Wave resource spatial and temporal variability dependence on WEC size

B. Robertson, G. Dunkle, T. Mundon, L. Kilcher

Abstract— **As the wave energy sector grows and looks to the Blue Economy for commercialization opportunities, there is a distinct and pressing need to clearly understand and quantify the coupled impacts of wave energy converter (WEC) size and wave resource characteristics on the annual energy production, spatial variability and temporal variability. Utilizing generic frequency domain representations of the Oscilla Power Triton WEC and spectral wave conditions at PacWave (Oregon), Los Angeles (California) and WETS (Hawaii), a series of interesting results emerge. Firstly, the 'optimal' WEC size, from an energy standpoint, is fundamentally dependent on the frequency distribution of the incoming wave variance density spectrum. Secondly, and from a seasonality perspective, the seasonal WEC energy generation doesn't necessarily follow the seasonal distribution of gross wave power. Finally, from an hourly power variability perspective, a reduction in WEC size generally decreases variability. However, for each of the locations investigated, there appears to be a WEC size threshold; a threshold where further reducing WEC size results in increased power variability.**

Keywords— **Wave Spectrum, WEC Modelling, Blue Economy, Wave resource assessment.**

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I. Introduction

As ambitious and necessary goals for decreasing our dependence on fossil fuels are implemented, the socio-economic opportunities associated with renewable energy are significant. Solar and terrestrial wind energy are dominant in the renewable sector and continue to grow, with applications mainly focused on utility grid implementation. However, the inherent intermittency and variably of these resources create grid integration challenges [1][2] and will limit their final penetration into the electricity grid. Furthermore, significant stakeholder opposition to land-based renewable energy systems are creating implementation challenges across the globe [3]–[5].

Inclusion of ocean renewable energy resources in our electricity mix will provide an increasingly diversified electricity mix and a valuable tool in the global decarbonization of the energy sector. Ocean wave energy is of interest due to its greater consistency, magnitude, and higher energy density [6]. Additionally, wave energy technologies have additional non-energy value to the electric system due to their limited terrestrial land footprint and visual obstruction [7]; perhaps limiting some of the social challenges with project development.

As the wave energy sector continues to develop towards utility level technologies, Blue Economy sectors [8], i.e. remote and distributed applications within the marine sector, are excellent candidates for initial devices and developing consumer confidence in these technologies. In many of the Blue Economy sectors, wave energy is able to provide power at a variety of levels in locations where no other source can, thus enabling longer and more complex operations. Additionally, and simply, blue economy operations dominantly take place in the ocean – co-located with the natural renewable wave energy flux. Blue Economy applications may include anything from oceanographic measurements and aquaculture farm electrification, to Autonomous Underwater Vehicle (AUV) charging and desalination systems. Many of these applications do not have large power demands and small or micro-scale wave energy converters (WECs) with power in the order of tens to hundreds of Watts are of significant interest.

Historically, WEC technology development has been focused on providing electrical power at the utility level.

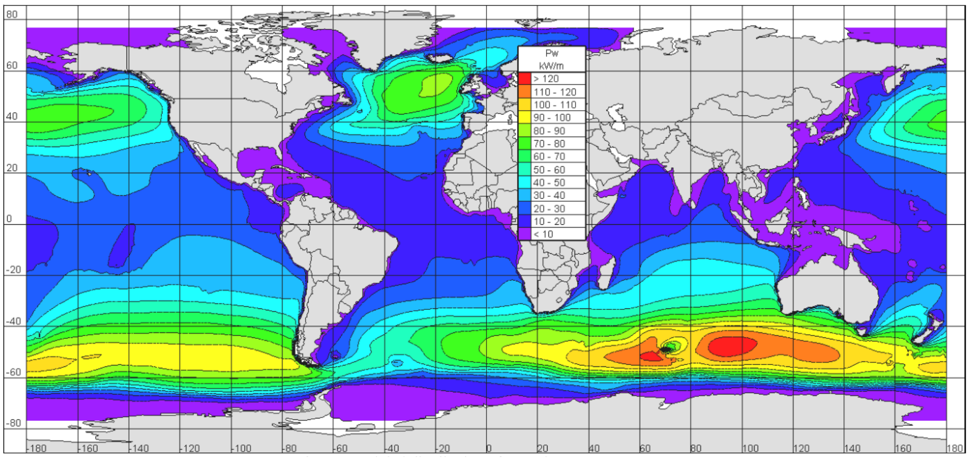

Figure 1: Global distribution of annual mean wave energy transport [6]. The colour bar indicates the total wave energy flux (kW/m)

As discussed in [9][10], this end-user focus has resulted in the development of large structures, with natural frequencies and power production peaks at 8 – 12 sec wave period, to better match the natural occurring wave period identified in the bulk parameter resource assessment. In contrast, many Blue Economy sectors are looking for less than 1 kW of power, with many able to see significant applications with powers less than 100W. This end-user focus requires much smaller devices. However, these smaller WECs have significantly higher natural frequencies and will respond to very differently than a large utility device in the same wave conditions.

