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Reliability-based design optimization in offshore renewable energy systems

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ABSTRACT

Offshore wind farm operations and maintenance costs currently total 6 m€/year, or 25–28% of total costs. For wave and tidal energy converters, this cost is projected to be twice that of offshore wind, but has high levels of uncertainty. As the wave and tidal energy industries mature, decreasing O&M costs through reliability-based design optimization is critical to increasing feasibility and competitiveness with other energy technologies. In this paper, we will synthesize existing information on reliability-based optimization in systems analogous to offshore renewable energy systems. We will conclude by highlighting opportunities for future work in this field.

1. Introduction

Offshore renewable energy (ORE) has the potential to be a significant source of future global electricity production, reduce carbon emissions, decrease dependence on energy importation, and stimulate economic growth in coastal and remote areas [1,2]. Available offshore wind, wave, and tidal energy on the US Pacific coast alone is estimated at 8750 million megawatt-hours (MWh) per year, equal to 800 million US households [3–5]. This energy availability, paired with growing population centers along coastlines [6] positions offshore wind, wave, and tidal energy conversion technologies as a viable way of making power in coastal areas. The key to making this technology feasible is providing electricity through reliable technology and at competitive prices.

Currently, offshore wind energy technology has reached commercial-scale installation in Europe, and the cost of energy associated with these systems continues to decrease, but it is still not cost competitive with other renewable energy technologies like solar photovoltaic systems. Tidal and wave energy technologies are even less mature, with less than 1000 MW of installed tidal energy capacity, and no commercial wave energy installations. Both tidal and wave energy are not yet market competitive.

One way to reduce the cost of ORE technologies is through the increased reliability of ORE systems [7–9]. Improving reliability of ORE technologies will enable devices to produce electricity during energy-dense sea-states, lengthen operational life, decrease costly operations and maintenance (O&M), and decrease financial risk premiums. Given that the ORE industry is still in an early development stage, there is an opportunity to use reliability-based design optimization (RBDO) techniques to achieve cost reductions and improve market feasibility. Using RBDO to consider reliability, cost, and performance during subcomponent, device, and system design stages will enable the exploration of optimal solutions, which is of particular interest to the wave and tidal energy industry as they seek technology design convergence.

In this paper, we will describe the current state of the ORE industry, as well as work that includes reliability information in research of ORE systems, with particular emphasis on RBDO techniques. Section 2 discusses fundamental concepts of offshore wind, wave, and tidal energy technologies. Section 3 describes how reliability is used by the ORE industry in the context of each industry. A literature review cataloging the uses of RBDO in ORE comprises Section 4. Lastly, we will synthesize research needs and opportunities within this field in Section 5.

2. What is offshore renewable energy (ORE)?

In this report, *ORE technology* refers to the most mature technologies that have achieved, or are closest to, commercial realization: offshore wind, wave, and tidal energy technologies. Less mature technologies (e.g., ocean thermal energy conversion) are not discussed. The most common offshore wind, wave, and tidal energy device types are briefly explained here. For further information about these concepts, refer to Aquaret [10].

Offshore wind turbines are classified by their turbine orientation (horizontal or vertical axis) and their foundation (fixed or floating). Just like their onshore counterparts, the blades rotate as they interact with oncoming wind: the more consistent the airstream, the more consistent the power output of the turbine. Wind is created by atmospheric pressure differences, which can make this resource variable. Deploying offshore turbines takes advantage of long fetch lengths, resulting in higher speed and more consistent winds compared to land-

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based sites. The most mature technology in the ORE industry is fixed-bottom offshore wind energy technology. Floating offshore wind energy technology is in early-stage development and deployment, with the first grid-connected test installation, Hywind (Scotland), beginning production in October 2017.

Tidal energy technologies primarily consist of barrages or in-stream turbines. The first commercial tidal barrages were installed in the 1960s with the La Rance (France) and Jangxia Creek (China) projects [11]. In-stream turbines account for 76% of research and development efforts, and are focused on horizontal-axis turbines [12]. MeyGen (Scotland) is the first commercial installation of tidal turbines, completing the first stage of construction in April 2018 [13]. Tidal barrages, like run-of-river dams, use the potential energy contained in the difference in hydraulic head between high and low tides to spin turbines in an impoundment. Tidal turbines use the kinetic energy of water moving past an axial or cross-flow turbine as the tide ebbs and flows. Requiring large tidal ranges and flow velocities, tidal energy technologies are often limited by site availability. However, tidal cycles are more consistent than waves or wind, making tidal energy more consistent and predictable than wind or wave energy. First generation tidal devices were mainly bottom-mounted devices, while more recent concepts utilize the middle and upper water column where tidal resource is greatest [12]. This shift has ramifications for the survivability and reliability of devices.

Wave energy converters (WECs) are devices that convert the energy of ocean waves into electricity. WECs are commonly categorized by their location (on-, near-, or off-shore) or mode of operation. Onshore devices have greater accessibility and incur lower O&M costs, but have less available energy to convert. Nearshore devices generally rest on the seafloor in water depths of 10–30 m, thus they require little mooring, and see more exploitable energy than their onshore counterparts. Offshore devices are in water depths greater than 30 m and are typically moored, floating structures. They incur larger O&M costs, are less accessible, and are subject to higher wave regimes than their on- or near-shore counterparts. Devices that are subjected to higher wave regimes see increased gross available energy for conversion, but are also more likely to incur greater damage (both over time due to consistently larger forces, and during extreme events). A number of device types are currently being tested to harness wave energy, including oscillating water columns, overtopping devices, point absorbers, submerged pressure differentials, oscillating surge, bulge wave, vertical axis pendulum, and others.

3. Reliability in ORE

While all three ORE technologies have potential to function successfully in the renewable energy sector, developers need to deliver reliable, efficient technologies that can survive their harsh environment to be economically profitable. This section describes how reliability currently shapes each ORE technology. Due to differences in maturity, offshore wind energy technology has been separated from wave and tidal energy technologies.

3.1. Offshore wind energy

While fixed-bottom offshore wind energy technology has extensive operational experience and is a mature technology, floating offshore wind energy technology is still in early stages of development. Significant research efforts are currently being made to accurately simulate floating offshore wind turbines as well as deploy small-scale demonstration devices. These efforts will result in the ability for researchers to analyze reliability in offshore wind turbines based on simulations, and the ability to leverage data from demonstration installments to better assess reliability in these floating systems. Due to the difference in maturity of fixed-bottom and floating offshore wind turbine technology, the rest of this subsection focuses on fixed-bottom offshore wind energy technology.

