Analysing the governmental support to offshore wind industry via CfD Auctions

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Introduction

The energy crisis in Europe has sparked vigorous debates about reforming the electricity market, with Contracts for Differences (CfDs) taking center stage. Experts and policymakers are advocating for these long-term contracts to become a fundamental aspect of the EU's future power market. Generally, CfDs

are financial contracts where payments are made from the buyer to the seller if the asset's price at maturity is below the strike price, and vice versa. These derivatives are utilized in foreign exchange, security, and commodity markets, typically traded between commercial entities. In the electricity markets, CfDs usually denote long-term agreements between electricity generators and governments, as described by the European Commission in a recent legislative proposal. A standard CfD, like the one used for offshore wind in the UK (UK Government, 2014), relies on the spot price and applies the payment only to the electricity produced by a specified asset.
The primary goal of CfDs is to mitigate price risk for investors, thereby reducing the cost of capital and levelized energy costs (Gohdes et al., 2022). CfDs are part of a tradition of renewable (and sometimes nuclear) energy support schemes, serving as an alternative to feed-in tariffs, feed-in premiums, and renewable portfolio standards (Newbery, 2023). Since their introduction in the UK in 2014, CfDs have been adopted by many European countries, including Denmark, Greece, Hungary, Poland (Szabó et al., 2021), and Ireland (Government of Ireland, 2019). Unlike most support schemes, CfDs generate public income during periods of high electricity prices, making them particularly appealing to policymakers, especially since the onset of the energy crisis (European Commission, 2023). In current reform discussions, CfDs are increasingly viewed as a cornerstone of electricity markets rather than merely a support policy (Fabra, 2023). Some propose applying them to a broader range of technologies, including existing assets, and enforcing them against plant owners' preferences.

Eventhough offshore wind is considered one of the UK's cheapest sources of electricity the UK fifth Allocation Round (AR5) CfD auction highlighted several critical issues. AR5 of the CfD auction in the UK failed to secure any funding for offshore wind farms. None of the UK’s biggest offshore wind developers participated, citing that the maximum administrative strike price (ASP) was set too low at £44/MWh to ensure economic profitability, while the reference price at the time was £87/MWh. The Floating Offshore Wind Technology (FOWT) pot in the AR5 allocation round suffered a similar fate, with the ASP set by the government at £116/MWh being considered too low given the rising supply chain costs, inflation rate, and other factors. To address the non-participation in the AR5 CfD auction, the UK government increased the ASP for offshore wind farms (OWF) by 66% to £73/MWh, and the ASP for FOWT by 52% to £176/MWh. Despite these increases being favorably received by the renewable energy sector, several important factors affecting energy production and the financial capabilities of OWF developers were overlooked. The allocated budget for each allocation round is being spent more rapidly, effectively buying less energy capacity with every pound. If developers bid at the ASP, the current budget would only allow for a maximum allocation of 3.1 GW, significantly below the necessary capacity to address the shortfall from AR5 and meet the 2030 targets (Mantell and Quinn, 2024). Any shortfall in energy capacity allocations during AR6 would put more pressure on future rounds to deliver the necessary energy capacity to meet the objectives set by the UK for 2030. This shortfall has a knock-on impact, such as increased reliance on gas-fired power stations to meet electricity demand, raising UK emissions, and missed opportunities for growing the UK renewable energy sector, economic gains, and job creation. Although floating wind is expected to play a crucial role in achieving the UK government's targets, it remains an emerging technology requiring substantial support for commercialization. The budget allocation for AR6 in FOWT is very low at £95 million, likely allowing only one or two eligible projects to secure a CfD, with a maximum capacity of 135 MW if bids are at the ASP. If the UK government aims to reach the 2030 targets, it must be willing to invest more in improving port infrastructure and innovative projects to drive cost reduction.

In this paper, we identify five major problems with the current UK Contracts for Difference (CfDs) strike price setting mechanism that has led to the lack of participation from the FWOT developers in the last CfD auction AR5. First, the CfDs omit the macroeconomic impact, failing to consider broader economic consequences and neglect the impact of weather and location, crucial factors in renewable energy production. Second, the data used in CfDs is often inaccurate: the cost data is based on the year 2020, and the hurdle rate is based on the 2015 pretax rate. Third, material costs are inaccurately modeled using a uniform distribution, and there is an optimism bias, where costs are underestimated, and benefits are overestimated. Fourth, CfDs promote a "produce-and-forget" approach, where producers generate electricity without considering market demand or price fluctuations. This happens because CfDs stabilize income, removing the incentive to produce electricity when it is most needed (Meeus, 2023). Fifth, CfDs disrupt the real-time markets that manage electricity supply and demand, such as the intraday and balancing markets. These disruptions occur because CfDs guarantee a fixed price to producers, making them less responsive to actual needs and prices (Guidehouse and Fraunhofer, 2023).

The main contribution of this paper is to propose a novel CfD strike price setting methodology that considers various important macroeconomic variables, including inflation rate, interest rate on debt, electricity market price, corporate tax rate, capacity factor based on hourly wind speed, construction duration of the energy plant, debt-to-equity ratio, and expected operational years of the Floating Offshore Wind Turbine (FOWT). By setting a strike price that accounts for these economic variables and their expected fluctuations over the duration of the CfD contract, as well as the financial risks in the electricity market, the five identified problems will be addressed. The methodology incorporates crucial macroeconomic variables such as inflation rate, interest rate on debt, electricity market price, and corporate tax rate. By integrating these variables into the strike price calculation, the methodology ensures that the pricing accurately reflects the broader economic landscape. The methodology anticipates and adapts to expected fluctuations in these economic factors over the duration of the CfD contract. This forward-looking approach enables the strike price to remain relevant and effective throughout the contract period. The methodology accounts for financial risks inherent in the electricity market, including price volatility and uncertainty. By factoring in these risks, the strike price is adjusted to appropriately reflect the financial challenges faced by investors and producers. The methodology tailors its approach to the unique characteristics of the plant Floating Offshore Wind Turbines (FOWT), considering factors such as capacity factor based on wind speed per hour, construction duration, debt-to-equity ratio, and expected operational years. This specialized treatment ensures that the strike price accurately captures the complexities and challenges specific to FOWT projects. By addressing these elements comprehensively, the proposed methodology aims to offer a robust and adaptable solution to the limitations of the current CfD framework, ultimately enhancing the efficiency and sustainability of renewable energy investments.

This paper will evaluate both the current UK government's CfD strike price setting method and the proposed macroeconomic and financial risk-adjusted CfD strike price through three case studies: the UK Floating Offshore Wind Turbine (FOWT) market as a whole and the Kincardine Floating Offshore Wind Farm. Through these case studies, we aim to demonstrate the superior relevance and applicability of our proposed approach compared to the current method adopted by the UK. This paper will show how accounting for macroeconomic variables and financial risks, leads to more accurate and sustainable strike price and leads to increased investments from the private sector in the FOWT industry.

Literature review

Offshore wind energy has become a vital part of the transition to renewable energy sources. Numerous studies have highlighted technological advancements and cost reductions, making offshore wind increasingly competitive with fossil fuels. Musial et al. (2013) provide a comprehensive analysis of the technical potential for offshore wind energy, emphasizing scalability and efficiency improvements. This research underscores the importance of innovation and investment in offshore wind technologies to meet global energy demands sustainably.

The CfD mechanism is crucial for promoting investments in renewable energy by providing price stability and reducing revenue risks. Introduced by the UK Government in 2014, CfDs support low-carbon electricity generation through financial agreements based on the difference between a strike price and the market price. Studies by Newbery et al. (2018) and Winskel et al. (2014) have shown how CfDs incentivize investments and reduce costs in renewable energy projects, particularly offshore wind. Gohdes et al. (2022) highlight that CfDs mitigate price risks, lowering capital costs and levelized energy costs. The traditional CfD model in the UK, which ties payments to actual electricity output, adds complexity in terms of incentives and risk distribution.

Auction design under the CfD scheme is critical for its success. Research has focused on the efficiency and effectiveness of different auction designs. Kitzing et al. (2017) examined various auction formats and their impacts on bidding behavior and outcomes, suggesting that well-designed auctions can enhance competition and reduce prices. Del Río and Linares (2014) discussed the implications of auction design on market entry and the sustainability of renewable energy projects. This research highlights the importance of strategic auction design in achieving CfD goals. Despite progress in offshore wind deployment and CfD implementation, challenges remain, including regulatory and grid integration issues, financing and investment risks, and technological uncertainties. Wiser et al. (2016) and Söderholm and Klaassen (2007) explored these barriers and proposed policy and technological interventions. Additionally, Kröger et al. (2022) and Szabó et al. (2021) note that many European countries and others outside Europe, such as Australia and Canada, have adopted CfDs. These studies provide insights into the complexities of large-scale renewable energy projects and the need for comprehensive strategies to mitigate risks

UK CfD auction mechanism

This section explains the methodology used by the UK government for determining the CfD Administrative Strike Prices (ASPs) for Allocation Round 6 (AR6). The ASP represents the maximum price per MWh for generating electricity, known as the strike price, that a project of a particular technology type can receive. Should an auction be triggered, ASPs limit the maximum price that projects of a particular technology type can receive, even if the auction clears at a higher price. The UK adopted methodology for setting the ASP consists of 5 steps:

Step 1: Gather data to estimate lifetime cash-flows:

The data input considered by the UK government are the current year generic CAPEX (Pre-development costs, Construction costs, and infrastructure costs), OPEX (Fixed OPEX, Variable OPEX, Insurance, Connection costs, Fue costs), decommissioning cost, and the energy generation data (Capacity of the plant, load factor, and hurdle rate) obtained from the updated assumptions from the 2023 Electricity Generation Cost Reports. Without accounting for several important economic factors such as inflation rate, interest rate on debt, corporate tax rate, financial risk proxied by the volatility in electricity markets and the construction duration. Furthermore, these variables are considered constant over the years for the energy generation plant.

CAPEX	OPEX	Energy generation data
Pre-development cost Construction cost Infrastructure cost	Fixed operating and maintenance costs Insurance cost Connection cost Fuel cost	Capacity of the plant Load factor Hurdle rate

Step 2: Sum the NPV of total expected costs and revenues in each year:

Costs and revenues are summed in each year over the lifetime of the project, and discounted by the hurdle rate[1] for the technology to give the net present value (NPV) of lifetime cash-flows

$$NPV_{FOWT} = \sum_{n} \frac{Revenues - (CAPEX + OPEX + Decommissioning\ costs\ )}{(1 + discount\ rate)^{n}}$$

Where the revenues are proxied by the real value of electricity price (not accounting for the impact of inflation), and the total costs are considered constant over the years.

