Influence of Wave Resource Assessment Methods on Wave Power Production Estimates

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Abstract

Global wave energy inventories have shown that the West Coast of Canada possesses one of the most energetic wave climates in the world, with average annual wave energy transports of 40-50 kW/m occurring at the continental shelf. With this energetic climate, there is an opportunity to generate significant quantities of electricity from renewable sources through the use of wave energy converter (WEC) technologies. However, a complete understanding of the influence of wave resource assessment methods on wave power production estimates is required to ensure power estimates provide the most accurate predictions possible.

A variety of different methodologies are currently available to characterise and quantify the same fundamental wave resource information. This study investigates a regular wave time-series methods as well as the suggested TC-114, binned representative and spectrally partitioned irregular wave methods. The West Coast Wave Initiative (WCWI), within the Institute for Integrated Energy Systems at the University of Victoria, maintains both a series of buoys along the west coast of Vancouver Island and a highly resolved SWAN model for this region. These two data sources are analysed for 2013.

The use of buoy data generally resulted in the prediction of an additional 5% in gross wave energy transport resource. Additionally, differing methodologies resulted in a 30% variation in the total extractable wave energy transport resource, when using the same input wave time-series. The methods specified in the International Electrotechnical Commission (IEC) Technical Committee 114 (IEC, 2014) Technical Specification provided the largest estimates of the gross wave resource (2871.06 MWhrs), while use of spectral partitioning method reduced estimates to 2027.40 MWhrs. Given that these metrics are subsequently used to predict the annual power yields from WEC's, these uncertainties in resource characterization result in significant variations in estimated power production and future WEC development project viability.

Utilizing detailed WEC simulations conducted within the WCWI, specific device performance curves are used predict the total power produced during 2013, based on the various resource characterization methods. Estimated annual wave power production values varied between 301.52 MWhrs and 442.96 MWhrs, a difference of 47 %. WEC performance curves indicate that certain WECs are only able to capture wave energy within a certain frequency band. Hence, it is suggested that the spectrally partitioned methods of characterising the wave climate may provide a better estimate of the wave climate. Spectrally partitioning the wave spectrum results in annual power production estimates of 309.55 MWhrs and 354.29 MWhrs for SWAN and buoy data inputs respectively.

Finally, a wave system seeding sensitivity study indicated there is still significant variability in the power production estimations for individual identical wave spectrums. The extent of this variability is WEC architecture dependent and is not consistent for all devices, and results in limited uncertainty when investigating annual power production.

Keywords: Wave Energy Resource Assessment, Wave Energy Converters, SWAN model, Spectral Wave Partitioning,

Notation:

The following symbols and abbreviations are used in this paper:

f_i = ith frequency band

γ = JONSWAP peak-enhancement factor

H_{mo} = significant wave height

H = wave height (regular waves)

H_{bc} = calculated wave height

H_{bm} = measured wave height

m_n = nth wave spectral moment

S_i = variance density in the ith frequency band

T_e = energy period

T_p = peak period

T = wave period (regular waves)

ER = root mean square relative error

PTO = power take off

DOF = degrees of freedom

WEC = wave energy converter

WCWI = West Coast Wave Initiative

HNE =Heave Northing Easting

ECMWF = European Centre for Medium Range Weather Forecasts

COAMPS= Coupled Ocean Atmosphere Mesoscale Prediction System

RMSE =Root Mean Square Error

1 Introduction and Objectives

For the wave energy conversion industry to mature, the need for highly resolved estimates of theoretical power production cannot be overstated. These estimations allow developers to estimate costs per unit power, utilities to plan for reserve costing and policy makers to estimate the spatial extent extents involved in WEC activities. The accuracy of these estimations are a function of two areas of research; wave energy resource assessments and wave energy converter (WEC) technology modelling. Currently, these research areas are generally treated as independent stages of a serial process.

Firstly, wave resource assessments are generally completed without any knowledge of the WEC performance and provide an estimate of the gross resource available. Given that the waves arriving at the area of interest come from a multitude of different directions and frequencies, providing a simple single measure of the seastate is very complex. As a result, numerous methods have been proposed to quantify the gross resource. Given the substantial amount of data involved when looking at thousands of hours of wave resource data, it is necessary to “pack” this data into simplified metrics describing the annual wave climate; the standard metric is a bivariate distribution based on hourly significant wave height and energy period measurements. This “packing” procedure inherently introduces uncertainty to the wave resource assessment but is required to keep the data interpretation tractable.

Next, numerical simulation studies of WEC dynamics are used to construct WEC performance matrices to cover the majority of reported seastates included in the bivariate histogram. In order to run a numerical time-series simulation of WEC dynamics, the bivariate histogram frequency domain metrics must be “unpacked” to create statistically identical sea surface elevations. This decomposition or “unpacking” procedure increases the uncertainty associated with the WEC performance matrix. Even with detailed knowledge of exact wave spectrum for each hour, uncertainty is introduced through the time-series simulations.

Finally, theoretical annual power production estimates are created by overlaying the wave histogram with the WEC performance matrix. While this method will provide a reasonable estimate of annual power production, the uncertainties associated with “packing” and “unpacking” the wave resource data are significant.

However, the estimation of annual power production should be based on an iterative, parallel process. While basic WEC feasibility studies could continue to use the standard metrics, significantly improved power production estimates can be immediately obtained by re-analyzing the wave resource assessment with detailed knowledge of the WEC power production curve. In essence, through a detailed understanding of the WEC power production curve, it is possible to determine the amount of extractable wave energy transport is available to a specific WEC and limit the amount of unnecessary uncertainty which is inherently included in the gross wave resource assessment. These improved estimates will be used to inform the development of marine energy technical specifications and ensure power production estimates used to secure grants, financial investment and deployments sites provide good estimations of the final electricity produced.

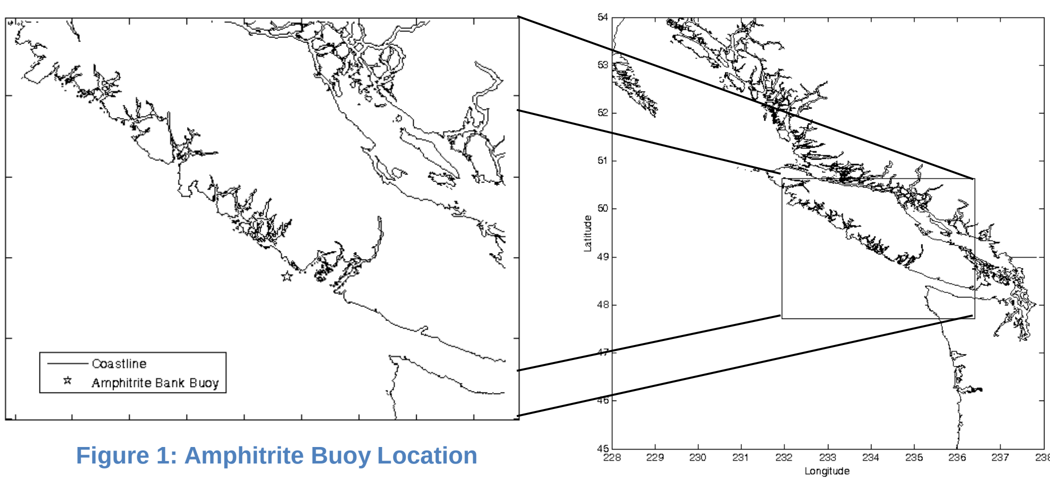

Figure 1: Amphitrite Buoy Location

Global wave energy inventories have shown that the west coast of Canada possesses one of the most energetic wave climates in the world, with average annual gross wave energy transports of 40-50 kW/m occurring at the continental shelf. In order to capture the necessary data resolution required for advanced wave resource assessments, the West Coast Wave Initiative (WCWI) at the University of Victoria maintains a SWAN model, which covers the entire west coast of Vancouver Island (Robertson et al., 2013b), and a series of four Axys Technologies wave measurement buoys off the west coast of Vancouver Island, one of which is situated on Amphitrite Bank (see Figure 1).