Fixed-bottom offshore wind energy technology has benefited from the experience of the onshore wind energy industry, and has reached widespread commercialization in Europe. Although the first site was installed in 1991 in Vindeby, only recently have markets emerged in the United States, East Asia, and India (just as the first European offshore wind turbines are reaching the end of their operational lifespan). In 2016, fixed-bottom offshore wind prices for proposed installations dropped significantly, with developers promising to provide power from facilities at 54.50 €/MWh in The Netherlands, and at 49.90 €/MWh [14] in Denmark. By 2026, the Dutch government expects that its offshore auctions will not require subsidies [15], and in an April 2017 German auction, tenders won at the wholesale electricity price, meaning the wind farms would be supported entirely by market prices, with no subsidy or government support required [16,17].

Europe provides considerable economic and regulatory support for offshore wind, and currently owns 88% of global offshore wind developments [18]. As a result, Europe now has a maturing supply chain, high level of expertise, and strong market competition. Growing investor confidence, decreasing financing risk premiums, and technology improvements further support industry growth. Technology advancements include larger, more reliable turbines; turbine size has increased from 3–4 MW to 8–10 MW, with 13–15 MW models likely to be available by 2024 [19]. Increases in expected operational life of turbines have also been made possible by technology advances, causing the average expected life to increase from 15 years (in 1991) to 30 years [19], with possibilities of life extension (continued operation of old equipment past its expected operational lifespan) and repowering (replacing old equipment for newer equipment with greater efficiency or nameplate capacity).

Despite these encouraging statistics that characterize the current state of the industry, fixed-bottom offshore wind performance and reliability need to improve to become cost competitive with other renewable energy technologies. The levelized cost of energy (LCOE is a metric that incorporates lifetime costs and expected production) for an offshore wind site in 2016 was estimated at 120–130 €/MWh [19], which is 40% more than onshore wind in comparable regions, 20% more than solar photovoltaic cells, and 100% more than that of conventional sources such as coal and gas [20]. Furthermore, expected lives of fixed-bottom offshore wind turbines are proving to be overestimates in some cases. A study looking at the performance of 30 offshore wind installations in Denmark reported an average load factor reduction of 24% in the first 10 years of operation [21] (load factor being defined as the total power output over the maximum possible power output for a given length of time, normalized for wind availability). These results have implications for shorter operational life expectancy for offshore turbines and decreased estimates of lifetime power production.

While decreased performance over time is expected, fixed-bottom offshore wind turbine failures are especially costly. At Horns Rev 1 for instance, two turbines failed and will remain non-operational for the last 10 years of the wind farm life due to the high expense of repair [22,23]. Short weather windows for repairs, limited trained personnel and vessels, and profit loss from lack of production during downtime compound the cost of failure. Developing offshore areas allows for exploitation of greater resource, but potentially increases failure likelihood and decreases accessibility. First, consistently stronger winds increase probability of failure, as turbines are exposed to higher wind and wave loads, both in nominal and extreme conditions. Secondly, accessing equipment that requires repair or maintenance is more difficult by helicopter or boat in areas further offshore, given that wind speed and wave height are strongly correlated.

Failure likelihood and accessibility directly impact availability, or the portion of time the installation is capable of producing electricity. Availability at offshore wind farms is typically between 90% and 95% [24,25], but is sensitive to the location of the farm (distance from shore, depth of water, and metocean conditions at the site). Downtime in areas with larger resource results in a higher loss of energy production, per unit time [26]. This has ramifications for cost, since 25–30% of total project costs is spent on O&M [27–29]. This impact is expected to be higher for floating turbines, in which platform motions may reduce accessibility and increase failure rates further their than fixed-bottom counterparts [30].

Uncertainty is inherent in a system's ability to function under specified operation, and costly if not quantified and accounted for appropriately in design. In the case of Anholt Wind Farm, the Danish Parliament required an accelerated preparation time, which resulted in only one bidder (DONG Energy, now Ørsted) who claimed the preparation time was too short to reduce design uncertainties. Thus, Ørsted added a significant mark-up to the bid, resulting in Anholt being 32% more expensive than Horns Rev 3 (a wind farm tendered at the same time, but with a longer preparation period). This markup cost rate payers about 2.2 billion DKK (about 300 m€ or $340 m) over the life of the wind farm [29].

3.2. Wave and tidal energy

Reliability is challenging to assess in nascent systems such as wave and tidal energy systems. The first two reliability studies for WECs were completed in the 1970s and 1980s. These studies obtained failure rates from generic subsystems and components, and incorporated environmental and operational uncertainty by multiplying failure rates by safety factors of 15–30 [31]. One study assumed installations capable of generating 2000–3000 MW (for contrast, the largest offshore wind farm to date, the London Array, is 630 MW) [31]. Each array's availability was estimated using a Monte Carlo simulation, and ranged from 16.2% to 96.1%. Both studies used simple random failure rate modeling, with no consideration of common failures modes or mechanisms, or potential cascading failures [31]. This use of large safety factors, and large ranges for potential energy generation and availability reflects uncertainty associated with the performance of these WECs. Lack of performance and reliability data challenges engineers when designing unproven technologies.

Since these studies, reliability analysis and uncertainty quantification has progressed, but their application still faces challenges. In the wave and tidal energy industries, techno-economic analyses are used to evaluate device feasibility and attract investments. Unlike the offshore wind energy industry, the wave and tidal energy industries have little experience on which to base device design or industry standards, as both are in demonstration project phases.

To further complicate device assessment, there is considerable diversity in both wave and tidal energy technologies. Costly reliability analyses are unique to each device and subcomponent, limiting the amount of testing that has been performed on devices. While the offshore wind energy industry reached design convergence and optimized that design to meet reliability standards, the wave and tidal energy industries currently must optimize each device concept for an untested reliability standard. Lack of design consensus and standards increases the risk of not engaging sufficiently with potential manufacturers and subcomponent suppliers to create and stimulate supply chain formation [12]. Transitioning from custom-made to uniform, off-the-shelf components will increase device and subcomponent quality consistency, decrease cost, and decrease the variability of failures due to low-volume manufacturing.

Subcomponent and device testing in wave tanks and current flumes is critical to proving autonomous operation of single devices and small arrays. Along with serving as a necessary step in certification processes in wave and tidal energy, this testing will provide reliability data for academic and industry members, which can lead to validation of numerical models for device and component failure, and identification of high-risk components to be considered during design phases to limit failure and downtime.