Step 3: Set the strike price to make the NPV equal to zero:

The strike price is set at the level at which the NPV of the project's lifetime costs and revenues is equal to zero. The strike price represents the level of total revenue under the CfD required for the relevant project to achieve a rate of return equal to the hurdle rates (That is NPV =0). The strike price is set at the level at which the NPV of the project's lifetime costs and revenues is equal to zero. The strike price

1 https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/910814/Cost_of_Capital_Update_for_Electricity_Generation_Storage_and_Demand_Side_Response_Technologies.pdf and https://europe-economics.com/publications-news

therefore represents the level of total revenue under the CfD required for the relevant project to achieve a rate of return equal to the BEIS latest view on central hurdle rates[2].

$$NPV = 0 = \sum_{n} \frac{Revenues - (CAPEX + OPEX + Decommissioning\ costs\ )}{(1+hurdle\ rate)^{n}}$$

$$Revenues = CAPEX + OPEX + Decommissioning\ costs$$

where:
$CAPEX = pre\ development\ cost + construction\ cost + infrastructure\ cost$
$OPEX = Fixed\ maintenance\ and\ operating\ cost + insurance\ cost + connection\ cost + fuel\ cost$
$hurdle\ rate = discount\ rate + 2\%$

Step 4: Repeat for a range of project costs to create the supply curve

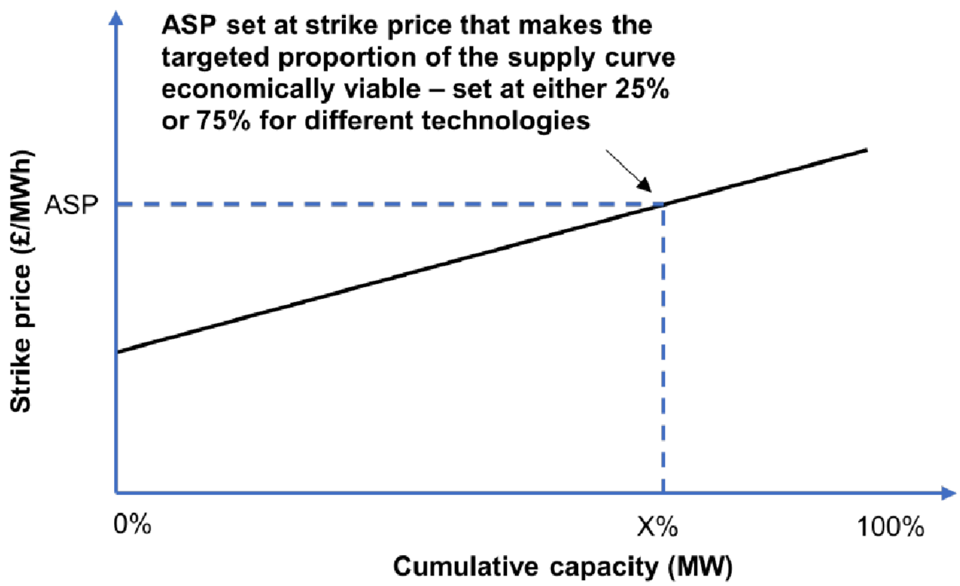
In the AR6 allocation round the UK department has set the strike price using a generic approach which makes the strike price less influenced by the specific project costs and therefore the ASP is less to fluctuate between allocation rounds.

To create the supply curve by technology, the range of viable strike prices has been estimated by assuming that pre-development, construction, and infrastructure costs increase linearly from the first project to the last project in the supply curve, where the low point on the supply curve assumes that low pre-development, construction, and infrastructure cost apply to this particular project. Operating costs and all other cost and non-strike price revenue assumptions (for example load factors(capacity factor), hurdle rates and fuel costs where applicable) are assumed to be constant across the length of the supply curve.

Step 5: Identify the percentage of pipeline capacity that would enable a high level of participation and set ASPs at the corresponding strike price

For this allocation round, the targeted proportion of the supply curve for technologies key to the decarbonisation pathways (Offshore Wind, Onshore Wind, Remote Island Wind, Floating Offshore Wind and Solar PV), is set at 75%, i.e. the ASP for each technology corresponds to the strike price that is estimated to make 75% of pipeline projects economically viable, as illustrated in the figure below.

[2] https://assets.publishing.service.gov.uk/media/613b59bdd3bf7f05b7bcb5d7/cfd-ar4-asp.pdf



Step 6: Payment structure of the CfD auction

Strike price (**K**) = *set by the UK government* and *reflects the cost of investing in a particular low-carbon technology,* it is *the price at which the Low Carbon Contracts Company agrees to pay a developer for each unit of electricity produced by a low-carbon technology*.

Reference price (S_t) = agreed market reference price

Market Reference Prices are used to calculate CfD Generator payments.

For intermittent Technologies (such as solar or wind), the Intermittent Market Reference Price is calculated using day-ahead data.

An IMRP is calculated for every hour of the day pursuant to condition 21 of the Contract for Difference Standard Terms and Conditions.

$$Reference\ price = \frac{\sum_{t=1}^{T} p_t * g_t^{FOWT}}{\sum_{t=1}^{T} g_t}$$

- p_t is the market electricity price
- g_t is the actual electricity generation of the FOWT
- If $K > S_t$ the strike price is above the reference market price, the state pays the difference between the strike price and reference price to the renewable producer.
- If $K < S_t$ the strike price is below the reference market price, the renewable producer pays the difference between the two prices to the state.

Developers

$K - S_t$ which can be both positive and negative

- $K - S_t > 0$ if $K > S_t$
- $K - S_t < 0$ if $K < S_t$

Government

$S_t - K$ which can be both positive and negative

- $S_t - K > 0$ if $K < S_t$
- $S_t - K < 0$ if $K > S_t$

Macroeconomic and financial risk adjusted Strike price

The proposed methodology identifies the optimal strike price by considering the following factors that are ignored by the UK government such as impact of macroeconomic factors such as inflation rate, interest rate on debt, tax rate, electricity market price fluctuations, fluctuations in capacity factor (load factor)), impact of different construction durations, impact of weather information such as wind speed (used to simulate future values for the capacity factor), accurate modeling of material costs, by considering the impact of macroeconomic and weather variables not for the current year but for the next 25 years, and our applied datasets are obtained from reliable data sources not surveys, and we consider 1000 scenarios per year for the next 25 years to make sure that our dataset considers all possible scenarios (to ensure non biasness of the data).

This approach considers setting the optimal strike price as a function of a time varying LCOE measured annually for the next 25 years instead of the constant CAPEX and OPEX adopted by the UK government.

Evaluation Methodology of Levelized cost of energy

The probabilistic cash-flow model developed in this paper returns five key indicators for every floating-offshore-wind pilot: General Levelised Cost of Energy (LCOE), the National Renewable Energy Laboratory (NREL) simplified LCOE, Weighted-Average Cost of Capital (WACC), Return on Equity (ROE) and Capacity Factor (CF). Producing these metrics requires a carefully organised set of input variables.

Data collection

The data required is grouped into two datasets i) primary data about the specific Floating Offshore Wind Farm (FOWF) such as Farm capacity, Equity ratio, CAPEX components, OPEX and expected life time of the plant; and ii) secondary data about the macroeconomic variables (Interest rate on debt, inflation rate, corporate tax rate and Feed in tariff) and Capacity factor (Weibul distribution parameters Scale and Shape, wind speed, turbine power curve, and wind turbine losses due to degradation).

Macroeconomic variables:

- **Inflation rate.** Monthly consumer-price indices are downloaded from the London Stock Exchange Group (LSEG) Data & Analytics platform, which republishes Eurostat series in a harmonised format. After alignment to a common base year the index is converted to annual growth rates.
- **Nominal interest rate.** Policy and interbank reference rates are taken from the same LSEG database. Used to measure the cost of debt, and weighted average cost of capital.
- **Corporate income-tax rate.** Statutory rates are collected from official government websites. The tax parameter adjusts both after-tax cash flows and the debt-interest tax shield that appears in the WACC calculation.
- **Feed in Tariff (FiT).** Is the guaranteed purchase price per megawatt-hour (Mwh) for the electricity to be generated by the FOWT plant. The FiT feeds into the measurement of the Return On Equity (ROE).
- **Capital-structure share.** The share of CAPEX raised through debt to equity. Within the simulations it is allowed to vary slightly, reflecting the bandwidth observed in recent European offshore-wind financings. This share feeds directly into WACC and ROE.

Capacity-factor variables

The annual **Capacity Factor (CF)** expresses how efficiently a floating-offshore wind farm converts its installed capacity into electrical energy. To compute CF, the simulation engine draws on a concise but interconnected set of input variables. These variables originate either from public environmental databases for meteorology or from the engineering documentation for FOWT. The list below describes each variable, explains where it is obtained and clarifies the specific stage of the CF calculation, probability distribution, turbine power curve, or park-level adjustment in which it is used.

- The **shape factor (*k*)** defines how sharply wind speeds are clustered about the mean at a given site. Lower values denote a broad spread of calm and gusty hours, whereas higher values imply steadier winds. *k* enters the probability distribution that governs hourly wind speeds; by doing so, it influences every subsequent step that converts wind to energy. Ten-year series of *k* are derived from hourly hub-height data downloaded from the **New European Wind Atlas (NEWA)**; if a pilot lacks the full record, an interim default is taken from the long-term mean of the closest offshore grid cell in the same national zone.
- The **scale factor (*λ*)** provides the second Weibull parameter required to anchor the distribution to the absolute wind-speed range observed at the site. While *k* controls the distribution's shape, *λ* fixes its horizontal stretch and therefore determines the expected frequency with which winds exceed the turbine's cut-in speed. Like *k*, *λ* is calculated from the same ten-year NEWA record and is stored solely for driving the statistical representation of the wind climate.
- The **average hub-height wind speed ($\overline{v}$)** offers a concise measure of the wind resource and acts as an independent check on the plausibility of the fitted Weibull parameters. The model reads $\overline{v}$ directly from the interactive layers of the NEWA web map and stores it alongside *k* for each pilot site. Although $\overline{v}$ is not itself used in the probability draws, it helps validate that the chosen *k* and scale values reflect the observed wind climate.

- The **aging factor** represents the gradual reduction in aerodynamic and electrical efficiency that offshore turbines experience in service. Within the model this factor scales the manufacturer's power curve downward year after year, thereby lowering projected energy output and, by extension, capacity factor. The default rate is taken from multi-year performance studies that reported an annual decline of roughly two-thirds of one percent.
- **Wind-farm losses** aggregate the effects of wake interactions between turbines, electrical conversion losses and scheduled maintenance down-time. After single-turbine production is summed across the array, the loss percentage converts gross megawatt-hours to net export at the grid connection. Each pilot team supplies its own loss allowance through the common engineering template; an illustrative figure of ten percent is shown in the capacity-factor calculation document.
- The **number of turbines** fixes the physical scale of the plant. It multiplies single-turbine generation to yield farm-wide output before that total is normalised by installed capacity to produce the capacity-factor series. Turbine counts come from the approved site layout included in the same engineering template that lists park losses; for example, the reference case in the documentation assumes sixty-seven machines.

FOWT specific input data

The data specific to the FOWT is grouped into two parts, CAPEX components and OPEX. The CAPEX consists of the following cost inputs:

- **Development and consenting cost:** This entry covers site studies, environmental impact assessments, legal fees and all regulatory application charges required before construction may begin. The cash-outflow appears early in the schedule and therefore strongly influences the model's financing drawdown. Values are taken from partner project-management budgets and verified against third-party permitting consultants' quotations.
- **Turbine cost:** The procurement price of nacelles, blades, towers and spares is recorded under this line. It drives the largest single slice of upfront investment and sets the baseline for depreciation in the cost ledger. Prices are imported from turbine-supply agreements or, where contracts are not yet signed, from vendor term sheets collated by the engineering leads.
- **Platform cost:** Platform cost refers to the fabrication of steel or concrete floating substructures sized for the reference 15 MW turbine class. The figure feeds into construction-phase cash flows and is needed to calculate interest during construction. Estimates come from competitive tenders received by the marine-structures work package.
- **Anchoring and mooring cost:** This variable covers drag-embedment anchors, chain or synthetic lines, load shackles and associated installation consumables. Because mooring layout varies by bathymetry, the cost serves as a key sensitivity input for deep-water pilots. Data is supplied in the mooring-engineering template completed by each site partner.
- **Installation cost:** All vessel spreads, port fees, heavy-lift day rates and offshore commissioning services are aggregated here. Installation expenditure establishes the final milestone for

capitalisation of interest and thus affects total financing cost. The numbers originate from logistics schedules prepared by the balance-of-plant contractor.

