Power Generation and Revenue Forecasting in UK Wind Farms

EDHEC Infrastructure & Private Assets Research Institute

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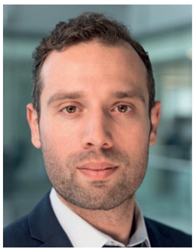
About the Author



Menelaos Vakalopoulos is a Senior Analyst within Scientific Infra, a leading provider of unlisted infrastructure equity and debt index data and analytics. In his role, he specializes in conducting research, performing investment valuation, and analysing the energy and infrastructure sectors. Previously, Menelaos served as a Derivatives Products Analyst at EDF Trading, offering functional support across all desks and energy products, and in earlier roles he contributed to S&P Global's Oil Markets and Downstream consulting team, providing ad-hoc market analysis, investment appraisals, and business strategies for international clients. Menelaos is currently Head of Greek Energy Forum's London branch. Menelaos holds an MSc in Petroleum, Energy Economics & Finance from the University of Aberdeen, complemented by a BSc in Geology from Aristotle University of Thessaloniki.

This survey was conducted among investors and other professionals who were invited to a presentation of our latest research paper

Executive Summary

This study develops a robust asset-level revenue forecasting model for wind power assets in the UK electricity market, integrating half-hourly generation data from Elexon BMRS, market pricing from OFGEM, and power price projections from Oxford Economics. The model estimates P10, P50, and P90 revenue levels under multiple economic scenarios, providing insight into revenue the revenue of wind assets in the UK.

A back-analysis of 58 wind farms (2019–2023) validates the model's accuracy, with an R^2 of 94% for generation forecasts and 80% for revenue forecasts.

A key application of these revenue forecasts is their integration into the infraMetrics Valuation Model, which estimates the fair market value of unlisted infrastructure equity investments. By providing detailed asset-level revenue projections, this study strengthens valuation accuracy for TICCS Industry class code IC70 (renewables) in the UK, with planned expansion into other markets.

This methodology moves beyond a static approach to revenue growth forecasting by capturing asset-specific dynamics, providing a more adaptive way to assess valuations within infraMetrics. Our initial analysis showed that the updated methodology enhanced revenue forecast accuracy for individual wind farms by 2% to 39% compared to reported figures and past forecasts, with a median adjustment of 22%.

Contents

Introduction

The UK electricity market was chosen as the focus of this study due to its high transparency and the availability of high-quality data. Market participants are required to report power production, pricing, and other key metrics, ensuring that all datasets can be fully traced and verified. While the European electricity market also exhibits a high level of transparency, the complexity of multiple countries and operators can create additional challenges in data collection and standardization. Given these factors, the UK provides an ideal foundation for developing and validating the forecasting methodology.

Furthermore, this study aligns with our broader objective of expanding revenue forecasting models to European markets, where we have already identified key data sources. The UK serves as a natural starting point due to its well-structured market and strong regulatory framework. Additionally, the study has strategic relevance to our flagship infrastructure equity index, infraGreen, which tracks the performance of unlisted infrastructure firms in the wind and solar sectors. UK renewable assets comprise 20% of the index, the highest share of any individual market, with wind power making up the majority.

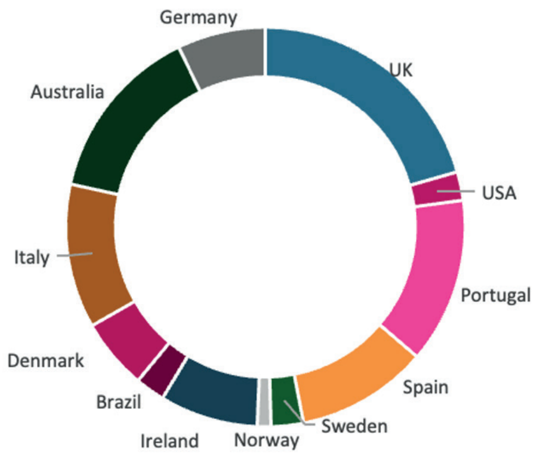
Market Structure

The UK's electricity generation mix has evolved significantly during the last decade driven by the energy transition. The country has set a legally binding target to achieve carbon neutrality (net zero emissions) by 2050. Decarbonizing the energy sector has been a huge bet for the country as it used to be the highest emitting sector since the 1990s, but during the last decade the level of emission from energy have been declining significantly, as electricity is being generated by low carbon sources such as wind, solar, biomass and gas has soared.

As shown in Figure 2, gas has been the largest source of electricity in the UK in the recent years followed by renewable energy sources, primarily wind (both onshore and offshore).

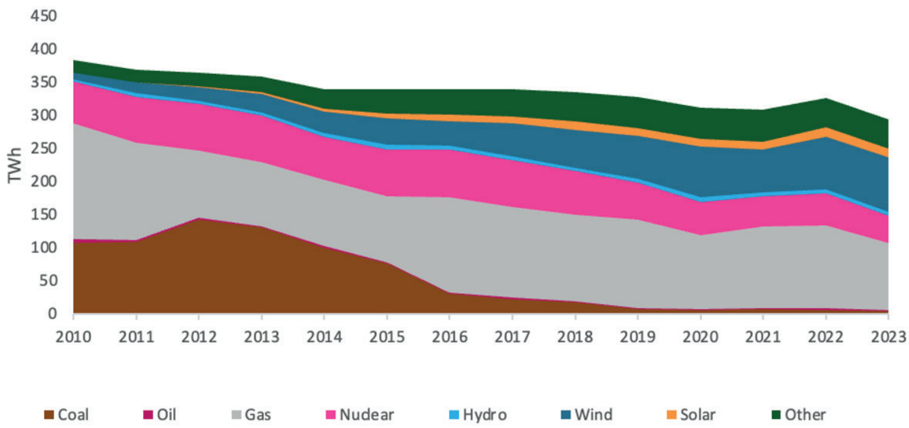
Specifically, in the case of wind installed capacity has been growing strongly in recent years and as a result generation has skyrocketed. Combined onshore and offshore wind installed capacity reached almost 28 GW in 2023 as shown in Figure 3.