Many of the tidal and wave energy concepts have yet to be tested in mild- or high-resource sea states, or areas in which there are strong waves, winds, and tides, for long periods. This testing will provide operations data, which is required to validate mechanical and structural performance, enhance control and monitoring systems, and develop array tools. Long-term demonstration of operability, reliability, and survivability of devices and pilot arrays in energetic sea-states or tidal streams is critical to addressing industry need for reliability data and standards, as well as information and feedback on installation, operations, and decommissioning costs and methodologies. Throughout their twenty-ear expected life, tidal and wave energy devices need to deliver efficient operability at sufficient reliability levels to compete commercially. Initial design target availability levels are 75–85%, and capacity factors of at least 25–30%, with expected improvements once initial targets have been achieved [12]. Before this open-water testing, a site assessment must be completed to characterize the temporal and spatial variation and uncertainty of the energy resource. This resource characterization allows the prediction of device performance and reliability, and enables spatial optimization of an array. For instance, with increasing wave activity, there is more wave energy available to convert, as well as higher loads on the device, incurring higher costs in operations and maintenance. Environmental conditions and location can be linked to cost in other ways; offshore developments experience higher gross wave energy resource, as well as increased mooring and anchoring costs. Further, devices interact with their environment and other devices, so that the layout of devices in an array affects power development of the site [32–36].

Researchers and developers have made efforts to overcome issues with the application of reliability analysis and uncertainty quantification to wave and tidal energy systems. For critical components, accelerated life testing [37,38] is appropriate if environmental and operating conditions can be simulated accurately. An accelerated life testing method has been developed and tested for marine power cables and mooring lines [39,40]. A factor approach—or multiplying a base failure rate by a series of independent factors that allow for changes from related standards [31]—can also be used. Where failure data is available, researchers have been able to validate Failure Mode and Effects Analysis specific to a device design [41].

In tidal device applications, there has been more research completed in reliability testing than in wave energy applications, mostly for horizontal axis turbine blade reliability and hydrodynamic loading. For instance, the influence of tip-speed ratio on blade-root fatigue was explored by Blackmore et al. [42], and hydrodynamic loads experienced by blades in random seas was analyzed by Guo et al. [43]. Lawrence et al. [44] investigated the effect of free stream turbulence on hydrodynamic performance, and concluded that their results could indicate accelerated fatigue under elevated free stream turbulence.

There have also been efforts to build industry-specific reliability databases and standards. The SuperGen database [45] collates published reliability and safety factor data. Since the start of SuperGen, DNV-GL and Carbon Trust have published guidelines for designing and operating WECs [46,47]. The European Marine Energy Centre published design [48] and reliability, maintainability, and survivability [49] guidelines to include wave and tidal energy devices, updating and expanding upon DNV-GL's. Codifying these guidelines, the International Electro-technical Commission Technical Committee 114 created a comprehensive set of standards for wave, tidal, and other wave current converters [50]. While these efforts in ORE reliability research have advanced the industry, there is an opportunity to accelerate progress through the use of RBDO.

4. RBDO in ORE

In design optimization, engineers use advanced computation to balance design objectives (e.g. minimizing cost, maximizing performance) to obtain optimal designs. Optimization is the process of

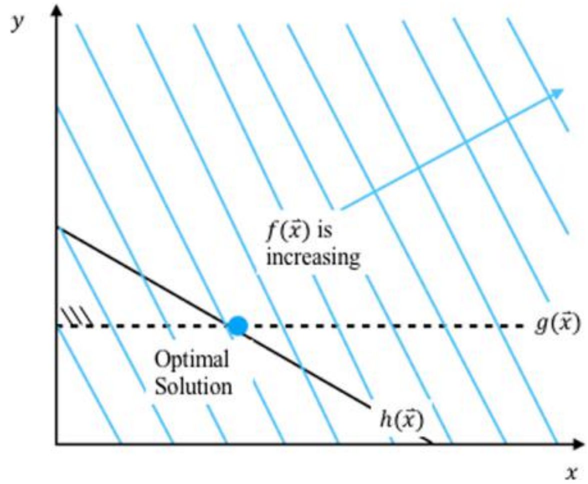

Fig. 1. Example optimization problem in 2D Space.

adjusting the inputs to or characteristics of a device or process to find the minimum or maximum output or result. Inputs consist of variables, while the means of evaluating a potential new design is referred to as the *cost*, *objective* or *fitness* function. The resulting output, then, is the cost or fitness. In this review, we refer to the optimization process of finding the minimum of an objective function, as illustrated in the standard optimization form presented in Eq. (1).

$$\begin{array}{ll} \underset{x}{\text{minimize}} & f(\vec{x}) \\ \text{subject to} & h(\vec{x}) = 0 \\ & g(\vec{x}) <= 0 \\ \text{where} & x_{min} < x < x_{max} \end{array} \tag{1}$$

In this form, the objective function, $f(\vec{x})$, is minimized with respect to the selection of the design variables $\vec{x}$, subject to the equality constraint, $h(\vec{x})$, and inequality constraint, $g(\vec{x})$. Here, equality constraints mean that the solution must lie on the equality constraint function, while the inequality constraint means that the optimal solution must be equal to or less than the inequality constraint function. For instance, in Fig. 1, the optimal solution must lie on the solid black line ($h(\vec{x})$), but on or to the upper right of the dashed line ($g(\vec{x})$). The objective function–the blue line–is dependent on the variables x and y.

At times, finding the optimal solution can be simple and performed visually, such as with the formulation shown in Fig. 1. The solution space, however, can quickly become complex when more variables are added and are inter-dependent, or the objective function is dynamic, nonlinear, or discontinuous. Searching the solution space (all possible function values) for the minimum objective evaluation can be complicated by the peaks, valleys, and ridges of the cost surface. Solution spaces can have many locally optimal solutions, and the best (global) minimum can be difficult to find.

An optimization algorithm is like a hiker trying to find the minimum altitude in a hilly wilderness. Starting at some random location within the park, the goal is to find the minimum altitude with the least stops for assessment as possible. There are many ways to find a minimum altitude from a single random point, however, there is no guarantee that an even lower point doesn't lie over the next ridge. Constraints influence the path of the search.