- **Intra-array cables cost:** Procurement and lay of inter-turbine medium-voltage cables appear under this heading. The cost influences both CAPEX and subsequent electrical-loss assumptions. Lengths and unit rates are provided by the electrical-systems package based on cable-routing studies.
- **Export cable cost:** This item records high-voltage export cable supply, seabed trenching and landfall works up to the grid substation. It is required to capture grid-connection CAPEX and any associated contingency funds. Figures come from grid-connection budgets and are cross-checked against transmission-system-operator benchmarks.

While the OPEX is the summation of the following variables[3]:

- **Fixed operations cost:** Fixed operations cover control-room staffing, marine coordination, insurance premiums and other costs that do not scale with output. They establish a baseline annual charge applied from the first full year of service. Data are pulled from operator business-plan spreadsheets submitted during the partner survey.
- **Fixed maintenance costs:** These are scheduled preventive tasks—annual inspections, gearbox oil exchange campaigns and statutory certification fees—that occur regardless of turbine availability. The costs influence long-term cash-flow stability and are gathered from original-equipment-manufacturer maintenance manuals and service-contract drafts.
- **Variable operations and maintenance costs:** Unplanned corrective works—component replacements, vessel call-outs and unscheduled crane hire—are entered here. The item introduces stochastic spread to lifetime OPEX, as failure rates vary with turbine ageing. Baselines are taken from historical failure statistics provided by the operations partner and checked against offshore-wind reliability databases.

Levelised Cost of Energy (LCOE) - General model

The **Levelized Cost of Energy (LCOE)** is a metric that measures the average cost per unit of electricity generated over a project's lifetime. In essence, it is defined as the **ratio of the total discounted costs** of a power plant to the **total discounted energy output** over its lifetime. All relevant life-cycle costs are included from upfront **capital expenditures (CAPEX)** (e.g. development and construction) to ongoing **operating expenditures (OPEX)** (operations and maintenance). Both the costs and the electricity generation are expressed in net present value (NPV) terms by discounting future cash flows and outputs to today's value. This ensures that later-year costs or generation (which are less valuable due to the time value of money) are appropriately weighted in the calculation. The result is typically given in currency per energy unit (e.g. £/MWh or EUR/MWh), allowing a comparison of different generation technologies on a "cradle-to-grave" cost basis. The LCOE formula is given by:

[3] https://guidetoanoffshorewindfarm.com/wind-farm-costs/

$$LCOE = \frac{CAPEX_0 + \sum_{t=1}^{n} \frac{OPEX_t}{(1+WACC_t)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+WACC_t)^t}}$$

Where CAPEX is the capital expenditure, OPEX is the annual operating and maintenance costs of the plant during its operational years, E is the energy production of the FOWT and WACC is the weighted average cost of capital, a proxy for the discount rate.

However, note that when LCOE is used without taking into account future uncertainties such as changes in OPEX, Inflation rate, interest rates and wind turbine energy production degradation it becomes misleading (H. Amlashi and C. Baniotopoulos (2024)). For floating offshore wind farms, many key inputs (from capital cost to energy yield) are uncertain and can vary significantly over a project's lifecycle. To address this, we have developed probabilistic or stochastic LCOE methodologies that treat input parameters as random variables rather than fixed values. The general approach is to perform a **Monte Carlo simulation**:

- Instead of a single OPEX value, a probability distribution is assigned to reflect its uncertainty. For example, we might assume a ± 20% variability in OPEX around a mean estimate. Each simulation run draws a random value from these distributions.
- Likewise, **annual energy production** can be treated probabilistically. Wind speed variation is commonly modelled with a **Weibull distribution**, and combined with turbine power curves to derive a distribution for the capacity factor or annual output. This accounts for inter-annual variability in wind resource, turbine performance, and array losses.
- The model then calculates an LCOE for each simulation run (using the same formula as above but with that run's sampled inputs). After a thousand runs, we obtain 1000 paths for LCOE outcomes rather than a single value. This distribution is then summarized with statistics (median, 95% confidence interval bounds) to indicate the range of possible LCOE values and their likelihood.

Moreover, treating inputs as random variables allows analysts to identify which uncertainties drive the LCOE the most (via **sensitivity analysis**). Some key uncertain parameters in floating offshore wind LCOE analyses include:

- **Operational Expenditure (OPEX):** Yearly O&M and operational costs can fluctuate (e.g. unexpected maintenance, vessel costs, insurance). Because OPEX recurs every year, its uncertainty can compound. Studies have found that **variation in OPEX can significantly influence LCOE** in fact, one probabilistic analysis showed the LCOE distribution was more sensitive to OPEX assumptions than to CAPEX or decommissioning costs. This is intuitive, as higher-than-expected ongoing costs each year will directly increase the average cost per MWh.
- **Capacity Factor:** This is often the **single largest driver of LCOE uncertainty** for wind. The capacity factor depends on wind resource quality, turbine performance, and array effects. If actual winds are lower than predicted (or turbine downtime higher), the energy output drops, driving LCOE up (since costs are then spread over fewer MWh). **Probabilistic LCOE models treat capacity factor or annual energy as a distribution** – e.g. using wind speed probability distributions or a range of possible loss factors. A small absolute change in capacity factor (say 5% lower) has a direct proportional increase in LCOE, making this a critical uncertainty to capture.

- **Discount Rate:** The discount rate (often related to the project's financing or Weighted Average Cost of Capital) has a strong effect on LCOE because it alters the present value of future costs and generation. Higher discount rates give less weight to long-term outputs, effectively raising LCOE for capital-intensive projects. Different organizations use different discount rates for offshore wind, reflecting varying risk and financing assumptions. In a sensitivity analysis, applying a higher discount rate will increase LCOE, while a lower (or subsidized) rate lowers it, all else equal. Therefore, scenarios examining variation in the discount rate are important. Some researchers have even proposed alternative risk-adjusted discounting or **certainty-equivalent** methods to better account for project risk in LCOE calculations (Soojin et al. (2021), underscoring that how we handle the discount rate can noticeably change the outcome. In our analysis we proxy the discount rate using an annual WACC.

In practice, a **probabilistic LCOE evaluation** for a floating wind farm would proceed by assigning each of the above factors a reasonable range or distribution (based on empirical data or expert judgment), then running simulations. The outcome is often presented as a probability density or cumulative probability curve of LCOE. This provides valuable information to decision-makers: for example, the probability that LCOE will fall below a certain target, or the **confidence interval** for the expected LCOE. It also enables **tornado charts** or other sensitivity outputs to rank which uncertainties contribute most to LCOE variance. In summary, while the traditional (deterministic) LCOE formula gives a single-point estimate useful for baseline comparison, **incorporating stochastic methods and uncertainty analysis yields a more robust evaluation methodology** for floating offshore wind farms. This comprehensive approach aligns with recent academic recommendations to support better risk-informed investment decisions and policy planning in the offshore wind sector.

Weighted Average Cost of Capital (WACC)

The **Weighted Average Cost of Capital (WACC)** represents the average rate of return that a project must pay to its capital providers (debt and equity holders). It is a foundational input in project finance modelling, determining how future cash flows are discounted and thus influencing metrics like the levelized cost of energy (LCOE) and investor returns. In the context of floating offshore wind farms, which are capital-intensive and relatively new, accurately evaluating WACC is crucial. The U.S. National Renewable Energy Laboratory (NREL) provides widely respected guidance on WACC through its Annual Technology Baseline (ATB) and financing publications. These resources outline how to compute WACC and integrate it into renewable energy financial models. According to NREL's ATB, WACC is used as the discount rate in LCOE calculations, feeding into the capital recovery factor that annualizes capital costs. This section develops a detailed WACC evaluation methodology for floating offshore wind, explaining how WACC is computed, how it factors into LCOE and return on equity (ROE) calculations, and how debt and equity costs under a given capital structure are accounted for. We also discuss the limitations of using a static WACC in offshore wind models and explore methods to incorporate dynamic or annual WACC in probabilistic analyses. In financial terms, WACC is the blended cost of a project’s financing, weighted by the proportion of debt and equity in the capital structure. The WACC is calculated as:

$$WACC_t = \frac{1 + [(1-DF) * \{(1 + ROE_t) * (1+\pi_t) - 1\}] + [DF * \{(1+r_t) * (1+\pi_t) - 1\} * (1-TR)]}{1+\pi_t} - 1$$

$$r_t = \frac{1+i_t}{1+\pi_t} - 1$$

Where:

- *i = nominal interest rate,*
- π = inflation rate,
- DF = debt factor,
- ROE = Return on Equity,
- r = real interest rate
- R = corporate tax rate

While WACC represents the discount rate, the return on equity (ROE) is a component of WACC that represents the equity investors target internal rate of return. Equity investors typically target a certain IRR (internal rate of return) on their invested capital, which we refer to as the cost of equity in the WACC. In a project finance model, analysts often solve for the feed-in tariff that yields a target ROE for equity investors, given assumptions about debt terms. The ROE feeds into the WACC. It’s important to clarify that WACC is not the same as ROE, but a composite. For a highly leveraged project, the WACC will be much lower than the equity’s required return, because cheaper debt capital dominates the mix. Conversely, for a project financed mostly with equity, WACC approaches the equity return. For floating offshore wind projects, which might initially involve somewhat higher risk, equity investors could demand higher returns, but if substantial debt financing is available at moderate interest, the WACC could still remain in single digits. Financial models ensure consistency between WACC and ROE by linking them through capital structure.

Fixed WACC vs time-varying WACC:

A single, unchanging WACC is straightforward to apply in LCOE applications, yet it obscures fundamental realities that shape financing costs for floating-offshore wind. First, the risk profile of a project does not stay fixed. Capital is most expensive during construction, when technology and schedule uncertainties dominate; once turbines have been commissioned and power is flowing under a long-term contract, the same project can refinance on markedly better terms. Treating WACC as constant therefore overstates the cost of capital in later, de-risked operating years and understates it in the risk-laden build phase. Second, WACC moves with the macro-economy and is affected by Interest-rate cycles, inflation surprises, tax rates and ROE. Therefore, a static WACC cannot capture these dynamics. Also, a fixed discount rate is deterministic. It provides no way to express uncertainty in future operating costs, leaving analysts blind to how much levelized-energy cost (LCOE) might rise or decrease in the future. A more realistic modelling lets WACC vary. One option is a time-varying approach which apply a stochastic treatment representing the cost of debt, target return on equity and debt fraction as probability distributions and sample them in a Monte Carlo simulation, producing a distribution of WACC values and, by extension, a distribution of LCOE. Advanced studies may go further by linking these WACC draws to other variables such as higher inflation can raise nominal WACC yet also index tariff revenues so that each simulated future remains internally consistent. Any of these methods adds limited complexity but yields a far richer and more credible picture of financing risk for floating-offshore wind than a single, static discount rate.

