A Systematic Framework for Projecting the Future Cost of Offshore Wind Energy

Matt Shields, Philipp Beiter, and Jake Nunemaker

National Renewable Energy Laboratory

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15013 Denver West Parkway
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Executive Summary

Various analyst groups have published cost forecasts for fixed-bottom and floating offshore wind energy. These projections are useful for understanding the economic viability of offshore wind and informing investment and research and development decisions. However, the methodologies used to estimate these future costs are often not transparent and fail to characterize the uncertainties in the forecast. In this report, the authors introduce the **F**orecasting **O**ffshore Wind **R**eductions in **C**ost of **E**nergy (FORCE) model, which we use to estimate cost reductions of fixed-bottom and floating offshore wind technologies through 2035 and associated uncertainties. The model is available on GitHub for use by the broader analyst community.

The FORCE model is based on an empirically derived learning rate for project capital expenditures in combination with assumptions of expected global deployment. We use historical project cost data to derive learning rates for fixed-bottom and floating wind technologies and establish bounds on these estimates to provide scenario ranges for the learning rate. These bounds reflect the uncertainty in historical cost data. We prescribe current and future values of operational expenditures and capacity factors from literature to derive a total cost of energy because available project data to derive learning rates for these two parameters are very limited. Further, we define a set of fixed-bottom and floating reference sites to characterize how costs vary by spatial conditions.

The average future costs of fixed-bottom and floating wind technologies in 2035 that we estimate using the FORCE model are \$53/megawatt-hours (MWh) and \$64/MWh, respectively, with corresponding uncertainty ranges of \$48/MWh–\$60/MWh and \$47/MWh–\$100/MWh due to uncertainty in the estimated learning rate and site-specific capital cost variance. These values are within the range of estimates by other analyst groups. This model provides additional value through its transparent methodology, quantification of forecasting uncertainty, and flexibility to accommodate new data or assumptions.

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List of Acronyms

AEP_{net}	annual energy production
ATB	Annual Technology Baseline
BNEF	BloombergNEF
CapEx	capital expenditure
FORCE	Forecasting Offshore wind Reductions in Cost of Energy
IRENA	International Renewable Energy Agency
LCOE	levelized cost of energy
NCF	net capacity factor
NREL	National Renewable Energy Laboratory
OpEx	operating expenditures
ORBIT	Offshore Renewables Balance-of-system and Installation Tool
VIF	variance inflation factor

1 Introduction

Understanding the future cost of offshore wind energy is critical for evaluating its economic performance and optimally allocating investment and research-and-development resources. Cost data of power generation assets, including offshore wind, are often challenging to ascertain because of their commercially sensitive nature. These challenges are exacerbated when projecting the cost of generation assets that are deployed at a future date; however, cost projections that stretch decades into the future are often a critical modeling input to support today's decision-making. Many factors influence the future cost of power assets, and their interdependencies are usually poorly understood and challenging to quantify. As with any projection about the future, costs are subject to many inherent uncertainties, such as fluctuating material and commodity prices, technology, and the broader market environment (Junginger and Louwen 2020). A particular challenge to projecting costs is posed by groundbreaking technology innovations or rare but profound macroeconomic changes (e.g., general interest rate level, supply chain shortages), which typically have an extraordinary impact on cost but occur infrequently and often unexpectedly.

Offshore wind energy technology costs have declined significantly in recent years, and many forecasts indicate that these cost reductions will continue for the foreseeable future. Between 2014 and 2019, the levelized cost of energy (LCOE) of offshore wind energy declined by more than 40% (Figure 1). Looking ahead, further cost reductions are expected to reach levels of approximately $50/megawatt-hour (MWh) by the decade's end; however, these forecasts are inherently uncertain and vary significantly between different analyst groups.

The multitude of approaches in projecting offshore wind costs and the lack of frameworks that make explicit the inherent uncertainty in cost modeling motivate the development of a well-documented and robust cost projection modeling framework. As a result, the authors introduce a rigorous framework to estimate the future cost of offshore wind energy technologies that is transparent, practical, and replicable. Although the methods used within this framework are well-established, to our knowledge, such a tool is not available in the broader literature.

A vast body of literature has explored future offshore wind energy cost trajectories—see, e.g., BloombergNEF (2019), Wiser et al. (2016), Lazard (2019), (IRENA) (2020), and NREL (2021). Four principal ways have emerged to assess the future costs of renewable energy technologies, including offshore wind:

- Learning curve
- Expert elicitation survey
- Bottom-up cost assessment
- Analysis/re-engineering of auction bids.

There are various applications of these methods to the offshore wind energy sector. Learning curve approaches are well-established within the broader literature, but only a few assessments have been made for offshore wind technologies to date (Wiser et al. 2016). A learning rate indicates the fractional reduction in the cost for each doubling of cumulative capacity (Rubin et al. 2015). Estimated learning rates for offshore wind energy technologies tend to be highly varied (Wiser et al. 2016), ranging from 3%–31% (Odam and Vries 2020; Junginger and Louwen 2020; Samadi 2018; Voormolen, Junginger, and Sark 2016; Schwanitz and Wierling 2016; Rubin et al. 2015; Dismukes and Upton Jr. 2015). Using offshore wind power plant data from 2001 to 2022, Junginger and Louwen (2020) found a learning rate between 26.8% and 31.2%; however, Junginger and Louwen (2020) cautions of strong fluctuations in offshore wind costs in the past, which could impede the ability to derive meaningful one-factor experience curves and learning rates that would allow extrapolation for future cost projections. Further, Junginger and Louwen (2020) note that a multifactor learning curve approach that considers raw material costs, location-specific properties, and financing costs show more promise, but more data are required to assess how effectively these models can project future costs. Bolinger, Wiser, and O'Shaughnessy (2022) suggest an approach to evaluate time-varying learning curves for LCOE (instead of capital costs) of land-based wind energy, which they suggest provides a better estimate of historical and projected cost reductions. They derive a full-period LCOE learning rate of 15% for land-based wind energy (Bolinger, Wiser, and O'Shaughnessy 2022).

A seminal elicitation of 163 wind energy experts in 2015 found LCOE reductions of 30% (fixed bottom) and 25% (floating) by 2030, with wind turbine upsizing and foundation/substructure design as major drivers (Wiser et al. 2016). Reductions of 41% (fixed bottom) and 38% (floating) were elicited by 2040. A narrower expert elicitation was conducted by Valpy and English (2014) for fixed-bottom offshore wind technologies focused on identifying 57 technology innovations and their quantitative impacts on future costs. The resulting estimates were updated in 2017 (Valpy et al. 2017) and extended to floating offshore wind technologies (Hundleby et al. 2017). Detailed data for the Valpy and English (2014) assessment have been made available through the DELPHOS project (InnoEnergy 2020).

Bottom-up cost assessments typically use engineering models to derive functional relationships among offshore wind system design elements, engineering requirements, and their cost and performance. Examples include Nunemaker et al. (2020), Beiter et al. (2016), Maness, Maples, and Smith (2017), and Stehly et al. (2018). Bottom-up models are often used to quantify changes in the design or size of wind power plants and the resulting impact on LCOE (Shields et al. 2021a).

To date, only two assessments have used auction results to derive insights for future cost trends. Jansen et al. (2020) harmonized offshore wind auction results in Europe to derive their "harmonized expected revenue," allowing for project comparability and some inferences to LCOE. Using auction and power purchase agreement data, Beiter et al. (2021a) assessed the "levelized revenue and value of energy" for 10 global offshore wind energy projects. Levelized revenue and value of energy captures all relevant monetized value streams, including revenue from energy production, fiscal support from tax and depreciation rules, and beneficial infrastructure and development expenditures. Beiter et al. (2021a) argue that levelized revenue and value of energy allows for "like-for-like" comparisons to LCOE.

Each method has its respective advantages and limitations (Table 1). Learning curve assessments rely on empirically derived relationships between deployment and costs and assume that these past relationships hold for the future. Data on LCOE and installed capacity can be obtained; however, as noted by Junginger and Louwen (2020), the lack of data can limit the confidence level of the derived learning rate. The quality of the data, particularly the LCOE data used, typically varies and can obfuscate the results. Expert elicitations highly depend on expert sample selection and can suffer from various surveying biases. Bottom-up cost modeling offers a detailed insight into the relationship between technology innovations and cost impact (and, in the best case, a highly transparent methodology), but they greatly depend on high-quality, up-to-date input data and need consistently granular levels of resolution to capture system-level impacts of incremental technology changes. Achieving this level of detail can be challenging because new and emerging concepts might not be fully designed yet when captured by bottom-up models and is further complicated by the systemwide impacts of any single technology innovation (Beiter et al. 2021b). Finally, analyses of auction results utilizes publicly available data and can be calibrated for projects in different countries or regions, but significant manual effort is required to compile and analyze information from multiple sources to standardize output metrics.