The reduction of WEC size, and associated technology and wave condition specific system dynamics, create uncertainty in application of traditional wave resource assessments for the identification of future project development locations. There is clear knowledge gap in understanding the spatial and temporal implications of utilizing smaller WECs for power generation in the world's oceans.

Additionally, realistic estimates of WEC performance, regardless of size, require detailed knowledge of the distribution of wave energy density across the wave frequencies present in the ocean; traditionally represented by the wave spectrum. Even at utility level, the frequency-domain distribution of wave spectrum and the WEC performance rarely overlap perfectly and a significant portion of the wave spectrum is simply 'unextractable'. These mismatches between resource wave spectra and WEC performance curves will be increasingly important to quantify as converter sizes reduce. In this paper, 'extractable' wave energy is defined as the overlapping region between the gross wave variance density spectrum and the WEC performance curve.

Utilizing generic representations of the Oscilla Power Triton WEC [11][12], this novel study investigates the impact on the temporal and spatial variability of wave energy resources, with specific focus on smaller size WECs. Utilizing detailed wave spectra, the study filters the wave spectra to only account for 'extractable' energy at PacWave (Oregon), Los Angeles (Southern California) and the Wave Energy Test Site (WETS – Hawaii). These locations represent a wide variation of gross wave resources and temporal availability. Given the dependence of smaller size WECs on low energy period wave conditions, or wind seas, the study quantifies the altered distribution of size-appropriate wave resources, and the associated temporal variability of these extractable resources.

II. Wave Resource Assessments

Wave energy resource assessments provide wave energy technology and project developers with standardized and consistent assessments of environmental conditions for technology design and deployments. These assessments are vital to the development of the marine energy industry and, as such, there exists a long history and academic record of research methods and metrics utilized quantify wave energy resources. To provide context, the global annual mean wave energy transport is shown in Figure 1.

Under the International Electrotechnical Commission (IEC) [13], there is an on-going international effort to standardize the Technical Specifications for the resource assessment. At the simplest reconnaissance level, resources are generally classified by three main parameters: significant wave height (H_{m0}), energy period (T_e), and omni-directional wave power (J).

Utilizing the outputs from a 32-yr Simulating WAves Nearshore (SWAN) wave hindcast model developed by Wu et al [14], the following bivariate histograms provide a quick overview of the gross wave energy and distribution of wave conditions available at each of the previously identified sites. The SWAN model was forced by WaveWatchIII [15] wave boundary conditions and CFSR [16] winds, and output hourly wave spectra outputs.

For each bivariate histogram, the values in each bin represent the mean annual hours recorded for each sea state combination, and the colouring is the percentage contribution to the total wave energy flux at the site [17].

Wave energy resource at the PacWave wave energy test site in Central Oregon has been characterized multiple times in recent years [18]–[20]. As shown in Figure 2, the most frequently occurring and most energetic sea states were found to be 1.75m at 8.5s (557hrs) and 2.75m at 10.5s (307hrs) respectively.

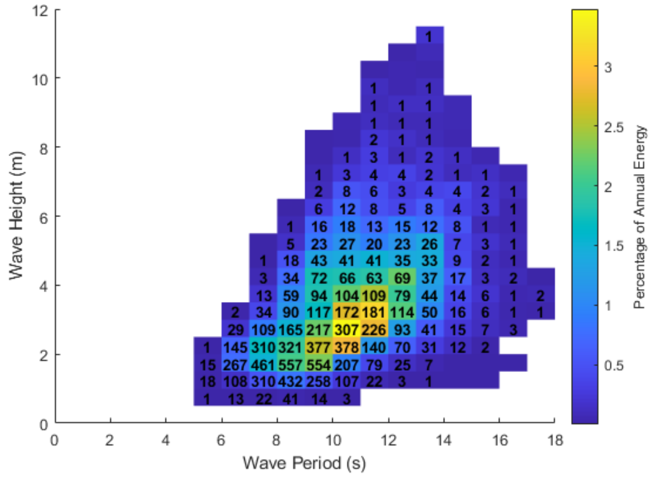

Figure 2: Omni-directional sea state histogram from 2000-2010 at PacWave, OR (mean annual conditions)

In Los Angeles County in Southern California, the wave energy resource differs greatly from Oregon, and the most common and most energetic sea state combinations are one in the same: 1.25m at 8.5s (955hrs), as shown in Figure 3. Additionally, the maximum hindcast wave heights are just 40% of those experienced at PacWave.

