Statistical Availability Analysis of Wave Energy Converters

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ABSTRACT

Availability of a Wave Energy Converter (WEC) is of paramount importance if it is to become a commercially successful technology. This paper presents a statistical Monte Carlo methodology to assess the availability of WECs which is driven both by the reliability of components and the time to repair a failure which is dependent on external factors such as weather windows and other restrictions on marine operations. This methodology is applied here to the Oyster® WEC design which is being developed by Aquamarine Power Ltd. but can be modified to investigate other technologies which have different operation and maintenance philosophies.

KEY WORDS: Availability; wave energy converter; reliability; maintenance; Oyster.

INTRODUCTION

The push towards the requirement for new and renewable energy sources in recent years has lead to a rapid increase in the number of commercial wave energy device developers. Aquamarine Power Ltd. (Aquamarine) was founded in 2005 to develop Oyster®, a device designed to interact with the dominant surge forces found in the nearshore wave environment.

Oyster is a unique design of Wave Energy Converter (WEC) due to its nearshore location, the use of a bottom-hinged flap that completely penetrates the water column, and an onshore hydroelectric power take-off (PTO). The oscillating motion of the flap is used to pressurise water and pump it to shore via a hydraulic piston and pipeline system. The pressurised water is then converted into electrical power through the use of a Pelton wheel system to turn an electrical generator. The water is then recycled through the system via a low pressure return pipeline.

The Oyster 1 315kW proof-of-concept prototype was successfully installed at EMEC on Orkney in 2009. To date it has operated for over 6000 hours. This paper focuses on Oyster 2, the next generation device and a pre-commercial demonstrator with 3 flaps pumping to a single onshore hydroelectric power plant, rated at 2.4MW.

The availability of any generator is key when calculating the economics (in particular, cost of power) of the device as the development progresses from demonstration to a commercial product. An availability model should be developed as early in the design process as possible, ideally comprising both reliability and maintenance capability aspects, in order that the device design encompasses not just efficiency but also the requirements for the maintenance strategy and component access. A design with high conversion efficiency has compromised commercial potential if it cannot be maintained cost-effectively. A study of the availability of offshore wind farms used Monte-Carlo simulation approaches and attempted to take weather windows into account (Van Bussel, 1999). The drop-off in availability of a wind farm with distance to shore was modelled, using trend curves developed from many Monte Carlo runs rather than modelling the availability using M-C methods directly, and a storm database that was used to determine the 'inaccessibility factor' for maintenance crews due to poor weather for a given wind speed. This found that a nominal onshore availability of 97% dropped to 76% for a farm located 15km offshore for a wind speed of 8 m/s. This study was extended (Van Bussel & Zaaijer, 2001) to investigate possible design improvements and their associated costs for offshore wind farms to increase availability. It was found that significant availability improvements could be made for relatively modest increased effort and costs, but that the analysis must be performed at an early point in the design process, to allow the investigation of different concepts before technology maturation.

The relative immaturity of WEC technology means that few developers have had the opportunity to investigate in depth the principal drivers underlying availability using quantitative tools. Few, if any, of the components involved have been tested under such onerous conditions, and therefore component lifetimes and failure likelihoods are poorly understood.

In terms of availability and the modelling thereof, the key feature of the Oyster WEC is that the majority of the complex equipment and all of the electrical and electronic plant is located onshore where it can easily be accessed for inspection and maintenance. The availability model discussed here is concerned with only the offshore components of Oyster, the accessibility and maintenance of which are constrained by the weather and other factors affecting marine operations.

This paper presents a numerical modelling approach developed with the purpose of determining device availability for the Oyster 2 WEC, and examines the key drivers underlying availability for WECs in general.

A definition of availability is provided and an overview of the modelling approach and layout of the model is given. The main body of the paper presents and discusses the results of the modelling work, including the forecast availability and sensitivity studies into the impact of changing the model assumptions; the maximum sea-state in which maintenance vessels can operate, the rate at which components wear out, the ability to carry out maintenance outside of daylight hours, and the inclusion of tidal restrictions on maintenance.

The limitations of the modelling and further work required are highlighted and summary conclusions are presented.