Additionally, the proposed iterative wave resource assessment requires detailed knowledge of the power production curves for individual WEC designs. As a result, this method is not WEC architecture independent and the extractable wave resource will vary between different WEC designs for the exact same location. For this study, the WEC model being tested is a two body axisymmetric point absorber. The model is based on the WaveBob, previous commercial WEC concept, and is a full scale version of the WEC used by Beatty et al. (Under review). See Figure 2.

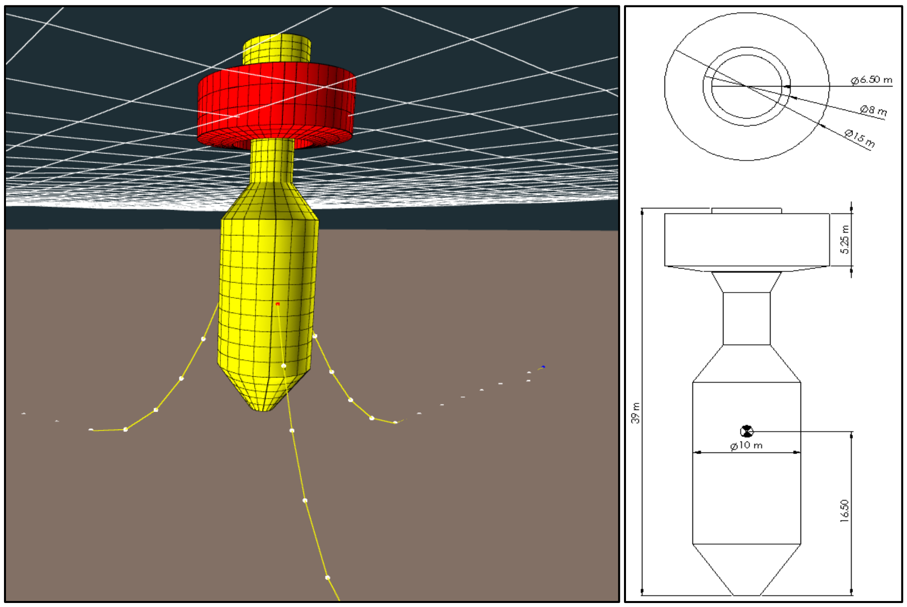

Figure 2: A schematic of the WEC setup and a dimensioned drawing

Through detailed analysis of both the performance curves from the UVic concept WEC and the wave climate off the coast of British Columbia, the objective of this paper will achieved; to determine the influence of wave resource assessment methodologies on wave power estimates.

The paper proceeds as follows: Section 2 details the database of SWAN and buoy measurements used to quantify the wave conditions. In Section 3, the WEC technology modelling procedure and performance curves are introduced. Section 4 presents the details of the differing methodologies available to characterise the same wave resource. In Section 5, detailed analyses of the wave data is completed and bivariate distributions for each method presents. Section 6 quantifies the impact of the differing wave resource methodologies on annual WEC power production estimates. Section 7 investigates whether WEC performance estimates are affected by numerical wave phase seeding, within the context of annual power production estimates. Finally, Section 8 presents conclusions and recommendations for future work.

2 Wave Database

Numerous previous wave resource assessments have either used directly measured wave buoy data or numerical model data (García-Medina et al., 2014; Hiles et al., 2010) to quantify the wave climate at a specific location. This study will utilize both buoy measurements and SWAN model outputs to compare the performance of numerical model results against those from buoy measurements, and comment on the applicability of using numerical results for wave resource assessments.

The Amphitrite Bank buoy was deployed in 2012, in approximately 50m of water, at 48° 52.8'N, 125° 36.9'W. Amphitrite Bank has often been cited as a high interest location for future wave energy conversion (Cornett, 2008). The buoy measures the full directional frequency spectrum with 121 frequency bins and 5° directional resolution.

In addition, a complete numerical hindcast of wave conditions at the Amphitrite Bank Buoy location over the period from 2004 – 2013 was completed (Robertson et al., 2013b). The numerical hindcast utilized the Simulation WAves Neashore (SWAN) model and input boundary conditions from both the European Centre for Medium Range Weather Forecasts (ECMWF) and the US Navy Fleet Numerical Meteorology and Oceanography Centre (FNMOC). In order to appropriately model the wave conditions on Amphitrite Bank, the computational grid spacing was reduced to approximately 150m spatial resolution across the bank.

In order to provide a full year of buoy and SWAN data for further analysis, the mean annual wave energy transport, from the 10 year hindcast at Amphitrite Bank, was calculated. By minimizing the difference between the mean 10-year wave energy transport values and the individual annual wave energy transport values, it was determined that 2013 well represented the long term wave climate for the British Columbia coast.

3 WEC Technology Modelling

The architecture of differing WEC's vary dramatically depending on which wave physical phenomenon they hope to extract power from; wave-induced particle motions, sea surface elevation changes or transient pressure differentials. In order to apply more advanced wave resource assessment methods, which differentiate between the gross wave resource and the WEC-specific extractable wave resource, detailed knowledge of the WEC is required.

The WCWI WEC utilizes the time varying sea surface elevation and consists of two self-contained concentric bodies, a torus and a spar, which move relative to each other along their combined axisymmetric axis. Operating between them is a power take off (PTO) that produces force opposing and in proportion to the relative velocity. The system is deployed in 50 m of sea water and is moored with 3 mooring lines, evenly spaced and attached to the spar at its centre of gravity. The cables are based on 81 m of chain that are anchored to the sea floor, 73 m horizontally, from the centre of the WEC.

Table 1: Standard parameters defining the WEC tested.

Parameters	**Unit**	**Value**
Spar Mass	Kg	1646875
Spar Moments of Inertia, Ixx, Iyy, Izz	Kgm^2	5656250, 5656250, 648437.5
Float Mass	Kg	201406.25
Float Moments of Inertia, Ixx, Iyy, Izz	Kgm^2	5785156.25, 5785156.25, 1445312.5
Chain Density	Kg/m^3	7700
Chain effective diameter	m	0.03655
Chain Axial rigidity	N	$4.2x10^8$
PTO damping coefficient	Ns/m	1625 000

The WEC is simulated using the software package ProteusDS (DSA, 2013). ProteusDS is a non-linear, time domain solver that operates in 6 DOF. The software's physics model has been extensively validated and includes non-linear cable dynamics, interconnections of articulate hulls and mooring lines, PTO dynamics, viscous drag forces and wave radiation and diffraction loading. Wave hydrodynamic information has been calculated in the boundary element method code, WAMIT and used within the ProteusDS environment (Bailey et al., 2014; DSA, 2013). The parameters used in the model are presented in Table 1, and a dimensioned drawing and a schematic of the numerical simulation are presented in Figure 2.

WEC power extraction is non-linear across the frequency bands and depends on the natural frequency of the bodies, PTO interactions, moorings, device control strategies and a number of other factors. As shown in Figure 3, the performance of the considered WEC is maximised at ~ 9 seconds and almost no power is produced when the wave periods are higher than 20 seconds or below 3 seconds. It is noted that advanced power take off (PTO) control or architecture optimization will alter the WEC performance curve.

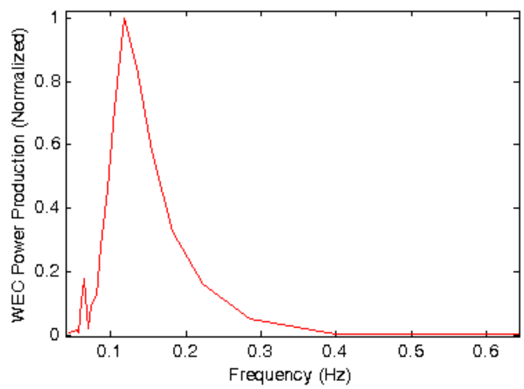

Figure 3: WCWI WEC Performance Curve

In order to provide the required performance matrices for the WCWI device, ProteusDS simulations for every seastate were required. For time-series analysis methods, regular waves of known height and period were simulated within the ProteusDS environment. WEC power production for each run was determined by averaging power production values over 5 wave periods, once WEC production had reached equilibrium.