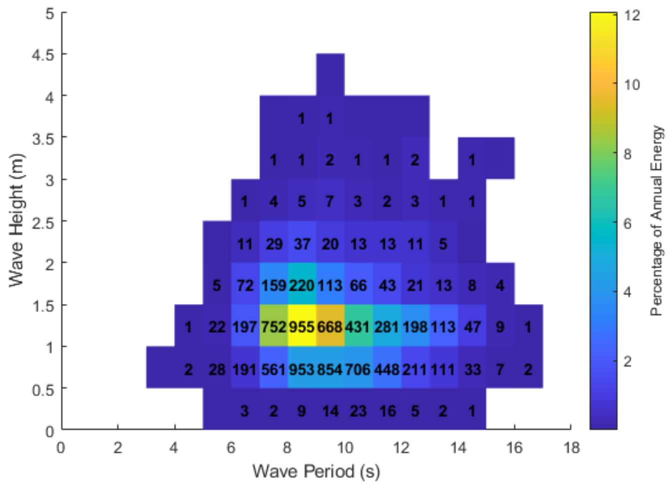

Figure 3: Omni-directional sea state histogram from 2000-2010 off the coast of Los Angeles, CA (mean annual conditions)

Figure 4 shows the bivariate at WETS on the island of Oahu, Hawaii. As with Los Angeles County, the most frequently occurring and most energetic sea states at WETS are the same on average each year at 1.75m at 6.5s (1448hrs). WETS is additionally exposed to eastern trade winds – creating temporally consistent, but smaller, wind seas.

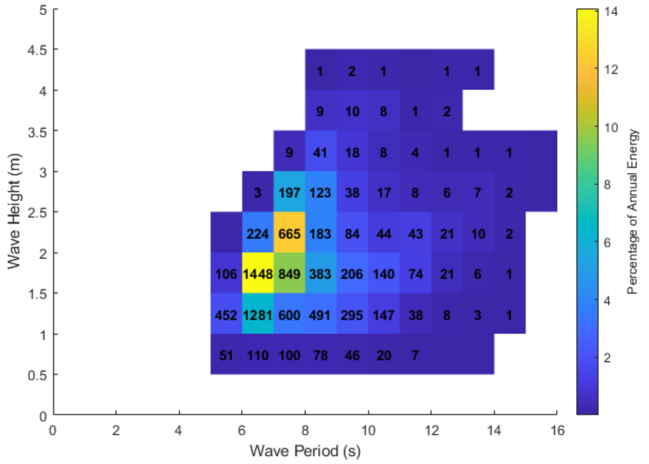

Figure 4: Omni-directional sea state histogram from 2000-2010 at WETS in Oahu, Hawaii (mean annual conditions)

The average, 10th, and 90th percentile monthly J values are shown in Figure 5. Compared to PacWave, both WETS and Los Angeles show lower gross wave energy flux (J) and reduced monthly variability. The results shown reinforce the relative reduction in wave energy and wave conditions in lower latitudes – as illustrated in Figure 5.

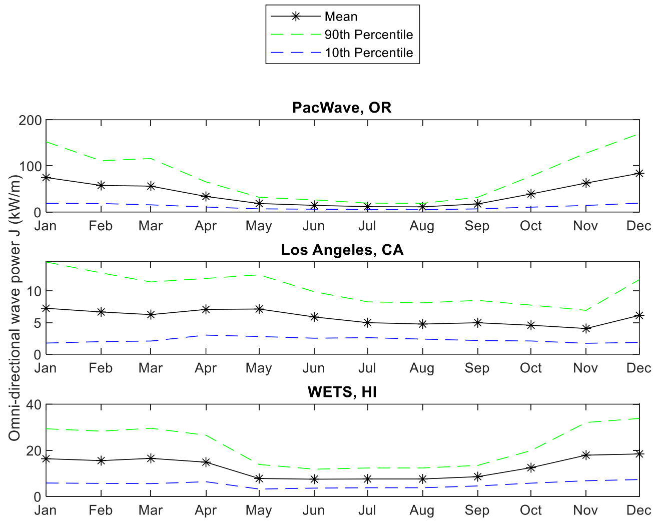

Figure 5: Monthly mean, 10th, and 90th percentiles of omni-directional wave power (J) from 2000-2010 at each site

At all locations, the maximum Js are seen during the winter months from Nov-Mar, followed by the minimum Js occurring in the summer from May-Sept. This was expected, as winter months possess more energetic wave climates due to increased storms [21]. During this time of year, the percentile values are noticeably more varied from the mean, indicating a widespread range of J values. By contrast, in the summer, these locations see less varied percentile measurements, due to a less energetic sea state. Details regarding the selected locations for analysis can be found in Table 1.