Return on Equity

Return on Equity (ROE) measures the annual return that project shareholders earn on the capital they have invested. ROE is expressed as

$$ROE = \frac{Net\ income}{shareholder\ equity} * (1 - Tax\ rate)$$

$$Net\ income = Feed\ in\ tariff * Capacity\ factor * Hr - (CAPEX + \sum_{t=1}^{Life\ of\ plant} \frac{OPEX_t}{(1+WACC_t)^t})$$

$$Shareholder\ equity = Initial\ investment\ by\ owners = CAPEX * Equity\ fraction$$

Where Hr = number of hours per year, Capacity factor refers to the actual energy produced by a power plant over a specific period to the maximum possible output if the plant, CAPEX is the Capital expenditure, OPEX is the operating and maintenance expenditure during the operation years of the FOWT plant, and WACC is the discount rate.

Capacity Factor

Annual wind power production

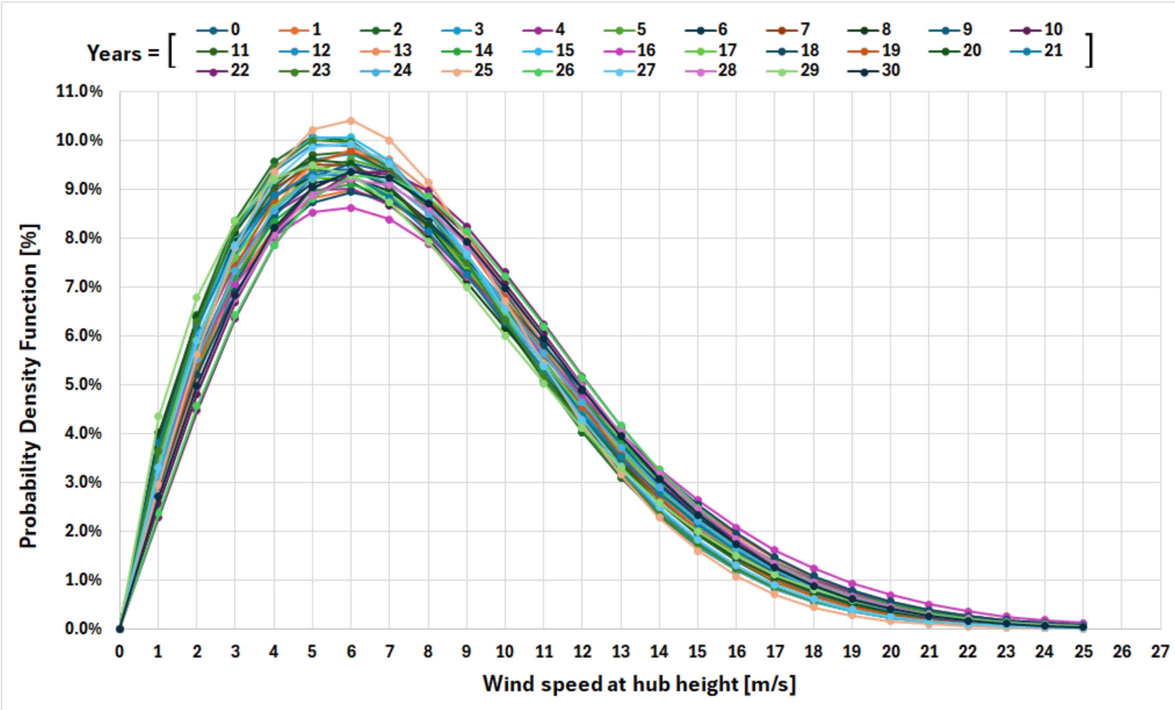
The capacity-factor workflow begins by describing the site wind climate with a Weibull probability-density function. The **shape parameter, *k*,** controls how sharply the annual wind-speed distribution peaks: larger values yield a narrower range of speeds and therefore a steadier resource. For each pilot, *k* is calculated year-by-year from ten years of hourly hub-height data downloaded from the **New European Wind Atlas (NEWA)**. Where a full decade of measurements is still being compiled, an interim default is assigned from the ten-year mean at an offshore grid cell that best matches the licence area; typical defaults span roughly 1.9 in the Sicily Strait to about 2.3 in the central North Sea, and are replaced as soon as site-specific records become available. The **scale parameter, *C*,** is estimated alongside *k* from the same NEWA data set and anchors the distribution to the observed speed range, thereby dictating the absolute level of expected energy capture. A third meteorological input, the **average hub-height wind speed, $\bar{v}$,** is read directly from the interactive NEWA map. Although it plays no direct role in the Monte-Carlo draws, $\bar{v}$ provides an important cross-check on the plausibility of the fitted Weibull parameters and offers a fallback estimate of energy yield should the parameter fit prove unstable. Note that due to the complexity of modeling year-to-year variability in these parameters, the Box-Muller transformation [G. E. P. Box and Mervin E. Muller, *A Note on the Generation of Random Normal Deviates*, The Annals of Mathematical Statistics (1958), Vol. 29, No. 2, pp. 610–611] was used to generate a multi-year synthetic dataset of Weibull parameters. This method allows for the generation of pairs of normally distributed, independent random numbers with zero mean and unit variance. Each parameter was assumed to follow a normal distribution centered around its 10-year mean, with variability limited to within two standard deviations. Using the random sequences obtained through the

Box-Muller method, multiple Weibull distributions were generated to represent interannual variations in wind resource at the site $\left(PDF_y(v)\right)$ calculated by the following:

$$PDF_y(v) = \frac{\kappa_y}{\lambda_y}\left(\frac{v}{\lambda_y}\right)^{\kappa_y - 1} e^{-\left(\frac{v}{\lambda_y}\right)^{\kappa_y}}$$

Turbine power-curve parameters

Wind climate alone does not determine electrical output; the turbine's aerodynamic response is encoded through five design variables. The **rotor diameter** sets the swept area that captures kinetic energy, while the **hub height** guarantees that the wind-speed data and the manufacturer's power curve refer to the same elevation. Three threshold speeds—**cut-in, rated (nominal) and cut-out**—define the operating envelope; wind below the cut-in or above the cut-out produces no power, and between those limits the curve rises to its rated plateau. The **generator-system efficiency** then converts aerodynamic power into electrical output through a uniform scalar adjustment. Long-term performance decay is represented by an **ageing factor** that reduces the entire power curve by a fixed proportion each year, reflecting empirical evidence from operational offshore fleets. Together, these variables map every hourly wind speed generated by the Weibull model to an instantaneous electrical power value. The shape and scale parameters are given by:



For each synthetic year, wind distributions were used to simulate the expected power production from a turbine at hub height. The turbine model selected for this study was the IEA-15-240-RWT (https://github.com/IEAWindSystems/IEA-15-240-RWT), which defines the expected power output as a function of wind speed at hub height. The power curve of the turbine was implemented following the methodology described in [RDS Lanni 2023], based on the following equation:

$$P_y(v) = \frac{1}{2} * \rho * A * \eta_y * C_p(v) * v^3$$

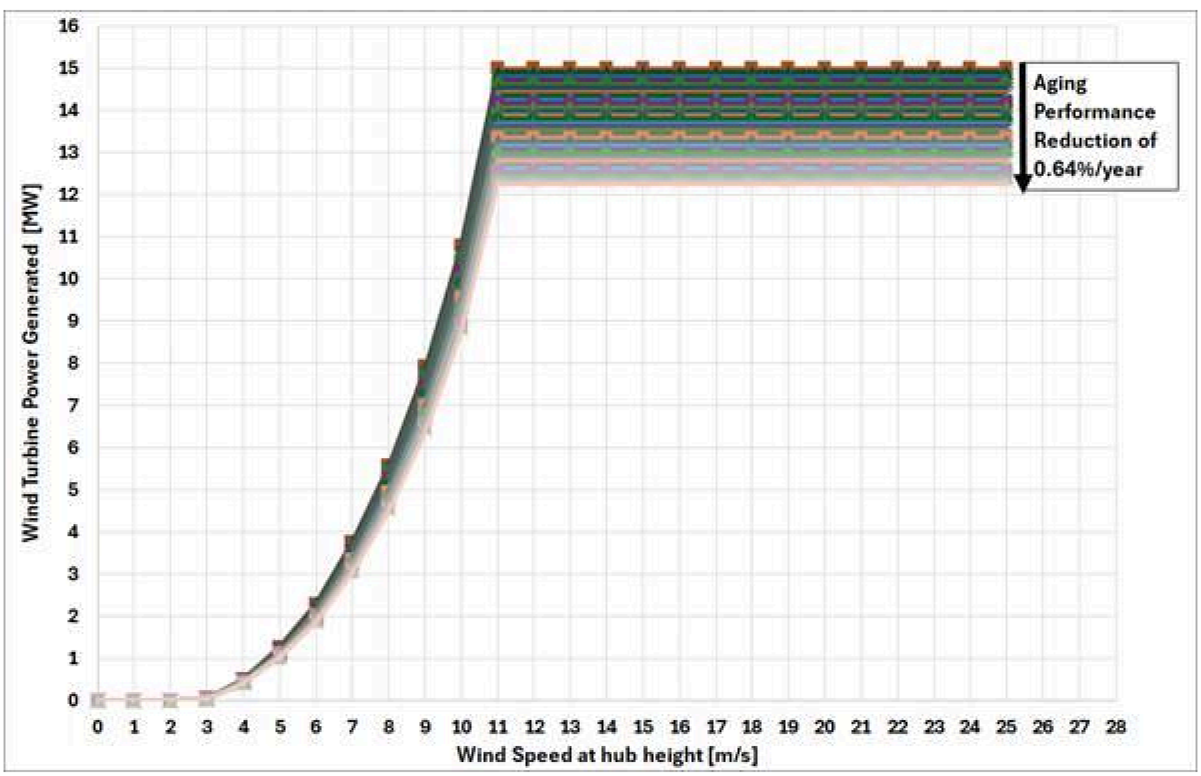
Where is the air density at hub height, A is the rotor swept area, y is the yearly overall efficiency of the turbine, CP(V) is the power coefficient at wind speed v, and v is the wind speed at hub height.In our analysis the input data used for the turbine model are the same as those provided by the IEA task that developed the IEA-15-240-RWT reference turbine. These data are publicly available on GitHub. The specific values adopted for this analysis are summarized in the table below:

Parameter	Value	Unit
Turbine Size	15	MW
Rotor_diameter	242.237756 5	m
Cut-in Wind Speed	3	m/s
Nominal Wind Speed	10.8677069 4	m/s
Cut-out Wind Speed	25	m/s

Hub Height	150	m
Generator_Rated_efficiency	0.958979992	%

Plant-level configuration parameters

To estimate the LCOE of an offshore wind farm, we define the size of the plant in terms of the number of turbines it comprises. Accordingly, the expected energy production must be calculated, accounting for realistic system losses typically expressed as a percentage of gross production. Additionally, to account for the degradation in turbine performance over time—an effect documented in multiple studies—an aging factor was introduced in the computational tool. This factor directly affects the turbine's power curve efficiency, which nominally is around 0.959 as reported in Table 2. According to Mathew et al. (2022) in *"Estimation of Wind Turbine Performance Degradation with Deep Neural Networks"*, a degradation rate of approximately **0.64% per year** was observed in Norway, consistent with trends identified in the UK and US. Assuming a 30-year operational lifetime for an offshore turbine, the resulting reduction in the power curve was implemented in the model as shown in the figure below.