Table 2: Sample WCWI WEC performance matrix

	Wave Energy Period (Te)											
	3.5	4.5	5.5	6.5	7.5	8.5	9.5	10.5	11.5	12.5	13.5	14.5
0.25	0	0	0	0	0	0	0	0	0	0	0	0
0.75	0	0	5651	9387	9909	8831	9800	6949	5887	0	0	0
1.25	0	0	16757	25404	28667	27518	22628	20737	16990	0	0	0
1.75	0	0	33910	51863	57317	53862	59561	39110	29917	19668	0	0
2.25	0	0	0	64253	57317	53862	59561	39110	42273	41279	0	0
2.75	0	0	0	0	138211	74185	122668	60803	80961	61020	0	0
3.25	0	0	0	0	168478	159038	144908	97735	92193	68936	0	0
3.75	0	0	0	0	0	186089	154950	158663	138447	0	0	0
4.25	0	0	0	0	0	0	200327	169167	143914	0	0	0
4.75	0	0	0	0	0	0	254913	260286	0	0	0	0
5.25	0	0	0	0	0	0	0	0	0	0	0	0
5.75	0	0	0	0	0	0	0	0	0	0	0	0

Wave Height

For spectral wave analysis methods, the wave height and period information included in bivariate histograms was to synthesize a wave time series. The phase of the discrete waves was randomly chosen and varied between all seastates investigated. Maximum and minimum spectrum frequencies included in the simulation were $4/T_p$ and $1/4T_p$ respectively. The number of discrete waves was chosen to ensure that the sea surface repeated every 600 s. Simulations were run for 640 seconds and the first 40 seconds were removed from the analysis due to initial condition affects. A sample WEC performance matrix is presented in Table 2.

4 Wave Resource Quantification Methods

The oldest method of analysing waves is through the analysis of a sea-surface time-series (McCowan, 1894), and provides an initial estimation of wave characteristics and breaking conditions. This method does provide an estimate of the annual wave climate. The WCWI wave measurement buoys collect a vast suite of wave data including both frequency-direction wave spectrums and the vertical heave of the wave buoy. This heave information is synthesized from rate gyro and accelerometer data and calculated at 1.75 Hz, or every 0.57 seconds. Through a standardized zero-up crossing analysis (Mizuguchi, 1982) of the resulting surface elevation time-series, is possible to identify individual wave heights and periods. Assuming linear wave theory, it is possible to determine exactly how many waves, of specific wave height and period waves, would impinge on a WEC in a given year by creating a wave histogram of individual wave heights (H) and zero-crossing periods (T). The assumption of linear theory results in the non-linear effects of wave-wave interactions to be omitted.

In order to address the limitations of surface time series analysis, spectral analysis of waves became the dominant method of studying wave conditions. Spectral analysis is able to represent the entire frequency and direction distribution of waves, at any location over a given time frame, at the expense of the individual wave phase information. However, the spectral analysis includes the necessary information to quantify both the gross and extractable wave climates. While the wave energy industry is yet to publically release a standardized method to quantify a wave resource, significant effort has been undertaken by the International Electrotechnical Commission (IEC) Technical Committee 114 (IEC, 2014) to produce a draft technical specification. This draft document initially recommends calculating the wave spectral moments according to Eq. (1), using the full directional frequency spectrum from either the SWAN model or the buoy data.

$$m_n = \sum_i f_i^n S_i \, \Delta f_i \tag{1}$$

Next, the energy period (T_e) and significant wave height (H_{m0}) for each spectrum was calculated using Eq. (2) and Eq. (3) below:

$$T_e = \frac{m_{-1}}{m_0} \tag{2}$$

$$H_{m0} = 4.004\sqrt{m_0} \tag{3}$$

Finally, these results should be used to create a bivariate histogram of H_{m0} and T_e, using 0.5 m wave height and 1 second energy period bins. The numeric values presented within each bin represent the number of hours per annum each seastate occurs. This “packing” procedure results in a loss of fidelity due to loss of information about the frequency based variance spread of individual spectrum. As a result, it is generally assumed that each histogram bin can be represented with a single peaked spectrum with a JONSWAP shape.

Initial improvements can be made by addressing the assumption of a JONSWAP spectrum shape. By binning the entire wave spectrums (rather than just the of H_{m0} and T_e parameters) into the appropriate histogram bins, an aggregate wave spectrum can be created by calculating the mean variance density within each frequency band, and then constructing an individual representative spectrum for each histogram bin. In order to determine the best fit theoretical spectrum for each representative aggregate spectrum, the peak enhancement function (γ) from the JONSWAP spectral formation (Eq. (4)) can be altered until the root mean square error (RMSE) between the measured and synthesized spectrum is minimized. For a standard JONSWAP spectrum γ = 3.3, while γ = 1 for a PM spectrum.

$$E(f) = \alpha g^2 (2\pi)^{-4} f^{-5} \exp\left[-\frac{5}{4}\left(\frac{f}{f_{peak}}\right)^{-4}\right] \gamma^{\exp\left[-\frac{1}{2}\left(\frac{f/f_{peak}-1}{\sigma}\right)^2\right]} \tag{4}$$

Unfortunately, both proposed gross wave resource methods still assume a single peaked wave spectrum and include the variance density across all frequency bands in the calculation of H_{m0} and T_e parameters. Given that the energy period does not represent the true peak of a physical wave spectrum, it will provide inaccurate representations of the wave conditions in multi-modal seastates. As shown in Figure 4, these methods can result in an over prediction of the maximum variance density level and a significant translation of the spectrum along the frequency axis.

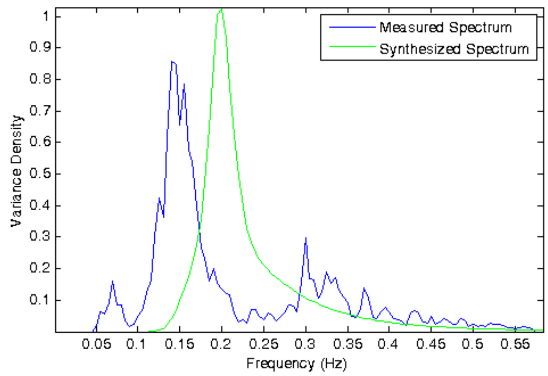

Figure 4: Measured and Histogram Equivalent Spectrum

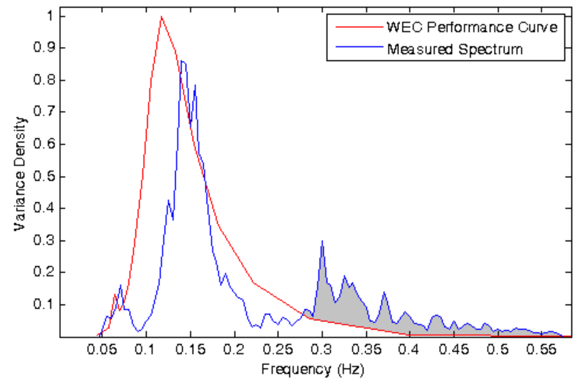

Figure 5: Power Production Spectrum

For WEC developers, detailed information about the true extractable wave resource, considering a specific device power production curve from their device, is more important than gross wave resource assessments. Given that the majority of WEC production curves are single peaked and only extract power across narrow band of frequency values (Figure 3), any estimates of WEC power production should be based on distinct measured wave systems, rather than those mathematically created through use of the wave energy period parameter. Wave spectral partitioning has been ongoing in oceanography for over two decades (Boukhanovsky and Guedes Soares, 2009; Gerling, 1992) but is yet to be applied to the WEC industry. The partitioning of the full directional wave spectra into distinct wave systems greatly improves estimates of both the extractable resources and the associated theoretical power production. Through the decomposition process, it is possible to eliminate the need for the energy period parameter and extract both the individual wave system with the highest energy content and the wave system with the greatest overlap with the WEC performance curve. For a detailed review of spectral partitioning algorithms, see Gerling (1992). As shown by the shaded portion in Figure 5, the inclusion of the distinct spectral peak at ~ 0.30 Hz doesn't overlap with the normalized WEC power production curve, should not be included in the estimates of the extractable wave resource and only introduces additional uncertainty when using gross resource assessment methods.