TABLE 1: RESOURCE ASSESSMENT LOCATION SPECIFICATIONS

Name	Lat, Lon	Depth	Spatial Resolution
PacWave	44.557°N, 124.229°W	67.4m	300m
Los Angeles	33.854°N, 118.633°W	350m	300m
WETS	21.466°N, 157.751°W	34m	300m

III. WEC TECHNOLOGY AND SCALING

When the resource assessment is combined with the WEC Power Performance IEC Technical Specification [22], a first order estimate of power production can be achieved by multiplying the bivariate histogram of H_{m0} and T_e by a complimentary WEC performance matrix (generated via numerical modelling, physical scale testing, or both). However, the impacts of reduced WEC size, the limited representation of the complete frequency-domain wave spectrum and associated WEC-wave system dynamics are not well characterized by this high-level approach. At minimum, more consideration of the frequency dependence of the WEC is required.

In order to characterize the frequency dependence of WEC size on system performance, the performance data from Oscilla's grid-tied WEC (Oscilla Power Triton) [23] is utilized as a baseline and subsequently generalized to provide a broadly applicable understanding of performance vs. size. Figure 6 provide an overview of WEC design.

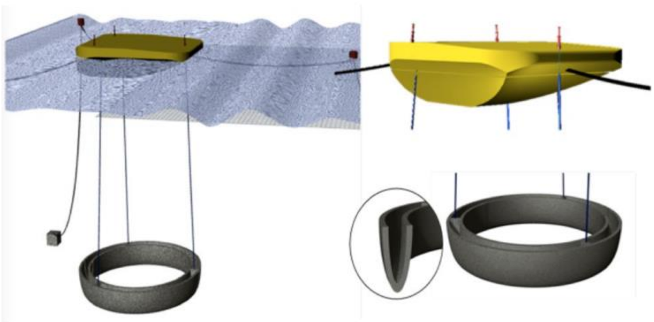

Figure 6: Oscilla Power Triton Architecture

As described in [23], the Triton WEC is a two-body, multi-mode WEC with a nominal full scale rated power of 1MW. A 30% smaller variant of this, the 100kW Triton-C, that shares the same geometry and architecture, is currently under test in Hawaii. The upper floating body of the 1MW system is 23m x 30m, while the reaction heave body is 30m in diameter, and the overall displacement is 1900 tonne. Performance data has been collected at various scales from 1:50 to 1:3 and has been used to thoroughly validate the numerical model performance [11].

Generalized performance curves have been generated from the numerical model through a velocity response amplitude operator (RAO) approach, using a wide bandwidth wave excitation. By using fixed linear damping in the model, the velocity RAO can be translated into a power QTF (Quadratic Transfer Function), which can be multiplied by a specific wave variance density spectrum (S_f) to give an estimate of the device power output in a particular sea state. For the purpose of this paper, Froude scaling has been applied to generate power QTF curves at a range of physical sizes down to 1m. These are shown normalized in Figure 7 which illustrates that the peak response varies between 0.12 Hz (for 30m size) and 0.87 Hz (for 1.0m size).

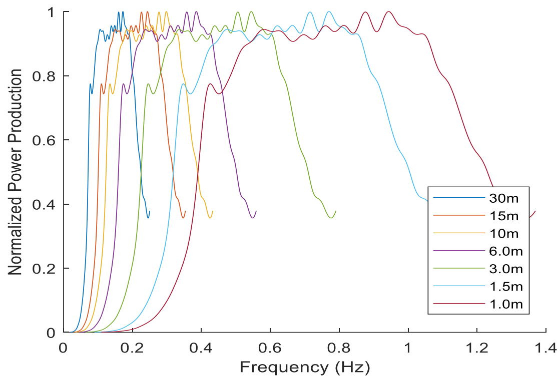

Figure 7: Performance curves for Triton System with varying characteristic dimensions.