AVAILABILITY

In order to forecast device availability effectively, it is first necessary to define an appropriate metric. This is commonly defined as the percentage of the time a system is functional when needed (Barlow et al. 1975) which requires specifying the definition of a functional system. A more useful definition for a WEC is the ratio of the average electrical energy produced (incorporating downtime due to both planned and unplanned maintenance) to the average electrical energy that would have been produced over the same period if it had operated with no downtime.

$$\text{Availability} = \frac{\text{Electrical energy generated}}{\text{Electrical energy generated with no failures or maintenance}} \tag{1}$$

This definition is used here and shown in Eq. 1. This formulation is preferred because it captures the importance of avoiding downtime during the winter months when energy production is highest and also the impact of operating a WEC at reduced performance. In addition it is the most useful definition for feeding into a business model because it allows the annual Average Electricity Production (AEP) to be calculated as the product of availability and the annual AEP with no failures or downtime due to maintenance.

MODELLING METHODOLOGY

This section describes the numerical model used to forecast availability. The model attempts to simulate the operation of the Oyster 2 WEC using a time-step method. An outline of the model showing the key inputs is given below (Fig. 1).

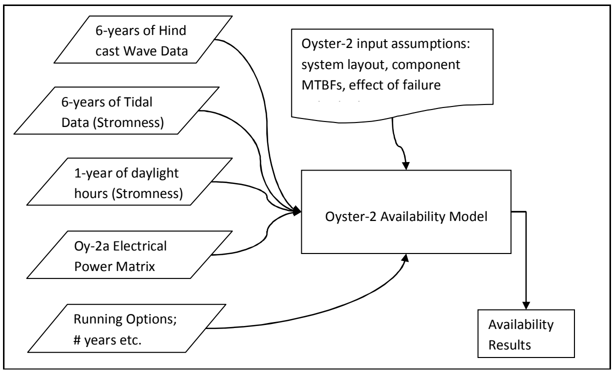

Fig. 1. Outline of availability model showing key inputs

The model uses a 3-hour time step. A one-hour time step was found to be computationally expensive, while a one-day time step was considered to provide too little flexibility. The 3-hour time step was therefore chosen as a good compromise, combining feasible run-times with appropriate granularity in the results detail. A 3-hour time step was chosen because no maintenance activity is expected to take less than 3 hours including mobilization.

Model Structure

The flowchart shown in Fig. 2 provides an outline of the model operation for each time step. This is described further in the following paragraphs.

The top 3 blocks shown in Fig. 2 are setting up the model and structured input data to drive it. Wave, tidal and daylight data for the location to be modelled is imported, along with the electrical power matrix for Oyster 2. The power matrix is the predicted electrical power over all sea states.

The system to be modelled (i.e. the offshore components of the Oyster 2 array) is then imported and assembled; creating this structure 'on-the-fly' during the model run rather than hard-coding it facilitated changes to the system layout, allowing the impact of doing so to be easily assessed.

A Monte Carlo approach is used to model component failures. At each time step a pseudo-random number from a standard uniform distribution is generated for each component and compared to the probability of failure for that component on that time-step to determine if the component has failed (the probability of failure for a given component will change between time steps if component aging is included). If a component fails it is added to a list of currently failed components. The forecast weather in future time steps is searched for a suitable weather window (or series of windows) in which the repair work can be undertaken; the time step in which the component can be fixed is recorded.