Table 1. Advantages and Limitations to Cost Projection Methodologies

	Resolution	Advantages	Limitations
Learning curve	Low	Empirical data basis	Top-down model
Expert elicitation	Medium	Contextual data	Subject to survey biases
Bottom-up assessment	High	Clearly documented	High data requirements
Auction results analysis	Low	Public and commercial data	High data requirements

A number of institutions have developed approaches for projecting future costs of offshore wind energy based on the methodologies listed in Table 1. Several examples of fixed-bottom project projections are presented in Figure 1. There is reasonable agreement in the trends depicted by the different models; however, the methodologies used to derive these projections are typically opaque, making it difficult to determine the source of the variance in the results. Often, it is also unclear as to which scenarios or assumptions are implicit for deriving these projections. As a result, it is difficult to disentangle technological, financial, or supply chain drivers and to replicate the projections.

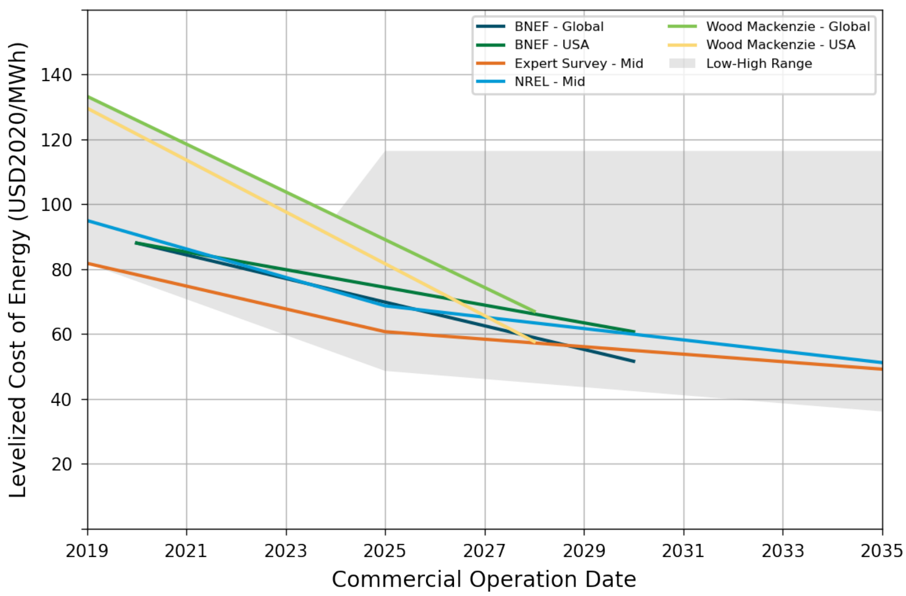

Figure 1. LCOE projections, 2019–2035. *Figure from Musial et al. (2021)*

2 Approach

In this report, we introduce a practical and transparent framework to project offshore wind energy costs. The **F**orecasting **O**ffshore Wind **R**eductions in **C**ost of **E**nergy (FORCE) model calculates a learning rate from available data on installed global offshore wind projects and project cost reductions forward in time based on anticipated future deployment. The learning rate is intended to capture the combined effects from (1) single innovations; (2) learning, standardization, and economies of scale in the supply chain and manufacturing; (3) wind turbine upscaling; and (4) interaction effects (Figure 2).

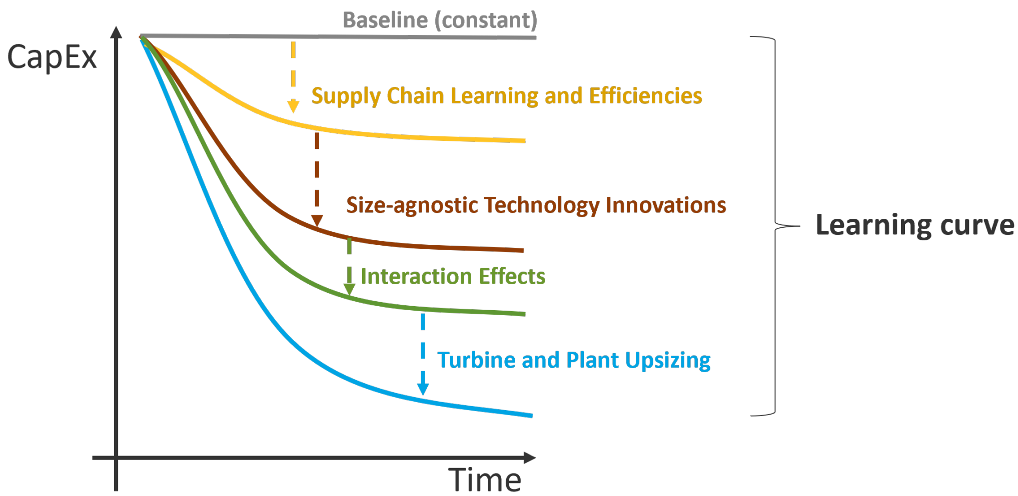

Figure 2. Conceptual approach to cost projections (CapEx = capital expenditures)

Capturing (nearly) all effects in a learning rate avoids any complications that might arise from "double-counting" any factors that might not be captured by the learning rate. We deem a learning rate approach the most transparent and practical means to establishing an overall cost trajectory for the future. Although deriving the learning rate is data-intensive and requires statistical analysis, it offers the benefit that only a simple assumption about future deployment needs to be made to derive a future cost level. Further, the statistical approach to derive learning curves produces uncertainty bounds that can be used to describe the certainty with which future cost estimates are made. It is also possible to quickly evaluate the sensitivity of the projected cost reductions to different levels of global offshore wind energy deployment. In contrast, the alternative means to derive future costs seems less equipped to make cost projections far into the future. The causal relationships of individual cost reduction drivers tend to be complex and data are typically sparse, which limit the ability to project costs holistically with bottom-up models (e.g., engineering tools). Expert elicitation surveys are at risk of quickly becoming outdated and are subject to various biases that are introduced when surveying human subjects. The analysis of auction bids is a promising way to elicit future costs, yet the bids typically only allow for an outlook of the next 5–10 years (Beiter et al. 2020), which often falls short of the need for cost projections that stretch several decades into the future. When feasible, however, we consider these alternative means useful to *explain* the various shares of individual cost drivers. For instance, bottom-up engineering analysis can inform the share of the learning rate that can be explained by a single innovation (e.g., reduction in costs due to improved installation strategies).

Although FORCE is capable of producing estimates for all LCOE components, the focus of our analysis has been on capital expenditures (CapEx). Data for CapEx from installed offshore wind projects are available, yet the same data availability does not apply to other LCOE components, such as operational expenditures (OpEx), maintenance expenditures, annual energy production (AEP), or the cost of capital. This report uses published estimates of future OpEx and AEP values from NREL's Annual Technology Baseline (ATB) (NREL 2021) along with empirical project

CapEx data to compute LCOE. Once sufficient and reliable OpEx or AEP data become available, they can be integrated into FORCE using the learning curve methodology described in this report for CapEx.

The FORCE model adds value to the existing suite of offshore wind cost projections in the following ways:

1. Future costs can be derived for a range of representative projects with customized locations, designs, and commercial operation dates.

2. A quantitative assessment of uncertainty is calculated by FORCE. Cost projections are inherently uncertain (because of unanticipated technological and supply chain trajectories and a poor understanding of their impact on costs), but a representation of this uncertainty is often missing from existing cost projection methods.

3. CapEx projections are directly derived from available project data and are projected based on global deployment estimates. This derivation provides an explicit relationship between the current and future states of the global industry and the associated project's capital costs. Costs can be easily updated as global deployment projections change over time.

4. The FORCE model offers a high level of versatility. First, a user can input different global deployment projections (for fixed or floating sites). Second, different reference sites can be defined from which to build the ensemble projection. In this way, the cost projections can be customized for different spatial or industry scenarios. Third, a user can customize the regression model so that the effects of various cost factors (e.g., wind energy plant or turbine size) are removed from the learning curve, depending on the specific research question and data availability.

5. To facilitate use and discussion within the offshore wind analyst community, the FORCE model is publicly available on GitHub.[1] We intend for this model to be easily populated by the wider analyst community with their respective assumptions (e.g., about offshore wind deployment trends) and to provide sufficient documentation so that results can easily be replicated. Users can modify key input assumptions and generate their own customized cost projection values and figures.

