Sustainable Energy Technologies and Assessments 45 (2021) 101059

Contents lists available at ScienceDirect

Sustainable Energy Technologies and Assessments

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

Original article

Spatial impacts of technological innovations on the levelized cost of energy for offshore wind power plants in the United States

Matt Shields [a,*], Philipp Beiter [a], William Kleiber [b]

[a] National Renewable Energy Laboratory, 15013 Denver West Pkwy., Golden, CO 80401 USA
[b] Department of Applied Mathematics, University of Colorado, Boulder, CO 80309, USA

ARTICLE INFO

Keywords:
Levelized cost of energy
Offshore wind energy
Impact of technological innovations
Spatial cost modeling

ABSTRACT

Recent studies predict significant decreases in the future levelized cost of energy (LCOE) of offshore wind energy, much of which is attributed to anticipated cost reductions from technological innovation. This study evaluates the spatial variability of LCOE caused by technology-induced decreases in a range of capital, operational, and financial cost categories. A spatial cost model of fixed-bottom and floating offshore wind plants is used to model the impact across thousands of potential United States sites. A specified change in an individual turbine subsystem cost produces a range of LCOE outcomes due to the varying geospatial characteristics of the considered sites and the nonlinear, interactive dependency on these input parameters; for example, a 10.8% improvement in net capacity factor can reduce LCOE by between 6% and 20% at different sites. This work expands upon the existing offshore wind literature, which typically evaluates cost sensitivities at a single site and does not consider the spatial variance in LCOE. The results suggest that the impact of technological innovations can be considerable and should be considered on a spatial as well as temporal basis when prioritizing technology innovation research or funding decisions to advance offshore wind technologies in the United States.

1. Introduction

The growing deployment of offshore wind energy in northern Europe has seen the levelized cost of energy (LCOE) drop from $150/MWh to below $100/MWh between 2014 and 2019 [19]. Despite this precipitous decline, these costs remain high relative to land-based wind and fossil-fueled generation technologies [21]; as such, identifying cost reduction potential is a priority for the offshore wind industry and stakeholders. Future costs are influenced by a myriad of overlapping factors, including technology innovation, economies of scale, derisking of projects, variations in site characteristics, and various macroeconomic and competitive dynamics. Evaluating cost reduction potential necessitates a detailed understanding of how these factors impact LCOE and trade-offs to inform research, project, and policy decisions.

Different approaches have been taken to understand offshore wind LCOE cost structures and their future trajectories. Expert elicitation [26,27,29], learning curve assessments [5,28], and empirical cost models [20] have been used to survey current and future costs and to separate LCOE into its constituent components. The results of these analyses provide a broad perspective of the composition, drivers and future trajectories of offshore wind costs. However, they have a limited ability to quantify and evaluate the complex relationships between individual technology innovations and improvements in performance and costs. More detailed, bottom-up cost models can provide deterministic or probabilistic estimates of how improved component technologies and project design choices impact LCOE [1,15,8–10,17,13]. These component-level approaches can also be used to evaluate the model's sensitivity to uncertainty in input values, which is typically conducted by varying individual parameters and reporting the subsequent change in LCOE for a representative project [25,14,9,11].

This work integrates these three modeling approaches to evaluate how the impacts of technological innovation vary over the U.S. Cost reduction potentials from various technological innovations are sourced from an expert elicitation conducted by [26]. The elicited values from [26] represent decreases in component costs that can be achieved in the near term through technology innovation. In the model used in this study, they are used to perturb baseline values of cost categories at thousands of sites in major U.S. coastal areas and to compute the net impact on LCOE at each location. The coupled, interactive relationships between each cost category result in a spatially-dependent range of attainable LCOE reductions for each cost reduction parameter. This contextualizes the results provided in representative project sensitivity

* Corresponding author.

https://doi.org/10.1016/j.seta.2021.101059
Received 28 October 2019; Received in revised form 22 June 2020; Accepted 1 February 2021
Available online 23 March 2021

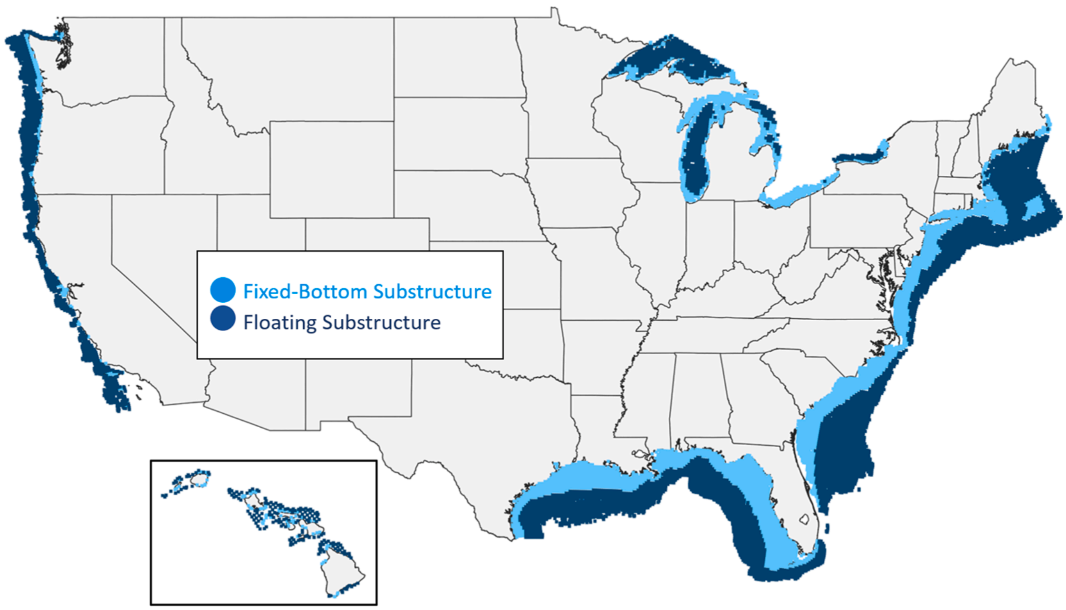


Fig. 1. Offshore wind project sites for the continental United States considered in ORCA.

analyses, which typically perturb baseline values by the same increment (e.g., ±10%) and may not capture the full LCOE variance attributed to a given component cost reduction. Considering both attainable cost reductions and their spatial impact yields improved capabilities for prioritizing research and development (R&D) technological investment on a local and national level.