Optimization algorithms can include deterministic methods (or methods that do not include randomness) such as exhaustive search methods and analytical methods, but can also include methods such as stochastic algorithms and heuristic algorithms. An exhaustive search systematically samples the entire solution space at a sufficient resolution to ensure global optimality. Exhaustive searches also are computationally expensive, potentially rendering these approaches intractable. Analytical optimization methods find solutions at which the gradient of the cost function is equal to zero, and check to see if that extreme is a minimum. These methods work well, but only in simple solution spaces. They are efficient at finding local optima, but cannot guarantee finding global optima. Stochastic algorithms are algorithms that can ensure the globally optimal solution is found by sufficiently and randomly sampling the solution space. These algorithms can be more computationally efficient than an exhaustive search, and include methods such as the Monte Carlo method. Heuristic algorithms do not ensure global optimality, but instead intelligently sample the solution space to find the most optimal solution with the least number of function evaluations as possible. They include a level of randomness to allow them to search multiple optima, so they do not get stuck in a local optimum like analytical solutions, but they are not as thorough as a stochastic algorithm or an exhaustive search. They are used, therefore, when stochastic algorithms are too computationally expensive. Examples of heuristic methods include Evolutionary Algorithms, Ant Colony Optimization, or Simulated Annealing algorithms.

4.1. What is RBDO?

Reliability-based design optimization (RBDO) is characterized by two modifications to this definition of computational optimization. First, design objectives are optimized under reliability constraints, called limit state functions. Reliability constraints include, for example, a maximum likelihood of failure. Second, design variables can be represented by random variables. Instead of relying on a single value to define the variable, random variables are represented by a mean value and a coefficient of variation, so that each time the variable is called on by the function, a sampled value is given. This sampling allows uncertainty in the variables to be incorporated, such as variation in material strength.

This representation of design variables as random variables is particularly important in RBDO applications in ORE. In deterministic design optimization methods, optimal solutions are often found at the limits of design constraints, where even small uncertainties could influence the viability of optimal solutions. In ORE research, uncertainties are inherent to metocean conditions, data measurements, modeling, as well as device design and manufacturing. Not accounting for these uncertainties in design optimization can lead to inviable designs or higher probabilities of failure.

Unlike deterministic design optimization methods, RBDO integrates uncertainty into design optimization by prioritizing designs with a low chance of system failure. Although performance and reliability are often related in RBDO, there is a design trade-off between reliability and affordability, assuming system upgrades to ensure reliability are expensive. Uncertainty is generally characterized using probability theory, but more recent studies [51] have integrated quantification of different types of uncertainty, which may be more appropriate in representing uncertainty when stochastic information is not available.

RBDO has been used with success for fixed-bottom offshore wind turbines and WECs, but remains to be fully implemented in floating offshore wind turbines and tidal energy technology. In the following section, we will describe past research efforts to incorporate RBDO into 1) offshore wind, 2) wave, and 3) tidal energy systems.

4.2. RBDO applications in offshore wind energy

In fixed-bottom offshore wind energy systems, RBDO has been used to determine fatigue safety factors for design, schedule maintenance and inspections, and optimize structural design. In floating offshore wind energy systems, RBDO has yet to be explored.

4.2.1. Design safety factors in offshore wind energy

In structural design, the use of safety factors reflects uncertainty related to design parameters and reliability targets. When first designing offshore wind turbines, engineers used offshore oil and gas industry fatigue safety factors (or safety factors used with fatigue design and limit states), which were calibrated to high reliability levels to account for the potential to harm human life or the environment. Given that offshore wind turbines are less likely to cause human fatalities or environmental damage equivalent to those of manned offshore oil and gas installations, using offshore oil and gas fatigue safety factors led to the over-design and excessive cost of offshore wind turbines.

To address this issue, Marquez-Dominguez and Sørensen [52,53] calibrate fatigue design safety factors by defining limit state equations specifically for offshore wind turbines. The safety factors were calibrated for fatigue strength and load for three steel substructure cases: 1) wave-dominant loads, 2) wind-dominant loads for a single turbine, and 3) wind-dominant load conditions for a turbine in a wind farm. Strength and load were represented as random variables to incorporate their uncertainty. Both linear and bilinear damage accumulation were tested, as well as the impact of the inspection type on reliability levels.

Considering a no-inspection scenario, Marquez-Dominguez and Sørensen created limit-state equations based on both linear and bilinear crack growth assumptions for S-N curves, and Miner's Rule assumption of linear damage accumulation. Miner's Rule uses sequence-independent, linearized damage accumulation and assumes that fatigue failure occurs when the sum of the fatigue cycles across all stress ranges is equal to the cycles to failure.

Rainflow Counting (see [54] for details about Rainflow Counting) was used in conjunction with S-N curves to discretize the load time series into intervals, count the cycles within each interval, and plot the alternating stress magnitude against the number of cycles to failure. This then allows the modeling of the probability of failure over the operational life of the turbine. The S-N curves were then used to calibrate a fracture mechanics model, so that probability of failure could be represented via crack initiation and size. By using a fracture mechanics model, Marquez-Dominguez and Sørensen could use Probability of Detection curves to model the likelihood of crack detection based on the quality and type of inspection, and the crack size.

When including the effect of inspections on reliability levels, Marquez-Dominguez and Sørensen [52,53] again counted the number of stress cycles in grouped stress ranges by using Rainflow Counting. They then represented the intervals of the grouped stress cycles through stochastic matrices. Probabilities of failure were estimated using First-Order Reliability Methods (FORM), and verified via Monte Carlo Simulations. In FORM, the limit state function (or function that defines failure in a given system) is linearized and the reliability is estimated by modeling the uncertain parameters by either their mean, standard deviation, and correlation coefficient values, or by their joint distribution functions.

Marquez-Dominguez and Sørensen [52,53] compared their results with those from the oil and gas industry [55,56] using the same methods, and showed that safety factors for offshore wind turbines in wind-dominant load scenarios required a safety factor of 2.5, less than that of unmanned offshore oil and gas platform requirements. For wave-dominant load scenarios, a safety factor of 3.5 was required. Results also showed required safety factors could be reduced with three high-quality inspections over the life of the device.

4.2.2. Structural optimization in offshore wind energy

Rangel-Ramirez and Sørensen [57] build upon work in fatigue design safety factors by incorporating cost of maintenance strategies. Some offshore wind turbine components are designed to operate throughout the entire turbine lifetime due to the expense of replacement or difficulty of repair. If the component is not designed to last the entire life of the turbine, the component can be optimized for cost given inspection and repair planning. Using a reliability-based approach, they calibrated fatigue design factors based on a specific minimum reliability level, comparing inspection and maintenance strategies that minimize lifetime costs (answering the question: does the cost of scheduled maintenance outweigh the cost of potential later failure). A similar approach has been used for offshore oil and gas sub-structures [55,56,58,59]. Lower fatigue design factors were calculated as a result of this research. If inspections were included, the fatigue design factors were decreased further.