IV. METHODOLOGY

In order to assess the impact of WEC size on power production and variability, an independent preparation of the incoming wave spectra and WEC performance curves was required. The raw incoming wave spectra can then be multiplied by the WEC Power QTF response curves to provide an approximation of the net, or usable, power production.

The non-directional wave spectra detailed in Section II only provided variance density values to a maximum of 0.5Hz wave frequency. This is a relatively standard high-frequency cut-off for many wave models [24]. However, given the response of the smaller WEC sizes at higher frequencies, the variance density was required at frequencies up to 2 Hz. Assuming an f^{-5} tail to the spectrum, Equation (1) was utilized to extrapolate the high-frequency tail [24], [25]:

$$S_{(f)} = \alpha g^2 (2\pi)^{-4} f^{-5} \tag{1}$$

where α is an energy scale parameter (fitted at 0.5 Hz), g is gravity, and f is frequency.

The frequency domain response and performance of the differing WEC scales is represented via a Power QTF. The power in a given wave spectra ($\bar{P}_{irr}$) is defined as:

$$\bar{P}_{irr} = \int_0^\infty c\bar{V}_{(f)}{}^2 S_{(f)}\, df \tag{2}$$

where $c\bar{V}_{(f)}{}^2$ is the power from the WEC power-take-off and $S_{(f)}$ is the wave variance density (units: m²/Hz).

Utilizing the hourly frequency domain variance density spectra detailed in Section II, the WEC Capture Width Ratio (CWR) curves were subsequently used to create the available gross resource to identify a net, or usable, power output from the WEC at each scale.

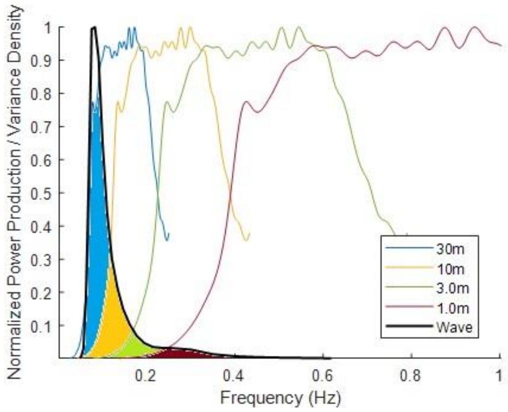

Figure 8: Impact of frequency domain response of WEC size with respect to wave spectra. The second y-axis is the WEC CWR.

Figure 8 shows an example wave spectrum and the normalized WEC power production curves (normalized by maximum power production for each respective WEC size). The figure provides simplistic visual to describe the impact of WEC size, and associated frequency dependent power performance, with respect to the incoming wave spectrum. The incoming wave spectra at PacWave on Feb 21st, 2020 had a peak wave period of 12.2s. This is best matched to the frequency response of the 30m WEC, allowing the WEC normalized power production to achieve a maximum of 0.83 and ability to extract power across almost incoming wave frequencies (all colour highlights). In contrast, if a 1.0m WEC was deployed, only a small portion would be 'available' to the WEC for power production (maroon highlight) and only to a maximum CWR of 0.05.

Note that the WEC performance curves are highly simplified and based on Froude scaling a single dataset. Nevertheless, results have been validated at multiple physical sizes, including the experimental 1m WEC performance curve as demonstrated in [23]. Realistic devices tailored for a given physical size are however unlikely to be scaled versions of larger systems, hence the use of the term small- *size*, rather than small- *scale* in this paper. This has real implications on accuracy and inherently requires disregarding a number of important assumptions key to hydrodynamic modelling. In particular, Froude scaling assumes that the wave resource is also scaled along with the device. The implications of this are discussed in Section VI. However, the objective of utilizing these generalized WEC representations is to develop an understanding of the spatial and temporal dependencies between WEC size and resource characteristics, rather than providing an exact solution. It is very likely that the geometries between smaller and larger WECs will differ to account for different wave excitations [26].

V. Results

Of primary concern to most project and technology developers in the Mean Annual Energy Production (MAEP). Figure 9 provides and overview of MAEP for the various WEC sizes at PacWave, Los Angeles and WETS. As expected, the total generation at PacWave is significantly larger than the other less energetic sites for the larger devices. For example, the same 30m device would generate 1960 MWh, 1060 MWh and 360 MWh at PacWave, WETS and Los Angeles respectively. A significant difference in overall production due to difference in the gross, or raw, wave energy flux.

However, as illustrated in Figure 10, when looking at devices of 10m or lower size, the MAEP is larger at WETS (67 MWh) than PacWave (53 MWh). This is a result of the natural frequency response and CWR of a 10m size WEC being better matched with the lower incoming wave period at WETS. The dominant wave periods in Los Angles are similar to those at PacWave, so the MAEP plots are relatively close to a gross energy downscaled version of PacWave conditions.