To compute the **annual Capacity Factor (CF)** for each year, the generated power (derived from the power curve) was multiplied by the expected occurrences of each wind speed value as described by the annual Weibull distributions. The CF for year *y* is computed using the following integral:

$$CF_y = \frac{\int_0^\infty P_y(v)\, PDF(v)\, dv}{P_{y=0}(v_{nom})}$$

Where $P_y(v)$ is the turbine power output at wind speed *v*, adjusted for year *y* including degradation, $P_y(v)$ is the Weibull probability density function for year *y*, v_{nom} is the rated wind speed, and $P_{y=0}(v_{nom})$ is the rated power output at nominal conditions. This integral was solved numerically using the trapezoidal method, requiring the definition of a sufficiently small wind speed step Δv. In this implementation, a step size of 0.01 m/s was found to provide good convergence without incurring excessive computational cost. A 20-year simulation was then conducted using the described input parameters.

Empirical study

Data input

For the UK lab, we use the Kincardine floating offshore wind farm as our case study for the comprehensive LCOE evaluation model. The table below provides the initial data input required to conduct the simulation analysis for the UK and the kincardine specific input variables. The initial **inflation rate (3.8%, bounded 0–10%, truncated normal)** establishes the price index used to move between nominal and real terms. It works in tandem with the interest rate to derive the real cost of debt and to apply the tax shield correctly in the discount rate. The **interest rate on debt (7.4%, bounded 0–14%, truncated normal)** sets the coupon on project borrowing; together with the equity share and the corporate tax rate, it determines the year-by-year weighted average cost of capital (WACC) used for discounting. The **feed-in tariff (271 per MWh in the selected currency)** defines the unit revenue applied to net energy, so it is the anchor for the income side of the cash-flow. The **corporate tax rate (25%)** is used to transform pre-tax operating surplus into after-tax income and to calculate the after-tax cost of debt in WACC.

Wind resource and energy yield.
The capacity factor is not imposed directly; it is generated from the site's wind regime using a **Weibull representation**. The **Weibull shape (k = 2.23)** and **Weibull scale (c = 11.329)** are the inputs to the Weibull probability density used to describe hub-height wind speeds. These parameters are mapped through the turbine power curve (with the tool's aging and loss allowances) to produce annual energy and, hence, the effective capacity factor. The table also lists an **annual production loss (0.064%)**, which is a gross-to-net adjustment applied after aggregating turbine output to the farm level (e.g., electrical or

availability losses). Finally, the **number of turbines (6)** provides a cross-check on plant configuration and underpins any per-turbine calculations embedded in the power-curve integration.

Project configuration and horizon.
The **farm capacity (50 MW)** sets the physical scale for both energy and cost scaling (e.g., converting per-MW OPEX to plant totals). The **operational life (25 years)** defines the analysis horizon for discounting, shaping the relative influence of early versus late cash flows in the LCOE ratio and the evaluation of financing metrics over time.

Capital and operating costs.
CAPEX (£7,600,000) identifies the initial investment to be recovered through the levelised cost. In the financing block it is also used, together with the equity share, to size the debt and equity contributions at financial close. (If this figure is intended per MW rather than total, it should be labelled accordingly; otherwise the model treats it as a project-total.) **OPEX** is specified **per MW-year** with an **initial value (£190,000 MW^{-1} yr^{-1})** and **admissible interval (£79 to £270 MW^{-1} yr^{-1}, truncated normal)**. In the calculations, a per-MW value within this interval is used for each operating year, then scaled by 50 MW to obtain the plant's annual operating cost. Providing both a central value and bounds ensures that annual operating costs remain within plausible limits while still reflecting site-specific uncertainty captured in the O&M literature for offshore wind.

Capital structure.
The equity share (initially 18%, bounded 5–80%, beta distribution) sets the financing mix at financial close and, with the interest rate and tax rate, determines WACC. Lower equity shares (higher leverage) tilt the discount rate closer to the after-tax cost of debt; higher equity shares tilt it toward the equity return. The use of a beta distribution is appropriate because equity share is a proportion confined to [0,1], and the stated bounds reflect typical ranges observed in project finance for offshore wind.

How these inputs work together.
With these initial settings, the LCOE numerator (discounted costs) is driven by CAPEX and the annual OPEX sequence scaled to 50 MW, while the denominator (discounted energy) is generated from the Weibull-based wind model adjusted by the stated production loss. The feed-in tariff and simulated energy jointly determine annual revenue for the return metrics, and the macro-financial entries (inflation, interest, tax, equity share) shape the discounting through WACC and the after-tax profitability through ROE. Because the table specifies both central values and, where relevant, bounds and a distribution type, the model has enough information to initialise the Kincardine case and vary the inputs in a controlled, well-defined manner when running the analysis.

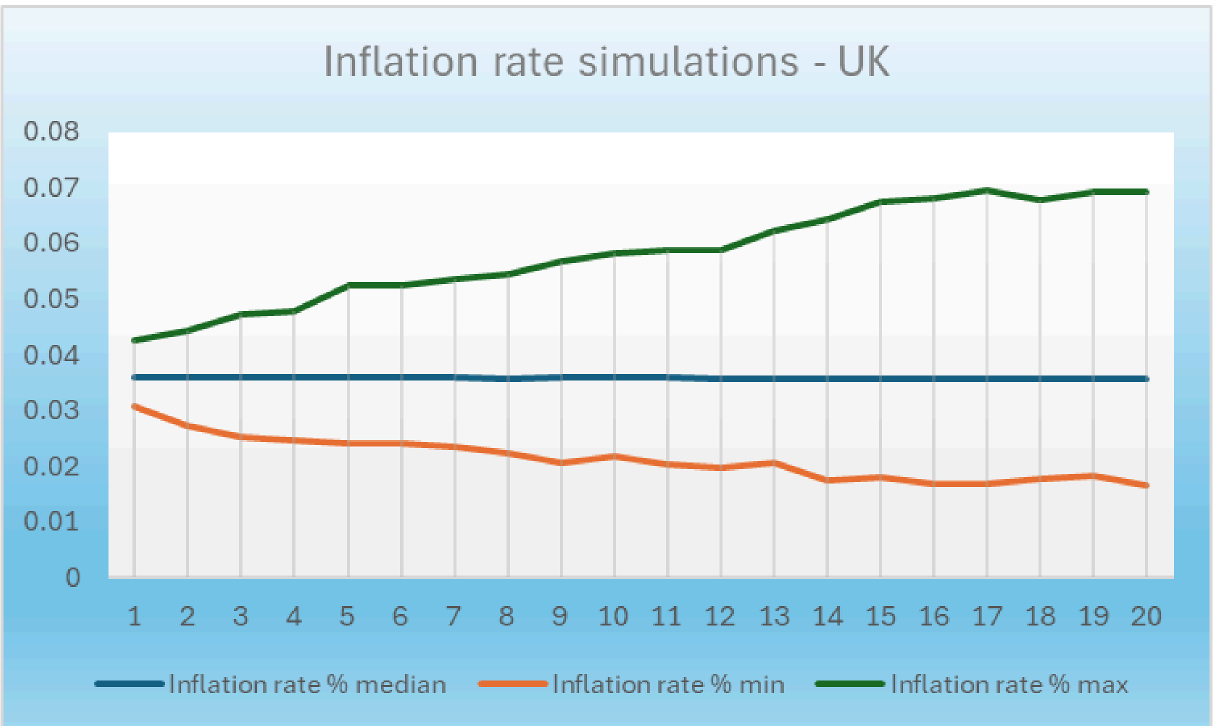
Notes on clarity and consistency.
Two practical checks help maintain dimensional consistency: (i) confirm the unit for the tariff "271" (e.g., £/MWh) and the currency alignment across all monetary inputs; and (ii) confirm whether the CAPEX figure is total-project or per-MW. Explicitly stating these conventions in the input sheet ensures that subsequent results for LCOE, WACC and ROE can be interpreted unambiguously for the Kincardine case

Macroeconomic data for the UK				
	Initial value	Lower bound	Upper bound	Distribution density
Inflation rate	3.8%	0%	10%	Truncated normal distribution
Interest rate on debt	7.4%	0%	14%	Truncated normal distribution
Feed in Tarif	271			
Tax rate	25%			
Capacity factor				
Weibull Shape factor	2.33			Weibull partial distribution function
Weibull scale factor	11.329			Weibull partial distribution function
Number of turbines	6			
Annual production loss	0.064%			
Site specific data				
Capacity of the Farm	50 mw			
Operational years of the farm	25			
CAPEX	£ 7,600,000			
OPEX	£200,000 MW/year	£79 MW/year	£270 MW/year	Truncated normal distribution
Equity share	18%	5%	40%	Random Beta Distribution

Macroeconomic variables simulation results

Inflation rate

The median inflation path is broadly flat at about 3.6% throughout the horizon, easing only slightly to 3.55% by year 20. The interval between the lowest and highest values widens over time—from 3.08–4.27% in year 1 to 1.65–6.93% by year 20—showing that more extreme outcomes become possible in later years. In the model, inflation interacts with the nominal debt rate to form the real cost of debt and therefore influences WACC. When prices run higher without matching revenue indexation, operating cash margins compress in nominal terms and ROE can soften; if indexation is aligned on both revenue and key cost lines, inflation mainly flows through the real/nominal conversion with little effect on real LCOE.