The versatility of FORCE is illustrated in the following sections (see Section 3.1.6.1) by configuring a learning rate that is different for fixed-bottom and floating offshore wind energy applications. We deem it necessary that they are different because today, fixed-bottom and floating projects differ greatly in project size and technology choices. Fixed-bottom projects typically comprise several hundreds of megawatts in size. We expect that the future growth of fixed-bottom project size is relatively limited because of regulatory and financial constraints. On the other hand, floating offshore wind projects are currently deployed as multiturbine demonstrations, with each project less than 100 megawatts (MW) in size. We expect that typical floating offshore wind projects will grow to similar plant sizes than current fixed-bottom projects. In relative terms, the upsizing and associated cost reduction potential is much higher for floating than for fixed-bottom applications; hence, we develop a learning rate in FORCE that excludes the effects from plant capacity on costs (by controlling for plant size in the regression), whereas for floating applications, we include these effects in the learning rate (by *not* controlling for plant size in the regression).

[1]The FORCE model can be accessed at `https://github.com/NREL/FORCE`. Because we use project CapEx data from 4C Offshore (2020), which requires a subscription, the FORCE repository includes only a formatted template for input data and does not include the actual values.

3 Learning Rates for Offshore Wind Capital Costs

The FORCE model is primarily based on a CapEx learning curve derived from a multivariate linear regression of recent offshore wind energy project data. A preliminary form of this methodology was implemented by Beiter et al. (2020) and Shields et al. (2021b) for offshore wind cost modeling studies in California and O‘ahu, respectively. Here, we provide a more detailed description of the regression modeling approach (particularly statistical checks to evaluate the quality of the model), use a more recent data set with a larger number of offshore wind projects in the sample, characterize the strengths and weaknesses of regression modeling and how they can impact the quality of the forecast, and elaborate on how the FORCE model can be regularly updated to accommodate new data.

3.1 Strengths and Weaknesses of Regression Models

A multivariate linear regression model is a well-known approach to estimating the relationship between a set of (independent) predictor variables and a (dependent) response variable. These models take the form:

$$y = \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + c + e, \tag{3.1}$$

where y is the response variable, $x_{1,2,\ldots n}$ are the predictor variables, $\beta_{1,2,\ldots n}$ are the weighted coefficients for the predictor variables, c is a constant term, and e is the residual error in the statistical fit. In general, the intent of a multivariate regression model is to identify a range of independent variables that, when appropriately weighted, predict the value of the response variable. The models are typically fit to existing data sets and can then be used to estimate the behavior of the response variable for new values of the predictors. In this way, a regression model can be used to forecast the value of the dependent variable beyond the confines of the known data set. Fitting a regression model requires finding the values of the β coefficients in Eq. 3.1, often using an ordinary least-squares approach that is straightforward enough that a multitude of software programs (including Excel, Python, and R) offer built-in tools that output these coefficients. We refer the reader to Saltelli et al. (2008) for a more detailed description of the underlying theory.

The apparent simplicity and broad adoption of multivariate regression modeling provide a number of advantages but also conceal significant challenges and nuances that can result in misleading or incorrect interpretations of the results. It is critical to understand and mitigate the limitations of regression modeling and to appropriately convey these limitations and inherent uncertainty of the ensuing forecasts. In this section, we briefly discuss some of the more relevant advantages and disadvantages of multivariate regression modeling in the context of estimating the capital costs of offshore wind energy projects. Ultimately, we select a multivariate regression model to estimate the future trajectory of offshore wind CapEx. We dedicate significant effort to characterizing how the limitations of this approach could impact the results, how we mitigated these results where possible, and how they could improve over time.

3.1.1 Strengths of Regression Modeling

Regression models have several advantages over alternative approaches:

1. **The model is based on empirical data from installed offshore wind energy projects.**

   Unlike other types of cost projection methodologies, as described in Table 1, a regression model is directly based on empirical project cost data. As a result, these data reflect the announced capital costs from project developers, which implicitly include the impacts of technology choices, site-specific conditions, supply chain maturity, and experiential learning over time. The last two categories are typically hard to capture in bottom-up models but are integral parts of a learning rate. CapEx is a large component of LCOE, and data are often readily available, at least relative to the other LCOE components (e.g., cost of capital or operations and maintenance). CapEx data are often disclosed as part of project announcements or in the context of highlighting the economic benefits of a project to local communities.

2. **We have *a priori* knowledge of (some) key predictor variables.**

The growth of the offshore wind energy industry has led to a better understanding of the key cost drivers for these projects—see, e.g., Stehly, Beiter, and Duffy (2020) or Shields et al. (2021a). We can use bottom-up models to identify the most relevant physical parameters that drive costs, and we can select those as predictor variables in the regression model; for example, the water depth at the site significantly impacts the cost of the foundations, and the distance to shore impacts export system costs (both of which are major components of the capital stack for a project). Having this *a priori* knowledge of significant predictor variables increases confidence in the predictive ability of the model.

3. **The modeling approach provides quantitative estimates of uncertainty.**

   Any forecast includes an inherent amount of uncertainty, and a regression model offers quantitative metrics that can be used to describe the quality of the fit of the existing data and the confidence level in the predictive ability of the model. The standard error of the learning curve can also be used to provide high and low bounds on the projections. Reporting a potential range of outcomes for future offshore wind costs instead of a single trajectory is a more transparent way to convey the uncertainty in the forecast.

4. **Regression modeling provides a direct estimate of the learning rate.**

   If the global installed capacity is used as a predictor variable, the β coefficient can be directly used to calculate the learning rate. We provide a more detailed explanation in Section 3.1.4.

5. **The simple approach provides readily understandable descriptions of the relationships between predictors and response variables.**

   The form of the regression model outlined in Eq. 3.1 provides a simple description of how individual predictors influence the response variable independent of changes in other variables. The magnitude of the coefficient reflects the sensitivity of the output variable, and the sign of the coefficient determines the direction of the response. In the case of offshore wind, this reflects how a predictor, such as water depth, impacts the capital cost of all the projects in the data set while controlling for the impacts of other predictors, such as distance to shore, wind turbine rating, or project capacity.

3.1.2 Weaknesses of Regression Modeling

1. **The modeling approach is prone to overfitting and misinterpretation of statistical checks.**

   It is possible (even easy) to include too many predictor variables in the regression fit because some primary statistical checks (particularly the coefficient of determination, R^2) do not penalize the inclusion of additional predictors. The addition of too many degrees of freedom encourages the model to fit itself to the noise in the data instead of the signal, which provides a good explanation of the training data set but significantly weakens the predictive ability of the model.

2. **The relatively low number of offshore wind energy projects in the time frame of interest result in a small sample size data set.**

   Offshore wind energy project costs were highly scattered (and, on average, increased) until 2014, before beginning to consistently decrease between 2015 and 2021 (Musial et al. 2021). Limiting the available data set to the post-2014 window reduces the number of projects to 56. Although a minimum number of data points is required for a regression analysis, a common rule of thumb is that 10–15 data points per predictor variable are needed (Babyak 2004). The low number of data points therefore caps the number of effective predictor variables that can be included, can lead to relatively high standard errors, and limits the history of installed capacity required to fit the learning curve. The low amount of available data also means that the regression model cannot be trained on separate data sets.

3. **The available data for project capital costs are limited and potentially biased.**

   The data set used for the regression analysis is provided by 4C Offshore and relies on publicly announced CapEx values from project developers (4C Offshore 2020). This reliance on project data implies several limitations, as outlined by Junginger and Louwen (2020), such as modeling price instead of cost, potentially biased or inconsistent CapEx numbers reported by project developers, and having insufficient data for a floating-wind-specific model.

4. **Key predictor variables can exhibit collinearity and nonlinear effects.**

   Several of the most physically relevant predictor variables are collinear, or correlated; for example, water depth tends to increase as distance from shore also increases. This collinearity can influence the individual coefficients in the regression model and lead to inaccurate β values (although the overall fit of the regression model can still be valid) (Saltelli et al. 2008). Individual predictors might also have a nonlinear relationship with the response variable. It is important to set up the regression model to mitigate interaction effects for any coefficients used for the analysis.

5. **The results of the model highly depend on the choice of predictor variables.**

   The 4C Offshore data set includes dozens of parameters that are reported for each project in the database, and each variable is accessible to the analyst to include in the regression model. The predictors used in the regression fit can significantly impact the results, thereby requiring significant analyst judgment when selecting them. Too few predictors might not capture all the key dependencies of the response variables, and too many might result in an overfit model with significant collinearity among variables. The CapEx forecasts from this study therefore depend on the specific predictor variables selected in the model.

6. **The cumulative effect of these limitations can lead to significant uncertainty in future predictions of offshore wind capital costs**.

   Regression-type models are fit to available data sets, which means they are inherently tuned to hindcast data. The sources of uncertainty and bias described in this section can subsequently lead to significant errors when predicting future costs. The uncertainty in forecasted costs is frequently underreported in the offshore wind literature.