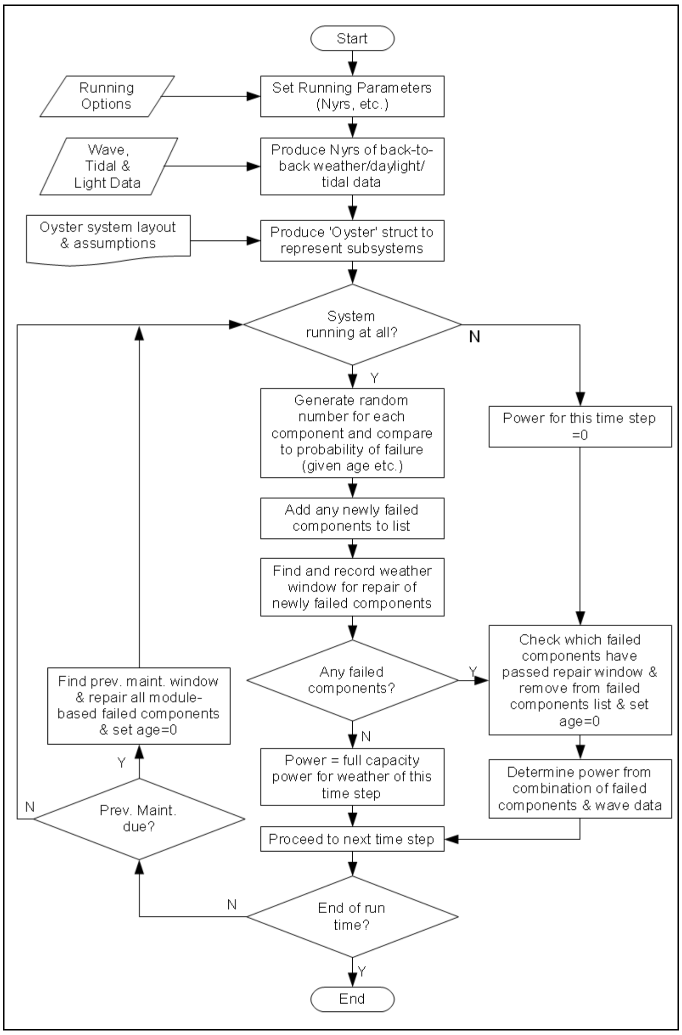

Fig. 2. Flowchart of the key processes for each time step.

All components that have reached the time-step in which they can be fixed are removed from the failed components list and their age is reset to zero. Finally, the power output for the time step is calculated based on the combination of failures currently present and the wave climate

for that time step.
If preventative maintenance is included, then when the required length of time has elapsed an appropriate weather window is sought and when it is reached all module-mounted components are repaired and their ages reset to zero.

Input Data and Assumptions

Weather: the performance of the WEC and the ability to maintain it is judged primarily on the wave conditions. Six years worth of hind-cast hourly data is read into the model and then repeated as many times as required to complete the model run time. The EMEC wave data comes from a DHI MIKE21 spectral wave model. The boundary conditions have been forced with measured data from a Datawell Directional Wave Rider Buoy and the model has been calibrated in the nearshore, using an ADCP (Acoustic Doppler Current Profiler).

Tidal: because of the relatively near-shore location of Oyster® there was a likelihood that some maintenance operations would be draft limited to take place above certain tidal levels. To allow for this, time-series hind-cast tidal height data for Stromness was sourced from Jeppesen's C-MAP database.

Light: depending on circumstances marine operations might be restricted to occurring only within daylight hours. Due to the limited daylight hours during winter this had to be incorporated into the model. The hours of daylight were calculated based on the latitude of Stromness according to Forsythe et al. (1995).

MTBFs: one of the most critical inputs is the Mean Time Between Failure (MTBF) for individual components. For commercial components industry databases (such as OREDA®) were used to find suitable MTBF values. Where these components were used outside their usual operating environment or duty cycle the MTBF values were factored using engineering judgement. For bespoke components a combination of results from accelerated life testing, database values for similar components and engineering judgment were used to produce appropriate MTBF figures.

Maintenance: the time taken to repair components and the sea states in which this could be achieved was based on a combination of Oyster 1 operating experience and operational reviews of the Oyster 2 design.

The MTBF values in particular are potentially subject to significant change as the data become available from Oyster 2 to allow an application-specific failure rate to be determined. As a consequence of this, the absolute availability values reported here should be considered as baseline figures only, and used as comparators for the sensitivity analyses performed.

Failure Modes and Effects

Each component can fail via a number of different modes, each of which will have a different impact on the device performance. Considering the individual failure modes and combinations of them is complex and is usually done qualitatively as part of an FMEA (Failure Modes and Effects Analysis) exercise. In this modelling work it is assumed that every failure for a given component is by the failure mode which has the greatest impact on output power for that component to give a conservative availability estimate.

Simplifying Assumptions

A number of simplifying assumptions were made when creating the model. It was assumed that all failures are independent; i.e. if one of the two cylinders on a given flap fails it does not increase the probability of failure of the other.
All failures were assumed to be repairable – i.e. there are no component failure modes that render components impossible to repair. It was assumed that maintenance operations are not resource-limited and that there is no logistical delay (for sourcing spares, chartering vessels etc.) between a failure and first available maintenance window. The first 3 hours of any weather window are assumed to be not used for maintenance but to be required for mobilization to site and establishing moorings.