Figure 1: Infragreen index segment allocation by country



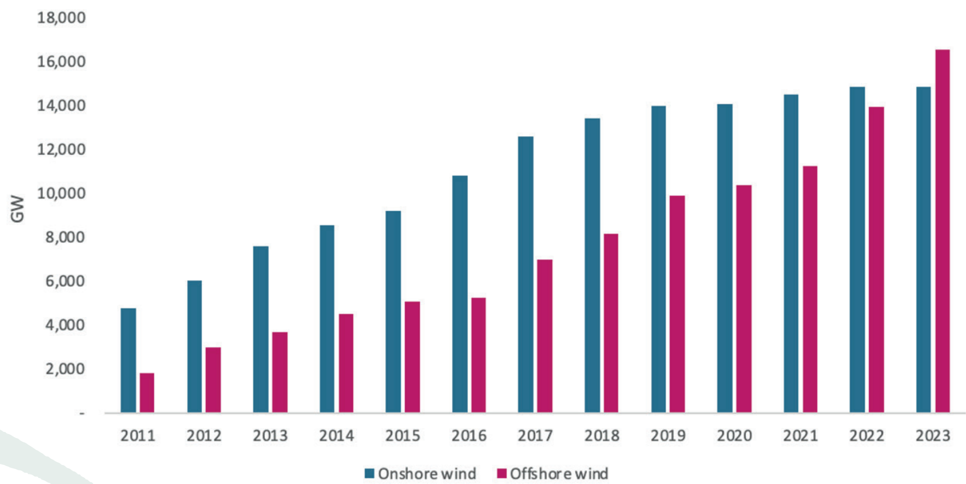
Source: Inframetrics

Figure2: Evolution of energy generation mix in the UK



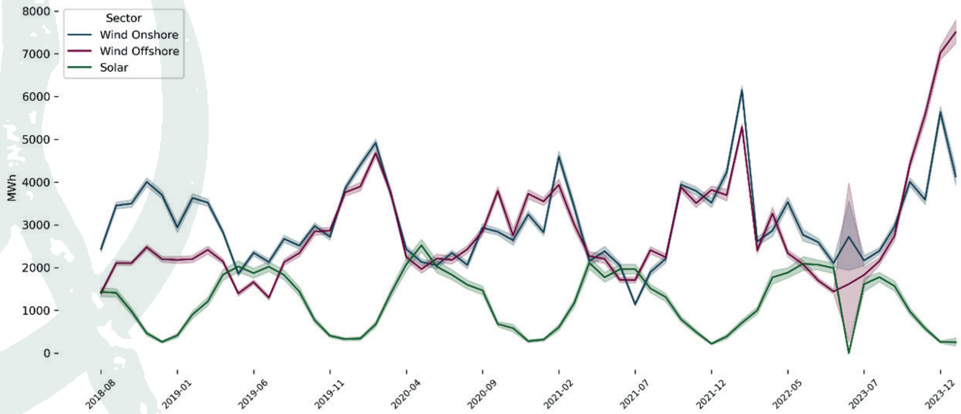
Source: Elexon

Figure3: UK wind power installed capacity



Source: Dukes

Figure 4: Monthly renewable electricity generation by technology

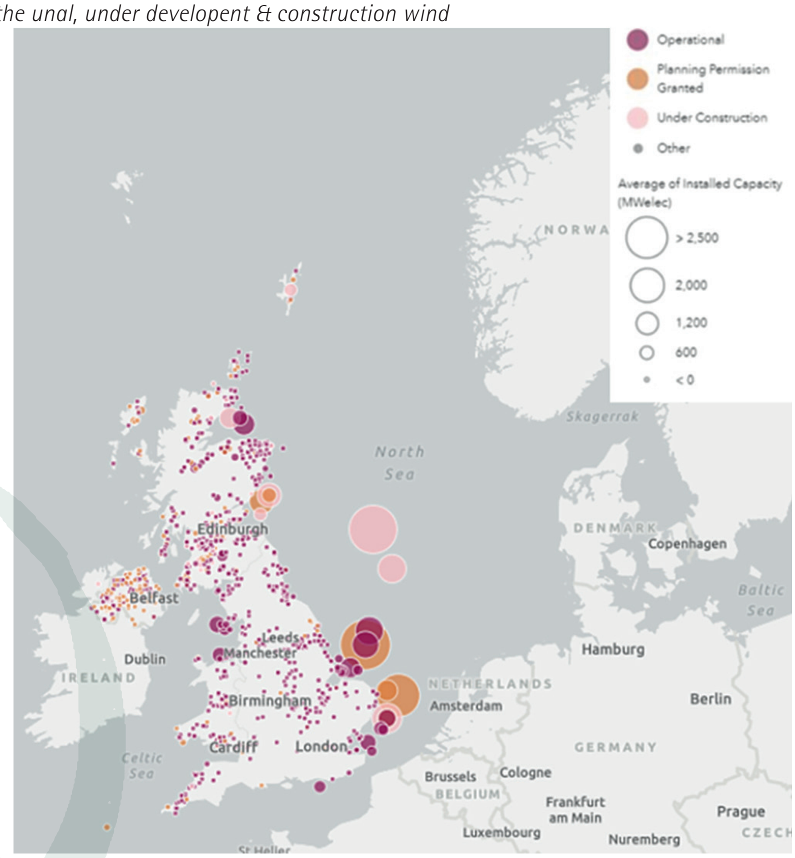


Source: Elexon

Wind generation is subject to seasonal variability, though to a lesser extent than solar power. As shown in Figure 4, wind generation is significantly higher in winter compared to summer, whereas solar power follows a more predictable seasonal pattern, with minimal production in winter and substantially higher output in summer. Despite its relative stability, wind generation can still experience prolonged periods of low output, known as wind droughts, which have been observed in recent years.

As shown in the map in Figure 5,most wind projects have been developed in rural areas or far offshore away from big cities and large industrial centres, where wind resources are abundant and there are less spatial constraints.

Figure 5: Operational, under development & construction wind projects in the unal, under developent & construction wind projects in the unal, under developent & construction wind



Source: Renewable energy planning database

However, increasing decentralised build-out of wind capacity and high generation have created certain issues to the power grid as electricity has to be transported from remote locations to demand centres to be consumed.

Electricity Market Structure

The electricity market in Great Britain operates under a competitive framework designed to maintain a continuous balance between electricity supply and demand in real-time, a necessity due to the non-storability of electricity. The market involves three primary participants:

- Generators: Responsible for producing electricity.
- Suppliers: Procure electricity to meet customer demand.
- Financial participants.

Electricity is traded and settled in half-hour intervals, referred to as Settlement Periods, which form the basic unit for operational and financial activities in the market. For each Settlement Period:

- Suppliers forecast customer demand and contract with generators to match this expected load.
- Contracts can be agreed upon until the Submission Deadline, which is the start of the Settlement Period.

However, despite contractual arrangements, real-time mismatches between forecasted and actual demand or generation often arise due to:
1. Forecasting errors by suppliers.
2. Unforeseen generator outages or shortfalls.
3. Transmission constraints impacting delivery.

To manage these imbalances, the Electricity System Operator (ESO), operated by National Grid, deploys the Balancing Mechanism. This mechanism facilitates real-time adjustments through:
- Bids: Proposals by participants to reduce generation or increase demand at a specified price.
- Offers: Proposals to increase generation or reduce demand at a specified price.

The ESO dynamically selects and dispatches the most cost-effective bids or offers to balance the grid while addressing system constraints, such as congestion or localized supply shortages.

Additionally, the system incentivizes accurate forecasting and contract adherence through the Imbalance Settlement process. Metered volumes are compared to contracted volumes, and any deviations—referred to as imbalances—are settled financially:

Generators or suppliers that underperform relative to their contracts must purchase the shortfall at the imbalance price.

Conversely, overperforming participants sell their excess generation or unused supply back to the system at the same price.

Pricing Model

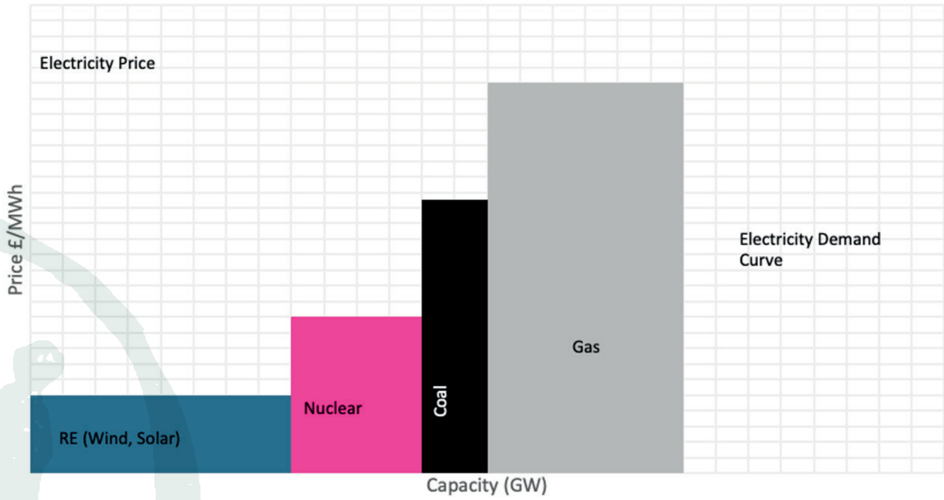
The UK electricity market operates primarily through two main mechanisms: the day-ahead market and the intraday market.