2. Methodology

2.1. Description of spatial cost model

The Offshore Regional Cost Analyzer (ORCA) used in this analysis is a deterministic cost model that estimates the LCOE of a 600-MW offshore wind power plant at more than 7,000 locations across major U.S. coastal areas [1]. It uses a set of parametric equations for various technological (e.g., turbine rating, substructure type), spatial (e.g., wind speed, water depth, distance to port, wave height), and financial parameters (e.g., debt-to-equity ratio, debt rate, equity rate) to estimate LCOE using Eq. 1:

$$LCOE = \frac{FCR(C_{\text{turbine}} + C_{\text{BOS}}) + C_{\text{ops}} + C_{\text{maint}}}{NCF \times 8760}, \tag{1}$$

where *LCOE* is the levelized cost of energy ($/MWh), *FCR* is the fixed charge rate that must be collected annually (%/year), C_{turbine} are the turbine capital expenditures ($/kW), C_{BOS} are the balance of system capital expenditures ($/kW), C_{ops} are the operational expenditures ($/kW-year), C_{maint} are the maintenance expenditures ($/kW-year), and *NCF* is the net capacity factor (scaled by the 8760 h in a year).

Individual cost terms are described in greater detail in Section 2.2.2. The *FCR*, capital expenditures (CapEx), and operation and maintenance expenditures (OpEx, or O&M) terms are represented in ORCA as multivariable (typically nonlinear) equations parameterized in terms of technological, financial, and geospatial inputs. The derivation of these equations is documented in [1]. Key equations used in this study are included in the Appendix for reference. Although the underlying cost equations are fully deterministic, the relationships between cost and spatial variables are sufficiently complex that the numerical sensitivity analysis approach used in this paper is considered more appropriate than analytic methods.

ORCA can be used to estimate LCOE for single or multiple sites for an assessment of LCOE variation within a region.[1] Constraints are implemented in ORCA to capture technological limitations; for example, fixed-bottom substructures are deployed only up to water depths of 60 m, and floating substructures are excluded from the Great Lakes area as they are deemed inadequate to withstand icing. A map showing the delineations between fixed-bottom and floating sites is provided in Fig. 1. To estimate LCOE, ORCA is populated with key technological parameters (e.g., turbine rating) and the locations of potential offshore wind energy sites off the U.S. coast. The cost model uses predefined spatial layers to determine the closest construction and O&M port, a point of grid interconnection, the prevailing wind and wave regime, and water depth. Costs are calculated using parametric relationships between CapEx, OpEx and Annual Energy Production (AEP) and these input spatial parameters. The relationships between costs and spatial parameters were calibrated using bottom-up engineering and techno-economic tools, such as NREL's Balance of Station model [15], the ECN O&M model [22], the JacketSE and TowerSE tools [4], the AWS Truepower Openwind model [2] and Power System CAD (PSCAD)[3]. Each tool has a different capability in modeling the cost or performance of an offshore wind farm. Scenarios with varying spatial inputs were defined for each model. For instance, several scenarios were defined in the ECN O&M tool varying the distance from a given offshore wind site to an O&M base, while holding all else constant. The ECN model identifies the optimal O&M strategy and calculates maintenance costs as a function of the difference between the site and O&M base (and other factors). A regression was then run using the scenario data to obtain a curve fit between maintenance costs and the distance between site and O&M base. These parametric fits from the various bottom-up tools are aggregated in ORCA to estimate LCOE and are reported in the Appendix of this paper.

[1] In ORCA, U.S. regions are assigned to individual sites in alignment with the Regional Energy Deployment System (ReEDS) model developed by the National Renewable Energy Laboratory [24].

[2] https://aws-dewi.ul.com/software/openwind/

[3] https://www.pscad.com/software/pscad/overview

The goal of this work is to quantify the spatial impact from a set of anticipated technology innovations on offshore wind LCOE. The impact on LCOE is analyzed using a modified Morris factor screening technique, which has been used in previous studies to prioritize key inputs for offshore wind O&M and greenhouse gas emission models [16,6]. Instead of prescribing a constant perturbation, in this modified Morris factor screening technique a different perturbation is prescribed for each independent variable. The independent variables in this study are specific cost categories. They are perturbed by an increment (i.e., a percentage value) that corresponds to their anticipated cost reduction potential as quantified by [26] and [27] through expert elicitations. In addition to assessing the LCOE impact from individual technology innovations, the spatial variation of this impact is assessed by perturbing the independent variables for thousands of potential offshore wind sites in the U.S. (each site characterized by its individual spatial conditions). Because ORCA can evaluate multiple sites simultaneously, it is an ideal tool for conducting a global analysis exploring spatial LCOE dependencies. The theory and modified implementation of the Morris factor screening method is summarized in the following section.

2.2. Implementation of the Morris method in ORCA

2.2.1. Description of the Morris method

Morris factor screening is a global, one-at-a-time sensitivity analysis technique that captures the nonlinear and interactive effects of different model parameters based on user-specified perturbations to these terms [18]. It has an advantage over local methods which perturb a single parameter while holding all else constant and therefore do not capture interaction effects between different variables [23]. Other global methods, such as linear regression, require sufficiently independent variables to extract the dependence of the output on each input parameter [12]. This is inherently challenging for offshore wind applications due to correlations in spatial parameters such as water depth and distance from shore. Finally, the Morris method can be used to perturb the results of parametric cost category equations calculated within the ORCA model. This makes it more useful for this analysis than variance-based methods which evaluate the sensitivity to the distribution of the input variables [23].

The Morris method calculates a range of j elementary effects, $EE_{i,j}$, for the i^{th} input variable, X_i, over the design space and then evaluates the sensitivity of the output variable to this parameter based on the resulting distribution [18]. For a deterministic model with k inputs where $i = 1,\ldots,k$ in the design space $\mathbf{X} = (X_1, X_2, \ldots, X_k)$, an elementary effect of the i^{th} variable is defined as:

$$EE_{i,j} = \frac{Y(X_1, X_2, \ldots, X_{i,j} + \delta, \ldots, X_k) - Y(\mathbf{X})}{\delta}, \tag{2}$$

where δ is a constant value used to perturb X_i. A distribution of $EE_{i,j}$ is then obtained by generating a random sampling of j instances of X_i over the design space and perturbing each sample by the same δ.