Failure Rates

The baseline assumption for the model is that failure rates are constant, so that at each time step a pseudo-random number is generated for each component and compared to the probability of failure (the reciprocal of the MTBF measured in number of time steps). This gives an exponential probability density function of failures as given in Eq. 2, where t is time, λ is the probability of failure, and f_e is the probability of failure at time t.

$$f_e(t) = \begin{cases} \lambda e^{-(\lambda t)}, t \geq 0 \\ 0, t < 0 \end{cases} \tag{2}$$

When age-dependent failure rates were included a Weibull probability density function was used. This is a commonly-used distribution in FMEA applications (Dimitrov et al., 2004). This is given in Eq. 3 below and has the additional 'shape parameter' (β) which indicates the extent to which probability of failure increases with age. A β value of 1 indicates no aging and gives the exponential probability density function of Eq. 2. Increasing β from 1 increases the extent of increasing failure rates with component age.

$$f_W(t) = \begin{cases} \beta\lambda(\lambda t)^{\beta-1} e^{-\beta(\lambda t)^{\beta}}, t \geq 0 \\ 0, t < 0 \end{cases} \tag{3}$$

Eq. 3 is a modified form of the standard Weibull distribution with an additional β factor in the exponent. This allows the simple implementation of the Weibull distribution by changing the probability of failure to λ' as given in Eq. 4 below.

$$\text{Failure Rate (at age} = t') = \lambda'(t') = \beta\lambda(t'\lambda)^{\beta-1} \tag{4}$$

RESULTS AND DISCUSSION

This section presents representative output generated by the availability model. The determination of the component MTBFs and repair times is both crucial to the model and difficult to establish. Therefore, sensitivity studies were performed and are presented for each results set. The effects on the availability value of changing the MTBF and repair time were investigated: in all cases, the availability value magnitude itself was affected, but the general shape of the relationship remained broadly similar, and the conclusions drawn remain unchanged.

Baseline Parameters

The baseline parameters used in all model runs are given in Table 1. Each of these parameters was then varied in turn in the subsequent sensitivity studies.

Table 1. Baseline model parameters

Model Parameter	Baseline Value
Maximum significant wave height in which maintenance is possible	1.5 m
Number of years model run	50
β (Weibull shape parameter)	1 (i.e. no component aging)
Tide height restriction on maintenance	None
Preventative maintenance interval	>50yrs (i.e. no preventative maintenance)
Night diving	Not permitted
Mobilization/demobilization time	3hrs (lost from each window)

Annual Variation in Availability

Due to the statistical nature of failure and distribution of weather windows there will be a substantial variation in annual availability. Over the 20 years of the Oyster 2 design life this variation will be reduced to a few percent. Fig. 3 shows the extent of the variation in annual availability for the baseline model run of 50 years; the range of availability values covers nearly 40 percent, demonstrating that the availability achieved in a single year is not necessarily representative of overall device availability over the full 50 year run. The peak observed between 75-80% is due to the statistical nature of Monte Carlo simulations (the graph below represents only one 50-year run), and does not represent a bias in the model. Subsequent simulations using the same sent of baseline parameters did not show a peak in this availability range. In the subsequent results and sensitivity analyses, it is the overall device availability that is reported.

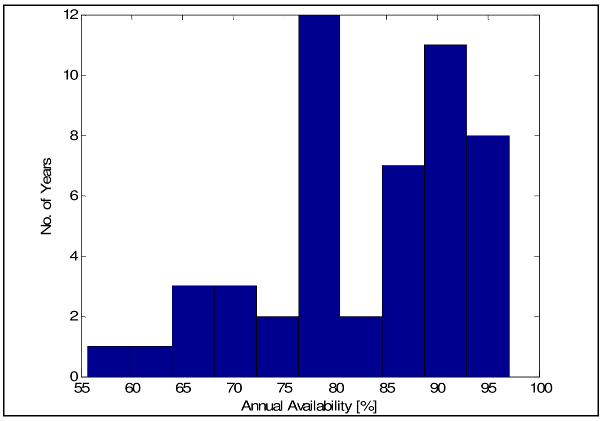

Fig. 3. Distribution of annual availability values over a 50 year run.

Sensitivity to Maximum Significant Wave Height

The device availability was expected to be strongly sensitive to the maximum significant wave height (Hs) in which maintenance operations can be carried out. The sensitivity was assessed by varying the limiting Hs for marine operations from 0.75 m to 1.75 m in steps of 0.25m to determine the impact on availability values. The resulting average availability value for each model run is presented in Fig. 5 below.