In order to minimise the number of variables associated with wave resource quantification methods, the current study focuses exclusively on non-directional wave spectrums. While this does simplify the problem greatly, it does also inherently exclude the effects of directionality on WEC performance. It is acknowledged that this could play a major role for directionally preferential WEC designs, yet the WEC used in this study is an axisymmetric point absorber and hence is less influenced by directional wave effects.

5 Wave Data Analysis

5.1 Time-Series Evaluation

Table 14 presents a detailed histogram of individual wave heights and periods, based on the 2013 Amphitrite bank wave buoy data. The zero-crossing heave time series methodology indicates optimizing WECs to perform in wave heights below 0.5m with a wave period of approximately 3.5 seconds (485 934 occurrences). While feasibility of designing WEC's for this small most frequent wave climate may be questionable, the third most frequent wave state, occurring at 0.75m wave height and 7.5 second wave period, may provide a better design guideline.

In additional to providing a general overview of the wave climate for power production estimates, a time-series analysis directly captures individual extreme waves. Extreme waves are of considerable interest when investigating WEC survivability and extreme loading cases. The largest wave captured through time-series analysis was measured at 13.5 m at 16.5 seconds (eliminated from the table due to space constraints). While this largest wave may not be the most destructive, a time-series decomposition allows for the extraction of the steepest (wave height/wavelength) waves in each frequency band and provides design constraints for future WEC dynamic analysis.

5.2 Standard Spectral Methods (TC-114 Spec)

Following the procedure outlined in the TC-114 Technical Specification, SWAN and buoy results were used to create bivariate histograms with 1 second energy period and 0.5 m wave height bins. See Table 3 for the SWAN model and Table 4 for the wave buoy results. The values presented in each bin represent the number of hours per annum each seastate occurs.

It is immediately evident that the SWAN and buoy data result in slightly different representations of the annual wave climate. This can be attributed to a number of factors. Firstly, the frequency resolution varies between the SWAN (36 frequency bands) and buoy (121 frequencies) data. Secondly, the SWAN model is additionally limited by the temporal resolution of the model boundary conditions; the ECMWF model is produced every 6 hrs, while the Coupled Ocean Atmosphere Mesoscale Prediction System (COAMPS) winds are produced every 3 hours. Higher temporal resolution would be required to capture the short term intra-hour effects of wind gusts and localized wave height changes. Finally, the SWAN model has been shown to emphasize the low-frequency components of the wave spectrum (Holthuijsen, 2008), while the wave buoys are more affected by localised “noise” due high frequency wind waves.

While the distribution of waves within the histograms may be different, the 5 most frequent wave conditions (bins) are separated by only a single second. The energy period shift toward higher periods (lower frequencies) for the SWAN model was expected.

Table 3: Standard SWAN Wave Histogram

Wave Energy Period (Te)

	0.5	**1.5**	**2.5**	**3.5**	**4.5**	**5.5**	**6.5**	**7.5**	**8.5**	**9.5**	**10.5**	**11.5**	**12.5**	**13.5**	**14.5**	**15.5**	**16.5**
0.25	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.75	0	0	0	0	0	0	9	108	93	84	0	0	0	0	0	0	0
1.25	0	0	0	0	0	0	108	627	1002	810	408	102	3	0	3	0	0
1.75	0	0	0	0	0	0	18	528	618	654	366	150	39	33	3	3	0
2.25	0	0	0	0	0	0	0	90	183	384	366	246	57	18	6	24	12
2.75	0	0	0	0	0	0	0	15	66	204	219	174	117	39	3	0	0
3.25	0	0	0	0	0	0	0	0	21	105	120	114	48	30	21	0	0
3.75	0	0	0	0	0	0	0	0	9	45	45	45	48	0	0	0	0
4.25	0	0	0	0	0	0	0	0	3	21	15	27	6	0	0	0	0
4.75	0	0	0	0	0	0	0	0	0	0	3	18	3	0	0	0	0
5.25	0	0	0	0	0	0	0	0	0	0	3	3	6	0	0	0	0
5.75	0	0	0	0	0	0	0	0	0	0	0	3	3	0	0	0	0

Wave Height (Hmo)

Table 4: Standard Wave Buoy Histogram

Wave Energy Period

	3.5	**4.5**	**5.5**	**6.5**	**7.5**	**8.5**	**9.5**	**10.5**	**11.5**	**12.5**	**13.5**	**14.5**	**15.5**	**16.5**	**17.5**	**18.5**
0.25	0	0	0	0	0	1	8	5	0	0	0	0	0	0	0	0
0.75	0	7	65	194	306	274	253	123	41	4	1	0	0	0	0	0
1.25	0	4	149	521	682	488	347	168	87	15	5	7	2	0	1	0
1.75	0	0	28	219	389	418	238	143	105	47	12	12	0	0	2	0
2.25	0	0	0	75	195	299	371	237	118	51	18	3	3	1	0	0
2.75	0	0	0	15	84	164	198	150	107	64	19	3	6	3	1	0
3.25	0	0	0	2	41	105	158	83	60	50	17	6	6	4	0	0
3.75	0	0	0	0	4	47	83	57	37	17	13	4	3	2	1	2
4.25	0	0	0	0	1	24	49	37	39	13	8	4	1	0	1	0
4.75	0	0	0	0	0	6	29	28	25	11	3	0	0	2	2	0
5.25	0	0	0	0	0	0	6	17	5	5	3	1	0	1	0	0
5.75	0	0	0	0	0	0	3	8	8	6	12	1	0	1	0	0
6.25	0	0	0	0	0	0	0	3	0	3	2	3	0	0	0	0
6.75	0	0	0	0	0	0	0	1	0	1	2	3	2	0	0	0
7.25	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
7.75	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Wave Height (Hmo)

Given that the standard wave histogram requires knowledge of only significant wave height (H_{mo}) and energy period (T_e) parameters, the histograms provide no clear indication of whether a JONSWAP, Pierson-Moskowitz (PM), TMA or other spectrum are more relevant for accurately recreating the frequency distribution of the wave energy within each bin. As a result, the JONSWAP spectrum is often assumed (Folley et al., 2012; Robertson et al., 2013b), but the power production effect of this assumption is generally neglected.

Finally, the distribution of wave heights and periods of the most frequent waves conditions presented in Table 4 is considerably different from those determined by using a time-series analysis of the same dataset (Table 14). The impact on power production estimates from these differing distributions is very important to the wave energy conversion industry.

5.3 Binned Representative Wave Spectra

In order to determine the best fit wave spectral shape, an iterative procedure was used. 60 different JONSWAP spectrums were created by varying the peak-enhancement factor (γ) between 1 and 7, in 0.1 increments. The best fit representative spectrum was determined by minimizing the root mean square error (RMSE) between the aggregated spectrum data and the representative JONSWAP spectrum using γ. Table 5 and Table 6 present the best fit γ value for each histogram bin.