In the day-ahead market, electricity prices are determined by balancing daily supply and demand. Generators submit bids to provide electricity to the grid, with these bids organized in a merit order—a system that ranks bids from the lowest to highest marginal cost of generation. Electricity sources with the lowest operating costs, such as renewables, are prioritized, while higher-cost sources like gas- and coal-fired power plants are dispatched later. This ranking reflects the fundamental principle of minimizing system costs and optimizing resource efficiency.

The bidding process takes place on Nord Pool UK's power exchange, where bids are accepted sequentially until forecasted demand is satisfied. Renewables, with their near-zero marginal costs, typically dominate the initial accepted bids, whereas gas and coal plants, with higher operational expenses and additional costs for carbon allowances, are dispatched later

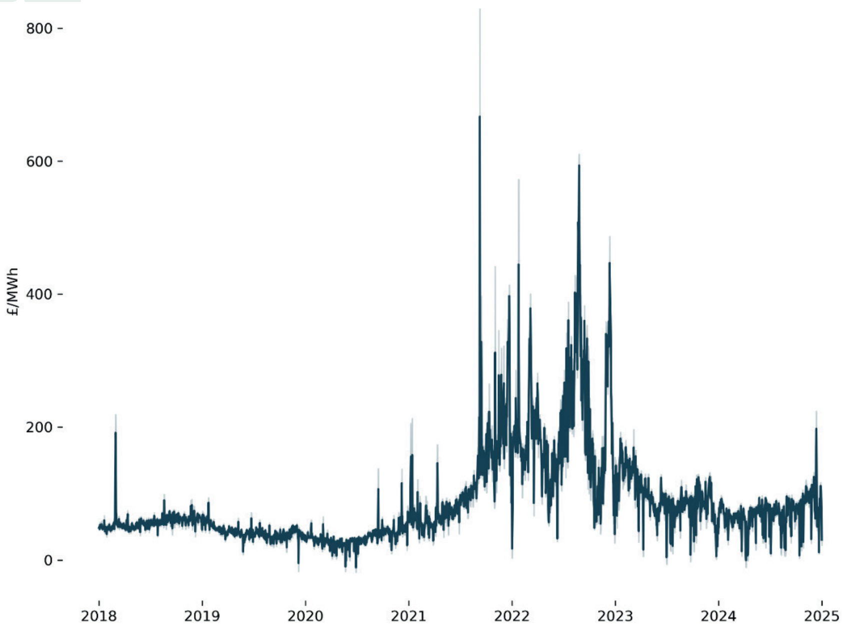
As shown in Figure 6 electricity prices during each half-hour trading period are set based on the marginal cost of the last generating unit required to meet demand. This system, known as a «pay-as-clear» model, ensures that all accepted generators are paid the same market-clearing price, regardless of their individual bid values. Buyers, such as energy suppliers or traders, pay this clearing price to sellers, including energy generators or other traders.

Figure 6: Illustration of the merit order system for electricity generators



In the UK, gas-fired generation frequently acts as the marginal producer, given its relatively high cost compared to other sources. Consequently, gas-fired plants often set the market-clearing price. Despite their higher costs, gas plants are highly flexible and capable of ramping up quickly to address short-term demand spikes, particularly during peak periods.

Figure 7: UK power prices



Source Elexon

Since late 2021, there has been a substantial increase in UK electricity prices (Figure 7) which was primarily driven by a surge in the price of gas. Electricity prices went from an average of £46/MWh during the period of 2010-2019 and a low of £36.9/MWh in 2020 (due to suppressed demand during lockdowns) to an average of £127/MWh in 2021 and £210/MWh in 2022, with the maximum monthly price reaching as high as £363/MWh.

The increase in electricity price from the average of the period 2010-2019 to the 2021 and 2022 prices was 175% and 355% respectively.

In a nutshell, this massive increase in gas prices was primarily caused by supply chain bottlenecks during the COVID-19 pandemic lockdowns as companies started cutting down production to respond to plummeting demand at first and then were not able to keep up with increasing demand as economies started gradually reopening at variable speed. On top of this the crisis was augmented with the Russian invasion to Ukraine in February 2022 that led many countries especially European ones to try reducing imports of Russian gas and trying to find alternative sources, mainly LNG. All the above led to unprecedented supply deficit on the gas markets which made prices go through the roof.

The UK was caught in the middle of this storm as a major gas importer that relies on gas for both power and heating.

In the latest years, gas and electricity prices came down a lot, almost back to pre-covid levels for gas, the danger of another supply deficit driving prices skyrocketing again.

Government Support Schemes for Renewable Energy

Government Support schemes have been determinantal in driving the expansion of renewable energy in the UK. The main schemes for large scale wind projects that we'll examine in this report are Renewable Obligations (RO) and Contracts for Differences (CfD).

The Renewables Obligation (RO) is a policy framework established to encourage the deployment of large-scale renewable electricity generation in the United Kingdom. The scheme was introduced in England, Wales, and Scotland in 2002 and closed to new entrants as of March 2017, but it remains a critical part of the UK's renewable energy policy landscape for operating generators.

Under the RO, licensed electricity suppliers in the UK are required to source a specified proportion of the electricity they provide to customers from eligible renewable sources. This obligation is enforced and monitored by the Office of Gas and Electricity Markets (Ofgem). The scheme is limited to large-scale renewable electricity generators larger than 5 MW.

ROCs are tradable certificates issued to accredited renewable electricity generators as evidence of renewable energy production. They serve as the primary mechanism for demonstrating compliance with the RO. A ROC is awarded for every megawatt-hour (MWh) of eligible renewable electricity generated.

The number of ROCs awarded per MWh depends on the type of renewable technology employed.

This is referred to as 'banding' and aims to reflect the varying costs and benefits of different technologies. For example:

- Offshore wind: 2 ROCs per MWh
- Onshore wind: 0.9 ROCs per MWh

These banding levels are reviewed periodically to ensure cost-effectiveness and to incentivize emerging technologies.

Currently, the **Contract for Differences (CfDs)** is the most common subsidy scheme used in the UK for electricity producers with greater capacity than 5 MW. CfDs were introduced following the Electricity market reform in 2014 in order to provide clean power generators with long term stability of cash flows and protection against wholesale electricity price fluctuations.

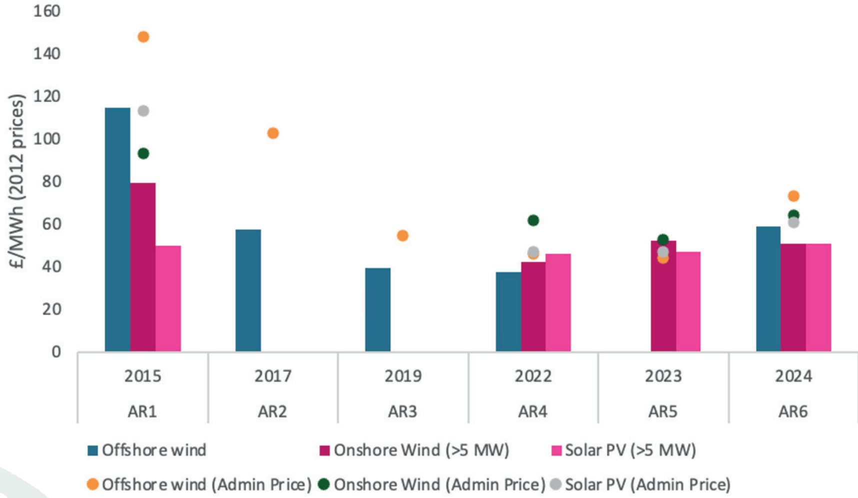
The CfD support scheme stabilizes revenues by guaranteeing a certain price level for the producer known as the 'strike price'. The strike price is the electricity price that reflects the cost of investing in a particular low carbon technology. The CfDs represent a two-way payment process. When wholesale electricity prices are below the strike price the generator receives the difference between the two and when electricity prices exceed the strike price the generator has to pay back the difference. The organization which deals with the CfD mechanism is the independent government-owned company called Low Carbon Contracts Company (LCCC).