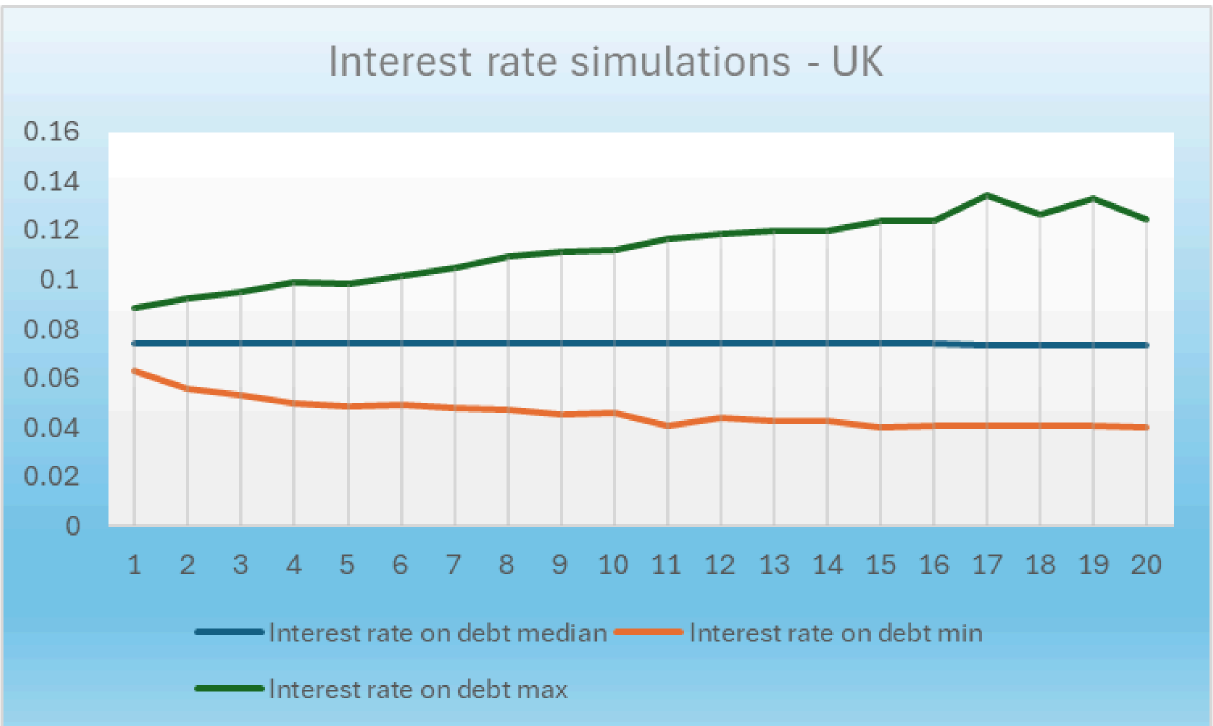
	Inflation rate % simulations UK		
Year	median	min	max
1	3.60038	3.08	4.27
2	3.59843	2.74	4.42

3	3.59538	2.53	4.73
4	3.58833	2.48	4.77
5	3.59445	2.42	5.24
6	3.59623	2.41	5.23
7	3.58167	2.34	5.35
8	3.57566	2.25	5.45
9	3.58248	2.07	5.69
10	3.58636	2.17	5.83
11	3.58486	2.04	5.89
12	3.57735	1.99	5.89
13	3.58025	2.07	6.22
14	3.57237	1.75	6.42
15	3.57861	1.8	6.74
16	3.57974	1.68	6.8
17	3.5724	1.7	6.94
18	3.56358	1.77	6.77
19	3.56738	1.84	6.91

20	3.55394	1.65	6.93

Interest rate on debt

Borrowing costs start near 7.40% and drift a touch lower to about 7.33% by year 20, while the upper end of the range allows for stress years (roughly 12–13% mid-life) and the lower end stays close to 4%. Because debt is a large share of the capital stack, even modest changes in the coupon move the after-tax cost of debt and therefore WACC. Higher-rate years push up debt service and reduce residual cash to equity, lowering ROE in those years. A lower coupon has the opposite effect and, via a lower WACC, tends to reduce LCOE by down-weighting long-dated costs and valuing later MWh more.



Interest rate on debt - UK			
Year	median	min	max
1	7.39601	6.31	8.83

2	7.39798	5.59	9.23
3	7.40204	5.35	9.51
4	7.38807	5	9.88
5	7.41279	4.88	9.85
6	7.40969	4.91	10.13
7	7.39836	4.83	10.5
8	7.41813	4.71	10.95
9	7.42496	4.54	11.12
10	7.43321	4.6	11.18
11	7.43801	4.1	11.64
12	7.42417	4.41	11.85
13	7.41814	4.28	11.96
14	7.40043	4.27	12
15	7.39872	4.04	12.4
16	7.38994	4.11	12.35
17	7.37282	4.1	13.43
18	7.35604	4.05	12.66

19	7.33432	4.06	13.3
20	7.32949	4	12.45

Equity fraction

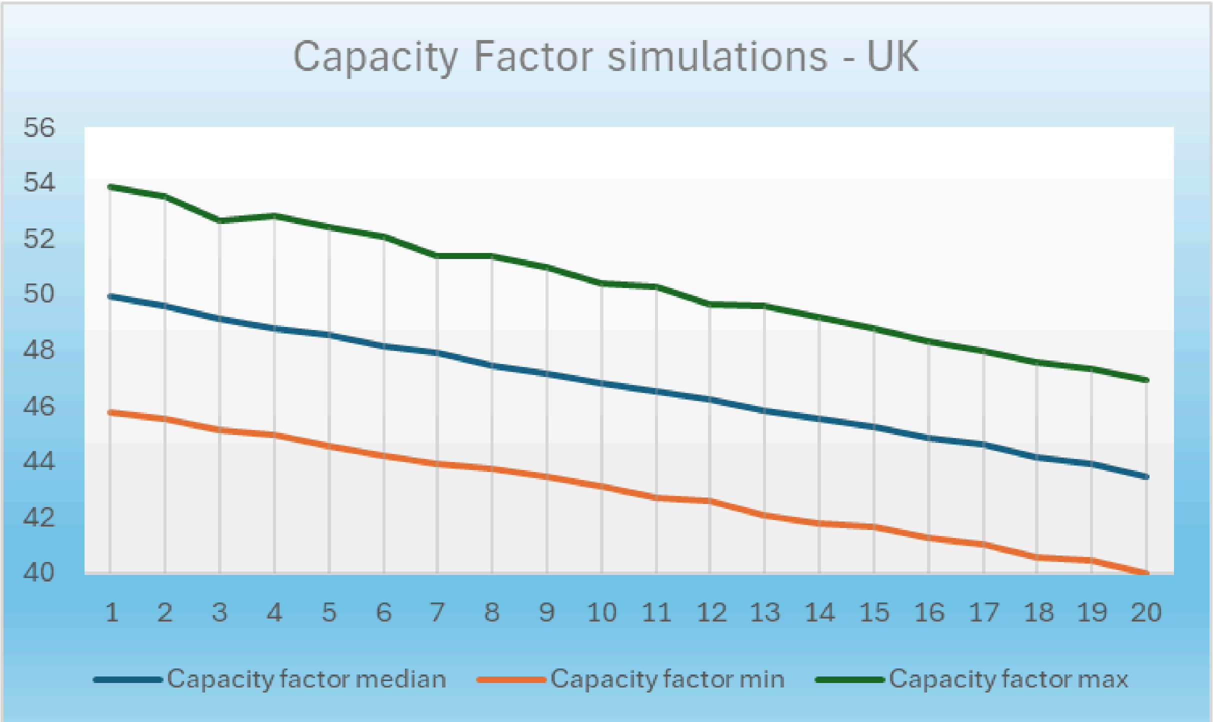
The average equity share declines steadily from about 30% in year 1 to about 24% by year 20, bounded within 10–40% each year. This tilt toward debt increases the weight of cheaper, tax-shielded capital and is a principal reason the model's WACC falls over time. The smaller equity base also amplifies percentage movements in ROE for a given cash-flow swing, contributing to wider ROE tails in some years. On LCOE, the increased use of debt typically lowers the discount rate applied to future costs and energy, which—other things equal—pulls LCOE down and partly offsets the effect of ageing on generation.

	Equity fraction - UK		
Year	median	min	max
1	29.8508	13.95	40
2	29.17115	10	40
3	28.8296	10	40
4	28.21686	10	40
5	27.76798	10	40
6	27.13349	10	40
7	26.5551	10	40
8	26.01154	10	40
9	25.45398	10	40

10	25.42682	10	40
11	25.14965	10	40
12	24.79131	10	40
13	24.70866	10	40
14	24.75405	10	40
15	24.36058	10	40
16	24.35178	10	40
17	23.87881	10	40
18	23.93609	10	40
19	23.71688	10	40
20	23.87141	10	40

Capacity factor

median capacity factor declines smoothly from roughly 50.0% in year 1 to about 43.5% in year 20. The minimum and maximum values also ease downward (for example, maxima contract from ~53.9% to ~46.9%), indicating that the upside envelope narrows with age. Because many cost items are quantity-independent, lower CF spreads fixed and quasi-fixed costs over fewer MWh, raising the unit cost of energy. In the model, this late-life erosion in CF places upward pressure on LCOE; the concurrent decline in WACC partly counterbalances that pressure by reducing the present-value weight of long-dated costs and valuing later-year energy more favourably.



Capacity factor			
Year	median	min	max
1	49.95074	45.76	53.88
2	49.57269	45.52	53.52
3	49.1352	45.15	52.64
4	48.7711	44.98	52.8
5	48.52352	44.54	52.44
6	48.14211	44.24	52.07
7	47.8833	43.93	51.39

8	47.46682	43.73	51.36
9	47.13443	43.45	51
10	46.80643	43.1	50.41
11	46.49569	42.71	50.28
12	46.20908	42.62	49.67
13	45.82782	42.1	49.56
14	45.51684	41.79	49.2
15	45.2264	41.67	48.79
16	44.87533	41.26	48.3
17	44.6269	41.06	47.99
18	44.15487	40.57	47.59
19	43.89964	40.47	47.36
20	43.47509	39.99	46.92

Production and Performance Degradation: The declining capacity factor (about 14% relative drop over the project life) has a compounding effect on economics. In early years, the farm yields ~218 GWh annually (enough for ~55,000 homes), but by the late 2040s annual output falls closer to ~190 GWh due to turbine aging and possibly more frequent maintenance outages. This gradual decline, combined with any escalation in O&M costs (modeled via the OPEX distribution), means that later years contribute less net revenue and relatively higher expenses. The simulation tracks this year-by-year, so the internal rate of return on equity (ROE) in each scenario reflects not just upfront costs, but also the mid-life performance slump. In scenarios with unfavorable winds or high downtime, the ROE may drop sharply in later years, whereas in benign scenarios the project continues to generate solid cash flows well into its second decade. These dynamics are entirely missed in a static LCOE calculation, which would assume a constant average capacity factor and cost structure. By explicitly modeling performance deterioration, our method provides a more realistic risk-adjusted cost of energy for long-lived assets like floating wind farms.

OPEX

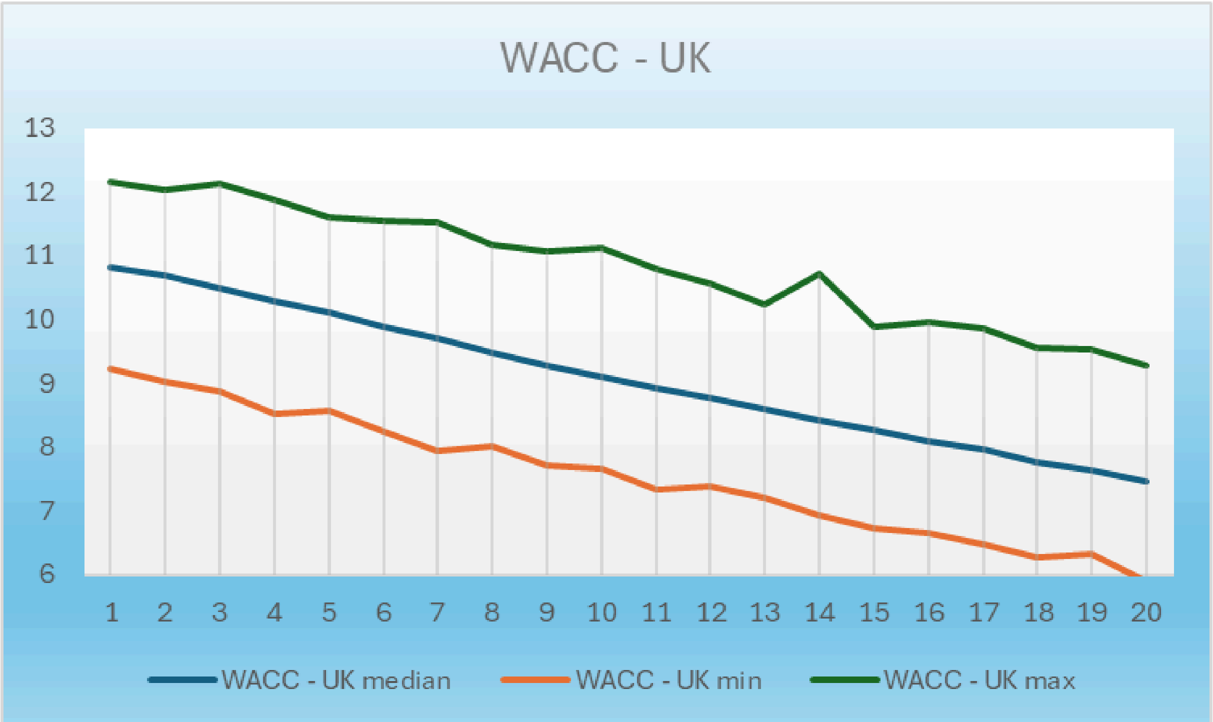
Average OPEX moves down early from about £158k/MW-yr in year 1 to a stable level near £190k/MW-yr, with a tight band around that median across the horizon. Because OPEX recurs annually, its level materially shapes the present-value cost numerator of LCOE. The quick convergence to a stable level and the narrow band limit the contribution of OPEX to LCOE dispersion. Years that combine lower CF with higher OPEX are the most demanding for equity cash flows, often coinciding with lower ROE; conversely, steady OPEX helps preserve margins and supports the WACC reductions obtained from the capital-structure shift.