Large-scale operations of offshore wind farms in extreme events can also provide potential cost savings by reducing the structural reliability level. Extreme environmental conditions currently drive the design of turbine towers and foundations, so Tarp-Johansen et al. [60] maximized profit by optimizing reliability levels for offshore wind turbines in extreme environmental conditions. Two failure modes were considered: tower buckling and foundation sliding. Results showed that the optimal level of reliability based on profitability was lower than the level required by industry, and that the cost model of the turbine is more sensitive to O&M costs than to initial construction costs.

Fatigue is a common failure consideration for wind turbine support structures, but also for turbine blades, which are highly fatigue critical [61]. According to Carroll et al. [28], the blade subsystem is among the top five subsystems to fail, has the second longest repair time (averaging just under 300 h to repair), and is the third most expensive subsystem to repair (material cost). Several factors make wind turbine blades susceptible fatigue: long and flexible structures, vibrations in their resonant mode, randomness in load spectra, continuous operation under varying conditions, and infrequent maintenance during their operational life [62]. The primary reason for fatigue damage accumulation of up-wind turbines is wind turbulence.

However, fatigue damage accumulation caused by tower shadow also contribute to fatigue damage accumulation [61]. Shadow effects refer the interaction of the passing blades with the modified flowfield around the tower, which can cause stress reversal in the wind turbine blades [63–66]. Stress reversal can occur at a critical point along a blade which experiences loads from different sources counteracting each other.

This finding of stress reversal led Thoft-Christensen et al. [67,68] to explore how damage accumulation from wake effects can be modified through tower design. Constructing a constant life diagram (or a diagram that defines a safe operating region in some stress space), eigenmodes (vibrations that cause the entire structure or component to move at the same frequency) for the wind turbine blades were determined to estimate mean and standard deviation of damage states. Results showed both lower average damage accumulation and lower limits of damage accumulation in the blades in a tripod tower design than the monopile design typically used in grid-scale applications. These findings have ramifications as available tenders are located increasingly deeper offshore where wave and wind loads increase.

Broadening the scope of wind turbine failures to include fatigue failure of the hub, shaft and main tower; local buckling of tower; and foundation failure, Sørensen and Tarp-Johansen [69] use RBDO to maximize profit (W) of offshore wind turbines using FORM and Second-Order Reliability Methods (SORM), along with varying operations and maintenance strategies. SORM techniques use a quadratic approximation to the limit state function, rather than a linear approximation like FORM. Design parameters included the foundation radius (R), tower thickness (t), and tower diameter (D), and design constraints were represented by limit state equations. The objective function represented building, inspection, maintenance, and failure costs. Different maintenance strategies were considered: systematic rebuilding given failure, no rebuilding given failure, and control system failure and efficiency. Sørensen and Tarp-Johansen used similar methods to those used by Marquez-Dominguez and Sørensen [52,53] to model fatigue and inspection quality.

When assuming systematic rebuilding given failure, the cost of local buckling due to wind loads and foundation sliding from wind and wave loads were almost equally important, emphasizing the importance of considering both loads when using RBDO. Further, the importance of cost of failure and interest rates was highlighted; as the ratio between failure costs and initial costs increased, the foundation radius decreased, while tower thickness, tower diameter, and reliability indices increased. Foundation radius, tower thickness, tower diameter, and reliability indices were not dependent on the annual benefit, but reliability indices were inversely proportional to interest rates. Considering the case with no rebuilding, optimal design values were almost the same as with systematic rebuilding, but the foundation radii and reliability indices were smaller while the tower diameters were larger. When control strategies were implemented in a wind turbine array (without rebuilding), all design parameters were almost independent of the number of wind turbines and the cost implications of control system failure rate and effectiveness (with effectiveness represented by factors of 0.01 and 0.001). While this suggests control strategy effectiveness and failure rate may have little influence on wind turbine array design, further investigation is needed to determine realistic values for failure rate and effectiveness.

RBDO applications were extended to array spacing by Sørensen, who related spatial parameters of a wind turbine layout to probability of failure based on wind speed [70]. Two failure modes were examined: standstill and operating (for ultimate limit state equations, or those limit state equations associated with extreme conditions). Additionally, the placement of a single turbine was compared to the placement of an array. FORM was used to solve the probability of failure equation developed. Results showed that as the distance between wind turbines decreased (thus increasing the turbulence intensity), the design modulus increased to maintain acceptable reliability levels. Furthermore, results showed that spatial reliability-based optimization of a wind turbine array depends on wind turbulence and turbine yield strength.

4.2.3. Risk-based inspection planning in offshore wind energy

A focus within RBDO in ORE applications is the study of reliability- or risk-based inspection (RBI) and maintenance planning. RBI planning provides means for quantifying the effect of inspections on reliability and thus for identifying optimal inspection strategies based on cost. By combining Bayesian decision analysis with structural reliability analysis, RBI uses available probability models of deterioration processes and inspection performances to present a consistent decision basis [71]. RBI has been used in offshore oil and gas applications [72,73] as well as offshore jacket structures [74], and is now being used in offshore wind turbine applications.

Incorporating inspection and monitoring information, Nielsen and Sørensen [75] developed a condition-based optimization scheme that minimizes costs due to O&M. The scheme uses a damage model that anticipates failures by incorporating physical process models of corrosion, fatigue, erosion, and wear, as well as information on how the failure develops. To reduce uncertainty and inform this damage model, Nielsen and Sørensen also incorporated inspection, monitoring, and failure data to make use of the real-time, online monitoring included on most modern turbines. The damage model simulated single-component deterioration, and then estimated the expected costs of different maintenance schemes (corrective and condition-based) for offshore wind turbines. Model mean time before failure and maintenance schemes are optimized to minimize cost, thus determining the inspection interval.

Nielsen and Sørensen [76] leverage this work by developing a computational framework for risk-based inspection and maintenance planning. This framework uses dynamic Bayesian networks to model deterioration of a single wind turbine component, and compares two decision models for determining the probability of failure, repair, and inspection. The first decision model directly estimates the aforementioned probabilities via Bayesian networks, and because it uses simple decision models and constant and observable input data, is computationally inexpensive. The second model allows for more complex decision models which can be updated with information from failures, repairs, or inspections. The second decision model is simulation-based, but relies on Bayesian decision support and is computationally more expensive. When condition based maintenance is included in the simulation, results showed decreased costs using the advanced decision model.