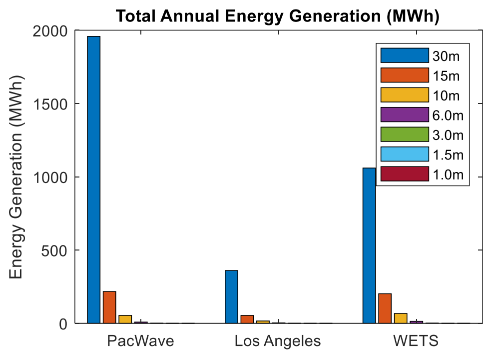

Figure 9: Total energy generation for various WEC size and locations

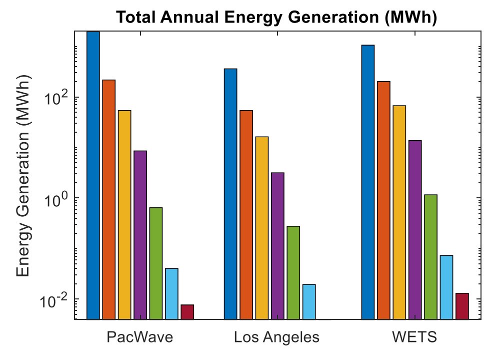

Figure 10: Logarithmic plot of total energy generation for various WEC size and locations

When assessing the seasonal distribution of power production, some additional interesting results begin to emerge. Focussing on the seasonal power production results shown in Figure 11, the interactions between gross wave resource characteristics and WEC size at individual sites becomes apparent.

At PacWave, immediately evident is the significant seasonal variation, and the inverse relationships between WEC size and seasonal performance for the different sizes. The largest size WEC (30m) produces ~70% of the energy during Winter and Fall, and just 10% during the summer. Conversely, at WEC sizes less than 6m, the seasonal variability levels off dramatically. Winter accounts for only slightly greater production levels, while Spring, Summer and Fall are all relatively consistent.

In Los Angeles and WETS, the impact of seasonal variability and WEC size is less pronounced. In general, the general increased occurrences of lower period wave conditions improve the relative productivity of smaller size devices. Surprisingly, in Los Angeles, the greatest percentage of energy generation occurs the spring; regardless of WEC size. While at WETS, the seasonal energy generation is almost constant for WEC sizes less than 6m.

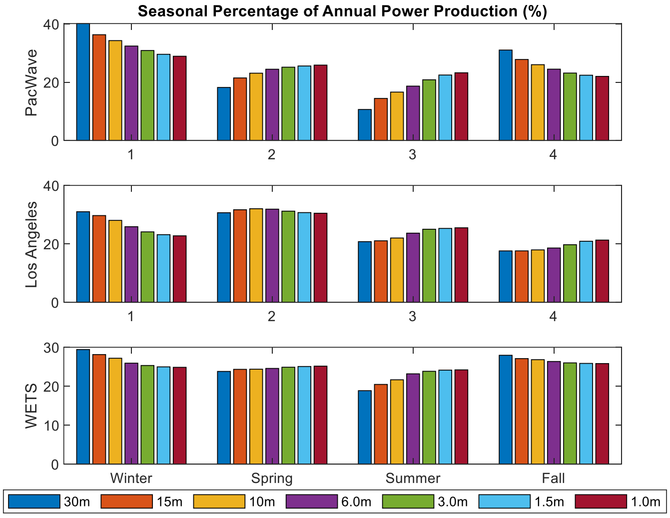

Figure 11: Percentage of annual power production per season and WEC size. (Winter: December, January, February; Spring: March, April, May; Summer: June, July, August; Fall: September, October, November)

As noted above, the normalized power QTF developed above can be used to straightforwardly generate the Capture Width Ratio (CWR) in a given climate. CWR is a commonly when assessing the relative performance of differing utility-level WEC concepts in a known wave climate, and is calculated using (3):

$$CWR = \frac{MEP}{J * w} \quad (3)$$

where MEP is the mean energy production over a period of interest, J is the mean gross energy flux (kW/m) over the same time period, and w is the WEC characteristic width (or size).