3.1.3 CapEx Data and Control Variables

The 4C Offshore database includes nearly 100 different categories of variables that are used to describe approximately 2,000 global offshore wind energy projects at varying stages of completion (ranging from early planning to full installation). We first limit the data set to include only projects that have an installed capacity of at least 150 MW and were commissioned between 2014 and 2021, which reduces the overall sample size to 56 projects. Although the 4C Offshore database contains information for planned projects, we consider these CapEx estimates to be less reliable and therefore exclude them from the regression model. We selected this data set to include projects with a higher confidence level in the reported CapEx. The selected predictor variables are listed in Table 2.

Table 2. Predictor Variables for Multivariate Regression Analysis

Predictor	Units	Impact on CapEx
Global installed capacity	MW	Increased experiential learning and supply chain maturity decrease costs
Project capacity	MW	Larger projects reduce costs through economies of scale
Water depth	meters (m)	Greater water depths increase foundation costs
Distance to shore	kilometers (km)	Longer distances to shore increase export system and installation costs
Installation country	–	Each country has different subsidy programs and cost structures

The response variable in the regression model is project CapEx. By including the global installed capacity as a predictor variable, the relationship between project CapEx and global installed capacity (controlled for, or independent of, project capacity, water depth, distance to shore, and installation country) can be established and used to define a learning rate. The effects of other project parameters (such as wind turbine rating, cable voltage, installation strategy, and supply chain decisions) that are not listed as explicit predictor variables are then encapsulated within the learning rate.

3.1.4 Extracting a Learning Rate from the Regression Model

A learning rate describes how costs are expected to decrease as the cumulative production of a good or service increases (Louwen and Subtil Lacerda 2019; Junginger and Louwen 2020). These costs often demonstrate an exponential decrease as a function of cumulative production due to learning by doing, learning by researching, improvements in the supply chain, manufacturing efficiencies, and investment (Louwen and Subtil Lacerda 2019). As a result, an experience factor, b, for offshore wind capital costs can be derived from a logarithmic linear regression between CapEx and cumulative installed capacity. The basic form of the regression model from Eq. 3.1 then becomes:

$$\begin{aligned}\log(\text{CapEx}) = b\log(\text{Global installed capacity}) + \beta_1(\text{Project capacity}) + \beta_2(\text{Water depth}) + \beta_3(\text{Distance to shore})\\ + \beta_4(\text{Installation country}) + c + e.\end{aligned} \tag{3.2}$$

The experience factor is used to define the learning rate (LR) using Eq. 3.3:

$$LR = 1 - 2^b. \tag{3.3}$$

The learning rate defines the percentage decrease in costs for each cumulative doubling of the independent variable. In the case of offshore wind CapEx, a learning rate of 10% means that an increase in cumulative installed capacity from 10 gigawatts (GW) to 20 GW results in a 10% decrease in capital costs. A learning curve then depicts the exponential decrease in cost over time where the slope of the curve is driven by the learning rate. It is usually plotted with deployment dates on the x-axis, meaning that a deployment projection mapping dates to installed capacity is also required.

3.1.5 Statistical Checks

A regression modeling approach permits a number of statistical checks of the fit to the existing data to help characterize how effectively the model estimates the response variable. In this analysis, we consider:

- A coefficient of determination (R^2): An estimate of how much of the variance in the data set is explained by the predictor variables. High values of R^2 indicate that the predictors effectively model the variance.
- An adjusted coefficient of determination (R^2_{adj}): A modified R^2 value that adjusts for the number of terms in the regression. If R^2_{adj} decreases after adding a new term, the new predictor has not improved the model fit (even if R^2 increases). Decreasing R^2_{adj} as more predictor variables are introduced can be indicate an overfit model.
- P-values: An estimate of the statistical significance of each predictor coefficient. P-values lower than the significance level (typically 5%) indicate that the null hypothesis can be rejected and that the measured effect is statistically significant.
- Variance inflation factor (VIF): A measure of collinearity between predictor variables. A typical rule of thumb is that VIFs of less than 4 for a particular predictor mean that it has an acceptable level of independence from other input variables.
- Residuals: The difference between an observed value and a predicted value for each set of inputs. An unbiased regression model should have no discernible relationship between the residuals and the input data.

3.1.6 Results

3.1.6.1 Selected Form of the Model and Statistical Checks

We fit a multivariate linear regression model to the 4C Offshore data set with project CapEx (converted to 2021 USD) as the response variable. The only required predictor variable to establish an experience factor is the cumulative global installed capacity. As shown in Eq. 3.2, we use the logarithm of both terms so that the typical exponential decrease in costs attributed to a learning curve is represented by a line between these terms. We then successively add the control variables listed in Table 2 and evaluate the quality of the fit using the statistical checks from Section 3.1.5. For each combination of predictor variables, we report the β coefficient, P-value, and VIF for each parameter as well as the R^2 and R^2_{adj} for the overall model.

This assessment is intended to characterize how effectively the model fits the data and how confidently it can be used to forecast future CapEx.

Table 3. Regression Model Results for Different Predictor Variable Combinations Sorted by Increasing R^2_{adj}

	Cumulative Capacity	Project Capacity	Water Depth	Distance to Shore	Installation Country	R^2	R^2_{adj}
β	-0.270					0.262	0.249
$P > \|t\|$	0.0						
β	-0.297	0.0					
$P > \|t\|$	0.0	0.06				0.309	0.283
VIF	1.06	1.06					
β	-0.267	0.0	0.019				
$P > \|t\|$	0.0	0.227	0.0			0.637	0.616
VIF	1.07	1.42	1.34				
β	-0.267	0.0	0.018	0.001			
$P > \|t\|$	0.0	0.191	0.0	0.295		0.645	0.617
VIF	1.07	1.44	1.53	1.26			
β	-0.177		0.002	0.001	-0.094 to -0.519		
$P > \|t\|$	0.0		0.485	0.376	0 to 0.229	0.770	0.731
VIF	1.48		3.11	1.77	1.15 to 3.8		
β	-0.152				-0.057 to -0.579		
$P > \|t\|$	0.0				0 to 0.392	0.762	0.733
VIF	1.19				1.08 to 1.75		
β	-0.100	0.0			-0.089 to -0.732		
$P > \|t\|$	0.017	0.002			0 to 0.479	0.805	0.777
VIF	1.42	1.96			1.12 to 2.80		
β	-0.100	0.0	0.006		-0.085 to -0.629		
$P > \|t\|$	0.017	0.0	0.070		0 to 0.489	0.818	0.788
VIF	1.42	2.07	3.15		1.17 to 4.36		
β	-0.133	0.0	0.005	0.002	-0.101 to -0.668		
$P > \|t\|$	0.001	0.0	0.116	0.019	0 to 0.389		
VIF	1.58	2.31	3.21	1.98	1.17 to 4.50	0.839	0.807

The results in Table 3 show that several combinations of project capacity, water depth, distance to shore, and installation country provide reasonable estimates of CapEx based on high R^2 values and acceptable levels of statistical significance and collinearity in the predictors. In particular, the β coefficient of the global cumulative capacity (which is used in Eq. 3.3 to compute the learning rate) consistently has a statistically significant P-value less than the threshold of 0.05 and a low VIF below 2. These values indicate that the coefficient effectively describes the relationship between project CapEx and global installed capacity when controlling for other exogenous variables.

The installation country in particular describes a significant amount of the variance in project CapEx because including only this term as a control variable results in an R^2 of 0.762 (meaning that 76% of the variance is explained by this fit). This is likely because the individual countries with major offshore wind programs have different policies, tariffs, and subsidy programs, along with potentially different physical conditions, such as water depth, grid connections, and port infrastructure, which significantly contribute to the reported project costs. We also note that increasing the number of predictors causes both the R^2 and R^2_{adj} to increase, indicating that adding more control variables improves the fit rather than detracts from it. We considered additional variables, such as cable voltage or overland distance to transmission stations, which decreased the quality of the fit and were therefore removed.

The FORCE model can ingest the learning rates from any of these forms of the model. The form of the model in the final row is useful because it removes site-specific effects (due to water depth, distance to shore, and installation country) as well as economies of scale (due to project capacity) from the experience factor. Removing project capacity from the list of predictor variables also provides a useful formulation that we consider to be more appropriate for floating wind energy projects. Because project size is not explicitly controlled for in this formulation, the effects of project size are captured by the learning rate, which is relevant as the floating wind industry grows from demonstration-scale to commercial-scale projects during the next decade. Fixed-bottom projects have already reached commercial scale, and variability in project sizes is more related to regulatory and financial constraints than to the readiness level of the technology; therefore, we use two separate forms of the regression model for fixed-bottom and floating CapEx projections.

We plot the residuals of the model forms in Figure 3 and see that there is no clear correlation between the accuracy of the model and the input data set, indicating an unbiased model. Ultimately, the review of these statistical checks indicates that the regression model does a reasonable job of fitting the underlying data and can be used to project future CapEx values with a reasonable degree of confidence.

