exit decrease on winning	dimensionless
α_{loss}	Exit increase on losing	dimensionless
α_{breach}	Exit increase on ceiling breach	dimensionless
$\alpha_{mismatch}$	Exit increase on capacity mismatch	dimensionless

Table B.2 illustrates all the values that have been attributed to the baseline model. These values were based on the sources this study found and calibrated to create a set of starting parameters. These values are present for the sensitivity analysis, ceiling price experiment and scenario analysis, with the exception of the variables under research.

Table B.2: Baseline parameter values used in the model, by category. Distributional parameters give the sampling rule rather than a single value.

Symbol	Description	Baseline value	Unit
Model framework			
N	Wind farm developer agents	15	#
$\bar{a}$	Tenders auctioned per year	2	tenders/yr
C^*	Deployment capacity target	40	GW
D_{CfD}	CfD support duration	15	yr
N_{life}	Project lifetime	30	yr
N_P	Length of price series	$\geq N_{auctions} + N_{CfD} - 1$	rounds
C_{total}	Total starting capacity	4,700	MW
C_{init}	Initial capacity per developer	≈ 313	MW
Electricity price series			
μ_P	Mean realised electricity price	91.88	€/MWh
σ_P	Std. dev. of realised price	27.44	€/MWh
CV	Coefficient of variation	0.2987	dimensionless
	Price truncation bounds	$\mu_P \pm 2\sigma_P$	€/MWh
Government agent			
C_{tender}	Tender capacity (per round)	$\mathcal{U}(600, 2000)$	MW
C_{min}	Lower bound tender capacity	600	MW
C_{max}	Upper bound tender capacity	2,000	MW
$p_{ceiling}$	Ceiling (administrative) price	104	€/MWh

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Table B.2 – *continued from previous page*

Symbol	Description	Baseline value	Unit
cf_{ref}	Reference generator capacity factor	0.418	dimensionless
Developer agent — costs and production			
μ_{CAPEX}	Mean capital expenditure	3.2	M€/MW
μ_{OPEX}	Mean operational expenditure	15	€/MWh
$\sigma_{CAPEX}, \sigma_{OPEX}$	Cost distribution std. dev.	0.02	frac. of mean
	CAPEX/OPEX truncation bounds	$[0.85\,\mu,\ 1.15\,\mu]$	—
μ_{cf}	Mean capacity factor	0.46	dimensionless
σ_{cf}	Capacity factor std. dev.	0.02	frac. of mean
cr_{min}, cr_{max}	Cost reduction bounds	$\mathcal{U}(0, 0.025)$	dimensionless
Developer agent — capacity range			
μ_c	Mean preferred capacity	1,300	MW
σ_c	Std. dev. of preferred capacity	200	MW
$\Delta_{min}, \Delta_{max}$	Capacity window bounds	$\mathcal{U}(300, 700)$	MW
$\underline{c}_i, \overline{c}_i$	Capacity bounds (floor / cap)	600 / 2,000	MW
Developer agent — bidding and risk			
r_{min}, r_{max}	Initial discount rate bounds	$\mathcal{U}(0.07, 0.10)$	dimensionless
	Discount rate floor	0.04	dimensionless
	Discount rate increase on win	×1.015	per win
	Discount rate adjustment cap (loss)	0.2	per loss
	Zero-bid discount fallback	0.005	per round
p_{mid}	Mid (expected) price level	91.88	€/MWh
p_{low}	Low price level ($\mu_P - \sigma_P$)	64.44	€/MWh
p_{high}	High price level ($\mu_P + \sigma_P$)	119.32	€/MWh
δ	Probability floor per price level	0.05	dimensionless
Developer agent — exit mechanism			
e_i	Initial exit probability	0.0	dimensionless
α_{win}	Exit decrease on winning	0.05	dimensionless
α_{loss}	Exit increase on losing	0.0025	dimensionless
α_{breach}	Exit increase on ceiling breach	0.0025	dimensionless
$\alpha_{mismatch}$	Exit increase on capacity mismatch	0.00125	dimensionless