2.2.2. Customized elementary effects

The standard Morris method uses the same (normalized) value of δ for every $X_{i,j}$ in Eq. 2 [18]; however, expert elicitations in the offshore wind literature predict different cost reduction potentials for specific cost categories [26,27]. These future scenarios are typically applied to a single, representative project and the anticipated decrease in LCOE is reported. This does not provide insights into how these impacts on LCOE vary over a multitude of potential project locations. In order to address this, Eq. 2 is customized such that:

$$\Delta LCOE_{i,j} = \frac{Y(X_1, X_2, \ldots, X_{i,j} + \delta_i, \ldots, X_k) - Y(\mathbf{X})}{\overline{(Y(\mathbf{X}))}}, \tag{3}$$

where $\Delta\mathrm{LCOE}_{i,j}$ is the j^{th} elementary effect for the i^{th} input variable, $Y(\mathbf{X})$ is the functional relationship by which ORCA calculates LCOE, $\overline{(Y(\mathbf{X}))}$ is the mean baseline (unperturbed) value of LCOE in the design space, and δ_i is a perturbation defined specifically for each input variable. The process of creating the elementary effects for a given input variable is depicted in Fig. 2. Because there exists a range of input values for $\mathbf{X}$ over which δ_i is applied, $\Delta\mathrm{LCOE}_{i,j}$ captures how input variable interactions and nonlinearities affect the sensitivity of the output over the entire design space. This matters when evaluating the potential impact of a particular technological innovation as the achievable reductions in LCOE will not be consistent for every location and project in which it is implemented.

The δ_i perturbations were chosen to reflect anticipated short-term reductions in a given cost category based on expert elicitation of industry practitioners [26,27]. The individual values of δ_i, expressed as a percentage of the maximum value of a cost category for a given design space, are provided in Table 1; while the percentages of the maximum value are listed in Table 1, δ_i is dimensional and has the same units as $X_{i,j}$. Using these values for the perturbations allows the elementary

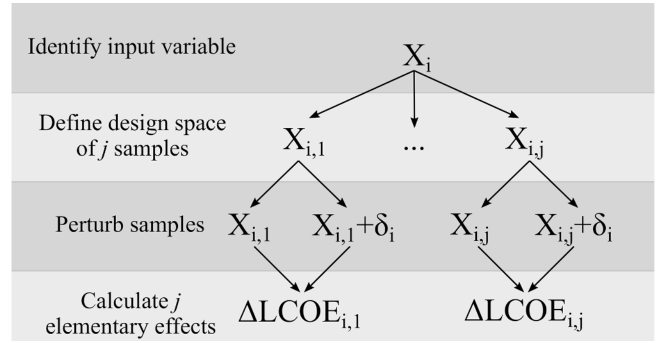


Fig. 2. Process for calculating the mean elementary effect for an ORCA input variable.

Table 1
Cost category perturbations based on innovation categories from [27]. Cost reduction potential for array and export cable installation are included in the Array Cable and Export Cable categories [1].

ORCA cost category	Symbol	Innovation category	Perturbation [%]	
			Fixed	Floating
Development	C_{dev}	Wind farm development	2.5	4.5
Rotor nacelle assembly	C_{RNA}	Wind turbine nacelle Wind turbine rotor	13.1	14.3
Substructure	C_{sub}	Balance of plant	14.2	18.0
Foundation	C_{found}	Balance of plant	14.4	14.3
Array cable	C_{array}	Balance of plant	13.3	16.9
Export cable	C_{export}	Balance of plant	13.0	17.7
Turbine installation	$C_{turb,inst}$	Balance of plant	12.2	12.1
Substructure installation	$C_{sub,inst}$	Balance of plant	19.2	21.3
Operations	C_{ops}	Operation, maintenance, and service	16.1	16.2
Maintenance	C_{maint}	Operation, maintenance, and service	18.1	17.9
Net capacity factor	NCF	Total losses Gross AEP	10.8	10.8

Table 2
Perturbations for financial inputs to ORCA.

ORCA input	Symbol	Perturbation [%]
Rate of return on equity	$RROE$	10
Debt fraction	DF	10
Capital payback period	t_{life}	10

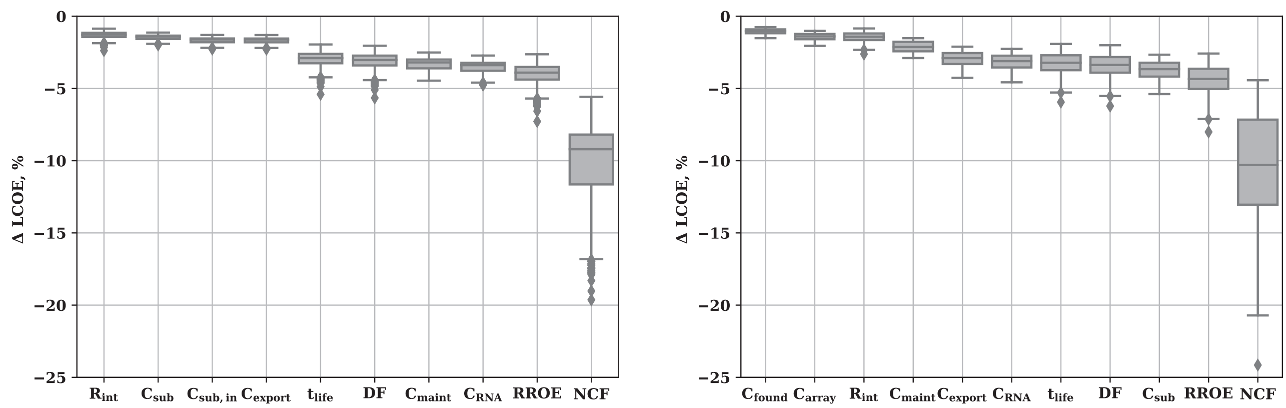


Fig. 3. Spatial variability in LCOE attributed to technological and financial innovations for fixed-bottom (left) and floating substructures (right) in the United States. Input variables that produce ΔLCOE < 1% are not shown. The average LCOE for fixed-bottom and floating substructures across all U.S. sites considered is \$152/MWh and \$191/MWh, respectively.

effects to be interpreted as the achievable LCOE reductions attributed to the cumulative effect of technological innovations within each cost category. Financial parameters, which are not subject to cost reduction potential because of technological innovations, are arbitrarily assigned a percentage of 10% to consider their impact on the cost of energy; these inputs are listed in Table 2.