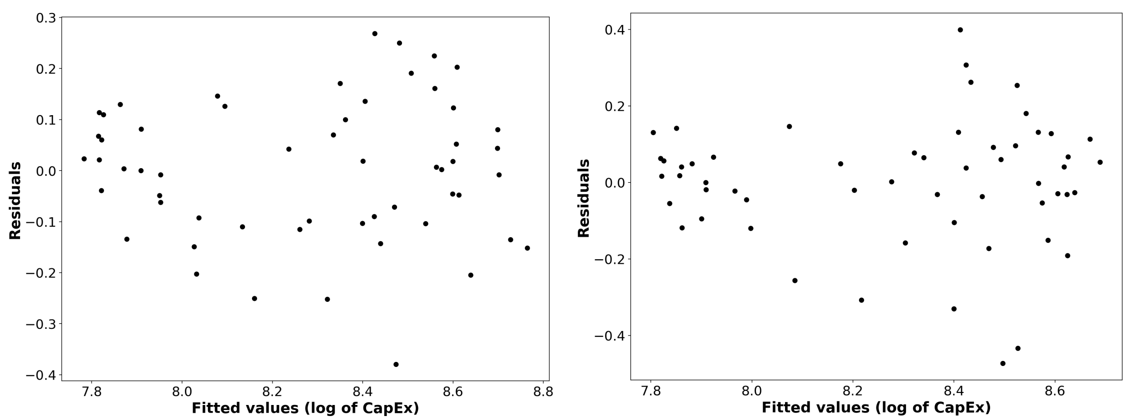

Figure 3. Residuals of the regression model of project CapEx on global cumulative capacity. Both forms of the regression model control for water depth, distance to shore, and installation country; the plot on the left also controls for project capacity.

3.1.6.2 Learning Rate and Implications

The final forms of the regression model yield experience factors of $b = -0.133$ for fixed-bottom projects and $b = -0.177$ for floating projects, which result in respective learning rates of $LR = 8.8\%$ and $LR = 11.5\%$ using Eq. 3.3. The interpretation of these learning rates is that, for every doubling in global installed capacity of fixed-bottom offshore wind, the capital costs will decrease by 8.8%. Similarly, for every doubling in installed floating wind capacity, the capital costs will decrease by 11.5% as additional effects of increasing from demonstration-scale to commercial-scale projects are realized. These learning rates are independent of the effects of the control variables, but they incorporate effects from incremental technology advancement (including increasing wind turbine rating), increasingly mature supply chains, experience from developing previous projects, evolving perceptions and policies related to offshore wind, and other effects that cannot be directly linked to quantifiable variables.

Although the regression model passes the statistical criteria to indicate that it satisfactorily fits the empirical project CapEx data, it is still important to understand that a significant amount of uncertainty remains in the projected future costs. The experience factors derived in the regression analysis are statistically significant and are satisfactorily independent from other variables, but they have standard errors of 25%–30% of the coefficient value. This wide range of outcomes is attributed to a low sample size of only 56 projects in the data set, and it could improve over time as more projects are installed and more data are available; however, this also represents the uncertainty in future offshore wind costs. It is important to quantify and report on this uncertainty as part of any projection.

A summary of the fixed-bottom and floating learning rates derived from this methodology is provided in Table 4. To help quantify the uncertainty associated with the regression fit, we report an average learning rate based on the b coefficient as well as conservative and advanced learning rates that are one standard deviation above or below the average value of b. The conservative and advanced learning rates will be used to help bound the range of cost projections, as described in the following section.

Table 4. Summary of Learning Rates Selected for Fixed-Bottom and Floating CapEx Forecasts

Project Type	Experience Factor	Standard Error	Learning Rate, %			Predictor Variables
			Conservative	Average	Advanced	
Fixed bottom	-0.133	0.039	6.3	8.8	11.2	Project capacity Water depth Distance to shore Installation country
Floating	-0.177	0.045	8.7	11.5	14.3	Water depth Distance to shore Installation country

4 Methodology for Aggregated LCOE Forecasts

The CapEx learning rates derived in Section 3 form the basis of the FORCE model, although we introduce additional features into the approach to develop forecasts for CapEx and LCOE. We define LCOE as specified in Eq. 4.1 following Short, Packey, and Holt (1995):

$$LCOE = \frac{1,000\,(FCR \times \mathrm{CapEx} + \mathrm{OpEx})}{NCF \times 8,760}, \tag{4.1}$$

where $LCOE$ is the levelized cost of energy ($/MWh); FCR is the (real) fixed charge rate that must be collected annually (%/year); CapEx are the project capital expenditures, comprising the turbine, balance-of-system, and soft costs ($/kilowatt [kW]); OpEx are the annualized operations-and-maintenance expenditures ($/kW-year); and NCF is the net capacity factor (scaled by the 8,760 hours in a year in Eq. 4.1). In this study, we hold FCR constant at the 5.8% used by Stehly, Beiter, and Duffy (2020). The factor of 1,000 converts the CapEx and OpEx values from per kilowatt to per megawatt.

4.1 Procedure To Develop Ensemble LCOE Projection

The FORCE model aggregates different estimation approaches for each component of Eq. 4.1 to compute the LCOE of a range of reference scenarios for both fixed-bottom and floating projects. Costs are first evaluated in a baseline year and then projected forward in time. The procedure is outlined as follows and described in greater detail in the next sections:

1. Define a set of reference site and project characteristics in the baseline year for the projection. Compute the average CapEx and LCOE in the baseline year with bottom-up cost models.
2. Derive the CapEx experience factors from the empirical data and use them to project the average CapEx for the future.
3. Prescribe the future OpEx and NCF trajectories based on NREL's Annual Technology Baseline projections.
4. Combine the CapEx, OpEx, and NCF trajectories into an average LCOE forecast.
5. Repeat steps 2–4 using high and low baseline CapEx values coupled with conservative and advanced learning rates to characterize the uncertainty in the projection.

4.1.1 Define Reference Sites and Project Characteristics

Because the costs of individual offshore wind energy projects will vary for different sites and designs, reporting a single cost trajectory (as in Figure 1) does not provide sufficient context for how cost variances among projects affect the overall LCOE trends for the global industry. The FORCE model addresses this by developing a series of reference sites and project designs and then averaging these together to establish a baseline forecast. The site definitions include both geospatial and technological parameters, allowing projects to be customized for the site location by an analyst using the model. The reference sites outlined in this report are selected to broadly represent the U.S. project pipeline. The key site parameters are listed in Table 5.

CapEx in the baseline year is computed using NREL's Offshore Renewables Balance-of-system and Installation Tool (ORBIT) (Nunemaker et al. 2020). The underlying cost rates within ORBIT are calibrated for the industry's best estimates of costs for commercial-scale fixed-bottom projects, which is appropriate for estimating the baseline costs of fixed-bottom reference projects but does not fully capture the high costs of demonstration-scale floating reference projects. The capital costs for demonstration-scale projects in the United States are expected to be on the order of $10,000/kW due to immaturity in the supply chain and limited experience from project developers (Musial et al. 2019). To capture this in the forecast, we use ORBIT to model the floating reference projects with a capacity of 600 MW and then scale these costs by a factor of 2.6. We developed this scaling factor with input from industry practitioners to estimate the difference between overall CapEx for demonstration-scale and commercial-scale projects. It is close to the ratio of 3.03 reported by Musial et al. (2019) for a 24-MW demonstration project and a 600-MW floating project, and it likely reflects some reductions in demonstration-scale costs since Musial et al. (2019) published their report.

Table 5. Site Characteristics for Fixed-Bottom and Floating Reference Projects

	Capacity, MW	Depth, m	Export Cable Length, km	Distance to Port, km
		Fixed-bottom sites		
Site 1	1,200	28	25	125
Site 2	800	30	48	285
Site 3	800	25	43	100
Site 4	800	42	33	100
Site 5	600	50	60	135
		Floating sites		
Site 1	600	832	42	55
Site 2	600	835	30	122
Site 3	600	640	49	248
Site 4	600	279	32	55
Site 5	600	100	52	52

4.1.2 Project Average CapEx Into the Future

The multiple reference sites listed in Table 5 provide a range of values for CapEx in the baseline year. From this range, we assign an average CapEx value for the forecast along with high and low values that are offset by one standard deviation. By establishing a range of initial conditions in the baseline year for the forecast and projecting costs from average, high, and low values, the FORCE model assesses how site-specific parameters can drive variability in offshore wind costs.

In Section 3, we described the process for deriving a learning rate for CapEx based on historic project data. Table 3 identifies conservative, average, and advanced learning rates for both fixed-bottom and floating projects. We assign these learning rates to the high, average, and low values of initial CapEx, respectively, to define the upper and lower bounds on the future range of CapEx values. The upper bound corresponds to the highest initial costs and the most gradual reduction over time, whereas the lower bound corresponds to the lowest initial costs and the most rapid reduction over time. In this way, the range of projected costs from the FORCE model encompass both uncertainty in the estimated value of the learning rate as well as spatial variance in offshore wind energy costs driven by different site conditions.