OPEX - UK			
Year	median	min	max
1	207810.5	167409.6	223995.3
2	198375.1	164098.4	223993.6
3	195939.5	164030.3	223998
4	194619.3	164034.8	223996.6
5	194109.5	164122.6	223875.6
6	193461.9	164005.5	223971.8
7	194065.5	164001.8	223868.9
8	193837.7	164025.2	223995.3
9	194386.1	164028.2	223885.9
10	194546.8	164127.5	223959.7

11	194982	164220.6	223974.4
12	194143.4	164016.3	223890.2
13	194051.6	164016	223958.3
14	194034.8	164076.7	223971.3
15	194232.1	164020.8	223979.4
16	194378.8	164114.2	223997.6
17	194116.8	164054.5	223814.6
18	193785	164068.6	223999
19	194117.1	164314.5	223994.7
20	193825.6	164247.9	223958.1

WACC

The discount rate falls from about 10.82% in year 1 to roughly 7.47% by year 20, with narrower tails in later years. This pattern reflects the combination of slightly easing coupons, higher debt weight as the project matures, and a lower perceived operating risk after commissioning. A lower WACC reduces LCOE by decreasing the present-value weight of cost streams that occur far in the future and by assigning more value to later-year MWh. It also cushions the LCOE impact of the gradual decline in CF, which is why the model's lifetime LCOE distribution remains relatively concentrated around the reported median.

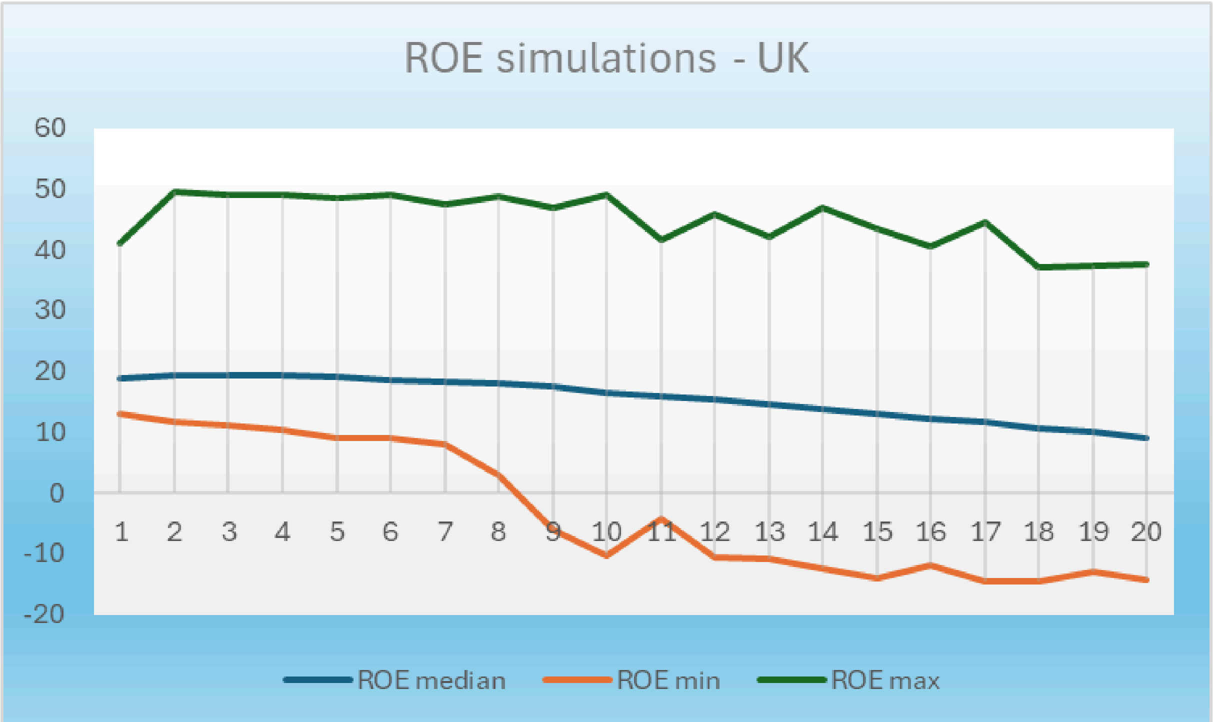


WACC - UK			
Year	median	min	max
1	10.81904	9.23	12.15
2	10.69191	9.02	12.03
3	10.48912	8.87	12.14
4	10.27825	8.52	11.88
5	10.10157	8.58	11.61
6	9.89447	8.25	11.54
7	9.70326	7.93	11.52

8	9.48833	8.02	11.17
9	9.28696	7.71	11.06
10	9.11028	7.66	11.12
11	8.9338	7.33	10.8
12	8.77662	7.39	10.56
13	8.58685	7.2	10.25
14	8.41744	6.93	10.72
15	8.2648	6.73	9.89
16	8.09395	6.66	9.97
17	7.95639	6.46	9.85
18	7.76468	6.26	9.56
19	7.63154	6.32	9.53
20	7.46757	5.9	9.27

ROE

median ROE begins high—around 18–19% in the early years—and trends down to about 9% by year 20, with widening dispersion and occasional negative outcomes in late life. The pattern is consistent with healthy early-life margins when CF is strongest, followed by thinner residual cash as CF eases and OPEX continues, with debt-service requirements varying by interest-rate realisation. ROE itself does not enter the LCOE calculation, but decisions taken in response to ROE pressure—such as refinancing to lower debt cost or modestly adjusting leverage—feed back into WACC and thus affect LCOE. In aggregate, the results show CF ageing nudging ROE lower over time, while financing improvements and contained OPEX help stabilise returns and keep lifetime LCOE close to the ~£195/MWh median.



ROE - UK			
Year	median	min	max
1	18.82736	12.98	41.04
2	19.39916	11.71	49.59
3	19.43319	11.07	49.09
4	19.41251	10.46	49.13
5	19.14202	9.08	48.47
6	18.67737	9.13	49.14
7	18.30325	7.89	47.5

8	18.0075	2.88	48.7
9	17.5069	-5.96	46.79
10	16.48202	-10.29	48.95
11	15.94025	-4.29	41.69
12	15.26984	-10.6	45.98
13	14.56513	-10.9	42.03
14	13.89889	-12.38	46.86
15	12.9345	-14.01	43.53
16	12.24388	-11.99	40.57
17	11.6831	-14.48	44.51
18	10.70988	-14.61	37.13
19	10.0769	-12.94	37.43
20	9.0773	-14.23	37.72

LCOE

The table below presents the LCOE analysis for the Kincardine floating offshore wind farm (UK). Results reflect multiple future economic scenarios—including variations in inflation, debt costs, capital structure, and tax—together with the expected deterioration in wind-turbine electricity generation over time (capacity-factor decline and operational losses). The model LCOE is reported alongside a fixed-charge simplified LCOE for benchmarking, while the accompanying WACC and ROE ranges summarise financing and equity-return conditions consistent with those scenarios. Taken together, these indicators provide a decision-grade view of Kincardine's levelised cost of energy under plausible macro-financial paths and performance ageing, showing how changing discount rates, operating costs, and gradual reductions in net MWh combine to shape the project's lifetime unit cost of electricity. the model LCOE for Kincardine centres at £194.78/MWh, with a minimum of £173.01/MWh and a maximum of £209.61/MWh across the simulated futures. This band is consistent with a setting where two forces largely counterbalance: (i) a gradual reduction in annual net MWh due to turbine performance ageing and operational losses; and (ii) improving financeability over time, reflected in lower effective discount rates. The result is a distribution that is neither excessively tight (ignoring risk) nor overly wide (suggesting instability). The simplified NREL LCOE of £202.17/MWh sits above the model median because a fixed-charge calculation does not incorporate year-by-year movements in leverage, interest costs, and discounting that the MARINEWIND analysis applies to cash flows.

The WACC summary shows a median of 8.60% with a range of 6.57–10.93%. Scenarios at the lower end correspond to conditions with stronger debt capacity and moderate coupons, which increase the present value of later-life energy and temper the cost impact of ageing. Scenarios at the upper end capture periods of tighter credit or higher coupons, which raise the cost of capital and shift LCOE toward the top of the reported range.

The ROE distribution—median 13.35%, 1.40–28.93%—reflects how residual cash to equity evolves once debt service and operating costs are met under the same economic and performance trajectories. Higher-return cases align with years that combine favourable borrowing terms and stronger generation; lower-return cases coincide with weaker output and/or costlier debt. Importantly, even the lower tail remains positive on a lifetime basis, indicating that the project's equity performance is preserved across the plausible scenarios evaluated, while the LCOE remains concentrated at just under £200/MWh when both macroeconomic variability and expected generation losses are considered.