The reported results for ΔLCOE computed using Eq. 3 represent the sensitivity of LCOE to perturbations in an input variable expressed as a percentage of the mean value of LCOE for the region being considered. While the Morris method does not explicitly describe the nature of the coupling and nonlinearities between input parameters, the variance in output sensitivities does permit the impact of these interactions on LCOE to be quantified over the design space. By using the customized values of δ_i from Table 1 that represent the cumulative effect of innovations in each cost category, the range of impacts of these technological advances over the U.S. can be determined. It is important to note, however, that as the elementary effects corresponding to different input parameters are perturbed by different values in Eq. 3, the sensitivities of LCOE to each parameter should not be directly compared. Doing so requires a constant value of δ to be applied uniformly across all input parameters, which permits a ranking of the relative importance of each cost category. This approach is taken in Section 3; the interpretation of these results is more similar to the standard Morris method defined in Eq. 2.

2.2.3. Sampling distribution

Spatial analyses in ORCA are performed by calculating LCOE at a range of individual sites that satisfy exclusion criteria described in [1]; this results in 3,849 permissible fixed-bottom sites and 4,792 permissible floating sites across the U.S. The conventional Morris method approach to evaluating the sensitivity of LCOE to site-specific parameters and cost categories would involve selecting a random sample of these sites [18]; however, as the ORCA code is computationally inexpensive to run (on the order of seconds to calculate LCOE for the entire U.S.), the sensitivity module simply calculates elementary effects for every site. Previous work has shown that a selection in the order of 100 samples should be sufficient to avoid convergence problems [3], and indeed no significant difference in the statistical properties of the output distribution were found in additional tests where the number of samples were varied.

Table 3
Range of cumulative ΔLCOE from summing effects of individual cost categories.

Technology	Minimum [%]	Mean [%]	Maximum [%]
Fixed	−22.0	−33.1	−56.1
Floating	−22.1	−37.2	−67.6

3. Results

The modified Morris method described in the previous section was used to evaluate the range of LCOE impacts attributed to technological innovations across U.S. sites. First, the impact of the anticipated short term cost reductions listed in Table 1 on LCOE was computed using Eq. 3. These yield a geospatially resolved range of LCOE impacts from the prescribed perturbation of each cost category and are described in Section 3.1. Second, the perturbation prescribed to each cost category was held constant at $\delta = 10\%$. This approach allows for a ranking of the relative sensitivity impact of each cost category on LCOE. Results from this second approach are discussed in Section 3.2. The paper concludes with an illustration of how the estimated LCOE impact can vary depending on whether the assessment is based on an individual reference site or multiple sites with varying spatial conditions in Section 3.3.

The results are presented as box-and-whisker plots centered at the median elementary effect value for each independent variable. The variance in elementary effects over the design space is conveyed by quartile boxes and the corresponding whiskers that encompass the remainder of the distribution. Outlier points are shown as diamonds outside the edge of the whiskers. For each test case, a relevance threshold for the median value of $\Delta \mathrm{LCOE_i}$ is specified and input variables that produce changes in LCOE less than this value are not plotted.

Each independent variable is perturbed by the values provided in Table 1 or Table 2. The sign of the perturbation is in the direction that will produce a reduction in LCOE; for example, CapEx categories are perturbed by a negative δ_i, whereas net capacity factor is perturbed by positive δ_i. As a result, the values of ΔLCOE are negative and represent the potential reduction in cost attributed to changes in an input variable. These results inherently depend on the underlying cost structure within ORCA (e.g., how individual cost line items are assigned to top-level items). LCOE sensitivities are reported for fixed-bottom and floating substructure designs as the differences between subsets of these categories (monopiles/jackets and semisubmersibles/spars) are small relative to the broader topologies.

3.1. Spatial impact of cost and financial innovations

ΔLCOE was calculated for all potential sites in major U.S. coastal areas for fixed and floating substructures and is shown in Fig. 3. It is apparent that a range of ΔLCOE values exist for each cost category. This indicates that different sensitivities to a given cost reduction exist for each site considered in the design space; for instance, the 10.8% increase in net capacity factor (*NCF*) suggested by [26] for a fixed-bottom project will introduce a reduction in LCOE between 6% and 20% depending on the site at which it is implemented. This represents a significant range of spatially-dependent outcomes attributed to a uniform technological

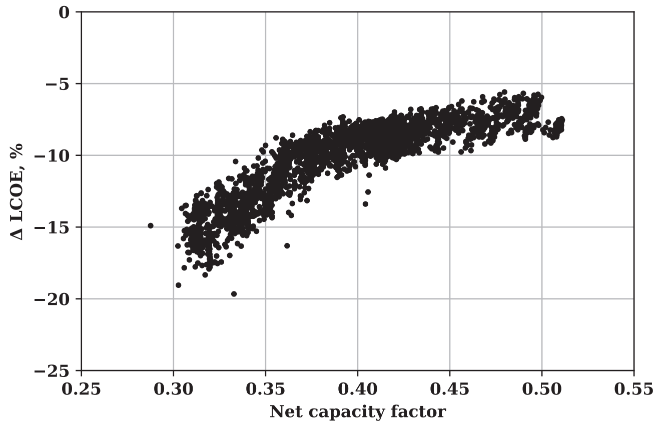


Fig. 4. Spatial variability in LCOE compared with net capacity factor for fixed-bottom substructures at all sites in the United States.

innovation. While *NCF* exhibits the largest ranges, variances exist for all reported cost categories in both fixed-bottom and floating technologies. Consequently, providing a single value for the cost reduction potential of a given technology innovation may be misleading because its impact will vary for geospatially diverse projects. The cumulative impact of this variance can drastically impact future cost predictions, as reported in Table 3. Summing the minimum and maximum ranges of the bounds plotted in Fig. 3 leads to ΔLCOE ranges between −22% and −56.1% for fixed-bottom technologies and −22.1% and −67.7% for floating.