The CfDs are allocated to low carbon electricity generations through auctions for 15 years. Before every auction round the government sets an administrative strike price for each technology that represents the maximum support it is willing to offer. The clearing price for each year of expected delivery is determined by the last bid made for a project in that delivery year.

Administrative strike prices tend to decrease in each allocation round to incentivize competition and innovation. These prices are set based on the most recent renewable energy generation cost data. The objective of this procedure is to create a projects' supply curve which represents the "estimated volume of capacity in MW that could be built at different strike prices, ranked from cheapest to most expensive".

The results from the six CfD allocation rounds presented in Figure 8, clearly indicate the cost reduction achieved throughout the seven-year period.

Figure 8: CfD price (administration & clearing) per allocation round for selected technologies



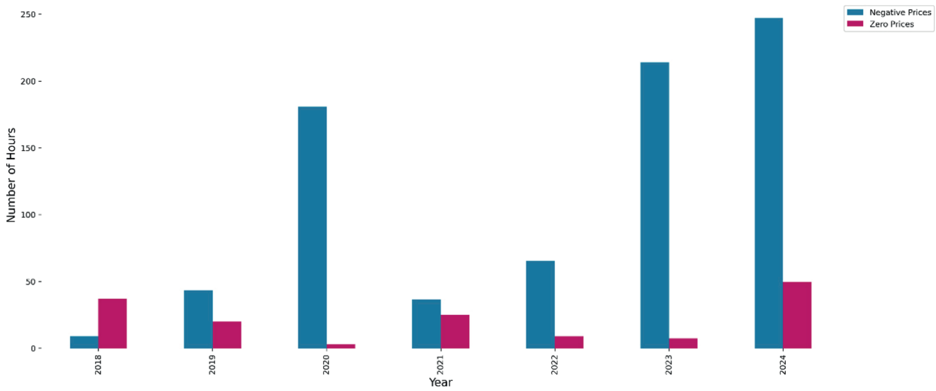
Source: LCCC

Negative Prices and Capture Price

As mentioned earlier, high renewables penetration coupled with the lack of storage and grid limitations creates the issue of cannibalization, either due to lack of demand or lack of available grid, power producers (primarily wind) are incentivised to turn down production through negative prices and are compensated for it.

In recent years, the UK power market has faced challenges related to electricity price cannibalization and curtailment. Price cannibalization occurs when the increasing penetration of renewable energy, particularly during periods of high generation and low demand, drives wholesale electricity prices down—sometimes even into negative territory. This phenomenon disproportionately affects variable renewable energy especially wind in the UK, whose generation patterns are dependent on weather conditions. Negative pricing events, where generators must pay to dispatch electricity to the grid, have become more frequent, particularly during off-peak hours or when weather conditions are highly favourable for renewable generation. As presented in Figure 9, in 2024 the UK saw a pick in the number of negative hours to more than 240 based on the APXMIDP price index provided by Elexon.

Figure 9: Annual count of negative & zero price hours



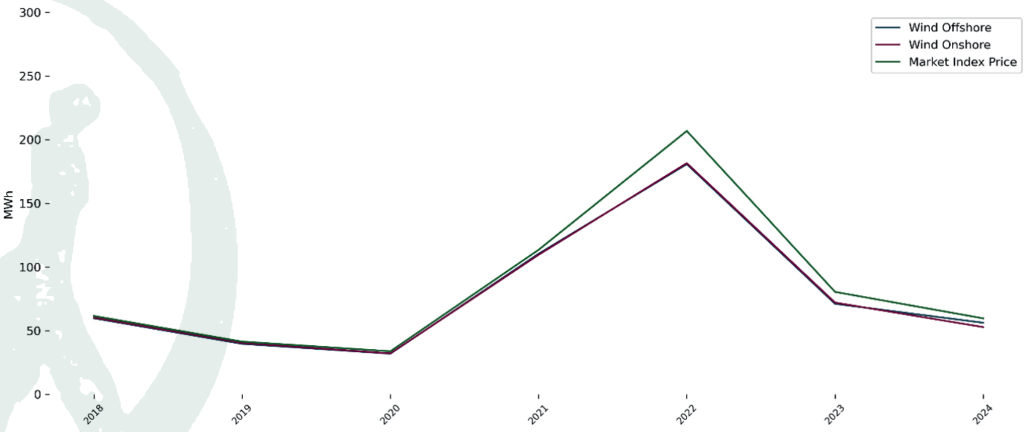
Source: Elexon

Curtailment further compounds generators' challenges. Renewable producers are occasionally instructed to reduce or stop their output to prevent overloading the grid. This often occurs due to limitations in grid infrastructure or imbalances between supply and demand.

Both situations expose wind power producers to increasing market revenue risk. Since 2022, the capture rate for wind generation has fallen to approximately 90% of the average market price as shown in Figure 10.

The capture rate is a measure of the average price that a renewable generator receives for its electricity relative to the average market price. It reflects the value of electricity generated by specific technologies in the market and is expressed as a percentage.

Figure 10: Annual capture price by technology vs market price



Source: Elexon

This decline highlights the growing impact of price cannibalization, where increased renewable penetration lowers wholesale prices during peak generation periods, reducing revenue for wind asset operators.

Data Sources

Our methodology utilizes a comprehensive set of publicly available and subscription-based datasets to evaluate historical and forecast revenue streams for individual assets in the UK electricity market. The datasets used include hourly electricity generation, pricing, subsidy schemes, and long-term market projections, providing a robust foundation for both historical calibration and future forecasting.

Generation Data from Elexon BMRS

Data from Elexon's Balancing Mechanism Reporting Service (BMRS) forms the backbone of the analysis for asset-level performance. The specific endpoints used are:

B1610: Half-Hourly Generation Output: This dataset provides granular, half-hourly generation data for individual assets, enabling detailed analysis of production trends and probabilistic metrics such as P10, P50, and P90 generation values.

B1420: Installed Capacity per Unit: Information on the nominal installed capacity of each generating unit is used in conjunction with generation data to calculate key performance indicators, such as capacity factors.

These datasets facilitate an in-depth understanding of the historical performance of generating assets and allow for accurate projections of future output.

Historic Electricity Prices

Historic electricity prices, sourced from OFGEM, are essential for calibrating the revenue model. These prices, combined with generation data, enable the estimation of realized revenues for individual assets over time.

Renewable Obligation (RO) Scheme

Historic RO Prices: Data from OFGEM provides historical values of Renewable Obligation Certificates (ROCs), which represent the tradable certificates awarded per megawatt-hour of eligible renewable generation.

RO Banding: This dataset specifies the banding levels, which determine the number of ROCs allocated per megawatt-hour based on the asset type. By integrating these datasets, the revenue model accounts for the historic contributions of the RO scheme to generator income.

Contracts for Difference (CfD) Scheme

For assets contracted under the Contracts for Difference (CfD) scheme, data from the Low Carbon Contracts Company (LCCC) is used. This data is critical for assessing historic revenues and validating forecasts for assets benefiting from CfD contracts.

Forecast Data

To project future revenues, the study incorporates premium datasets from Oxford Economics Global Climate Scenarios:

UK Power Prices (to 2050): Long-term forecasts of electricity prices provide the basis for estimating future revenues under both market and subsidy conditions.

Data Sources

Inflation Expectations (to 2050): Inflation forecasts are used to model the real-term evolution of subsidy prices, such as ROCs and CfDs. This ensures consistency between historical calibrations and future revenue projections, accounting for macroeconomic influences.