In Section 3.1.6.1, we discussed how we derived a separate learning rate for fixed-bottom and floating projects. Floating offshore wind presents a challenge for using learning rates based on historical data as no commercial-scale floating wind projects have been built, and therefore no cost data are available for these projects. We used fixed-bottom cost data to derive the learning rate for floating projects under the assumption that many of the infrastructure, manufacturing, and installation aspects of fixed-bottom wind technologies will translate to floating wind. However, we control the learning rate for different variables for the fixed-bottom and floating learning rates; specifically, the latter includes the effects of plant scaling, which will be realized as the floating wind energy industry progresses from demonstration-scale to commercial-scale projects over the next decade.

The rate of decrease in CapEx depends on the deployment rate of fixed-bottom and floating wind. We used the fixed-bottom deployment rate through 2035 from Musial et al. (2021), which leads to a total global deployment of 276 GW at the end of 2035. We linearized this deployment projection to provide a smoother CapEx trajectory. The global floating wind deployment projections are more uncertain. We used 2030 deployment projections from Wood Mackenzie, the University of Strathclyde, DNV, 4C Offshore, Equinor, and the Global Wind Energy Council to establish an average deployment in 2030 (Shreve and Kragelund 2020; Hannon et al. 2019; 4C Offshore 2020; Lee and Zhao 2020). We selected a 2050 target of 95 GW based on projections from ORE Catapult. We then linearly interpolated between the current deployment and the 2030 and 2050 averages to establish a floating wind deployment projection. We selected this simple linear projection due to uncertainty in the actual growth trajectory in floating wind beyond 2030. The deployment projections used in FORCE are provided in Figure 4.

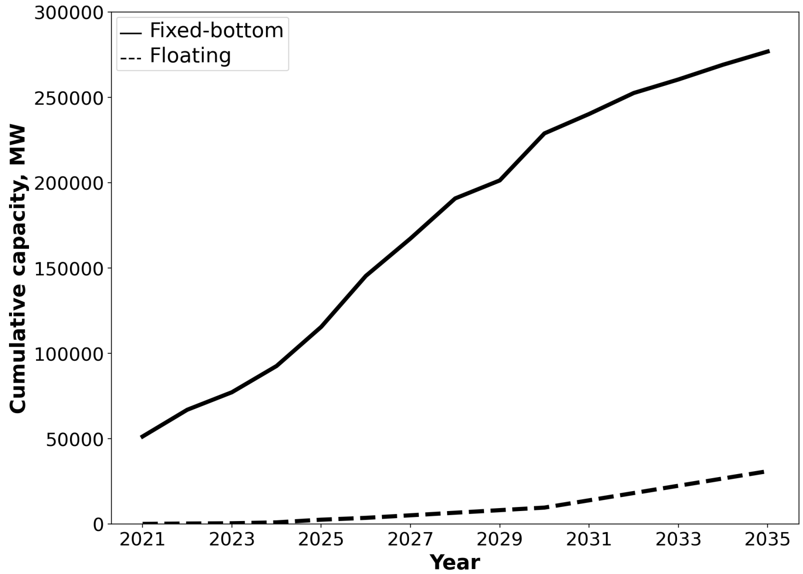

Figure 4. Global deployment projections for fixed-bottom and floating wind energy technologies through 2035

4.1.3 Prescribe Future OpEx and NCF Values at Reference Projects

A publicly accessible database of project-level OpEx and AEP values does not exist; therefore, the learning curve approach used to project CapEx costs into the future is not possible for the other components of Eq. 4.1. Instead, we assign values to each reference project from NREL's ATB for wind classes for the base year and the final year of the projection, and we assume a linear progression in costs between the two values. Fixed-bottom sites primarily represent North Atlantic projects, with relatively strong wind resources and close proximity to shore. Floating wind energy projects span a larger variety of site characteristics and wind classes. OpEx in 2021 are taken from Musial et al. (2019) for demonstration-scale projects, and all other floating parameters come from the ATB projections.

The improvements in OpEx and NCF are attributed to increasing wind turbine ratings, improved supply chains, and ongoing innovations in controls, materials, and strategies that will reduce cost and increase performance (NREL 2021). These trends are all captured within the CapEx learning curve as well, although the CapEx results are based on real-world empirical data. As new data sources or methodologies become available that permit a similar regression analysis to be conducted on OpEx or NCF data, the estimates of these terms can be revised to incorporate empirical data as well. OpEx and NCF values for each reference site are provided in Table 6.

4.1.4 Combine CapEx, OpEx, and NCF Trajectories Into LCOE Forecast

The final step in the FORCE model is to combine the CapEx, OpEx, and NCF forecasts into a LCOE projection using Eq. 4.1. The FORCE model provides an LCOE projection based on the average CapEx and learning rate, but it also characterizes high- and low-ranges for these estimates based on the variability in site-specific initial costs and the uncertainty in potential learning rates based on historical data. The FORCE model captures some highly relevant aspects of uncertainty in the future LCOE of offshore wind energy through the advanced and conservative learning rates. These learning rates essentially reflect an imperfect understanding of historical CapEx trends and the resulting variance from projecting these costs forward in time. The range in learning rates implies that variations in future offshore wind CapEx will be driven by different levels of advancement in a variety of factors: Learning,

Table 6. OpEx and NCF Values for Fixed-Bottom and Floating Reference Projects

	OpEx in 2021, \$/kW-year	OpEx in 2035, \$/kW-year	NCF in 2021, %	NCF in 2035, %	ATB Wind Class
		Fixed-bottom sites			
Site 1	111.5	79.8	45.2	47.6	3
Site 2	111.5	79.8	45.2	47.6	3
Site 3	110.5	83.7	44.3	46.5	5
Site 4	111.5	79.8	45.2	47.6	3
Site 5	111.5	79.8	45.2	47.6	3
		Floating sites			
Site 1	243	66.4	49.2	50.3	11
Site 2	243	59	50.8	51.9	9
Site 3	243	70.6	46.2	47.4	12
Site 4	243	72.4	37	37.8	13
Site 5	243	70.6	46.2	47.4	12

standardization, economies of scale, and technological innovation in future offshore wind power plants and their supply chains. Other sources of uncertainty also exist. These sources include annual offshore wind deployment rates, regulatory or policy drivers that may accelerate or constrain deployment, global supply chain bottlenecks, the applicability of fixed-bottom project data to floating wind cost projections, uncertainty in OpEx and NCF values, or bias in the underlying cost data used to derive the learning rates. The FORCE model does not directly consider these effects, which could increase the confidence bounds around the projected cost trajectories.

5 Cost Forecasts for Offshore Wind Energy

In this section, we present the results of the forecasting methodology outlined in Section 4. The results focus on projected CapEx and LCOE values because OpEx and NCF are more prescriptive. We present results for both fixed-bottom and floating projects, and we conduct sensitivity analyses for the prescribed deployment projections and values of OpEx and NCF to demonstrate how these inputs affect the range of cost forecasts.

5.1 Projected Capital Costs

Figure 5 shows the CapEx forecasts through 2035 for fixed-bottom and floating projects. The solid line represents the average value of CapEx in the baseline year throughout the reference sites projected forward in time using the average learning rate (8.8% for fixed bottom and 11.5% for floating). The blue bands reflect the variability in site-specific CapEx along with the uncertainty in the derived learning rate. Figure 5 shows both the global installed capacity and the corresponding date to demonstrate how the costs vary with both time and capacity. The expected rapid growth in floating deployment in the first half of the 2020s therefore results in the nonuniform spacing of the dates on the top x-axis.

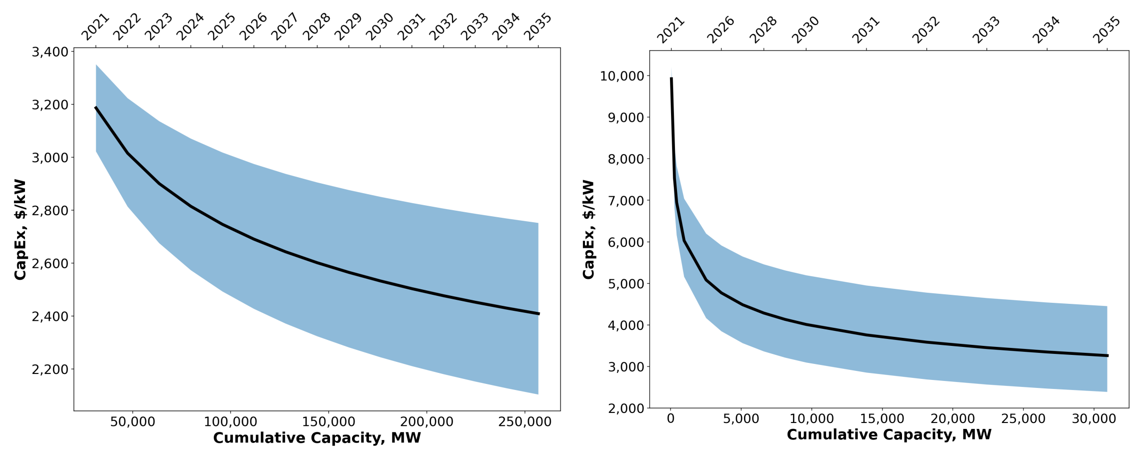

Figure 5. CapEx forecast for fixed-bottom (left) and floating (right) offshore wind projects. The uncertainty bounds incorporate the effects of site-specific cost drivers as well as uncertainty in the estimated learning rate.