The range of LCOE outcomes impacted by a given improvement in *NCF* is considered in more detail by plotting the ΔLCOE of each fixed-bottom site in the United States against its net capacity factor in Fig. 4. As *NCF* appears in the denominator of Eq. 1, perturbations to this term have a diminishing effect for larger baseline magnitudes. This is evident in Fig. 4, in which the sites with higher capacity factors experience smaller reductions in LCOE than lower capacity factor sites for the same 10.8% increase in *NCF*. In effect, there is more advantage to be gained by implementing technological innovations at sites with low

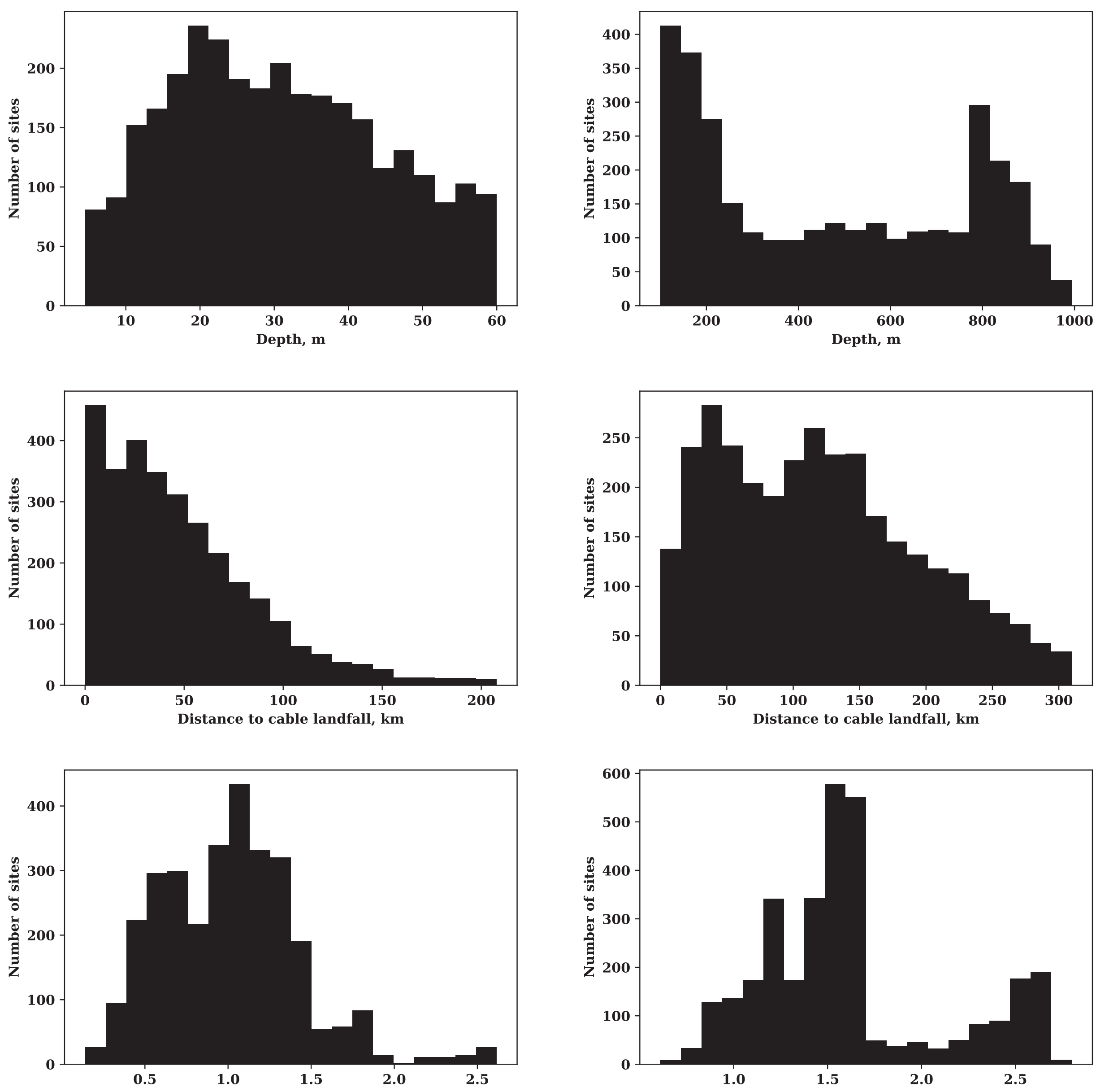
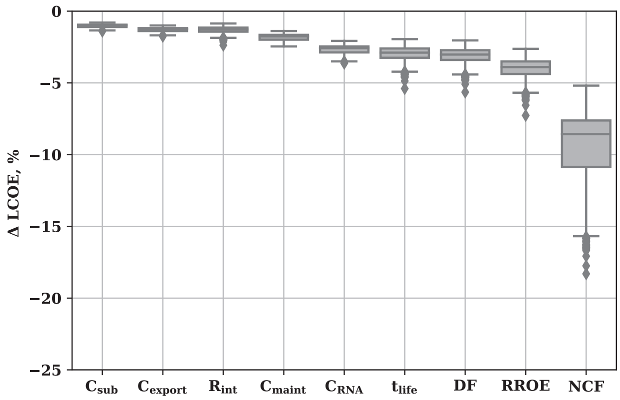


Fig. 5. Distributions of key spatial parameters for fixed-bottom sites (left) and floating sites (right) in the U.S.



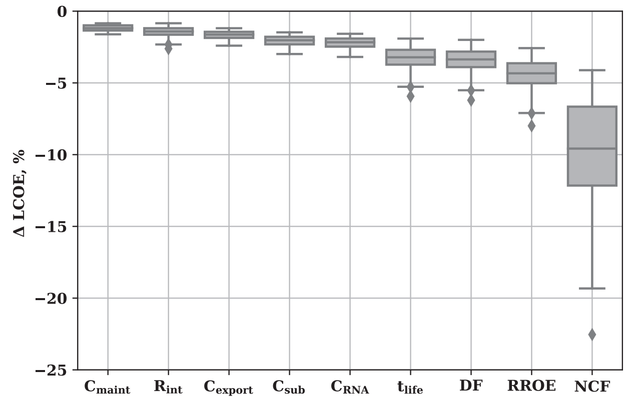


Fig. 6. Sensitivities of LCOE to cost and financial categories using constant perturbations of $\delta = 10\%$ for fixed-bottom (left) and floating (right) substructures in the United States. Input variables that produce ΔLCOE < 1% are not shown. The average LCOE for fixed-bottom and floating substructures across all U.S. sites considered is \$152/MWh and \$191/MWh, respectively.

capacity factors; however, the higher variance observed at these sites indicates that these innovations will have a broader range of potential impacts than they would at higher capacity sites. Research and funding agencies can use these results to target their efforts. Cost categories with lower variance may be of more interest to institutions with a regional or national focus, as similar LCOE outcomes may be expected for a realized cost reduction, whereas categories with broader ranges may be of more interest to local entities near sites associated with the higher cost reduction potential.