By combining these datasets, the study establishes a detailed model for both historic and forward-looking revenue analysis at the individual asset level. Historic data is leveraged to validate and calibrate the model, ensuring alignment with actual performance. Forecast data extends the analysis into the future, providing insights into revenue trends under varying market conditions and policy frameworks.

Methodology

This study employs a systematic and data-driven methodology to estimate the historical and forecasted revenues of individual power-generating assets in the UK electricity market. As discussed above the approach integrates granular production data, subsidy schemes, market pricing, and long-term forecasts to achieve a comprehensive asset-level revenue analysis. The key steps in the methodology are outlined below:

Data Integration and Initial Processing

The primary datasets include Elexon BMRS (B1610 and B1420), OFGEM pricing and subsidy data, LCCC CfD price data, and Oxford Economics forecasts for power prices and inflation. All data sources ans the specific data sets used for the analysis have been discussed in detail in the section Data Sources.

Data Handling:

Half-hourly generation data (B1610) and installed capacity data (B1420) from Elexon are analysed to calculate generation metrics, including the P10, P50, and P90 production levels and capacity factors for each generating unit.

Charts indicating the distribution of capacity factors, like Figure 11, have been produced for each independent generation unit. The indicative example in the below figure shows the capacity factor distribution for Achruach and Aberdeen Bay wind farms. Additionally, distribution curves indicating the mean capacity factor distribution by technology like Figure 12 and Figure13 have also been constructed.

Start dates of generation assets are sourced from Elexon, with assumed lifetimes of 25 years. Subsidy durations are standardized at 20 years for RO and 15 years for CfD schemes.

2. Identification of Revenue Streams

Subsidy Allocation: Each generating asset is classified as operating under Renewable Obligation (RO), Contracts for Difference (CfD), or exposed solely to merchant market conditions based on its commissioning date and subsidy eligibility.

Revenue Stream Calculation:
For RO-eligible assets, revenues are split into:

- RO Revenue: Calculated using the banding multiplier, the ROC price for the respective year, and the annual generation.
- Market Revenue: Determined by multiplying annual generation with the historic or forecasted market price.

For CfD assets, revenues are based solely on CfD strike prices during the CfD period.

Merchant assets' revenues are derived exclusively from market prices.
Historical revenue streams are computed using published OFGEM and LCCC data to calibrate the model against observed financial outcomes.

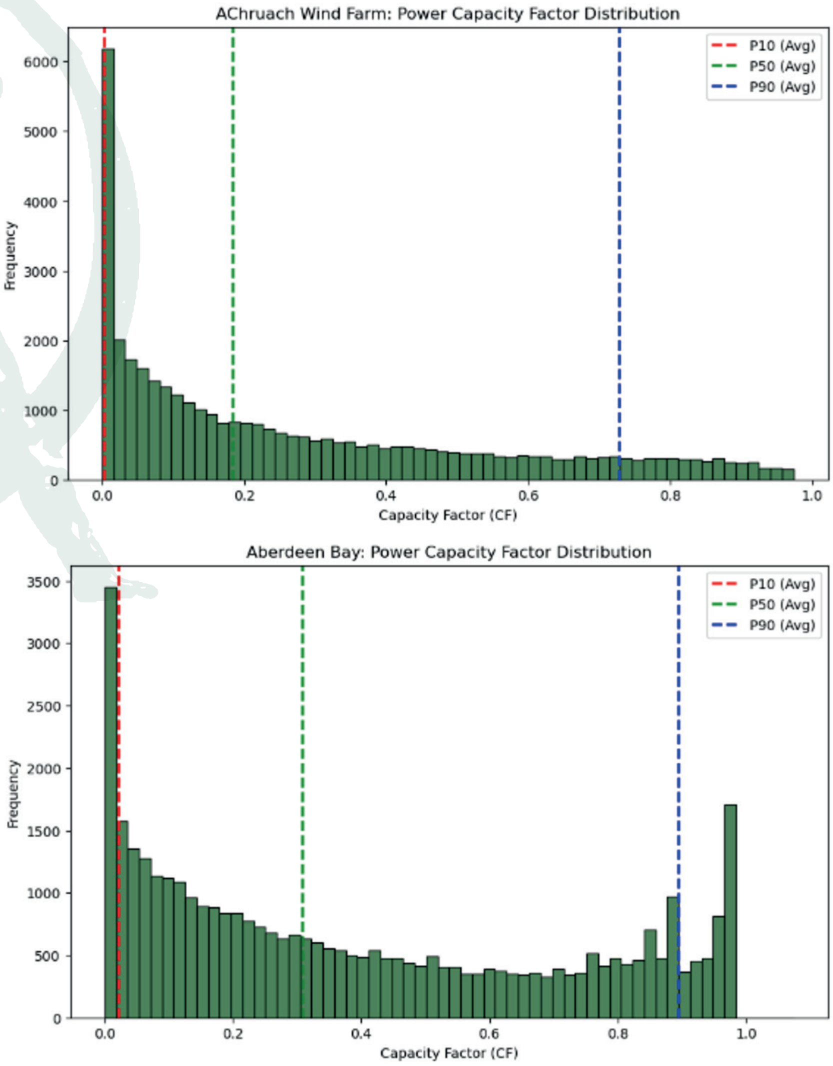
Forecasting Future Revenues

Inflation Adjustments: Future ROC and CfD prices are adjusted for inflation using Oxford Economics' Global Climate Scenarios consumer price index (CPI) forecasts, with unique strike prices maintained for each CfD asset.

Market Revenue Projections: Future market revenues are estimated also using power price outlooks up to 2050 from Oxford Economics' Global Climate Scenarios, with adjustments made for asset-specific lifetimes and subsidy expiry.

Scenario Analysis: Multiple economic scenarios provided by Oxford Economics Global Climate Scenarios are incorporated to assess the sensitivity of revenue forecasts to varying market conditions and policy trajectories.

Figure11: Indicative example of capacity factor distribution of individual wind farms



Filters are applied to exclude negative generation figures, typically associated with storage assets or anomalies.