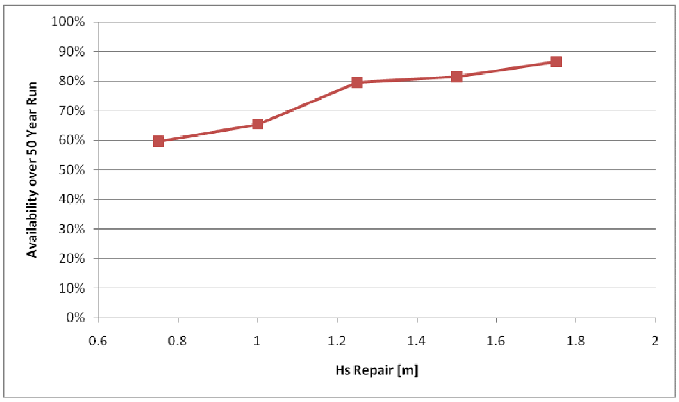

Fig. 4. Modelled availability VS maximum permitted Hs for maintenance operations.

The significant wave height was the only parameter used to restrict marine operations in producing Fig. 4. above and it shows that an increase in maximum permitted Hs from 1.0 m to 1.5m Hs would increase availability from 65% to 82%. In reality the mean wave period also has a significant affect and the sensitivity of availability with mean wave periods may depend on the vessel and mooring configuration used. High winds would also be likely to restrict operations; inclusion of such additional factors would be a useful refinement of the model. These effects will be an issue for any WEC developer needing to undertake maintenance of offshore components and systems. The Oyster 2 design has been developed to account for the impact of marine operations restrictions on maintenance. Where possible, the offshore systems have been modularised, such that modules can be replaced after failures or for routine maintenance in a single day. This increases the number of potential maintenance windows throughout the year, including in the often-challenging conditions during winter.

Effect of Age-Dependent Failure Rates

To investigate the effect of preventative maintenance intervals it is necessary to introduce age-dependent failure rates: this was done as demonstrated in Eq. 4. To do this a single shape parameter of 3.0 was used for all components, and a number of maintenance intervals were tested to see what effect they had on predicted availability. The results are given in Fig. 5.

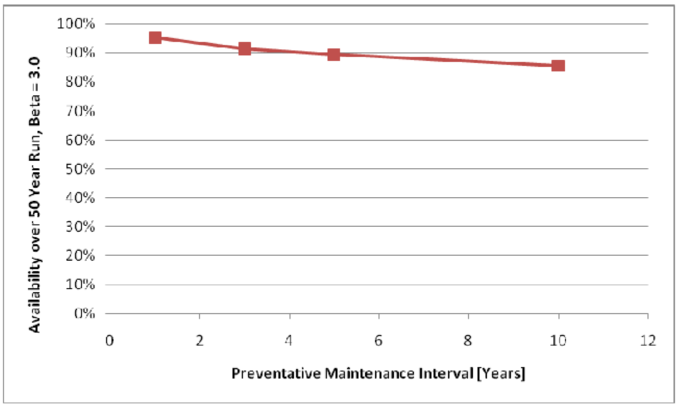

Fig. 5. Modelled availability VS Preventative Maintenance Interval

Fig. 5 demonstrates that if the components all exhibit strong age-dependent wear ($\beta \geq 3$) then a maintenance interval of 3 years rather than 10 years could be expected to improve availability from 86% to

91%. It is worth noting that both these figures are higher than the baseline case availability because the baseline case includes no aging or preventative maintenance and therefore does not show the low failure rates in early life that would be expected with either new or recently refurbished components.
In reality each component will have its own β parameter and extent to which failure rates are dependent on component age. Inclusion of appropriate β parameters for each component would be a useful development of the model. A condition monitoring system has been developed for Oyster 2, to enable preventative maintenance to be undertaken before component failure. Data from the condition monitoring sensors will allow an improved estimate of component lifetimes and failure curves in the energetic and demanding near-shore environment.

Maintenance Outside of Daylight Hours

The baseline assumption is that Oyster will be maintained during the hours of daylight only. However, night diving operations are possible and safe if carefully planned, so the effect of allowing maintenance in the hours of darkness was investigated, and the results are presented in Table 2 below.

