Impact of Resource Uncertainties on the Design of Wave Energy Converters

Markel Penalba*, Ander Zarketa-Astigarraga, Paul Branson, Bryson Robertson

Abstract—**Precise resource characterisation is crucial for the assessment of the performance of wave energy converters (WECs). Wave data from *in-situ* observations is considered to be the most accurate, but is expensive and complex, while re-analysis datasets, although very accessible, may not be fully reliable. However, apart from energy potential characterisation and site selection, little attention is usually paid to the precision of the metocean datasets during the WEC design process. The present paper evaluates the impact of resource uncertainties on the WEC design process, including design aspects, such as power production capabilities, structural integrity and operation and maintenance. Overall, it is demonstrated that the raw ERA5 re-analysis datasets are unreliable, with design parameters misestimated by up to 50%. However, the application of statistical bias correction techniques enables reducing the bias significantly, providing estimates of the design parameters that are very similar to those obtained based on observation datasets.**

Index Terms—**Resource assessment, Wave data uncertainties, Statistical bias correction, Wave Energy Converters design.**

I. Introduction

ACHIEVING a worldwide transition from fossil fuels to clean energies and realizing a carbon-neutral energy system requires a massive expansion of renewable energy sources. This transition aligns with the objectives outlined in the Paris Agreement [1] and the latest report from the International Panel for Climate Change (IPCC) [2] to mitigate the most severe impacts of climate change [3]. While mature and reliable renewable technologies like wind and solar energy exist, the scale and pace of this transition will necessitate the involvement of other renewable technologies. According to the International Renewable Energy Agency (IRENA), the total global installed capacity of renewable energy needs to increase by a factor of five, equivalent to an additional 14 TW by 2050 [4]. Offshore renewable energy (ORE) systems are considered a viable alternative to facilitate this transition. The International Energy Agency predicts that approximately 45% of CO_2 emission savings by 2050 will come from technologies still in the development phase [5]. Offshore wind power, for instance, is projected to multiply its current worldwide installed capacity by a factor of 30 over the next three decades [4]. Similarly, wave and tidal energy, although still in the early stages of development, are anticipated to make significant contributions to the future energy mix, potentially covering around 10% of the global electricity demand [6], [7].

However, wave energy converters (WECs), tidal energy converters, and even floating offshore wind turbines (FOWTs) require substantial development to become competitive in the energy market. Key aspects for the advancement of these technologies include:

i. Optimizing the design of floating structures by reducing material usage while ensuring reliability and structural integrity (SI).
ii. Increasing energy generation capacity through the consideration of nonlinear hydrodynamics and the design of control algorithms.
iii. Enhancing the durability of critical components such as mooring lines and power take-off (PTO) systems by utilizing new materials and designing them to operate within better-adjusted regions.
iv. Improving accessibility and availability through the optimization of operations and maintenance (O&M) strategies.

Accurate metocean data plays a crucial role in the effective and reliable design of successful ORE technologies, encompassing all the aforementioned aspects. The use of incomplete or inaccurate metocean data introduces higher uncertainty into the design process, which is already inherently uncertain [8]. This uncertainty leads to excessive conservatism in the design of ORE technologies, resulting in large and expensive systems that struggle to compete in the current energy market [9]. Since resource assessment is the initial step in the energy conversion chain of any ORE system, the uncertainty in metocean data impacts all subsequent stages, from predicting system responses to estimating energy generation [10], [11]. Offshore renewable energy technologies are typically designed for two distinct operational modes: power production mode (*PP*) and survivability mode (*Surv*). Understanding and reducing metocean data uncertainties across the entire operational domain, encompassing both modes, are of utmost importance.

Moreover, considering spatio-temporal variations, including inter- and intra-annual variability [12], as well as the potential non-stationarity of the resource [13], [14], necessitates the use of long datasets for a

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comprehensive understanding of the resource. Various international organizations recommend considering relatively lengthy data periods. For instance, the International Organization for Standardization (ISO) suggests a minimum of 10 years of data (25% of the return period of interest) for ORE systems with a lifespan of 20-30 years [15], while the Institute of Marine Engineering, Science & Technology (IMAREST) recommends a longer period of 30 years to accurately characterize extreme events [16].