Figure 12: Offshore wind capacity factor distribution

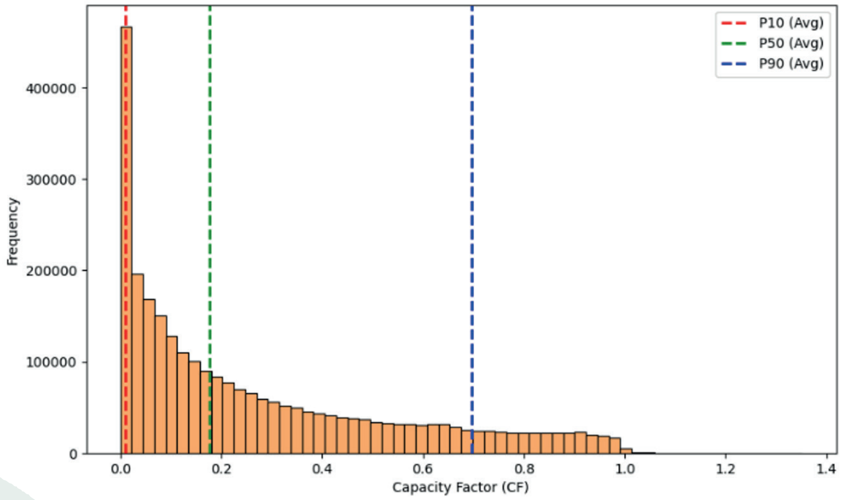


Figure 13: Onshore wind capacity factor distribution

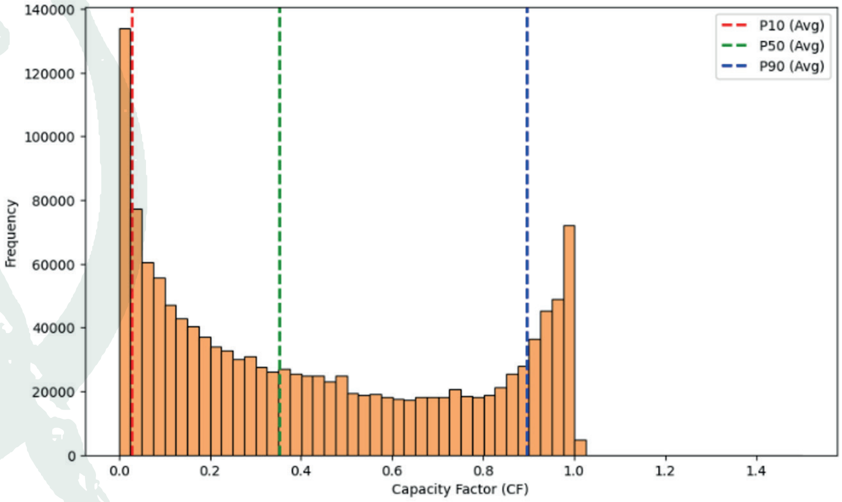
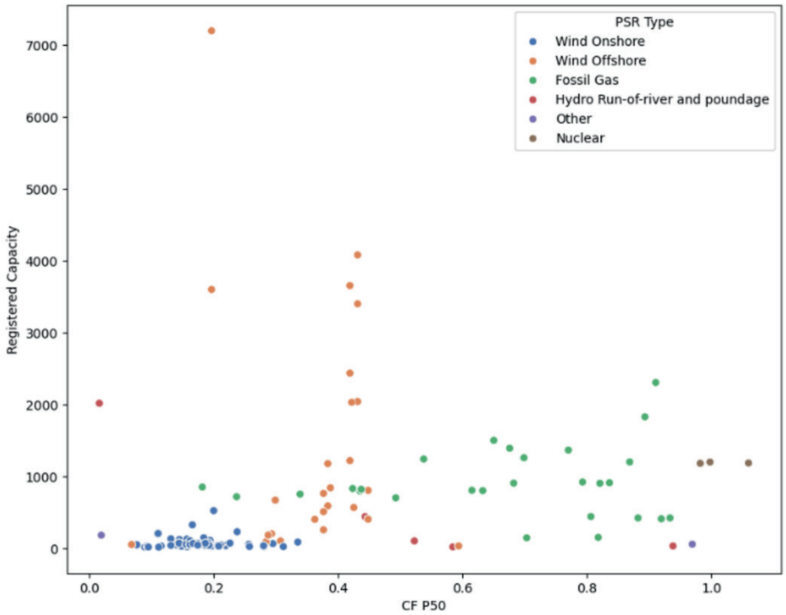


Figure 14: P50 capacity factor vs registered capacity per asset by technology



Methodology

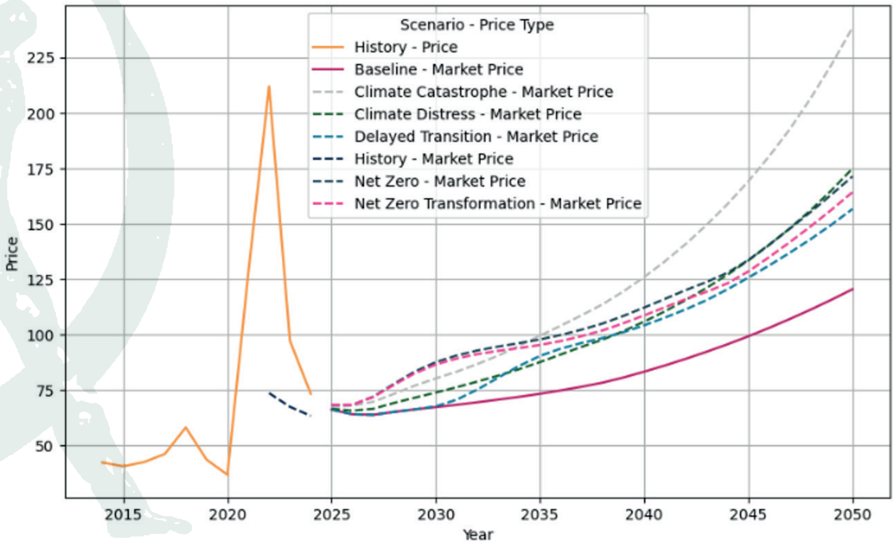
In Figure 15, are the scenarios used in our modelling are presented. Note that we currently only use the Baseline scenario for all our analysis and valuation process. Furthermore, we analyzed the P50 capacity factor relative to registered capacity for each technology across all individual assets, as shown in Figure 14.

This analysis aimed to investigate potential positive correlations between technology, asset size, and capacity factor while also identifying potential outliers within the sample.

Revenue calculations are performed for each probability level (P10, P50, P90) to capture the variability in generation outputs. Total revenues are consolidated across all streams:

- Historic Revenues: Based on actual generation and market/subsidy conditions.
- Projected Revenues: Incorporating forecasted subsidy and market prices until 2050 or the end of each asset's operational lifetime.

Figure15: Nominal market price by year for all scenarios



Outputs and Analysis

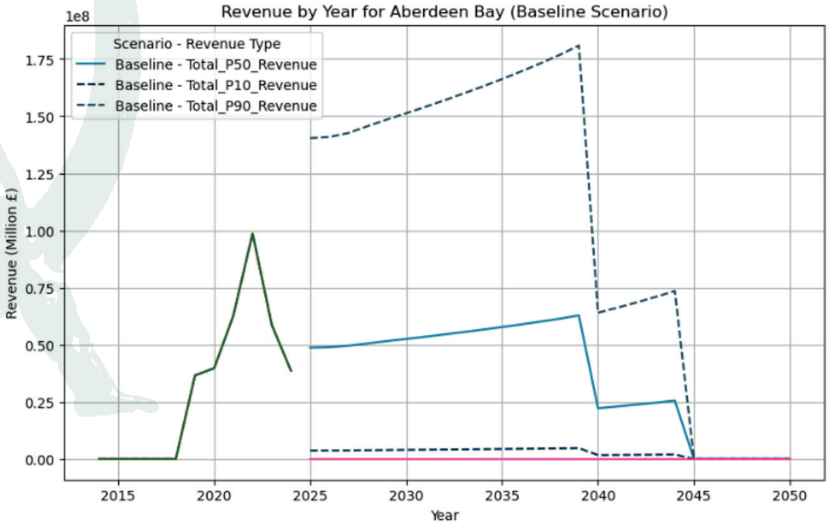
The final dataset includes detailed revenue forecasts for all assets in the UK Balancing Mechanism under different economic scenarios.

Key metrics include total revenues, scenario-specific variations based on Oxford Economics, and P10, P50, and P90 revenue levels for the baseline scenario. These metrics enable a comprehensive evaluation of revenue performance across different probability levels and economic scenarios, providing a robust understanding of potential outcomes under varying market conditions.

In Figure 16, an illustrative example of the revenue forecast of Aberdeen bay wind farm is presented. The green line represents the historic revenue , the blue solid line the forecast P50 baseline scenario revenue, and the dashed lines represent the P10, and P50 revenues in the baseline scenario. Similar illustrations have been generate for all the UK wind assets included in the analysis.

All revenue forecasts are expressed in nominal terms, incorporating inflation expectations to reflect anticipated price evolutions over time. This approach ensures a clear and consistent framework for analyzing long-term revenue trends across the UK electricity market.