Table 5: Gamma values for representative spectrum (SWAN data)

Wave Height (Hmo) \ Wave Energy Period (Te)	0.5	1.5	2.5	3.5	4.5	5.5	6.5	7.5	8.5	9.5	10.5	11.5	12.5	13.5	14.5	15.5	16.5
0.25	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.75	0	0	0	0	0	0	1.4	1	1	1	0	0	0	0	0	0	0
1.25	0	0	0	0	0	0	1	1	1	1	1	1.1	1.3	0	1.8	0	0
1.75	0	0	0	0	0	0	1	1	1	1	1	1	1.4	1.3	1.3	1.8	0
2.25	0	0	0	0	0	0	0	1	1	1	1	1	1.1	1.3	1.5	2	2.3
2.75	0	0	0	0	0	0	0	1.2	1	1	1	1	1.1	1.1	1.4	0	0
3.25	0	0	0	0	0	0	0	0	1.2	1	1	1	1.3	1.2	1.6	0	0
3.75	0	0	0	0	0	0	0	0	1	1	1	1	1.3	0	0	0	0
4.25	0	0	0	0	0	0	0	0	1.2	1	1	1.1	1.6	0	0	0	0
4.75	0	0	0	0	0	0	0	0	0	0	1	1	1.6	0	0	0	0
5.25	0	0	0	0	0	0	0	0	0	0	1	1.2	1.4	0	0	0	0
5.75	0	0	0	0	0	0	0	0	0	0	0	1.3	1.3	0	0	0	0

Table 6: Gamma values for representative spectrum (buoy data)

Wave Height (Hmo) \ Wave Energy Period (Te)	3.5	4.5	5.5	6.5	7.5	8.5	9.5	10.5	11.5	12.5	13.5	14.5	15.5	16.5	17.5	18.5
0.25	0	0	0	0	0	6.5	4.6	4.6	0	0	0	0	0	0	0	0
0.75	0	1.5	1	1	1	1	1	1	1.2	1.7	3	0	0	0	0	0
1.25	0	1.1	1	1	1	1	1	1	1.5	1.7	1	1.3	2.9	0	5.4	0
1.75	0	0	1	1	1	1	1	1	1	1.6	1.3	1.3	0	0	1	0
2.25	0	0	0	1.2	1	1	1	1	1.2	1.5	1.4	1.6	1.8	4.7	0	0
2.75	0	0	0	1.3	1	1	1.1	1	1.3	1.8	1.8	1.8	1.7	1.9	2.1	0
3.25	0	0	0	3	1	1	1.1	1	1.5	2	1.9	2	2.3	2.8	0	0
3.75	0	0	0	0	2.6	1.1	1.1	1.1	1.5	1.6	2.5	2	2.3	4.2	5.7	6
4.25	0	0	0	0	2.2	1.2	1.4	1.2	1.5	1.9	1.8	3.1	3.5	0	5.3	0
4.75	0	0	0	0	0	1.9	1.7	1.2	1.4	2.1	2.7	0	0	7	4.1	0
5.25	0	0	0	0	0	0	2.3	1.5	1.1	2.1	1.8	1.3	0	7	0	0
5.75	0	0	0	0	0	0	2.7	1.9	1.7	1.5	2.2	2.3	0	5.4	0	0
6.25	0	0	0	0	0	0	0	1.2	0	1.2	1.4	2.1	0	0	0	0
6.75	0	0	0	0	0	0	0	1.2	0	6.2	2.9	2.4	2.7	0	0	0
7.25	0	0	0	0	0	0	0	1.2	1	4.4	0	0	0	0	0	0
7.75	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Given that a standard JONSWAP spectrum requires a gamma value of 3.3, the tables indicate that a JONSWAP spectrum is a poor choice for numerically modelling the sea-states off the west coast of Canada. A gamma value of 1, the most dominant value in tables, represents a fully developed seastate or a PM spectrum. Therefore, a PM spectrum is more representative of the actual seastates off the BC coast and should be used for all future studies where assumptions of spectral shape are required.

Additionally, the comparison of the two tables below indicates an increasing difference between the SWAN and the buoy representative spectrums. While the most frequent wave height/wave period histogram bins vary only slightly between the buoy and SWAN data, the representative sea state γ values vary substantially.

In order to quantify the <u>relative</u> difference between the measured aggregated spectrum and the synthesised representative spectrum, the Root Mean Square Relative Error (ER) was calculated using Eq. 5 (Rattanapitikon and Shibayama, 2000; Robertson et al., 2013a):

$$ER = 100\sqrt{\sum_{i=1}^{n}(H_{bc} - H_{bm})^2 / \sum_{i=1}^{n} H_{bm}^2} \qquad (5)$$

As shown in Table 7 and Table 8 below, the relative errors between these representative spectrums and the aggregated spectrum can still be substantial. The average respective ER values for the fitted SWAN and buoy data are 25% and 27%. However, these are significantly improved from 66% and 51% resulting from the assumption of a simple JONSWAP spectrum with SWAN and buoy data respectively.

Table 7: ER between the aggregate spectrum and the representative spectrum (SWAN Model)

Wave Height (Hmo) \ Wave Energy Period (Te)	0.5	1.5	2.5	3.5	4.5	5.5	6.5	7.5	8.5	9.5	10.5	11.5	12.5	13.5	14.5	15.5	16.5
0.25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.75	0	0	0	0	0	0	56	62	31	28	0	0	0	0	0	0	0
1.25	0	0	0	0	0	0	49	51	65	59	39	24	17	0	19	0	0
1.75	0	0	0	0	0	0	27	38	43	31	32	27	14	8	37	30	0
2.25	0	0	0	0	0	0	0	30	35	27	23	22	17	12	22	29	23
2.75	0	0	0	0	0	0	0	13	29	21	19	20	13	7	13	0	0
3.25	0	0	0	0	0	0	0	0	11	23	23	23	7	12	22	0	0
3.75	0	0	0	0	0	0	0	0	15	23	24	16	10	0	0	0	0
4.25	0	0	0	0	0	0	0	0	19	18	23	9	9	0	0	0	0
4.75	0	0	0	0	0	0	0	0	0	0	22	24	11	0	0	0	0
5.25	0	0	0	0	0	0	0	0	0	0	44	12	9	0	0	0	0
2.75	0	0	0	0	0	0	0	0	0	0	0	13	14	0	0	0	0

Table 8: ER between the aggregate spectrum and the representative spectrum (buoy data)

Wave Height (Hmo) \ Wave Energy Period (Te)	3.5	4.5	5.5	6.5	7.5	8.5	9.5	10.5	11.5	12.5	13.5	14.5	15.5	16.5	17.5	18.5
0.25	0	0	0	0	0	65	62	61	0	0	0	0	0	0	0	0
0.75	0	46	61	39	42	92	57	44	38	39	32	0	0	0	0	0
1.25	0	55	40	38	45	37	37	26	10	20	48	35	27	0	45	0
1.75	0	0	31	21	29	22	21	39	21	11	16	17	0	0	84	0
2.25	0	0	0	15	24	23	17	14	17	14	27	35	41	20	0	0
2.75	0	0	0	20	20	24	11	21	18	19	25	31	35	35	39	0
3.25	0	0	0	25	27	8	10	11	21	19	18	28	15	31	0	0
3.75	0	0	0	0	29	9	10	22	23	15	11	40	30	15	19	26
4.25	0	0	0	0	29	18	8	13	22	16	15	14	36	0	39	0
4.75	0	0	0	0	0	20	21	13	17	20	39	0	0	20	42	0
5.25	0	0	0	0	0	0	15	26	19	24	10	40	0	37	0	0
5.75	0	0	0	0	0	0	13	22	13	21	17	18	0	20	0	0
6.25	0	0	0	0	0	0	0	56	0	21	22	15	0	0	0	0
6.75	0	0	0	0	0	0	0	39	0	9	23	17	33	0	0	0
7.25	0	0	0	0	0	0	0	23	42	21	0	0	0	0	0	0
7.75	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

5.4 Spectral Partitioned Methods

For this study, a wave system was considered to be discrete and independent if the following criteria were met: the ratio of discrete peak frequencies was greater than 1.25, the difference between peak directions was greater than 20° and the wave modes weights' greater than a factor of 10 (Gerling, 1992).

As shown in Table 9 and Table 10, the histogram for the spectrally partitioned wave systems provides a significantly different representation of the wave climate from those presented in Table 3 and Table 4. Immediately noticeable is the reduction in the reported significant wave height, as expected due to the elimination of non-extractable variance densities. The fitted gamma values vary slightly and suggest using a PM spectrum; with the mean values of 1.07 and 2.03 for the SWAN and buoy results respectively.