The variance in the ΔLCOE elementary effects is attributed to the nonlinearity in the underlying parametric equations in ORCA and the interactive effects between input variables [18]. These equations, which are listed in the Appendix, are primarily dependent on the geospatial parameters of each site; the key parameters of water depth, distance to cable landfall, and significant wave height are plotted in Fig. 5 for fixed-bottom and floating technologies. The distributions differ as fixed-bottom solutions are assigned to water depths below 60 m whereas floating technology is selected for greater depths. The different distributions mean that the inputs to the parametric cost equations in ORCA are weighted towards different regions of the nonlinear relationship; for instance, fixed-bottom sites are skewed towards shorter distances to cable landfall, whereas floating sites show multiple peaks with a relatively large tail. These differences impact the export cable cost equation which only depends on distance to cable landfall, with the floating sites more heavily populating the higher distance regions. This subsequently leads to greater variance in export cable costs for floating technologies than fixed-bottom technologies in the U.S., as seen in Fig. 3. This trend is consistent for the reported CapEx categories, indicating that technological innovations will have a wider range of impacts for floating sites due to differences in the distribution of spatial parameters relative to fixed-bottom sites.

3.2. Relative sensitivity of LCOE to key cost categories

While the results presented in Fig. 3 provide insights into the range of impacts that a particular technological innovation may have on the costs of offshore wind, they are not appropriate for ranking the importance of different cost categories as each input is perturbed by a different δ_i. A more common approach in the sensitivity analysis literature is to perturb each category by the same relative amount, which permits a direct comparison of the resulting sensitivity of LCOE [18]. Again using Eq. 3 to compute ΔLCOE, but now using a constant perturbation of $\delta = 10\%$, the relative significance of the different input parameters can be ranked. The corresponding magnitudes of the LCOE sensitivities are effectively a proxy for the impact of R&D investment. The results, plotted in Fig. 6, are similar for fixed-bottom and floating systems. Both are primarily impacted by technological innovations in net capacity factor, followed by the rate of return on equity (*RROE*), debt fraction (*DF*), the capital payback period (t_{life}), and the capital costs of the rotor-nacelle assembly. OpEx maintenance costs and the capital costs of the substructure and export cables are also seen to produce significant sensitivities in LCOE, although the relative importance of these parameters varies between fixed-bottom and floating systems.

Table 4
Average site characteristics for sample Atlantic offshore wind lease areas.

BOEM lease area	Project name	Capacity factor	Depth, m	Wave height, m	Distance to landfall, km
OCS-A 0519	Skipjack	0.56	22.6	1.2	33.9
OCS-A 0522	Liberty Wind	0.61	41.1	1.6	102.6

It is also notable that the financial parameters have a larger impact on LCOE than the most significant capital cost categories for both fixed and floating technologies. While much of the research into cost reduction potential of offshore wind energy focuses on technological innovations, it is important to note that the development of the offshore wind industry in Europe has led to increasingly favorable financial structures because lenders are willing to fund projects through nonrecourse debt and with debt-to-equity ratios of at least 70:30 [2,7]. Although initial investments in offshore wind projects in the United States may be viewed as riskier than the more mature European industry, project financing in the domestic industry may develop in parallel with technological innovation.

3.3. Impact of technological innovations at active U.S. lease areas

A common practice in the offshore wind cost modeling literature is to calculate LCOE magnitudes or sensitivities at a representative wind plant site; however, as geospatial characteristics can vary significantly between sites, the conclusions drawn from these studies may not be equally applicable for a range of neighboring locations. In order to evaluate this, LCOE sensitivities calculated for fixed-bottom substructures at the 2,058 permissible sites in the Atlantic are compared with sensitivities calculated at two specific locations corresponding to active U.S. offshore wind lease areas in the same region. ORCA input files were developed based on the average geospatial characteristics for each site, which are listed in Table 4. Although a larger number of parameters are required to run ORCA, the LCOE calculation is most sensitive to the values in Table 4. These values are averaged over the lease areas as described in [1].

As a set of at least 100 points is required to compute elementary effects for each input variable, a uniform, random distribution of 100

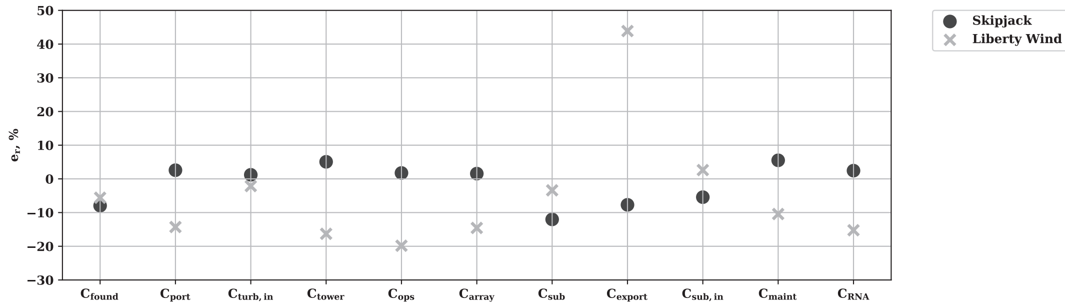


Fig. 7. Percent variation in ΔLCOE for individual lease areas relative to the aggregated Atlantic region.

input conditions was created using a Latin Hypercube (LHC) sampling method within a range of ±25% of the site-specific values listed in Table 4. Each of the artificially generated data points in each cost category is then perturbed by the appropriate δ_i values from Table 1. The relative error, e_r, of the average ΔLCOE for each cost category at an individual site relative to the aggregated regional sensitivity from all Atlantic sites was calculated using Eq. 4.

$$e_r = \frac{\overline{\Delta LCOE_{\text{site}}} - \overline{\Delta LCOE_{\text{region}}}}{\overline{\Delta LCOE_{\text{region}}}}. \tag{4}$$

The relative error describes the accuracy with which an individual site represents LCOE sensitivities over an entire region. As e_r approaches zero, the degree to which an individual site adequately represents an LCOE sensitivity for a given cost category increases. The relative error between individual sites and the regional average for cost category sensitivities is plotted in Fig. 7.