However, as shown in Figure 12, the CWR ratio may not be a suitable metric to assess performance across both WEC sizes and locations. For differing WEC sizes, the CWR varies slightly between the most energetic (PacWave) and least energetic (WETS) sites, but varies very significantly for differing WEC sizes; down to effectively zero for WECs less than 3.0m. This is due to a number of influences, but primarily the magnitude of MAEP for differing WEC sizes and the use of a consistent gross resource. As an example, the MAEP for a 30m and a 15m device at PacWave are 1958MWh/yr. and 217 MWh/yr. respectively. This is a 9x reduction in MAEP for a 50% reduction in WEC-incident wave energy transport ($J * w$). Additionally, the CWR maintains the same gross wave energy transport value (J) across all WEC scales, so the calculated CWR will be inherently be reduced with smaller WEC sizes.

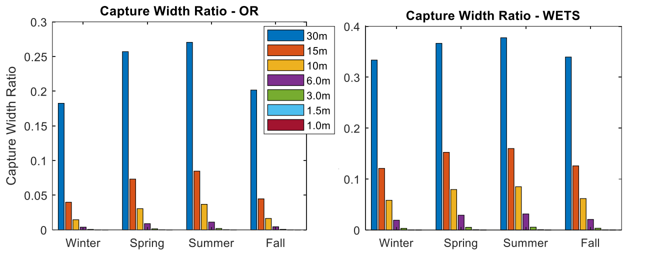

Figure 12: Capture Width Ratio for various WEC sizes in Oregon and Hawaii

Despite the unsuitable nature of CWR for this research, a number of interesting relative results can be extracted. For both PacWave and WETS, the CWR is higher during summer (local low period waves) than winter (distant high period waves). Additionally, WETS wave resources allow for higher CWRs for all WECs due to lower incoming wave gross wave energy.

One of the major hurdles for any renewable energy generator is the natural variability of the resource flux. For wave energy, this depends on both the wave resource characteristics and WEC size. As shown in Figure 7, the size of WEC changes the CWR frequency response.

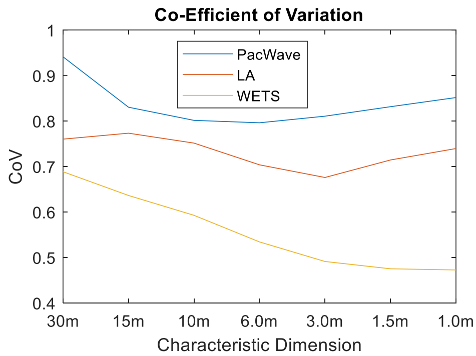

Figure 13: Co-efficient of Variation (CoV) for different WEC sizes

Figure 13 shows the co-efficient of variation (CoV) of various WEC sizes against the resource characteristics. CoV is the standard deviation of the power output over the mean production; or more simply, a measure of relative variability, with a higher value indicating a higher variability. For PacWave and Los Angeles, there is an interesting inflection in the WEC size which has lowest CoV. For PacWave and LA, the deployment of a WEC with less than 6m and 3m characteristic width respectively will actually increase the variability of power output. Conversely, WETS display a relative linear decrease in CoV with respect to the WEC size, with limited additional reduction below a 3m WEC.

VI. Discussion

This research and presented results have clarified and quantified a number of dependencies between the wave resource and WEC size. Immediately apparent in the presented results is the benefits accrued from matching the WEC size, and associated frequency response, to the dominant wave periods in the region of interest. For total energy production, it is immediately evident that WEC energy generation is significantly larger at PacWave than other locations. However, it does require the device to be larger than 15m, and benefit from the lower frequency response. If smaller devices are to be deployed, the better match between the frequency response of the smaller WECs and incoming wave conditions result in larger energy generation in locations with lower gross wave resources (illustrated by Figure 9 and Figure 10).

Figure 11 and Figure 13 both provide an indication of the variation in power production over the year and across the various WEC sizes. While a simplistic view would claim that less variability is preferred, the reality is the benefit and/or detriment of the variability is driven by the correlation with demand. There is little value in generating power when there is little/no demand for that energy. For larger devices which are primarily focussed on utility scale generation, it is more important to ensure seasonal power production correlated with electricity demand than to have a consistent output all year. For smaller devices focussed on Blue Economy application, the need for a consistent output might be paramount and any variability will increase overall system costs due to requirements for batteries or other energy storage/smoothing technology.

A series of important assumptions behind, and limitations of, this research need to be discussed. Firstly, the variance density spectrum extracted from this specific SWAN model is limited to wave frequencies below 0.5 Hz (or wave periods above 2s). This is a fairly standard cut-off frequency for large scale wave propagation modelling with hourly or greater wind field resolution. Given that CWR for the smaller WEC sizes had peak values below 0.5Hz (e.g. the 1m WEC has a peak CWR at 0.75 Hz), the variance density spectrum was artificially extrapolated by fitting an f^{-5} tail to the spectrum. While this is widely acknowledged as best practice in the scientific literature, it simply assumes this portion of the spectrum exists and discounts any scenarios with very limited wind and high frequency waves. It is postulated that this will artificially increase the WEC size relative power production.