Table 9: Spectrally partitioned wave histogram (SWAN model)

Wave Height (Hmo) \ Wave Energy Period (Te)	0.5	1.5	2.5	3.5	4.5	5.5	6.5	7.5	8.5	9.5	10.5	11.5	12.5	13.5	14.5
0.25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.75	0	0	0	0	0	0	0	94	174	171	100	26	0	0	0
1.25	0	0	0	0	0	0	48	452	1047	753	662	265	29	0	0
1.75	0	0	0	0	0	0	0	359	575	778	426	203	84	42	6
2.25	0	0	0	0	0	0	0	58	165	307	391	326	81	0	0
2.75	0	0	0	0	0	0	0	0	0	210	252	178	129	0	0
3.25	0	0	0	0	0	0	0	0	19	100	0	129	0	0	0
3.75	0	0	0	0	0	0	0	0	10	42	48	0	0	0	0
4.25	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0
4.75	0	0	0	0	0	0	0	0	0	0	0	19	0	0	0
5.25	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0

Table 10: Spectrally partitioned wave histogram (Buoy)

Wave Height (Hmo) \ Wave Energy Period (Te)	3.5	4.5	5.5	6.5	7.5	8.5	9.5	10.5	11.5	12.5	13.5	14.5	15.5	16.5	17.5	18.5
0.25	6	0	0	3	13	23	36	39	36	10	3	0	0	0	0	0
0.75	74	84	191	494	933	846	869	617	310	123	26	10	0	0	0	0
1.25	10	13	310	1072	1647	1399	1089	636	352	181	32	23	10	13	3	6
1.75	0	0	45	465	963	1066	853	426	310	249	65	26	26	6	0	0
2.25	0	0	0	152	468	749	1011	778	359	239	74	23	10	13	6	3
2.75	0	0	0	39	207	362	575	388	384	200	74	13	23	6	3	10
3.25	0	0	0	0	94	310	420	265	162	145	87	16	23	10	3	3
3.75	0	0	0	0	13	126	236	174	120	48	42	10	6	0	0	3
4.25	0	0	0	0	0	58	145	113	110	52	36	0	10	0	0	3
4.75	0	0	0	0	0	19	65	84	74	32	19	0	0	0	0	0
5.25	0	0	0	0	0	0	23	55	16	13	0	0	0	0	0	0
5.75	0	0	0	0	0	0	6	29	23	19	0	0	0	0	0	0
6.25	0	0	0	0	0	0	0	6	6	0	19	0	0	0	0	0
6.75	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0
7.25	0	0	0	0	0	0	0	3	3	0	0	0	0	0	0	0

The ER values presented in Table 11 and Table 12 confirms that the fitted spectrums are better able to reproduce the spectrally partitioned wave systems than the full spectrum. This reduction in the input wave spectrum uncertainty will inherently be transferred to reducing the uncertainty in power prediction estimates.

Table 11: ER values between spectrally partitioned and fitted theoretical spectrum (SWAN)

Wave Height (Hmo) \ Wave Energy Period (Te)	0.5	1.5	2.5	3.5	4.5	5.5	6.5	7.5	8.5	9.5	10.5	11.5	12.5	13.5	14.5
0.25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.75	0	0	0	0	0	0	0	32	26	23	29	30	0	0	0
1.25	0	0	0	0	0	0	26	17	20	30	25	21	15	0	0
1.75	0	0	0	0	0	0	0	28	17	24	27	23	8	10	14
2.25	0	0	0	0	0	0	0	26	26	16	13	17	19	0	0
2.75	0	0	0	0	0	0	0	0	0	21	15	19	10	0	0
3.25	0	0	0	0	0	0	0	0	11	19	0	26	0	0	0
3.75	0	0	0	0	0	0	0	0	17	21	21	0	0	0	0
4.25	0	0	0	0	0	0	0	0	25	0	0	0	0	0	0
4.75	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0
5.25	0	0	0	0	0	0	0	0	0	0	31	0	0	0	0

Table 12: ER values between spectrally partitioned and fitted theoretical spectrum (Buoy)

Wave Height (Hmo) \ Wave Energy Period (Te)	3.5	4.5	5.5	6.5	7.5	8.5	9.5	10.5	11.5	12.5	13.5	14.5	15.5	16.5	17.5	18.5
0.25	48	0	0	37	44	50	60	24	29	41	44	0	0	0	0	0
0.75	45	87	32	11	11	21	28	43	17	16	19	15	0	0	0	0
1.25	43	24	15	31	21	19	23	27	11	23	21	47	38	36	29	29
1.75	0	0	21	19	12	8	15	12	12	10	14	30	14	31	0	0
2.25	0	0	0	20	15	11	13	13	15	16	29	17	24	26	34	21
2.75	0	0	0	25	19	13	12	12	13	12	31	18	19	20	35	28
3.25	0	0	0	0	26	16	10	14	13	10	24	27	13	33	35	34
3.75	0	0	0	0	24	12	15	18	18	15	25	22	38	0	0	37
4.25	0	0	0	0	0	29	11	13	15	12	20	0	27	0	0	35
4.75	0	0	0	0	0	35	10	15	19	11	19	0	0	0	0	0
5.25	0	0	0	0	0	0	22	33	18	11	0	0	0	0	0	0
5.75	0	0	0	0	0	0	34	34	18	17	0	0	0	0	0	0
6.25	0	0	0	0	0	0	0	30	21	0	21	0	0	0	0	0
6.75	0	0	0	0	0	0	0	25	0	0	0	0	0	0	0	0
7.25	0	0	0	0	0	0	0	32	46	0	0	0	0	0	0	0

6 Annual Wave Energy Capture Results

The wave energy conversion industry is indentured to provide highly resolved and accurate estimations both the amount of power their device will produce and the costs associated with that power prior to widespread adoption. Without accurate predictions of both power and cost, WEC developers will struggle to both find the necessary capital investment and gain traction with the local electricity utilities. The gross wave resource has been deconstructed according to numerous methods in the previous section, yet impact on the estimated power production is of primary important to the wave energy conversion industry.

In order to ease the computational effort required to numerically model every seastate bin created in the previous sections, only histogram bins with more than 6 or 24 hours of annual occurrence, for the regular and irregular wave methods respectively, were included in the following discussion. This will result in a slight underestimation of the final energy production, yet will not influence the relative power production estimates between the different resource characterisation methods.

Irregular wave spectrums are traditionally defined by a significant wave height and peak wave period. In contrast, the TC-114 technical specification calls for all histograms use to use energy period in an effort to account for double peaked wave spectra. Hence, prior to numerical simulation, a representative peak period was created for every histogram bin based on the spectral shape, spectrum peakness parameter (γ) and energy period value.

Table 13 details the power production estimates for the various methods discussed in Section 3.

Table 13: Annual Power Production Estimates

Method	Wave Type	Data Source	Wave Power (MWhr)	Extracted Power (MWhr)	Efficiency
Time Series	Regular Waves	Buoy	2682.56	479.87	0.18
TC-114	JONSWAP Spectrum	SWAN	2723.16	417.55	0.15
		Buoy	2613.73	434.37	0.17
TC-114	PM Spectrum	SWAN	2871.06	419.03	0.15
		Buoy	2755.05	442.96	0.16
Bin Representative	Fitted	SWAN	2867.37	430.45	0.15
		Buoy	2738.94	418.71	0.15
Spectrally Partitioned	Fitted	SWAN	2027.40	301.52	0.15
		Buoy	2029.25	326.07	0.16

6.1 Time-Series Evaluation

Given the extensive spread of the wave conditions presented in Table 14, regular wave ProteusDS simulations were conducted only for histogram bins which featured more than 6 hours of annual occurrence. Power estimates for individual waves were determined by taking the mean production over 5 wave periods, once the device has reached equilibrium.