The most common sources of metocean data in the ORE sector are observation buoys and re-analysis datasets. However, wave measurement buoys or other observation systems often struggle to cover such lengthy data periods, and their deployment and maintenance in the open ocean can be complex and costly. Consequently, re-analysis datasets and data from climate models are frequently employed. These datasets provide metocean data over extensive time periods (some dating back to 1900 [17], [18]) and are available at any location worldwide at little to no cost. Nonetheless, re-analysis datasets suffer from limited accuracy under certain conditions, particularly in extreme events. Calibrating re-analysis datasets helps reducing the differences (bias) between raw datasets and observations, enabling the generation of precise long-term metocean data that cannot be solely obtained from observations. Hence, the identification of the accurate calibration or bias correction (BC) technique is crucial. Such an analysis has recently been carried out along the Spanish coast in [19], where the effectiveness of different BC techniques is evaluated only based on resource data.

The present paper goes one step further and assesses the impact of BC techniques on different WEC design parameters, including most relevant aspects of the design process:

i. *Power production capabilities* by estimating the Annual Mean Power Production (AMPP),
ii. *Structural integrity* by evaluating the extreme event design point, and
iii. *Operational and Maintenance* (O&M) by computing the mean waiting time.

It should be noted that these aspects are possibly not independent from each other. For example, SI directly affects O&M and, in turn, O&M affects the power production capabilities. However, for the sake of simplicity, the three aspects are studied independently in the present study.

The reminder of the paper is organised as follows: Section II describes the different BC techniques considered in this study; Section III describes the case study, including the geographical location, the wave data and the WEC device employed in the analysis; Section IV shows the main results of the analysis and Section V draws the most relevant conclusions and future work.

II. Bias correction techniques

Bias correction techniques are statistical tools that adjust the values of raw data to match the statistical properties of observed data. These techniques have gained popularity in climate and meteorological studies over the past two decades [20], [21], and their application does not require a deep understanding of the underlying physics of models or data assimilation methods [22]. These techniques can be applied to various variables, but the quality of the corrected or calibrated datasets relies heavily on the quality of the reference dataset, typically represented by observations, which serves as the "ground truth." For more detailed information on BC in climate and meteorological datasets, refer to [21].

Four BC techniques are applied: Delta-change, Full distribution mapping (FDM), Quantile mapping (QM), and Gumbel quantile mapping (GQM). All BC techniques consist in adjusting the distribution of the assimilated dataset (y^{as}) by adding a correction factor computed via measured (y^{obs}) and assimilated datasets. The difference between the BC techniques lie on the method to compute the correction factor. It should be noted that the present study uses only the significant wave height (H_s) and peak period (T_p) datasets, since WECs' performance is assessed by combining these two variables.

A. Delta

The Delta-change technique involves adjusting y^{as} by adding a constant correction factor calculated based on the difference between the average values of the assimilated ($\hat{y^{as}}$) and measured datasets ($\hat{y^{obs}}$). The corrected dataset is obtained by adding the correction factor to the assimilated dataset:

$$y_i^{BC} = y_i^{as} + (\hat{y}^{obs} - \hat{y}^{as}), \tag{1}$$

where $i = 1, ..., N$, N being the number of timesteps considered from the datasest.

B. Full distribution mapping

The FDM technique uses the entire cumulative density function (CDF) of the assimilated and observed datasets to identify the statistical relationship between them. This relationship is then transformed into time-domain correction factors using an n-order polynomial function. The corrected dataset is obtained by adding the correction factors to the assimilated dataset (X^{FDM}), which is computed as the difference between the inverse CDF of the assimilated (CDF_{as}^{-1}) and observed datasets (CDF_{obs}^{-1}):

$$X^{FDM} = CDF_{as}^{-1} - CDF_{obs}^{-1}, \tag{2}$$

Hence, the dataset corrected via the FDM technique is given as,

$$y_i^{BC} = y_i^{as} + f(X^{FDM}, n), \tag{3}$$

where f denotes the n-order polynomial function.