The results of the CapEx projections suggest that average costs for fixed-bottom wind energy projects in the United States will decline by approximately 25% from 2021 to 2035, or from \$3,186/kW to \$2,409/kW. These cost reductions are attributed to improved supply chain maturity, experiential learning within the industry, increasing wind turbine rating, and continual technology and process innovations. The top-down nature of the learning curve approach does not allow the impact of individual innovations to be evaluated, but it aggregates these into a broader cost trajectory. There is significant uncertainty associated with this forecast because the range of initial CapEx values and the different bounds on the learning rate can lead to scenarios with capital costs between \$2,104/kW and \$2,751/kW by 2035. These uncertainty bands increase over time as the range of values for the learning rates cause the upper and lower bounds to diverge from the average forecast.

The floating wind projection in Figure 5 realizes a more rapid decline from the demonstration-scale projects, with average CapEx values of \$9,924/kW in 2021 to commercial-scale projects with CapEx values of \$3,263/kW by 2035, a decrease of 67%. The initial costs in 2021 are close to the approximately \$10,000/kW reported by Musial et al. (2019). The two-thirds decrease in costs by 2035 is driven by the growth in installed capacity, from less than 100 MW in 2021 to more than 31,000 MW by 2035. As the floating wind energy industry grows, it will realize the cost reductions through the same mechanisms as the fixed-bottom wind energy industry; however, as we describe in Section 3.1.6.1, our floating learning rate also includes effects from increasing plant capacity because we do not use this as a control variable in the regression analysis. Similar to the fixed-bottom forecast, the future capital costs of floating wind projects exhibit significant uncertainty and could range from $2,389/kW to $4,453/kW by 2035.

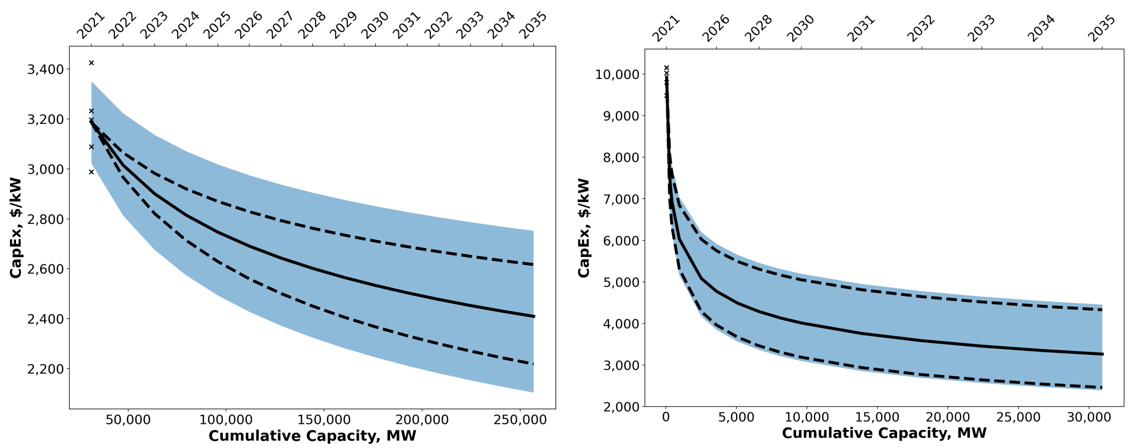

Figure 6. Depiction of uncertainty sources of fixed-bottom (left) and floating (right) forecasts. Initial CapEx values for each reference site in the baseline year are shown with × markers, and the average value of the initial CapEx is projected forward using the advanced and conservative learning rates (dashed lines).

To better describe the sources of uncertainty in the forecast, in Figure 6, we plot the initial CapEx values from the reference sites and apply the conservative and advanced learning rates to the average initial CapEx. The uncertainty bands in the baseline year represent the standard deviation of the spread of project costs. The fixed-bottom uncertainty bands are primarily driven by site-specific variability in the early years of the forecast because the capital costs of these projects are relatively well-known. By 2035, uncertainty in the learning rate causes the advanced and conservative learning curves to diverge. Figure 6 shows that even when using the same initial CapEx value, capital costs could range between $2,218/kW and $2,617 by 2035 when using the aggressive and conservative learning rates, respectively. This represents approximately 62% of the uncertainty in 2035. The floating forecast is almost entirely dominated by the uncertainty in the learning rate because the rapid decline in costs from demonstration-scale projects makes the site-specific costs less relevant. When projecting the average initial costs forward using the aggressive and conservative floating learning rates, the range in values in 2035 represents 90% of the total uncertainty.

Finally, we combine the CapEx forecasts from Figure 5 with the prescribed (linear) OpEx and NCF trajectories described in Section 4.1.3 to define an LCOE forecast. Because these values are prescribed, we cannot quantitatively evaluate the uncertainty in OpEx and NCF projections in the same manner as CapEx; however, we do conduct a sensitivity analysis in Section 5.1.1 to assess how differences in these inputs affect the forecast. We hold *FCR* constant at 5.8% for fixed-bottom and floating wind energy projects throughout the time domain. These results are shown in Figure 7.

The average LCOE for fixed-bottom projects decreases from $75.1/MWh in 2021 to $53.1/MWh in 2035, with upper and lower bounds of $72.4/MWh–$78.6/MWh and $48.4/MWh–$59.7/MWh, respectively. It is noteworthy that the trajectory of the curve is more linear than the fixed-bottom CapEx curve shown in Figure 5. As the forecasted capital costs decrease in the 2030s, the OpEx costs provide a more significant contribution to LCOE. Because the FORCE model assumes a linear decrease in OpEx, this has the effect of straightening out the curve. Because the final costs in 2035 are anchored in NREL's ATB projections, this approach does not greatly affect the LCOE trajectory shown in Figure 7; however, caution should be taken when extrapolating beyond 2035 because the linear decrease in OpEx and NCF will not continue indefinitely. Improving the representation of these parameters in the FORCE model will result in more reliable forecasts with a methodology that can extend farther into the future.

The average floating wind LCOE progresses from $207.0/MWh in 2021 to $63.9/MWh in 2035, with upper and lower

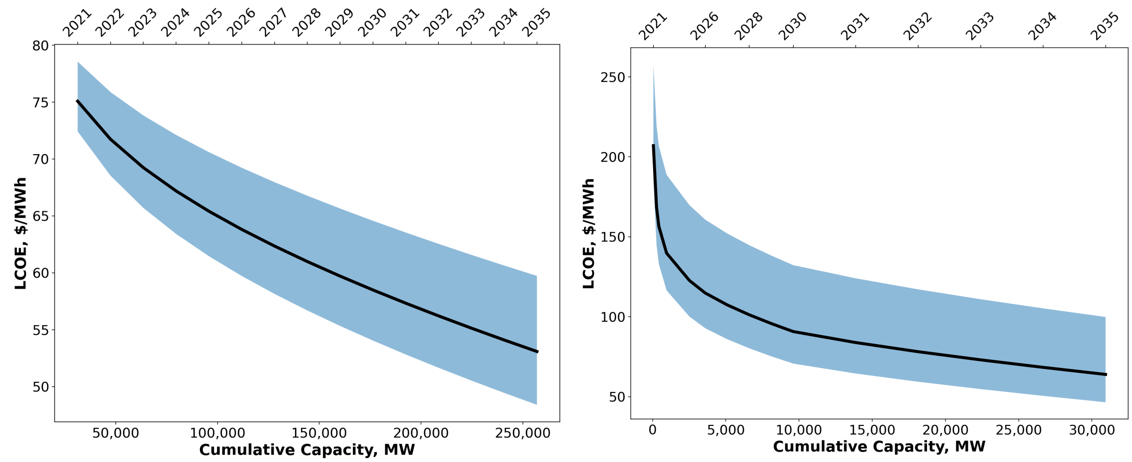

Figure 7. LCOE forecast for fixed-bottom (left) and floating (right) offshore wind projects. The uncertainty bounds incorporate the effects of site-specific cost drivers as well as uncertainty in the estimated learning rate.

bounds of $186.1/MWh–$257.6/MWh and $46.5/MWh–$99.9/MWh, respectively. This range is significantly higher than the fixed-bottom forecast, which reflects greater uncertainty in the CapEx projections along with greater variety in the site-specific conditions for OpEx and NCF (as shown in Table 6). The LCOE trajectory follows the CapEx exponential path because these costs are higher than fixed-bottom projects and remain a more significant contributor to LCOE.