As shown in Table 13, using the time series methodology on the wave buoy data predicts 479.87 MWhrs of annual wave power production. The time-series method could only be applied to the buoy data since SWAN is not a phase-resolved model. The time-series method predicts ~15% more power than the mean of the power production from spectral methods.

6.2 Standard Spectral Methods (TC-114 Spec)

As shown in Table 13, there is considerable variation in the power production estimates between both the SWAN vs. buoy data sources and the JONSWAP vs. PM spectrum assumptions. Regardless of spectral shape assumptions, the measured wave buoy data consistently results in approximately 5% of additional power production when compared against the SWAN model data. This can be attributed to the limitations of SWAN being able to simulate extreme wave events, as visualized by the higher H_{m0} values in Table 4.

The assumption of a JONSWAP or PM spectral shape results in only minor variation in the final annual power output (~ 1%), indicating that assumptions of JONSWAP shape are valid for annual power production estimates using the TC-114 specification.

6.3 Binned Representative Wave Spectra

Interestingly, by eliminating assumptions of spectral shape within histogram bins and using the best fitting γ values in Table 5 and Table 6, the power production estimates using buoy data where lower than when using the SWAN data (430.45 MWhr vs. 418.71 MWhr respectively). This contrasts the trend of SWAN data generally providing lower estimates of power production. This could be explained by the volatile nature of the high frequency noise associated with buoy measurements. Once aggregated, the effect of this high frequency noise is minimised. Regardless, the relative difference is between the two resource measurement methods is small (~ 3%).

6.4 Spectral Partitioned Methods

By partitioning the wave spectrum, and only using the peak with the majority of the incident wave energy, the wave histograms presented in Table 9 and Table 10 provide a more refined estimate of the extractable wave energy transport.

As shown in Table 13, the spectrally partitioned methods result in lower power production estimates of 301.52 MWhrs and 326.07 MWhrs for SWAN and buoy data respectively. These power production estimates are inherently lower due to the elimination of unextractable wave energy in gross wave resource assessment methods (such as the standard TC-114 method). The results indicate the use of gross wave resource assessment methods tend to overestimate the WEC power production by ~33% for the buoy data and ~39% for the SWAN model. This is indicated by the reduction in total wave heights between Table 3 and Table 9 for SWAN data, and Table 4 and Table 10 for buoy data.

7 Power Production Sensitivity Analysis

Numerical simulations of WEC performance allow developers to better understand WEC motions, PTO dynamics and non-linear loading between waves and their devices. Additionally, they mitigate some of the inherent risks associated with developing technologies by allowing for rapid analysis of device performance, failure modes and iterative performance gains. However, in order to produce the performance matrices for the considered WEC, the frequency domain wave spectrum is decomposed or "unpacked" to synthesize a water elevation time-series for the ProteusDS model. As a result of the statistical decomposition, the exact time series varies depending on the seeding, or phase of each synthesis regular wave system. Given the non-linear power production behaviour of many WEC's, this will affect the estimates of power production within each histogram bin and it is necessary to determine the sensitivity of production estimates on wave system seeding.

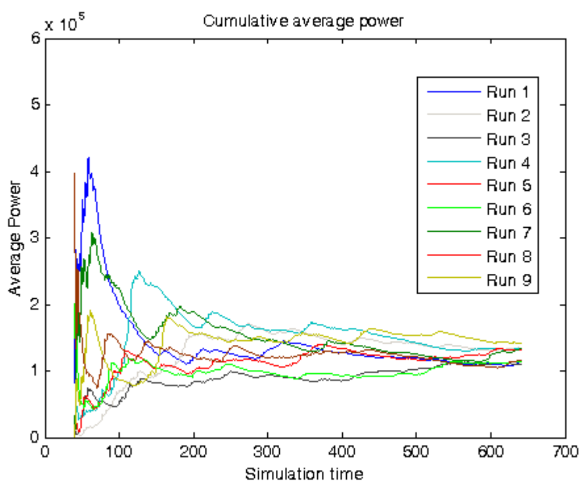

Figure 6: Cumulative Average Power

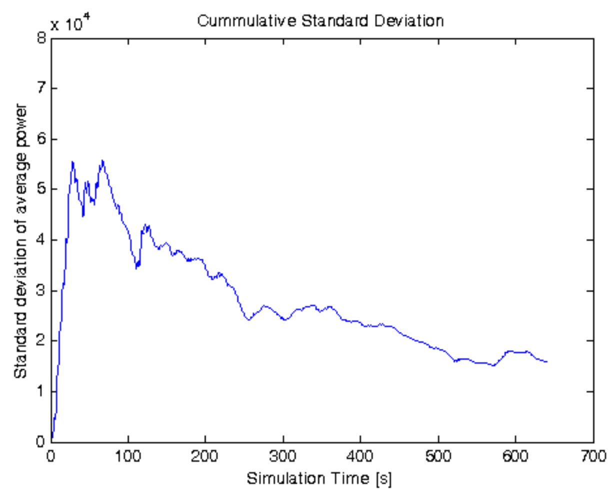

Figure 7: Cumulative Standard Deviation

In order to investigate this effect, multiple simulations of the WCWI WEC were performed using a standard JONSWAP wave spectrum with a significant wave height 2.75 m and peak wave period of 9.5 seconds. As shown in Figure 6, the cumulative average power between the various runs varied dramatically over the first 300 seconds of simulation time and the spreading was significantly reduced by the end of the simulation runs. However, the cumulative average power does not converge to a consistent average power across all runs.

The standard deviation in the cumulative average power between the different runs was approximately 16 kW (See Figure 7), which represents approximately 13% of the mean cumulative power (125 kW). Assuming a normal distribution, this indicates that 32 % of numerical power production estimates, using the same JONSWAP spectrum at 2.75m and 9.5 seconds, will predict values below 109 kW or above 141 kW.

However, when viewing this uncertainty through its effect on annual power production estimates, the effect is reduced. For all seastates included in the standard spectral methods histogram, assuming a consistent proportion of standard deviation and a normal distribution, the relative standard deviations for the total annual power recovery are 2.4% for the both PM and JONSWAP buoy data spectrums. The SWAN resource data features a 2.9% and 2.7% total power deviation using a JONSWAP and PM spectrum respectively.

8 Conclusions and Recommendations

As the wave energy conversion industry matures, the need for highly resolved estimates of theoretical power production cannot be overstated. These estimations allow developers to provide estimated costs per unit power, allow utilities to begin planning for reserve costing and allow policy makers to begin estimating the spatial extent of the sea activities.

When performing a wave resource assessment, a variety of different methodologies are currently available to characterise and quantify the same fundamental wave energy resource information. Given that these metrics are subsequently used predict the power and financial feasibility estimates for individual WEC designs, it is imperative to assess the discrepancies between these resource characterization methodologies and the impacts on the final predicted power generation from WEC installations.

Estimated annual wave power production values varied between 301.52 MWhrs and 442.96 MWhrs, a difference of 47 %. Obviously, this difference will play a significant role in determining the feasibility of wave energy conversion as large scale power generation.

Generally, the use of buoy data resulted in approximately 5% larger predictions of annual power production when compared against SWAN model results. This can be attributed to the inability for numerical wave models to predict extreme sea conditions. Additionally, on an annual power production basis, the difference between assumed spectral shape and the best fit shape were on the order of 1%. This is less than one standard deviation of the power variation, due to the randomized wave phase, so could be considered insignificant.

Interestingly, the annual power predicted by using regular wave numerical simulations and time-series wave analysis provided an annual power production estimate of 426.02 MWhr – on par with spectral methods over the same period. This was surprising since it was assumed simulations in regular waves would allow for “perfect” WEC motion and increased estimate of power production for each histogram bin. Understanding the non-linear nature of the WCWI WEC power production, it is suggested that the periods of increased and decreased power production, due to constructive and destructive irregular wave interaction, may negate each other when using an annual power production metric. This is certainly not the case for when investigating WEC power production with < 1 sec time resolution.