Considering the impact of the CapEx innovations from Table 1 at the individual sites described in Table 4 reinforces the key takeaway from the spatial results presented in the previous sections: a constant cost reduction associated with innovations in a specific CapEx category can produce significantly different decreases in LCOE at different sites. This is particularly evident in the ΔLCOE values attributed to a change in export cable cost computed for the Skipjack and Liberty Wind lease areas; the former is slightly less sensitive to cable innovations than the overall Atlantic region, whereas the latter is nearly 50% more sensitive. It is also worth noting that the relative errors are not consistently positive or negative for either site, indicating that analysis of a representative site would alternately over predict and under predict cost sensitivities in different categories for specific sites in the region. This reinforces the importance of considering the spatial variability of LCOE when reporting the cost sensitivities of a representative offshore wind site.

4. Conclusions

This analysis utilized a modified version of the Morris factor screening method to evaluate the spatial variation of offshore wind LCOE to changes in constituent cost categories and financial parameters over a broad range of sites in the United States. Perturbing the baseline input parameters with a single value resulted in a broad range of LCOE outcomes due to the interactive and nonlinear relationships between the underlying cost equations and the geospatial characteristics of each site. By using customized perturbation magnitudes that correspond to anticipated short-term reductions in each category, the resulting variance in LCOE demonstrates that a given technological or financial innovation can have a range of outcomes on project cost. This differs from existing sensitivity studies in the offshore wind literature, which typically report a single change in LCOE for a given perturbation. Furthermore, the magnitude of the LCOE variance was seen to be significant; for example, a 10% improvement in net capacity factor resulted in decreases in LCOE between 6% and 20% for the range of sites considered. The LCOE of both fixed-bottom and floating offshore wind projects was also seen to be particularly sensitive to financial parameters such as the rate of return on equity, the debt fraction, and the project payback period as well as the capital costs of the rotor-nacelle assembly. The cumulative variances of these key cost and financial categories indicate that the prescribed set of component level cost reductions could produce a range of LCOE decreases of between 22% and 56% from the baseline cost of $152/MWh for all potential fixed-bottom projects in the United States. Similarly, the baseline value of $192/MWh for floating projects could be reduced by between 22.1% and 67.6% at different sites if all cost reduction trajectories are fully realized. While the upper bounds of these LCOE decreases are site specific and can not be universally applied, they provide an indication of the high potential for significant cost reduction that can be obtained through innovation in a myriad of different cost categories.

These results illustrate the importance of considering the spatial variation of LCOE caused by component cost reductions. Costs of offshore wind energy remain high at this nascent stage of the United States industry and the impact of technological innovations is a critical factor for project developers striving to deliver competitively priced offshore wind energy. In this environment, the realization of even small reductions in LCOE can define the success or failure of a project. The results in this paper show that an innovation-induced reduction in component costs will not have a singular impact on costs, but instead will produce a range of values depending on the location of the project; future work will build upon these results to better understand the spatial dependency of LCOE sensitivity and where specific technological innovations can have the greatest impact. For developers estimating the value of a potential lease area years before the financial investment decision is made, it is important to understand the range of cost impacts that anticipated technology innovations can have at different sites. Government policy makers can prioritize research and development funding based on the spectrum of outcomes for a proposed technological innovation and whether these impacts will be consistent over a broad range of sites or will vary significantly depending on where they are implemented. These considerations are important to help advance the deployment of offshore wind in the United States.

CRediT authorship contribution statement

Matt Shields: Conceptualization, Methodology, Software, Formal analysis, Writing 2%80%93 original draft, Writing - review & editing, Visualization. **Philipp Beiter:** Conceptualization, Methodology, Formal analysis, Writing - original draft, Writing - review & editing, Funding acquisition. **William Kleiber:** Methodology, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was authored [in part] by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U. S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by the U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Wind Energy Technologies Office. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

Appendix A. ORCA cost equations

The levelized cost of energy, reprinted in Eq. A1 for convenience, comprises parametric equations for the individual cost categories listed in Table 1. These equations are provided in this appendix for reference; furthermore, the aggregation of various capital expenditures into the balance-of-system is also provided. The capital costs of the turbine, C_{turbine}, are provided as an input value based on current market trends.

$$LCOE = \frac{FCR(C_{\text{turbine}} + C_{\text{BOS}}) + C_{\text{ops}} + C_{\text{maint}}}{NCF \times 8760}, \tag{A1}$$

In ORCA, equations are defined for several substructure types and turbine ratings; for illustration, the equations are only shown for jackets and semi-submersible substructures using a 10-MW turbine rating (see [1] for the equations for monopiles, semi-submersible, and spar substructures, as well as turbine ratings other than 10 MW). The equations are derived from multi-dimensional curve fits of bottom-up empirical and modeled data, which results in lengthy and nonlinear parametric relationships [15,1]. The values of several coefficients are not provided in order to protect the proprietary data used to develop the equations.

A.1. Common variables

Variables commonly used in the following equations are provided in Table A1.

A.2. Rotor nacelle assembly

The total turbine capital cost used in Eq. A1 is a user input in ORCA; the cost of the rotor nacelle assembly, which includes the blades, generator, and hub, is derived from the overall turbine capital cost as shown in Eq. A2. The cost of the tower comprises the remainder of C_{turbine}.

$$C_{RNA} = 0.86 C_{\text{turbine}} \left(0.00044\text{e} - 4P_r^2 + 0.0445P_r + 0.7174\right). \tag{A2}$$

A.3. Substructure and Foundation

The support structure capital costs are split into the foundation and substructure, both of which have fabrication and installation elements. The fabrication relationships are provided in Eqs. (A3)–(A6) and the installation equations are given Eq. A7 and Eq. A8.

$$C_{\text{Substructure,Jacket}} = \left(e^{\left(3.7136+0.00176P_r^{2.5}+0.645\log D\right)C_{\text{Latticecost}}}\right) \times \left(-0.0131 + \frac{.0381}{\log P_r} - (2.3\text{e}-9)D^3\right)^{-1} C_{\text{Transitionpiece}} + C_{\text{Outfitting}}, \tag{A3}$$

where $C_{\text{Latticecost}}, C_{\text{Transitionpiece}}$, and $C_{\text{Outfitting}}$ are empirically derived cost factors for the jacket lattice, transition piece, and outfitting expenses.

$$C_{\text{Substructure,Semi}} = \left(a_1P_r^2 + a_2P_r + a_3\right)C_{\text{Stiffenedcolumn}} + (a_4\log P_r + a_5)C_{\text{Truss}} + \left(a_6P_r^2 + a_7P_r + a_8\right)C_{\text{Heaveplate}} + \left(a_9P_r^2 + a_{10}P_r + a_{11}\right)C_{\text{Outfitting}}, \tag{A4}$$

where $C_{\text{Stiffenedcolumn}}, C_{\text{Truss}}, C_{\text{Heaveplate}}$, $C_{\text{Outfitting}}$, and a_1 - a_{11} are empirically derived cost factors for the semisubmersible stiffened column, truss structure and heave plate.