Previous RBI methods were applied to new offshore structures, in which aging effects were not considered in fatigue models. Sørensen and Ersdal [77] address this need by incorporating aging structure effects in fatigue modeling and RBI methods. Their results showed widespread fatigue, increased risk for crack initiation, and increased crack growth in aging structures. This study is particularly salient under current industry circumstances, in which the first offshore wind farms are reaching their expected life, and repowering or life extension is being considered. This research advocates that, in the case of repowering or life extension, installations should be held to similar reliability standards as new installations.

4.3. RBDO applications in wave energy

Fatigue failures are speculated to be a common failure mode in wave energy devices in the future, occurring at welded joints or corroded bolts [78]. The consequences of component failure is assumed to be similar to failure consequences of offshore wind turbine components, therefore requiring lower safety factors than those used in the offshore oil and gas industry. For offshore wind turbines, the dominating load is wind induced whereas for WECs, fatigue is mainly caused by cyclical wave loading [56].

Following Marquez-Dominguez's and Sørensen's [52,53] calibration of fatigue safety factors, Ambühl et al. [78] similarly calibrated fatigue safety factors for the WaveStar device. Similar methods were used as those used in Marquez-Dominguez's and Sørensen's, but additionally, the effect of different control strategies were considered. Safety factors were calibrated to minimal annual reliability indices of 3.1 and 3.7, as well as minimal cumulative reliability indices of 3.1 and 2.5, which are accepted for offshore wind turbines. Loads were based on simulated wave conditions via wave-tank experiments.

Results revealed that the control method applied (proportional control and spring-damper controlled) had minor influence on safety factors compared to environmental conditions. Ambühl et al. also found that the number of inspections that minimized costs was dependent on economic decision theory and not by minimizing the required safety factor value. The safety factors were similar to those for floating wind turbines [79], but exceeded those for fixed-bottom offshore wind turbines [80] and those previously proposed for WECs [47]. Ambühl et al. postulate that this could be due to wave loads tending to have larger modeling uncertainties than wind load assessments.

Following this study, Ambühl et al. [81] explored how wave model uncertainty affects reliability calculations. After quantifying the bias, root-mean-square error, and scatter index of SWAN, WAM, MIKE 21, and WaveWatch III of a given wave state, Ambühl et al. corrected reliability index and annual probability of failure estimates of the WaveStar piles. Exploring the bending moment of WaveStar piles during extreme slamming loads of breaking waves, Ambühl et al. found that without uncertainty correction, reliability indices and failure probabilities were overestimated. Applications of RBDO have not yet, but should, incorporate wave model uncertainties to avoid incorrect reliability estimates or design.

In a different study, Ambühl et al. [82] presented methods to optimize the structural design of WECs using RBDO. Using Matlab's FERUM 4.1 First-Order Reliability Method and Reliability Index toolbox, they maximized profitability by maximizing the difference between income and expected expenses. They considered several failure modes: foundation sliding, overturning, soil bearing capacity failure, and bending of piles. Design parameters included the foundation radius, the pile diameter, and pile thickness. Three development phases were considered (prototype, pre-commercial, commercial) to account for technology maturity effects on profit from variations in power produced, placement in the ocean, forces experienced, and subsidies received. Results determined an optimal annual reliability index for components to be 3.3, and a system reliability index 3.0. Varying failure costs by up to 50% barely affected profitability (a change of ≤ 0.001). A 10% variation in benefit affected profitability, but not reliability. Interest rate was inversely correlated to profit, design parameters, and reliability indices. Most importantly, Ambühl et al. [82] determined limiting forces to this device design through this method, a significant need in the industry [7,12].

Ferri et al. [83] built on this structural WEC design optimization by incorporating effects of control strategies. Due to the high ratio between extreme and operational loads, WEC structural costs are expected to be 30–50% of the capital cost [84,85]. Since WEC costs are dependent on WEC structure, and the WEC structure is dependent on expected loads, exploring control strategy effects (as they are coupled with WEC fatigue behavior) can minimize capital cost of a WEC. Optimal control strategies are often judged based on the gained mechanical or electrical energy, but control strategy optimality based on cost had not yet been explored. Therefore, Ferri et al. explored the relative impact of control strategies on overall cost. Comparing proportional control (P), proportional-integral (PI) control, proportional-integral-derivative with memory compensation (PID) controller, model predictive control (MPC) and maximum energy controller (MEC), the authors presented a methodology optimizing energy output and structural fatigue loads over the expected life of the device via the WEC cross-sectional area.

The control strategies were used with load time-series resulting from numerical simulations to design structural parts based on fatigue analysis using Rainflow Counting, S-N curves, and Miner's Rule. P, PI, and PID control were defined up to the establishment of the control parameters (proportional, integral, and derivative gain) and were optimized for mean absorbed power using the Nelder-Mead method with random seeded starting points. The algorithm was repeated for each sea state, each controller, and each case (Case 1: unconstrained, Case 2: unconstrained with linearized viscous drag moment implemented as additional damping, Case 3: power-takeoff (PTO) constrained cases with linearized viscous drag moment, Case 4: End-stop of the PTO actuator, Case 5: PTO delay). Results show that energy and fatigue depend on the constraint of the PTO moment for all considered controllers rather than on the position constraint or PTO delay. Both active controllers (PI and PID) harvest 80% of the maximum achievable energy and twice as much energy as the passive controller, and need roughly 50% more structural material to achieve the same expected life as that achieved with the passive controller. Sensitivity analysis carried out with the PI controller showed that the controller parameters, which have been optimized with respect to maximum annual energy production, are also cost-optimal parameters.

4.4. RBDO applications in tidal energy

While RBDO has been applied to offshore wind and wave energy design problems, it remains limited in tidal energy applications.

Nicholls-Lee and Turnock [86,87] adjust twist and pitch of a horizontal axis tidal turbine to decrease cavitation inception and increase hydrodynamic performance through the use of Blade Element Momentum (BEM) methods.

Young, Baker, and Motley [88] developed a methodology for RBDO problem formulation in adaptive marine structure applications. In this context, adaptive marine structures refer to devices which automatically adjust to the surrounding environment by changing shape or property via passive or active control mechanisms. In their literature survey, they note that although RBDO has been used in related applications in non-adaptive marine structures as well as aeroelastic structures in aerospace applications, there is an opportunity to use RBDO in adaptive marine structures because the fluid loading is much higher (due to density and viscosity) and the flow may be highly unsteady (due to spatial and temporal variations in flow field, as well as transient structural motion). They apply their method to a rotor as an example, but it can also be applied to tidal turbines. They first quantify the impact of uncertainty in load and material characteristics of the structure on its performance. Then, they use a fully coupled BEM-FEM (blade element momentum-finite element method) method for the design and analysis of the structure, and create a response surface methodology to estimate the behavior of the device. From that behavior, the probability of failure is estimated using FORM. Using these techniques, the authors maximize propeller energy efficiency given an acceptable reliability level by altering the blades' fiber orientation angle.