As previously noted, the CWR curves presented in Figure 7 are based on a number of assumptions and simplifications. Firstly, this research assumes that the principles of linear superposition apply. As such, the CWR curves for the different WEC sizes were constructed based on individual numerical simulations of the WEC with complete wave spectra – following the same assumptions used by [27], [28].

Additionally, this analysis assumes the WEC body is 'small' with respect to the wavelength, and that wave height does not impact the CWR. The 'size' assumption scale allows diffraction forces to be neglected, leaving only Froude-Krylov pressure forces acting on the body [29]. As per Eq. (4), this ratio must stay above 5 to be reliable:

$$\frac{\lambda}{l} > 5 \qquad (4)$$

where λ is the wavelength of the incident wave and l is the characteristic length of the WEC body.

As the ratio of λ / l decreases below 5 [29], diffraction forces may no longer be neglected, and additional higher fidelity modelling efforts are necessary to account for relevant forces. However, it is noteworthy that as WEC length reduces, the wavelengths most relevant for power production also decrease, thus possibly mitigating some of the worst implications of neglecting diffraction.

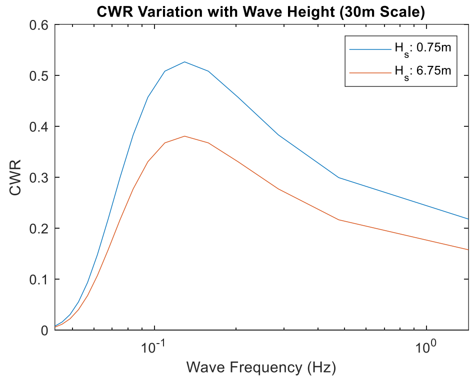

Figure 14: Example of CWR dependency on wave height

Neglecting the impact of wave height does influence the accuracy of the power production magnitudes. Changes in wave height (at a consistent wave period) have been shown to have both positive and negative impacts of relative performance. As an illustrative example, Figure 14 provides an a rather extreme example of the impact of wave height on the CWR for a 30m WEC size. As shown, the increase in wave height has the impact of reducing the next CWR. As such, it is expected that the relative performance changes quantified in this paper will change once on-going work to quantify wave height impacts has been completed.

This research has quantified some initial and impactful impacts of WEC size on the associated spatial and temporal availability of suitable wave resources. However, as detailed in this section, on-going research will provide the necessary additional fidelity to this assessment to better quantify the interactions between WEC size, resource characteristics and power performance.

VII. Conclusions

As the wave energy sector broadens the scope of commercialization opportunities for WEC technologies beyond utility level generators, there is a pressing need to quantify the temporal and spatial variability of the net, or usable, wave energy resources for smaller size WECs. Given the dependence of smaller size WECs on low energy period wave conditions, or wind seas, this study quantifies the altered distribution of size-appropriate wave resources, and the associated temporal variability of these extractable resources based on generic representations of the Oscilla Power Triton WEC and detailed variance density spectrums (wave resources) at PacWave in Oregon, Los Angeles in California and the WETS site in Hawaii. A number of interesting results emerged, particularly with regards to the MAEP and seasonality impacts of wave resources and WEC sizes.

When assessing the impacts of WEC size and resource characteristics, it is immediately evident that energy generation is maximised with the combination of larger sized devices and the more energetic wave resources at PacWave (MAEP ~2000MWh/yr.). However, for smaller devices (<10m), the shorter wave periods present at WETS are better matched to the WEC response and result in an increased MAEP (67 MWh/yr.) relative to PacWave (53 MWh/yr.)

The seasonality of energy generation is also impacted by both the wave resource and the WEC size. The WETS site provides the most consistent seasonal generation (across all WEC sizes), with Los Angeles and PacWave having increased seasonal variation respectively. It is noted that benefit or detriment of seasonality and the associated value to the produced energy is driven by the demand, rather than the metrics presented.

The presented results provide a snapshot of the spatial and temporal dependencies between WEC size and wave resource characteristics for a single device and three distinct locations. Clearly quantified is the significant changes in the magnitude, availability and variability of the energy generated. As the wave energy sector continues to enthusiastically explore and develop new products for Blue Economy applications, these results will help inform project location choices and open new regions for wave energy utilization.

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