The results from Figure 7 suggest that offshore wind has the potential to achieve significant reductions in LCOE as supply chains, technology providers, and practitioners continue to mature and gain efficiencies as deployment expands through 2035. Like any forecast, however, the FORCE model is subject to significant uncertainties, which we have attempted to present and describe in this report. It is also useful to understand how the FORCE cost projections compare with other perspectives. One of the most recent and comprehensive approaches to projecting future offshore wind costs was conducted by Wiser et al. (2021), who surveyed global experts and asked them to predict the costs of fixed-bottom and floating wind energy projects in 2025, 2035, and 2050 in different regions. We include some key results for European and North American projects in Table 7.

The fixed-bottom LCOE forecast from the FORCE model aligns closely with the projected costs of European fixed-bottom projects. This result is not surprising because the underlying data—both the cost rates in ORBIT, which are used to establish the baseline results, and the learning rates derived from historic project data—are based on insights from the European market. The North America fixed-bottom costs from Wiser et al. (2021) are higher than those predicted by the FORCE model, which could reflect uncertainty about the growth of a new domestic industry; however, recent power offtake agreements in the United States have suggested that these projects can be cost-competitive (or, in some cases, cheaper than) European projects (Musial et al. 2021; Beiter et al. 2021a). As such, it is encouraging that the FORCE forecast aligns with the expert predictions for the European market.

The FORCE estimates for floating wind LCOE in 2035 are also close to the predictions for European markets from Wiser et al. (2021). This comparison is less direct than the fixed-bottom results because Wiser et al. (2021) do not report baseline costs in 2019 but begin their forecast in 2025. The FORCE results are cheaper than the North America floating results reported by Wiser et al. (2021) ($73.4/MWh and $98.2/MWh, respectively), which, again, could be a result of uncertainty surrounding the development of the new offshore wind industry in the United States. Note that the average LCOE values for both Europe and North America in 2035 fall within the uncertainty bands of the FORCE model. These results are an important reminder that projecting future costs is inherently challenging and uncertain.

Table 7. Comparison of FORCE Model LCOE Forecasts with Expert Elicitations Conducted by Wiser et al. (2021) Wiser et al. (2021) used a baseline year of 2019, and FORCE uses a baseline year of 2021. Bounds on the average LCOE values are shown in parentheses.

	LCOE in Baseline Year, $/MWh	LCOE in 2035, $/MWh
FORCE (fixed bottom)	75.1 (72.4–78.6)	53.1 (48.4–59.7)
Wiser et al. (2021) (Europe fixed bottom)	72.0 (61.3–89.9)	43.4 (35.1–56.3)
Wiser et al. (2021) (North America fixed bottom)	94.0 (77.6–105.8)	57.0 (49.9–69.5)
FORCE (floating)	207.0 (186.1–257.6)	63.9 (46.5–99.9)
Wiser et al. (2021) (Europe floating)	N/A	59.7 (51.4–73.0)
Wiser et al. (2021) (North America floating)	N/A	98.2 (70.9–98.5)

5.1.1 Sensitivities to Input Parameters

In this section, we evaluate the sensitivity of the FORCE model results to key input parameters. First, we vary the 2035 deployment targets, which affect the impact of the learning rate as either more or less experiential development takes place within the industry. Second, we vary the final values of OpEx and NCF in 2035 to evaluate how much these prescribed parameters impact the final LCOE results.

We scaled the baseline deployment values plotted in Figure 4 by ±25% to evaluate the impact of expanded or constricted deployment on the projected LCOE. We scaled the cumulative installed capacity in 2035 for both fixed-bottom and floating offshore wind energy by 25% and then prescribed a linear deployment rate between the installed capacity in 2021 and the range of capacities in 2035. The deployment numbers for both scenarios along with the resulting average values of LCOE are shown in Table 8. Varying the total deployment by 25% affects the fixed-bottom LCOE by less than 5% in 2035, which reflects the increasing maturity of the industry and the diminishing returns that can be achieved by further incremental improvements in supply chains. Floating wind realizes a slightly higher impact, with an LCOE change on the order of 5%; however, the impacts are relatively minor for the overall LCOE estimate.

Table 8. LCOE Sensitivity to 2035 Deployment

Scenario	Cumulative Deployment in 2035, MW		Average LCOE in 2035, $/MWh	
	Fixed Bottom	Floating	Fixed Bottom	Floating
Low deployment	207,729	23,268	54.5	66.4
Baseline	276,972	31,025	53.1	63.9
High deployment	346,215	38,781	52.0	62.1

To evaluate the sensitivity of the LCOE results to the prescribed OpEx and NCF trajectories, we scale the 2035 values of these parameters by 10% and 5%, respectively, to adjust the overall cost trajectory. Because the prescribed values of NCF listed in Table 6 increase by only approximately 5% from the baseline values in 2021, reducing the 2035 value by 5% represents a scenario where there are no improvements in capacity factor between 2021 and 2035. Increasing by 5% effectively doubles the impact of capacity factor improvements. We apply two scenarios: one with high OpEx costs and low NCF values (both of which will increase LCOE) and a second with low OpEx and high NCF (both of which will decrease LCOE). The scaling factors for the 2035 values in both scenarios with the resulting value of LCOE are shown in Table 9. Scaling the OpEx and NCF values affects the 2035 values of LCOE by 5%–10%. This is significant but well within the uncertainty bounds established by the original forecast.

Table 9. OpEx and NCF Values for the LCOE Sensitivity Analysis

Scenario	OpEx Scaling	NCF Scaling	Average LCOE in 2035, $/MWh	
			Fixed Bottom	Floating
High OpEx/low NCF	1.1	0.95	57.9	69.1
Baseline	1	1	53.1	63.9
Low OpEx/high NCF	0.9	1.05	48.7	59.2

6 Conclusions

As offshore wind continues to grow into a reliable, clean, global energy source, it is becoming increasingly important to understand how the technology costs might evolve over time to allocate investment and research-and-development resources. Although many analysts provide cost projections for offshore wind, their methodologies are often opaque and do not report on the uncertainty inherent in their projections. In this report, we presented the FORCE model, which forecasts offshore wind energy costs using an empirically derived learning rate for CapEx along with prescribed OpEx and NCF trajectories over time. We derived average CapEx learning rates of 8.8% and 11.5% for fixed-bottom and floating offshore wind technologies, respectively, which encompass the effects of wind turbine upsizing, supply chain maturity, learning by doing, incremental innovations, and (in the case of floating wind) economies of scale from increasing project size. We established baseline CapEx, OpEx, and NCF values for five fixed-bottom and five floating offshore wind reference sites, which we used to set the average LCOE for offshore wind in 2021. LCOE was projected to 2035 based on anticipated deployment schedules for fixed-bottom and floating offshore wind. We characterized the range in potential outcomes for the forecast based on the standard deviation in the baseline year as well as the uncertainty in the estimate of the learning rate. Our results suggest that LCOE for fixed-bottom projects could decline from $75/MWh in 2021 to $53/MWh in 2035, with ranges of $72/MWh–$79/MWh and $48/MWh–$60/MWh based on uncertainty in the learning rate, respectively. We showed that LCOE for floating wind energy projects could decrease from $207.0/MWh in 2021 to $64/MWh in 2035, with ranges of $186/MWh–$258/MWh and $47/MWh–$100/MWh, respectively. The floating wind trajectory follows a more exponential path than the fixed-bottom global deployment, increasing rapidly from a few demonstration-scale projects in 2021 to more than 30,000 MW of commercial-scale projects in 2035; however, floating wind also has a wider range of costs in 2035 due to the uncertain nature of the technology. These results are approximately in line with cost projections provided by other analysts, and they are relatively insensitive to the uncertainty in the prescribed inputs, such as OpEx, NCF, and global deployment rates.

An important intent of the FORCE model is to appropriately address the uncertainty inherent in projecting future costs and to provide a framework for regularly updating the methodology or results as new data become available. We have provided a detailed description of the methodology and highlighted assumptions, limitations, and uncertainty throughout the discussion. In addition, we presented a range of potential outcomes for the costs of offshore wind energy instead of a single trajectory, and we quantified how these uncertainty bounds are developed. We also made the FORCE model publicly available on GitHub so that individual analysts can use the same underlying data framework and modify the methodology (for example, selecting different predictor variables in the regression analysis or inputting a different deployment projection). These features are intended to increase the transparency of the modeling approach and to provide better insights into both the average trajectory and the overall variability of offshore wind energy cost patterns through 2035.

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