Huang and Kanemoto [89] optimized front blade pitch angle to maximize power and thrust coefficients. The forces experienced by the horizontal axis tidal turbine was first analyzed via BEM and CFD (computational fluid dynamics) methods to develop a response surface method. This response surface is then coupled with a multi-objective Genetic Algorithm (NSGA-II) to obtain an optimal solution. A sensitivity study of blade design with respect to the NSGA-II parameters (population size, convergence criteria, crossover and mutation) is required to prove the robustness of this method, and leaves opportunity for future work.

Bir et al. [90] use a two-part optimization scheme, first optimizing blade properties, and then composite material layout. They begin by optimizing the blade twist angle and chord distribution along the blade to maximize power output in a given tidal velocity range through the development of a numerical optimization tool called Harp_Opt, which combines BEM with a genetic algorithm. Secondly, they define extreme operating conditions and optimize the structural layout of the composite materials (or the thickness of the unidirectional laminate, double-bias laminate, and core material), minimizing the blade weight while satisfying ultimate limit state requirements.

Lastly, Liu and Veitch [91] optimize blade sectional thickness and shape to meet ultimate limit state requirements while maximizing power generation and hydrodynamic efficiency. Using PROPELLA, a turbine performance prediction software, and a trial-and-error optimization resulted in 37.6% reduction in blade material.

5. Discussion

In this review, we have described major technologies within ORE, as well as how this industry currently uses reliability analysis. Across technologies, there is an opportunity to use RBDO methods to accelerate technology convergence, improve reliability, and enhance market competitiveness. Researchers have explored RBDO applications in ORE and contributed foundational work to this field, but as the ORE industry matures, technology advances, and new developments evolve, this work can be leveraged in emerging applications.

5.1. Discussion of offshore wind energy

In offshore wind energy applications, there has been extensive work in applying RBDO. RBDO methods have been developed and applied to single turbines and arrays, to new and aged structures, and to limit states for fatigue and extreme conditions. Researchers have calibrated safety factors to create technology-specific guidelines and save costs from over-engineering. With more commercial experience and accompanying data, common failure modes and components have been identified. Through development of RBI methods specific to offshore wind applications, researchers have incorporated advanced statistical and structural degradation models to optimize O&M strategies, incorporating technology advancements such as real-time condition monitoring system updates.

Despite the presence of this body of research, there are still areas that require further investigation. Wake and shadow effects on reliability have been considered in limited applications, lending opportunity for researchers to use this information in layout optimization. This layout optimization would directly relate coordinates of wind turbines in an array, and the environmental conditions at those coordinates, to component and system reliability and performance. In addition to layout optimization, the effects of control strategies and implementation on performance and reliability are too important to not include in RBDO and RBI frameworks. While researchers have included the effect of control schemes in wave energy applications, it has yet to be explicitly applied to RBDO in offshore wind. Another opportunity for future work includes optimizing part replacement or warranty renewal for cost and reliability. Although warranty renewal and part replacement is a common problem in this industry [92], it has been addressed historically through expert judgment based on worker experience, not by RBDO or RBI methods.

RBDO methods must also be adapted to new developments within the offshore wind energy industry: larger turbines, installations farther offshore in deeper waters, floating platforms, and new end-of-life uses (i.e.: lifetime extensions and repowering).

As wind turbine developers build increasingly larger turbines, RBDO can be used by researchers and wind turbine developers to optimize new structural dimensions and designs. For example, increasing turbine size requires increased foundation size. Additionally, if larger, heavier blades are able to reach higher altitudes where wind speed is higher and more consistent, mechanical and structural components will be affected by increased blade tip speeds. The blades will also experience greater direct wind load. In this way, tidal turbines and wind turbines can share experience as each sector strives for reliable blades through material and structural advances.

The relative contribution of wave loads (from diffraction, but also non-linear, higher frequency loads) to failure increases as wind turbines are built further offshore in deeper waters, resulting in a need to design offshore wind turbine foundations differently than they have been in shallower waters [93]. These deeper installations, often found farther offshore, may also require different O&M considerations. For instance, the cost of accessing turbines further from shore may be more expensive, resulting in less frequent inspections or more dependence on remote inspections via condition monitoring systems. This difference in cost-benefit of different maintenance strategies could have an effect on RBI results.

As their size increases and they are installed farther offshore in deeper waters, offshore wind turbines will not be designed the same as earlier generations. To make offshore wind energy economically competitive as subsidies are phased out, RBDO should be used to account for the difference in loads experienced by this new generation of turbines, as well as the O&M strategies employed to service them.

The industry's movement towards life extensions and repowering offshore wind turbines underscores the importance to consider reliability in design. Although repowering and life extensions have been seen mostly in onshore installations, offshore wind turbine arrays are approaching their intended end of life. The first Danish wind array to be decommissioned has already gained lifetime extension approval for a few months to wait for better accessibility in the summer months. While offshore wind turbines may experience shorter lifetime extensions than their onshore counterparts, there is great uncertainty associated with how replaced and aged turbine components and supporting structures will interact and behave in such environmental conditions. These turbines often have years of inspection and maintenance, condition monitoring, environmental, and SCADA data, which could be incorporated to estimate safe life extension periods for components through advanced RBI techniques. Moreover, if the industry is planning to use life extensions and repowering techniques, these end-of-life options need to be considered in the initial design of the array. By using RBDO techniques to plan for life extensions or repowering, designers can minimize the LCOE of turbines by varying the reliability of the component for planned replacement or not.

Lastly, floating offshore wind turbine design could benefit from RBDO techniques, although the use of RBDO would share similarities not just with fixed-bottom offshore wind turbines, but also WECs. Technologies from the offshore oil and gas industry have been adopted by the floating offshore wind turbine industry, but the design of these platforms is distinctive. Target reliability levels and safety factors have been scaled down from those in the offshore oil and gas industry by DNV-GL, but remain untested over long-term deployment. Further, these safety factors have not been calibrated and validated as Marquez-Dominguez and Sørensen did for fixed-bottom offshore wind turbines [52,53].