Figure 16: Indicative revenue forecast including sensitivity analysis for Aberdeen Bay Wind Farm



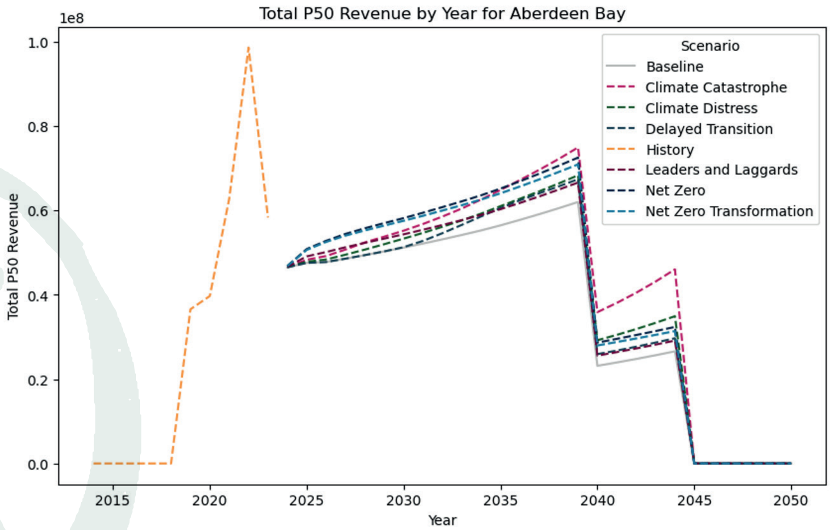
In Figure17, We present the P50 revenue forecast for all Oxford economics scenarios for Aberdeen Bay wind farm. As discussed in Figure 16, we have generated P50 revenue scenarios for all UK wind assets included in our database. However,, note that while the forecast model evaluates revenue under multiple economic scenarios provided by Oxford Economics and probability distributions, we only use the P50 baseline scenario revenue forecast for valuation purposes.

A notable feature of the revenue forecast is a decline in projected revenues for many assets starting in the mid-2030s. This trend aligns with the expiration of subsidy schemes such as Renewable Obligation (RO) and Contracts for Difference (CfD), which typically provide stable revenues during their operational periods.

Once these subsidy schemes conclude, the affected assets are modelled to transition fully to reliance on merchant market prices. This shift introduces greater revenue variability and lower overall price levels based on current projections.

This methodology ensures a robust analysis of asset-level performance and future revenue potential, enabling to move forward with assets' valuation and free cash flow projections.

Figure 17: Indicative revenue forecast including all Oxford Economics Scenarios for Aberdeen Bay Wind Farm



Model Robustness

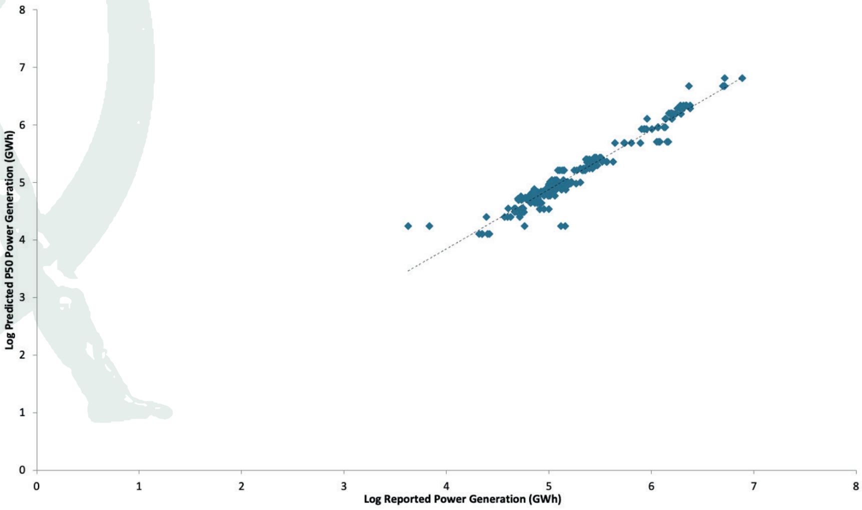
To validate the revenue prediction model, we conducted 2 individual back-analysis using data from the actual asset wind production and revenue figures from the latest available financial years (2019–2023).

The analysis focused exclusively on wind energy assets, comprising a sample of 58 onshore and offshore wind farms in the UK. In the first part the predicted values of power generation were compared to the actual output of the wind farm for the years 2019-2024. The log-transformed approach was applied to all dependent and independent variables to control for scale effects.

As shown in Figure 18 the predicted power generation exhibit a strong fit to the observed data , the analysis confirms the models' robustness regarding wind power generation as it has an R-squared of 94%.

In the second part of the validation process for the revenue forecasting model, a regression analysis was conducted to evaluate the relationship between reported revenues (observed) and calculated revenues (predicted by the model) for individual wind assets.

Figure 18: UK wind farms production: predicted vs reported (2019-2023)



This analysis aims to quantify the model's predictive accuracy and assess whether asset characteristics, such as capacity, explain variations in revenue deviations. As the analysis highlighted that larger wind farms exhibited greater revenue variability, prompting the inclusion of registered capacity (size) as a second independent variable to control for this effect. The log-transformed approach was also applied to all dependent and independent variables to control for scale effects.

The results of this analysis are presented in Figure 19 and Figure 20. In both charts a high degree of alignment between the model predictions and actual values is demonstrated.

Model Robustness

As discussed above the second regression model incorporates both reported revenue (X1) and registered capacity (X2). The results demonstrate a high explanatory power in the model, with an R^2 of 0.80. These results demonstrate a high degree of alignment between predicted and reported revenues:

Figure 19: Uk wind farm revenues: predicted vs reported revenue (2019-2023)

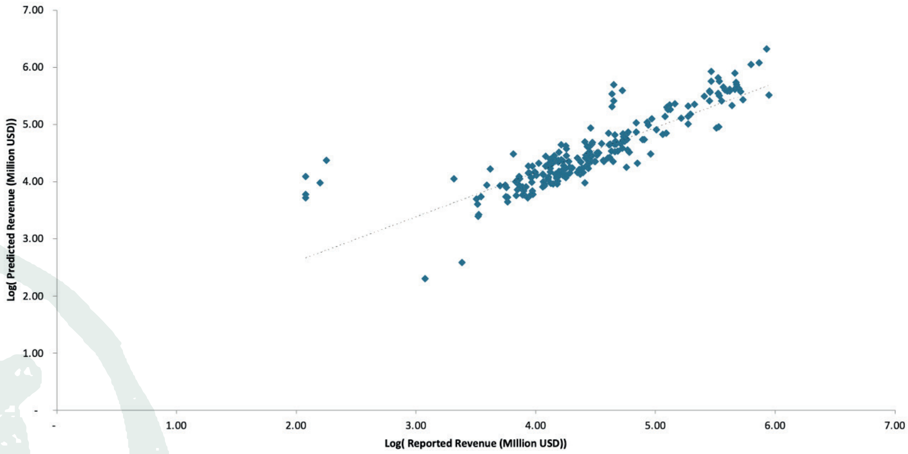
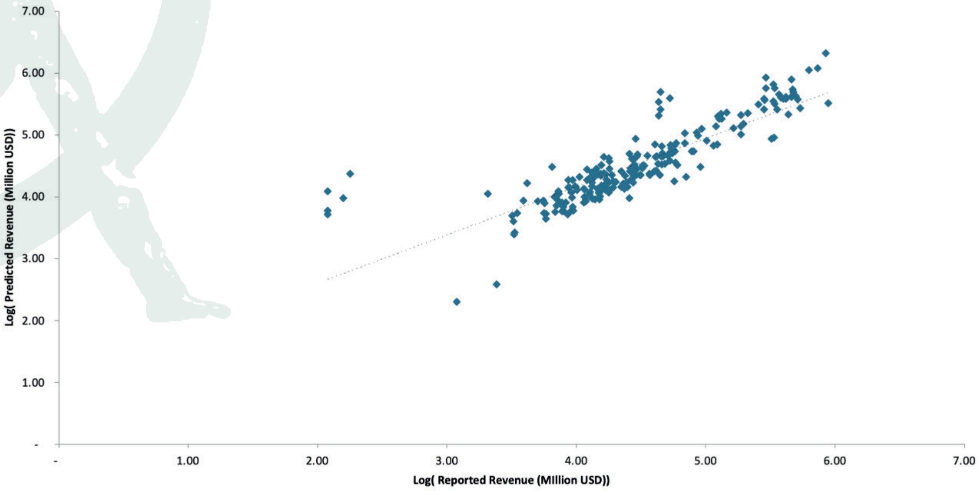


Figure 20: UK wind farm revenues: registered capacity vs reported revenue (2019-2023)



Conclusion

The above results affirm the model's robustness in accurately forecasting revenue streams for wind assets under varying operational and market conditions. Based on this strong correlation, we are confident in the model's ability to predict revenues for individual wind assets with a high degree of precision.