WEC performance curves indicate that certain WECs are only able to capture wave energy within a certain frequency band. Hence, it is suggested that the spectrally partitioned method of characterising the wave climate may provide a better estimate of the wave climate, from a WEC developer’s point of view, than the basic oceanography methods which have integrated into the TC-114 technical specification. Spectrally partitioning the wave spectrum, and only including the wave system with the highest energy content, results in annual power production estimates of 309.55 MWhrs and 354.29 MWhrs for SWAN and buoy data inputs respectively. A significant reduction when compared against the standard TC-114 methods.

Additionally, a wave system seeding sensitivity study indicates there is still significant variability in the power estimations for individual wave spectrum. The extent of this variability is WEC architecture dependent and is not consistent for all devices. Additionally, it should be noted that the presented wave climate resource methodology results are not universal and may differ considerably based on geographic location and incident wave climate.

Finally, it should be noted that there currently is no “gold standard” to determine the accuracy of the differing wave resource characterisation methods. This is due to a lack of publically available long-term power production data. As a result, the conclusions presented are based on scientific reasoning and detailed numerical analysis of device performance and wave climate databases.

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References

Bailey, H., Ortiz, J., Robertson, B., Buckham, B. and Nicoll, R., 2014. A methodology for wave-to-wire wec simulations, Marine Renewable Energy Technology Symposium, Seattle, WA.

Beatty, S.J., Hall, M., Buckham, B., Wild, P. and Bocking, B., Under review. Experimental and numerical comparisions of self-reacting point absorber wave energy converters in regular waves. Ocean Engineering.

Boukhanovsky, A.V. and Guedes Soares, C., 2009. Modelling of multipeaked directional wave spectra. Applied Ocean Research, 31(2): 132-141.

Cornett, A.M., 2008. Investigating nearshore wave energy resources, a case study - western vancouver island.

DSA, L., 2013. Dynamic systems analysis ltd proteusds manual. In: S. 2.2.1977 (Editor).

Folley, M., Cornett, A.M., Holmes, B., Lenee-Bluhm, P. and Liria, P., 2012. Standardising resource assessment for wave energy converters. The 4th International Conference on Ocean Energy, p.^pp.

García-Medina, G., Özkan-Haller, H.T. and Ruggiero, P., 2014. Wave resource assessment in oregon and southwest washington, USA. Renewable Energy, 64: 203-214.

Gerling, T.W., 1992. Partitioning sequences and arrays of directional ocean wave spectra into component wave systems. Journal of Atmospheric and Oceanic Technology, 9(4): 444-458.

Hiles, C., Buckham, B. and Wild, P., 2010. Wave energy resources in hesquiaht sound. Proceedings of the Canadian Society for Mechanical Engineering Forum, p.^pp.

Holthuijsen, L.H. (Editor), 2008. Waves in oceanic and coastal waters. Cambridge Press.

IEC, 2014. International electrotechnical commission tc 114: Marine energy - wave, tidal and other water current converters.

McCowan, J., 1894. On the highest waves of a permanent type. Philosophical Magazine, Edinburgh, 38(5): 351 - 358.

Mizuguchi, M., 1982. Individual wave analysis of irregular wave deformation in the nearshore zone. Proceedings of International Conference in Coastal Engineering: 485 - 504.

Rattanapitikon, W. and Shibayama, T., 2000. Verification and modification of breaker height formulas. Coastal Engineering Journal, 42(4): 389 - 406.

Robertson, B., Hall, K., Nistor, I., Zytner, R. and Storlazzi, C., 2013a. Remote sensing of irregular breaking wave parameters in field conditions. Journal of Coastal Research: 29.

Robertson, B., Hiles, C. and Buckham, B., 2013b. Characterizing the nearshore wave energy resource on the west coast of vancouver island. Renewable Energy, 71: 665-678.

Appendix A:

Table 14: Wave histogram from zero-crossing analysis of HNE data

	0.5	1.5	2.5	3.5	4.5	5.5	6.5	7.5	8.5	9.5	10.5	11.5	12.5	13.5	14.5	15.5	16.5	17.5	18.5	19.5	20.5	21.5	22.5	23.5	24.5	25.5	26.5	27.5	28.5	29.5
0.25	54	98885	231265	485934	177600	126107	85052	92877	22659	14134	13784	3013	1935	1364	1200	268	146	154	7	18	11	18	0	11	0	7	0	0	4	4
0.75	0	5234	62771	369452	240282	231257	200641	282623	89921	64638	73767	20174	13502	8946	9378	2470	1524	1589	378	207	107	96	11	18	4	4	0	0	4	0
1.25	0	32	5034	95044	97133	116321	119449	202837	76380	59723	77580	22837	16379	11028	12288	2924	1846	1953	493	253	171	175	50	29	11	21	7	4	0	0
1.75	0	0	357	19971	30052	44422	54011	109085	47485	41491	59201	19360	14626	10292	11688	2977	2028	2092	550	325	168	243	61	25	46	14	7	0	7	0
2.25	0	0	25	3802	8861	16650	22263	55439	27407	25004	39845	14102	10810	7968	9560	2560	1767	1806	453	253	161	221	39	39	14	25	0	4	4	0
2.75	0	0	0	771	2706	6173	9682	27742	15551	14948	24547	9300	7572	5473	7343	1878	1353	1457	311	232	143	111	50	25	11	7	0	0	0	0
3.25	0	0	0	139	785	2249	4202	13555	8197	8365	14316	5862	4477	3463	4545	1296	825	975	250	154	79	111	29	21	21	18	4	4	7	4
3.75	0	0	0	25	239	782	1803	6319	4680	4727	8414	3527	2813	2135	3088	775	585	625	218	100	86	96	25	7	11	0	0	4	4	4
4.25	0	0	0	0	32	268	828	3459	2595	2810	4994	2110	1721	1371	1849	589	400	393	100	71	39	50	0	0	7	0	0	0	4	0
4.75	0	0	0	0	4	57	257	1667	1299	1510	2970	1128	1017	860	1242	407	196	286	54	46	39	29	7	4	0	7	4	0	0	0
5.25	0	0	0	4	0	21	121	839	728	942	1749	782	546	528	725	218	161	168	57	32	14	14	0	0	0	0	0	0	0	0
5.75	0	0	0	0	0	14	36	343	450	475	917	461	318	357	471	157	154	136	18	32	18	0	4	0	0	0	0	0	0	0
6.25	0	0	0	0	0	14	7	193	246	225	621	293	232	168	307	129	82	79	18	25	4	4	0	0	0	0	0	0	4	0
6.75	0	0	0	0	0	0	7	104	96	139	389	121	154	121	175	75	57	57	14	14	4	11	0	0	0	0	0	0	0	0
7.25	0	0	0	0	0	0	4	32	57	71	186	125	75	71	171	46	25	29	11	0	7	4	0	0	0	0	0	0	0	0
7.75	0	0	0	0	0	0	0	14	32	50	125	36	54	54	89	32	43	36	0	0	4	0	4	0	0	0	0	0	0	0
8.25	0	0	0	0	0	0	0	0	7	39	64	46	36	57	50	11	18	18	4	0	4	0	0	0	0	0	0	0	0	0
8.75	0	0	0	0	0	0	0	7	4	14	54	18	25	25	25	14	11	7	0	4	0	4	0	0	0	0	0	0	0	0
9.25	0	0	0	0	0	0	0	0	4	11	18	7	7	7	11	14	7	11	0	0	4	0	0	0	0	0	0	0	0	0
9.75	0	0	0	0	0	0	0	0	7	4	0	7	0	0	18	4	14	4	0	0	0	0	0	0	0	0	0	0	0	0
10.25	0	0	0	0	0	0	0	4	0	0	4	7	4	4	4	0	4	7	0	0	0	0	0	0	0	0	0	0	0	0
10.75	0	0	0	0	0	0	0	0	0	0	0	4	0	4	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11.25	0	0	0	0	0	0	0	0	0	4	7	0	0	0	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11.75	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12.25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12.75	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13.25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0
13.75	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0