After calibrating fatigue design safety factors, researchers have the opportunity to apply RBDO to the multitude of platform designs. Like WEC design, floating offshore wind turbine design has not yet converged to a single concept. This lack of design convergence results in each concept having a set of common failure modes and mechanisms, as well as optimal design parameters, rather than ubiquitous ones on which the entire industry can focus their efforts. Furthermore, although the turbine itself is similar in design to fixed-bottom counterparts, the platform on which the turbine sits and the mooring that holds the platform to the ocean floor share more similarities with WEC design. These shared design considerations lend opportunity for collaboration and mutually beneficial research efforts applying RBDO techniques not only to improve existing technologies, but also help focus efforts on more feasible designs. Once these technologies mature to the point of commercial array installation, RBI techniques can be applied to more efficiently model, predict, and optimize O&M.

Unique to floating offshore wind turbines, there is an opportunity to better model and leverage the relationship between wave conditions, performance, and reliability. While the loads experienced by floating offshore wind turbines may be similar to WECs, the behavior of the structure can differ, and the relationship between that behavior and power production by the device is fundamentally different from other ORE technologies. This change in relationship will cause designers to consider different device loads and damage, but also prioritize designs that are more reliable given these changes in device response.

5.2. Discussion of wave energy

RBDO applications in wave energy technology are somewhat limited, but provide critical methodologies and information that can be leveraged for other ORE applications, and can be expanded to help us better incorporate RBDO in wave energy applications. Researchers have calibrated and validated fatigue safety factors (including the influence of control on these factors). Control optimization was also paired with structural optimization in an RBDO scheme and applied to WECs of different technology readiness levels. Wave model uncertainty effects on reliability calculations were also explored. Both the incorporation of control optimization and uncertainty quantification in RBDO methods are valuable contributions to this field, and should be incorporated in other applications.

There are limitations to the body of research that has already been generated in RBDO applications to wave energy technology. The research that has been completed in this field mainly pertains to a specific WEC design. While important in establishing general methodologies, the results of these studies are limited in their applicability to other WEC types or designs. Another consequence of lack of design convergence, common failure modes and mechanisms might not be mutual to all WEC designs. This issue extends to some results of these first studies; repeating studies for each WEC design is redundant and expensive, but results of one study may not be universally applicable or helpful. This issue, however, provides a unique opportunity to the wave energy industry to prioritize reliability to help in design convergence. Researchers should use this opportunity to explore common components amongst WEC designs, and assess their reliability. For instance, reliable mooring is critical to many WEC designs, and to optimize these systems given a reliability constraint would help not just many WEC designs, but could also provide information to those concerned with mooring of tidal devices and floating wind turbines. To assess the reliability of these components and systems, we need to be able to accurately simulate their behavior under realistic loading, another major focus of research currently. Understanding which loads are limiting and how they affect component or device operational life will provide insight into O&M needs, informing O&M strategy and RBI application results.

Although wave energy has not yet reached commercial installation, applying RBDO to WEC array design provides another opportunity to improve feasibility. Like offshore wind or tidal energy applications, reliability, performance, and array layout are related. Describing this relationship will help in understanding optimal development of commercial installations. Once system reliability and behavior is described, researchers can begin applying RBI, which has yet to be applied in wave energy applications. Fortunately, offshore wind energy applications of RBI can provide the wave energy industry with transferable methodologies and results.

Finally, a lesson learned from RBDO research in offshore wind energy applications is that, as operational data becomes available, fatigue, failure, and O&M models can be updated. Uncertainty needs to be quantified and incorporated into RBDO applications across ORE technologies early so that, as developers receive operational data, they can update their understanding of the system and optimize operations.

5.3. Discussion of tidal energy

Foundational work using RBDO in tidal energy applications has been performed, but remains to be fully developed. Tidal turbine operations simulations often are computationally expensive, especially when they are run for thousands of iterations as part of optimization schemes. Therefore, the research that has been conducted up to this point has enabled the use of RBDO techniques by summarizing computationally expensive simulations via response surface methods to be used by optimization schemes. These schemes then are able to vary twist, pitch, fiber orientation angle, chord distribution, blade sectional thickness, and blade shape to optimize performance and satisfy ultimate limit states.

While this work is important in understanding how to apply RBDO in tidal energy applications, there are research opportunities that could help inform tidal energy device design. To begin, RBDO applications have been applied to satisfy ultimate limit states, but not other design constraints, such as fatigue limit states. RBDO has not yet been used to calibrate or validate design safety factors. Applying RBDO to arrays of tidal turbines could also provide opportunity to explore wake and shadow effects on power production and reliability. Similar to offshore wind energy applications, advanced controls have the potential to significantly improve power production and extend operating life, and need to be incorporated into RBDO applications, especially in early design stages. Lastly, because tidal turbine designs have converged more than other ORE technologies, researchers also have the opportunity to focus efforts on optimizing multiple design parameters to achieve enhanced performance while maintaining reliability.

While tidal energy developers and researchers have learned valuable lessons about design from the hydropower and wind energy industries, tidal turbines have unique design challenges. Pertaining to the environment in which they are installed, tidal turbines experience forces that differ from those in other offshore renewable energy technologies. Tidal turbines can experience tidal forces in more than one direction, as well as wave forces. Further, the fluid they interact with can cause increased loads, corrosion from suspended sediment, and biofouling over time. To account for the dynamic interplay of these forces in modeling the behavior of tidal turbines is a focus of current research interests, but incorporating these loads into advanced fatigue or failure models is critical in accurately predicting design life and feasibility. Only after researchers can accurately simulate fatigue and failure over the tidal turbine's operational life can O&M strategies, and thus RBI, be explored.

6. Conclusions

Across technologies, there is an opportunity to use RBDO methods to accelerate technology convergence, improve reliability, and enhance market competitiveness. This study reviews the major ORE technology types and their status, how reliability is currently used in industry, and how RBDO is currently used in each application. The purpose of this study is to review RBDO technique use in ORE research to highlight research needs within this field. From this review, we find that while RBDO has been used in offshore wind turbine research, it is less explored in wave and tidal energy applications. The maturity of the offshore wind energy industry results in new opportunity to use RBDO techniques, such as applications to lifetime extension, larger turbines, and new foundations. RBDO applications in wave energy are increasing, but limited. Due to the early-stage development status of many WEC concepts, RBDO has the potential to impact design of these devices. Tidal energy applications of RBDO are similarly limited, but work has been completed to enable the use of RBDO techniques. As the industry matures, these technologies advance, and new developments evolve, RBDO techniques can be leveraged in emerging applications across all technology types.

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