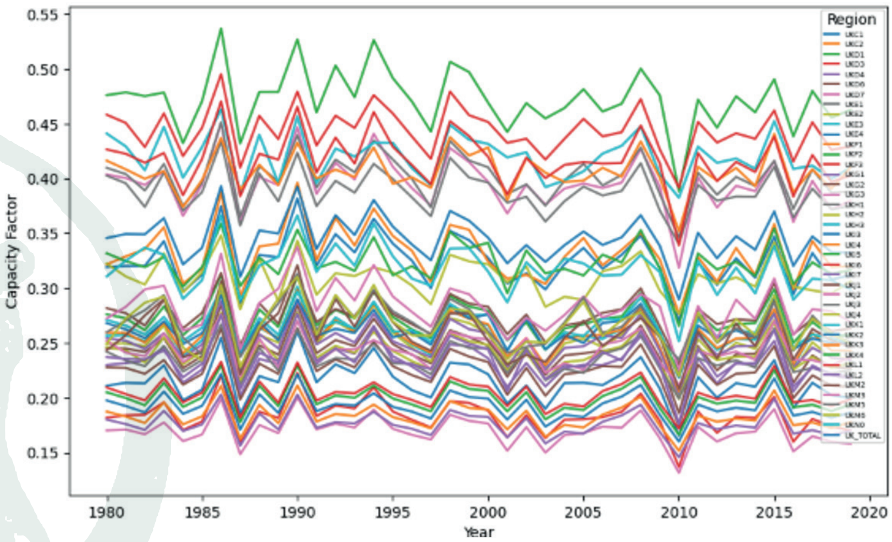
The revenue forecasts developed in this study are set to become a key input into the infraMetrics Valuation Model, enhancing the precision of infrastructure asset valuation in the UK. By incorporating asset-level generation probabilities and future revenue projections, this integration will improve the accuracy of discount rate estimations, expected cash flows and NAVs ensuring valuations align more closely with real market conditions.

Initially, these forecasts will be applied to IC70 renewable assets in the UK, strengthening financial modelling and risk assessment. Further expansions into additional markets are planned, leveraging the methodology developed in this study to support comprehensive, market-driven valuations across all our universe.

Methodology for Estimating Capacity Factors Using Renewables.ninja Data

To establish an alternative methodology for calculating capacity factors for assets in the UK and mainland Europe, we utilized "Renewables. Ninja", an open-access platform that provides simulated hourly capacity factors for renewable energy assets. These simulations, based on validated reanalysis and satellite data from 1989 to 2019, were developed to complement asset-level production data from Elexon in cases where granular data is unavailable, particularly for other technologies like solar and regions beyond the UK.

Figure 21: Average wind capacity factor by region in Great Britain



Hourly capacity factor data for each NUTS 2 region, as shown in Figure 21, was sourced from Renewables.ninja, incorporating variations due to local meteorological conditions, turbine characteristics, and geographic attributes. Wind farms listed in the UK Balancing Mechanism dataset were matched to their respective NUTS 2 regions using geographic coordinates, aligning Elexon data with the regional capacity factors provided by Renewables.ninja.

For offshore wind farms, capacity factors from the nearest onshore NUTS 2 region were used due to the absence of specific offshore data. This approach introduces minor inaccuracies as offshore wind speeds are generally higher, resulting in slightly underestimated capacity factors. Additionally, there is a gap in the data of Renewables Ninja for certain NUTS 2 codes in Scotland. The estimated wind farm capacity factor per UK NUT2 region are illustrated in Figure 22.

To validate this method, P50 capacity factors derived from Elexon's B1610 historic data were compared with the regional averages from Renewables.ninja. For a sample of 37 wind farms, the mean squared difference between the two datasets was calculated at 2.1%, as shown in Figure 23 demonstrating a high level of agreement. This validation highlights the robustness of Renewables. ninja data as a proxy for estimating historical and regional capacity factors.

Figure 22: Average wind capacity Factor by NUTS in the UK

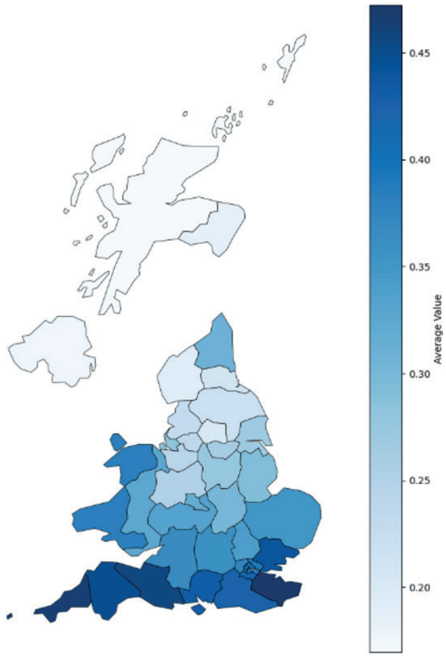
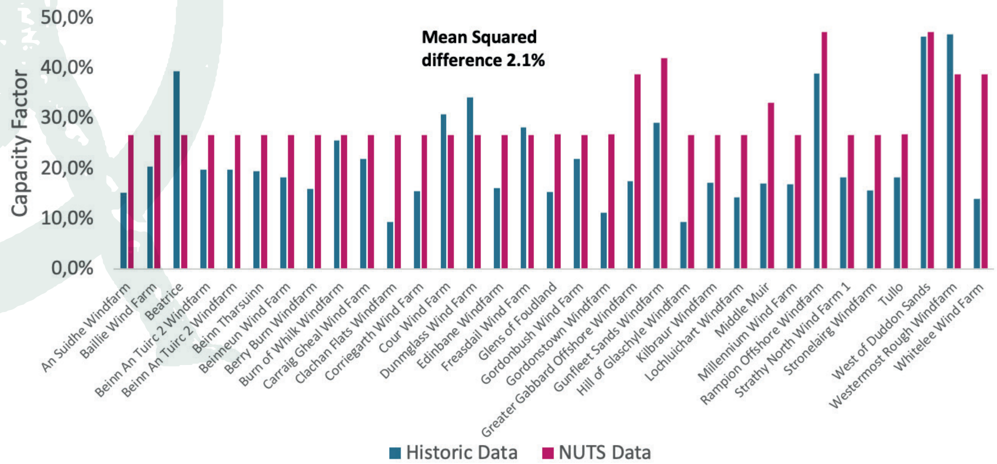


Figure 23: Comparison of capacity factors for wind in the UK between different methodologies



This methodology provides a scalable and reliable alternative for analyzing capacity factors in contexts where asset-level production data is unavailable. It supports scenario analysis by offering insights into historical performance and future capacity expansion strategies and facilitates inter-regional comparisons of renewable energy performance across Europe. While the reliance on onshore proxies for offshore wind farms introduces minor limitations, this approach effectively complements detailed analyses and broadens the applicability of revenue forecasting models to various geographies and technologies where granular asset level production data is not available.

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