Table 2. Availability impact of permitting night-time maintenance activities.

	Predicted Availability [%]
No night maintenance	82
With night maintenance	93

The increase in overall availability from allowing night maintenance is significant, at over 10%. This is not surprising if we consider that there are just 6 hours of daylight on the winter solstice in Orkney, combined with the scarcity of appropriate weather windows for repair and the high downtime penalty (because the average wave heights and therefore the potential energy output are highest over this period). Allowing night maintenance quadruples the time available for exploiting critical winter weather windows and so has a large impact on availability.

Sensitivity to Tidal Restrictions

The water depth at the Oyster device is shallow and there may be some low tidal conditions where deep draft vessels may have to work next to the flap rather than directly above it. If this scenario is conservatively assumed to prevent any maintenance work on the flap, then the effect on availability is shown in Fig. 6. To evaluate the impact of such restrictions on availability a tidal height constraint on maintenance ranging from 0m to 1.25m above Mean Low Water Springs (MLWS) was included in the model.
Fig. 6 shows that a severe tidal restriction requiring tidal heights greater than 1.25 m above MLWS for maintenance would have a more than 10% reduction in availability, but more modest tidal restrictions have low impact. This part of the model and the input data for it should be updated to model more accurately the impact of low tides on maintenance activities.
To develop a commercially-viable WEC design, care must therefore be taken during the design process to ensure that maintenance operations can be safely undertaken over the full range of tidal conditions, ideally also enabling operations to be performed outside daylight hours.

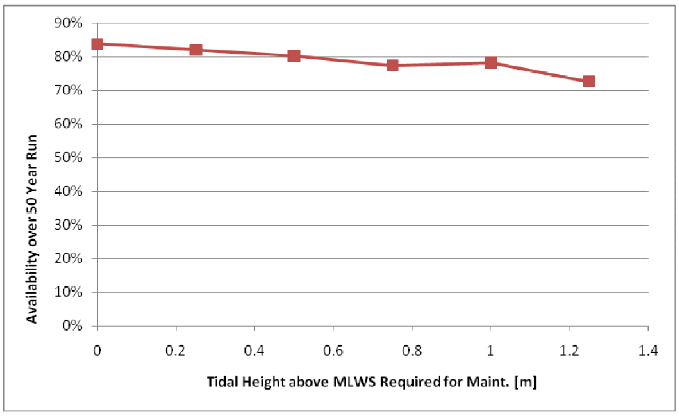

Fig. 6. Modelled availability VS Tidal Restriction on Maintenance

CONCLUSIONS

A Monte Carlo availability model of the Oyster® 2 wave energy converter has been produced and used to generate availability forecasts for business models and has been used to highlight key areas of the design which are availability drivers.
The model shows a predicted baseline availability of 82%, although this number is sensitive to the input assumptions, in particular the MTBFs, and is should be considered indicative only; as the data inputs improve in accuracy and the boundary assumptions become better defined, the absolute value will be subject to change. This is largely a result of the interaction of 3 effects during the winter months: the daylight hours are shortest during this period (the solstice having just 6 hours of daylight), the maintenance weather windows between high sea states are shortest and scarcest, and the average wave energy is highest. The first two effects mean that once a failure has occurred downtime will be longest during the winter, and the third means that a given length of downtime has a greater impact on availability in winter than in summer.
Sensitivity studies have been carried out to assess the importance of the following on availability: the significant wave height in which maintenance can take place; the preventative maintenance interval, carrying out maintenance outside the hours of daylight and tidal restrictions on maintenance.
The significant wave height in which repair work can be carried out and the ability to carry out repair works outside of daylight hours have the largest impact on availability. Increasing maintainable significant wave height from 1m to 1.5m would increase the availability from 65% to 82%.

FURTHER WORK

The following further work to improve the model has been identified:

The model should be enhanced to include a simplified version of the onshore equipment. In addition a model of grid availability should be included as this is likely to be lower in the winter months (this will affect total energy export, but not the headline availability figure).

Using a different Weibull shape (aging) parameter for each component would allow for some components showing more significant age-dependent failure rates than others.

Increasing the number of years of weather data used in the model run will give a more accurate reflection of the distribution of weather windows and the performance of Oyster.

In addition to significant wave height, the mean energy period and severe wind restrictions on marine operations should be included to better reflect the real world constraints.

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