Table A1
Common variables in ORCA parametric equations.

ORCA input	Symbol
Water depth, m	D
Significant wave height, m	H_s
Site to cable landfall distance, km	d_{S_L}
Number of turbines	n
Turbine rating	P_r
Site to construction port distance, km	d_{P_S}
Site to operations port distance, km	d_{OP_S}

$$C_{\text{Foundation,Jacket}} = 8C_{\text{Pilecost}}\left(e^{3.7136+0.00176P_r^2.5+0.645\log D}\right)^{0.5574}, \tag{A5}$$

where C_{Pilecost} is an empirically derived cost factor for the jacket piles.

$$C_{\text{Foundation,Semi}} = 3\left(b_1D^2\right) + b_2D + b_3\right)\left(b_4P_r + b_5\right), \tag{A6}$$

where b_1 - b_5 are empirically derived constants for the semisubmersible foundations.

$$C_{\text{Installation,Jacket}} = (1.3\text{e}8) \quad -2490356D + 174980.65d_{P\_S} + 80518.69D^2 + (7.3\text{e}-8)d_{P\_S}^2 - 4226.92D \times d_{P\_S} - 514.33D^3 - (6.4\text{e}-11)d_{P\_S}^3 - (4.5\text{e}-10)D \times d_{P\_S}^2 + 49.24D^2 d_{P\_S}. \tag{A7}$$

$$C_{\text{Installation,Semi}} = c_1 + c_2 \times D + c_3 d_{P\_S}, \tag{A8}$$

where c_1, c_2, and c_3 are empirically derived constants for the installation of the semisubmersible

A.4. Array and export cables

The cost of array cables is provided in Eq. A9 for fixed-bottom projects and Eq. A10 for floating projects.

$$C_{\text{Array,Jacket}} = \left(d_1 D^2 + d_2 D + d_3\right)\left(1 + \frac{n - 100}{300}\right), \tag{A9}$$

$$C_{\text{Array,Semi}} = \left(e_1 D^2 + e_2 D + e_3\right)\left(1 + \frac{n - 100}{300}\right), \tag{A10}$$

where d_1 - d_3 and e_1 - e_3 are empirically derived constants for the array cable costs.The cost of the export system (including the offshore substation and connection to the onshore grid) is provided in Eq. A11 for fixed-bottom projects and Eq. A12 for floating projects.

$$C_{\text{Export,Jacket}} = \left(f_1 d_{S\_L}^5 - f_2 d_{S\_L}^4 + f_3 d_{S\_L}^3 - f_4 d_{S\_L}^2 + f_5 d_{S\_L} + f_6\right), \tag{A11}$$

$$C_{\text{Export,Jacket}} = \left(g_1 d_{S\_L}^5 - g_2 d_{S\_L}^4 + g_3 d_{S\_L}^3 - g_4 d_{S\_L}^2 + g_5 d_{S\_L} + g_6\right), \tag{A12}$$

where f_1 - f_6 and g_1 - g_6 are empirically derived constants for the export cable costs.

A.5. Turbine installation

The cost of installing the turbine are given in Eq. A13,

$$C_{\text{Installation}} = 57108119 + 1166745.7D - 58333.39D^2 + 1217.1D^3 - 10.57D^4 + 0.03233D^5 + 24986.8d_{P\_S}, \tag{A13}$$

A.6. Maintenance

The maintenance costs incurred during the lifetime of the wind plant are provided in Eq. A14,

$$C_{\text{maint}} = 4.3079\log d_{OP\_S} + 2.1306H_s^2 + 7.3227H_s + 31.314. \tag{A14}$$

A.7. Net capacity factor

The net capacity factor of the wind plant is found using Eq. A15,

$$NCF = GCF(0.006 \times P_r + 0.9691)(1 - L), \tag{A15}$$

where GCF is the gross capacity factor and L represents the total losses from wakes, electrical, environmental, and technical sources. These terms are inputs to ORCA obtained from external tools, as described in Section 2.1.

A.8. Fixed charge rate

The fixed charge rate is a scaling factor for the capital costs of the project which aggregates relevant financial parameters; it represents the annual return which must be met to cover carrying charges on the initial capital investment. It is defined in Eq. A15,

$$FCR = \left(\frac{WACC - 1}{1 - WACC^{-t}}\right)(\text{ProFinFactor}), \tag{A16}$$

where t is the length of time for paying off assets, ProFinFactor is a financial multiplier to account for any applicable differences in depreciation schedule and tax policies, and $WACC$ is the weighted average cost of capital. WACC is defined by Eq. A17,

$$WACC = \frac{1 + ((1 - DF)((1 + RROE)(i + 1) - 1) + (DF((1 + IR)(i + 1) - 1)(1 - TR)))}{i + 1}, \tag{A17}$$

where DF is the debt fraction, $RROE$ is the rate of return on equity, i is the inflation rate, IR is the interest rate, and TR is the corporate tax rate.

A.9. Development

Project development costs, including site and resource studies, socioeconomic and environmental evaluations, and permitting, are found using Eq. A18,

$$C_{\text{Development}} = 0.04 \times \left(C_{\text{turbine}} + C_{\text{Substructure}} + C_{\text{Foundation}} + C_{\text{Array}} + C_{\text{Export}} + C_{\text{Installation}} + C_{\text{Installation,substructure}}\right). \tag{A18}$$

A.10. Balance of system

The aggregated balance of system costs are the sum of project development, management, lease costs, and capital expenditures; this summation appears in Eq. 1.

$$C_{\text{BOS}} = C_{\text{Development}} + C_{\text{Lease}} + C_{\text{Management}} + C_{\text{Substructure}} + C_{\text{Foundation}} + C_{\text{Array}} + C_{\text{Export}}, \tag{A19}$$

where C_{Lease} is the lease price paid to secure site control and $C_{\text{Management}}$ is the cost associated with project management.

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