Model	Median	Minimum	Maximum
LCOE	£227.16	£215.37	£249.61
simplified LCOE	£238.20	£238.20	£238.20
WACC	8.69%	6.57%	10.93%
ROE	13.35%	1.40%	28.93%

CfD strike price

Given the assumed strike price of £271/MWh (indexed), the project's equity investors would enjoy robust returns in most scenarios. The distribution of realized ROE has a median of 13.35%, with most outcomes between ~1.4% and ~28.9%. This wide range reflects how sensitive equity returns are to underlying conditions: in a handful of simulations, severe downside combinations (high costs, low output) yield ROEs in the low single digits – effectively near breakeven on equity. At the other extreme, if everything goes right (strong winds, low inflation, etc.), the fixed high strike price leads to windfall profits (ROE approaching 30%). Such variability highlights a core flaw of the UK's current static strike price approach: a single fixed price will inevitably be "wrong" for many realized futures, either overly generous or insufficient. In the UK Allocation Round 5 (AR5) in 2023, for instance, the government's Administrative Strike Price for floating wind was £116/MWh, which developers deemed far too low given inflation and supply chain costs. Our results corroborate this – £116 is well below even the lowest few percent of our LCOE distribution. *Even the AR6 revised cap of £176/MWh would fall at roughly the 10th percentile of our LCOE range.* Had we applied £176 in our Kincardine simulations, the median ROE would drop dramatically (likely into negative NPV territory), explaining the lack of participation by developers at those levels. Indeed, a recent government-commissioned review found that a floating project awarded £87.3/MWh (2012 prices, ~£104 in 2022 money) was unlikely to cover its costs. By contrast, the risk-adjusted method proposes a strike price grounded in the project's probabilistic LCOE. In this case, one could justify a strike price on the order of £195–£205/MWh – roughly the median to 75th percentile of the LCOE distribution – to ensure a high probability of full cost recovery. For instance, £202/MWh (the simplified LCOE) can be seen as a benchmark: it is higher than the median because it implicitly cushions some risk. Setting a strike price around this level would significantly improve the expected outcomes for investors while avoiding undue profiteering. To illustrate, at a £200/MWh strike, our model indicates the project's equity IRR would center around ~10% (with a tighter distribution), which is a reasonable reward for the risk profile. In contrast, at the government's static £176 level, the model shows the project would more likely underperform, with a considerable chance of a negative net present value, deterring investment.

Payoff

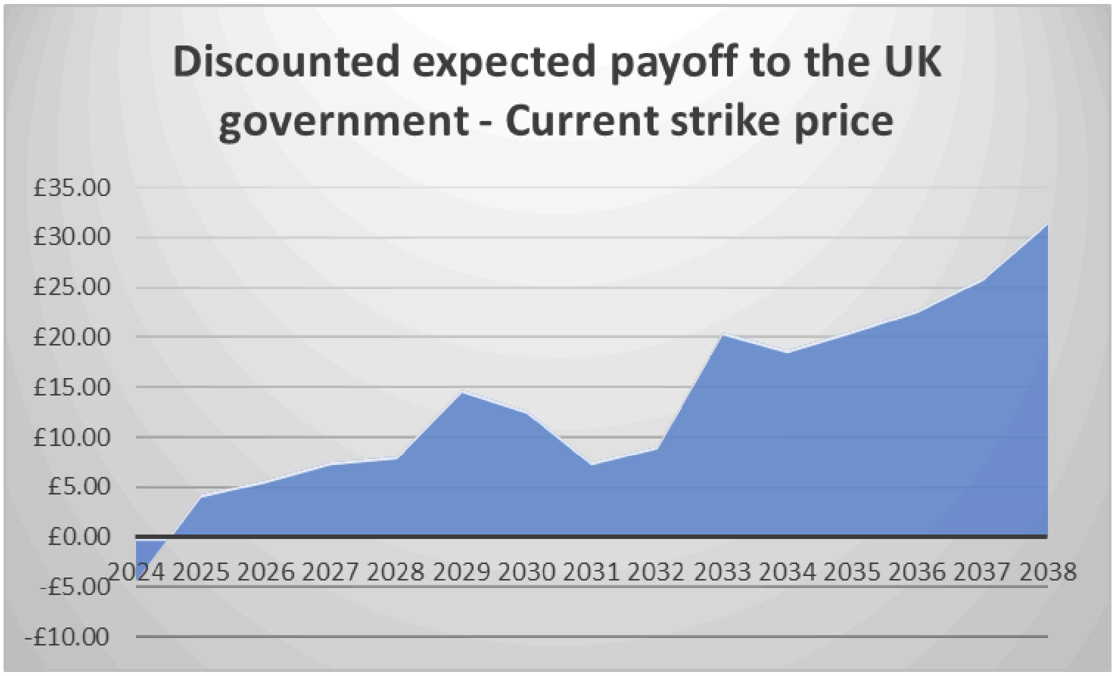
The payoff analysis compares developer outcomes under the current UK CfD strike price and the strike price derived from the proposed methodology. Under the UK approach, the payoff distribution is skewed toward negative values, indicating a high probability that projects fail to recover costs or meet equity return targets.

By contrast, the risk-adjusted strike price produces a payoff distribution centred around zero net present value, with substantially reduced downside risk. Although upside gains remain limited due to the symmetric structure of CfDs, the improvement in downside protection significantly enhances project bankability. From a policy perspective, this suggests that higher strike prices do not represent excessive subsidy, but rather a correction for the systematic underpricing of macroeconomic and financial risk in the current CfD framework.


macro and financial risk adjusted discounted expected payoff
£25.00
£20.00
£15.00
£10.00
£5.00
£0.00
-£5.00
-£10.00
2024
2025
2026
2027
2028
2029
2030
2031
2032
2033
2034
2035
2036
2037
2038


Current_expected payoff
£10.00
£5.00
£0.00
-£5.00
-£10.00
-£15.00
-£20.00
-£25.00
-£30.00
-£35.00
2024
2025
2026
2027
2028
2029
2030
2031
2032
2033
2034
2035
2036
2037
2038

discounted expected payoff - FOWT developers perspective		
Year	**Current**	**Macro and risk adjusted**
(2024-2028)	-£21.05	£43.09
(2029-2033)	-£64.35	-£5.13
(2034-2038)	-£119.87	-£19.70
(2024-2038)	**-£205.26**	**£18.26**
Payout (28.5 MW plant)	**-£51,244,762**	**£4,558,078**



discounted expected payoff - DESNZ (UK government) perspective		
Year	**Current**	**Macro and risk adjusted**
(2024-2028)	£21.05	-£43.09
(2029-2033)	£64.35	£5.13
(2034-2038)	£119.87	£19.70
(2024-2038)	**£205.26**	**-£18.26**
Payout (28.5 MW plant)	**£51,244,762**	**-£4,558,078**

Conclusions:

This study illustrates the technical and economic advantages of modeling time-varying LCOE and strike prices for renewable energy support schemes. By moving beyond static assumptions, we capture the reality that key drivers of project economics – inflation, interest rates, energy output, and operational costs – are not fixed, but fluctuate over a project's life. Accounting for these dynamics yields a more accurate and risk-aware strike price. Technically, our approach treats the levelized cost of energy as a time series of cash flows subject to uncertainty, rather than a single expected value. This allows the strike price to be "risk-adjusted" in a rigorous way: instead of adding large safety margins or using outdated hurdle rates, we simulate those risks directly. The result is a pricing that *adapts to real-world variations in cost of capital and performance*. For example, rather than assume a constant 7.5% WACC, we let WACC evolve with market conditions – thus if interest rates spike, the model effectively raises the required strike price to compensate investors for the higher financing costs. Similarly, by incorporating turbine degradation and variability in wind, the method internalizes weather uncertainty: low wind years or faster performance decay will raise the computed LCOE, signaling the need for a higher strike price to maintain viability. This dynamic modeling is a clear improvement over the UK's current static CfD approach, which has been hampered by inflexible assumptions. Recent allocation rounds have shown that when strike prices are set using historic cost data and neglecting current risks, projects either bid cautiously or not at all. Our findings support a shift to more nuanced, simulation-informed pricing that can adjust to new information and conditions.

From a policy perspective, adopting a risk-adjusted, dynamic strike price methodology could greatly enhance the effectiveness of Contracts for Difference. One immediate implication is the potential for dynamic Administrative Strike Price (ASP) setting. Instead of a fixed cap derived from a static model (which may quickly become obsolete in volatile markets), regulators could use probabilistic models to update ASPs with each auction, reflecting the latest macroeconomic outlook (inflation, interest rates) and technology performance data. This would help ensure that strike price caps are neither too low (jeopardizing project viability) nor excessively high (over-subsidizing developers). In practice, a dynamic ASP might involve setting a base strike price that adjusts with certain indices or project benchmarks. For instance, the model could calculate a strike price distribution for a "typical" project at the time of auction and choose a percentile (e.g. P50 or P75) as the administrative cap. This is analogous to the yardstick approach suggested by Newbery (2023), where payments could be tied to a reference output or capacity factor rather than a fixed output, thereby decoupling support from actual generation and reducing distortions. While our proposal focuses on adjusting the price level itself via risk modeling, it complements these ideas: both aim to fine-tune CfD design to better align incentives and actual costs. By incorporating evolving cost-of-capital and output risks, the CfD mechanism can maintain investor confidence without sacrificing market efficiency. Indeed, a well-calibrated CfD that reflects dynamic risks would continue to shield investors from market price volatility (the classic benefit of CfDs), *while also shielding investors and ratepayers from the unforeseen macroeconomic swings that can undermine projects or lead to windfall gains.* This ensures that public support is used efficiently, targeting just the necessary level of subsidy.

For investors and the renewable energy industry, the adoption of a dynamic risk-adjusted strike price is highly significant. It means greater assurance of viable returns and a lower risk of project failure. Under the traditional static CfD regime, developers faced a dilemma: accept a fixed strike price that might turn out insufficient if inflation rises or output underperforms, or refrain from investing (as seen in AR5's offshore wind outcome). By contrast, a CfD determined via our methodology would reassure investors that *all known risks have been accounted for in the contract price*. The median expected return (e.g. ~10–12% ROE for a floating wind project with a strike around £200/MWh) would be built on solid assumptions, and the downside risk of, say, only 1–3% ROE would be greatly minimized. This risk alignment is crucial for attracting capital at scale: as Gohdes et al. (2022) observe, reducing revenue risk lowers the cost of capital and thus the cost of energy. In our case, by stabilizing cash flows against macroeconomic swings (through an adequate strike price), projects can leverage higher debt ratios confidently, lowering the weighted financing cost – exactly the effect Newbery's incentive-compatible CfD is also designed to achieve (high debt-to-equity is made possible by assured revenue). Over the long term, this approach could make more projects bankable and accelerate deployment of emerging technologies like floating wind. Investors will be more willing to commit funds if they see that the contract terms are responsive to risk and not based on overly rosy or static projections. Furthermore, aligning strike prices with dynamic costs protects the government (and consumers) from systematic overpayment. Rather than adding a large arbitrary contingency to cover unknowns, the probabilistic method quantifies those unknowns, allowing for a balanced risk premium. In essence, capital is rewarded in proportion to the risks actually taken, and if conditions turn out better than expected (e.g. low inflation, high wind), the benefits accrue to ratepayers or the CfD counterparty rather than exclusively as excess profits to the generator. In conclusion, the integration of macroeconomic and performance-based simulation into CfD strike price setting offers a more resilient and efficient framework for renewable energy finance. Technically, it marries the precision of project finance modeling with the uncertainty-handling of Monte Carlo analysis, producing strike prices that reflect real project economics year by year. Policy-wise, it points to a more dynamic auction design – one that could prevent the kind of impasses observed in recent UK rounds by ensuring that price caps are neither naïvely low nor politically inflated, but grounded in evidence-based risk assessment. And from the investment standpoint, it promises a more stable environment where investors can achieve risk-adjusted returns and capital costs are minimized, ultimately lowering the subsidy burden required for the energy transition. The superior performance of the proposed method, as evidenced by the Kincardine case study, suggests that future CfD allocations would benefit from embracing these principles. By incorporating dynamic risk (inflation, interest rate swings), weather uncertainty, and the evolution of financial costs into strike price calculations, governments can better align renewable energy incentives with reality – ensuring both the success of projects and the prudent use of public funds.

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