C. Quantile mapping

The QM method is similar to FDM, but identifies the correction factors at each quantile (q_j) of the CDF. The assimilated and observed datasets are divided into quantiles, and the correction factor for each quantile is computed. The corrected dataset is obtained by adding the quantile-specific correction factor $X^{QM}(q_j)$ to the assimilated dataset. Hence, the correction factor for each quantiles is computed as,

$$X^{QM}(q_j) = CDF_{as}^{-1}(q_j) - CDF_{obs}^{-1}(q_j), \tag{4}$$

which is incorporated in the BC method as in Equation (3), except that the correction factor is applied at each quantile:

$$y^{BC}(q_j) = y^{as}(q_j) + f(X^{QM}(q_j), n). \tag{5}$$

In this study, 50 linearly-spaced quantiles are defined between the 1$^{\text{st}}$ and the 99$^{\text{th}}$ quantiles, both included ($q_j = 1, ..., 99$).

D. Gumbel quantile mapping

The GQM technique is a variation of QM, where the quantiles are placed following a Gumbel distribution function (GDF), as illustrated in 6. That way, the upper tail of the distribution is better represented, placing over 50% of the quantiles are commonly placed above the 99$^{\text{th}}$ quantile.

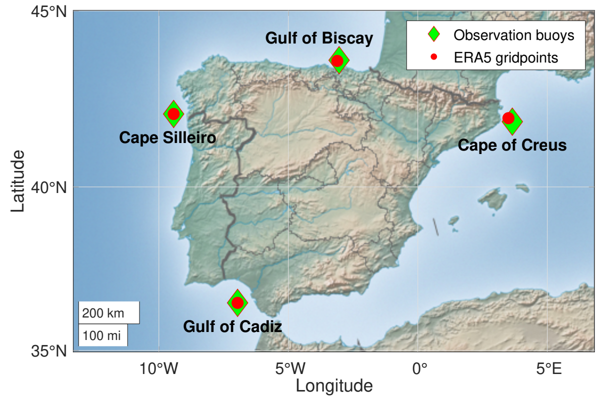
$$F(x; \mu, \beta) = e^{-e^{-(x-\mu)/\beta}}, \tag{6}$$

where μ and β are, respectively, the location and scale parameters.

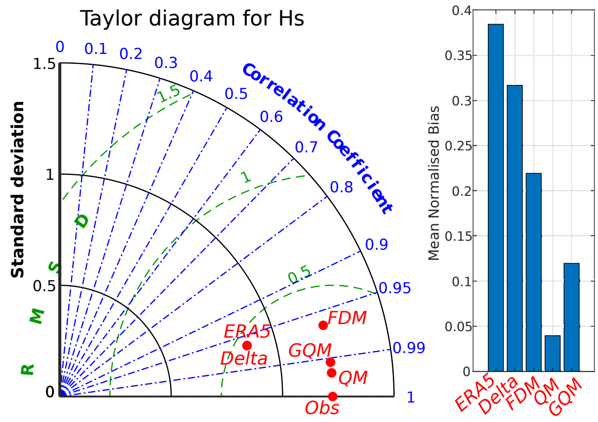
With the quantiles identified following the Gumble distribution, the correction factor is also computed based on the inverse CDFs at each quantile, as in 4, and applied to the assimilated data using a polynomial function as in 5.

III. Methodology and case study

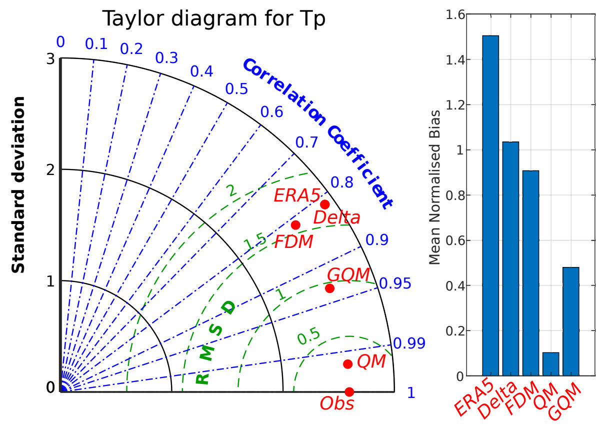
The methodology used in the present study is divided into two main aspects. On the one hand, BC techniques are applied to re-analysis datasets as in [19], including the pre-processing of the data. On the other hand, the corrected data is employed for the evaluation of the impact on the WEC design aspects described in Section I.



a) Geographical location of the case study, including the location of the measurement buoys (large green diamonds) and the ERA5 re-analysis gridpoints (small red circles) [19]



b) H_s [m].



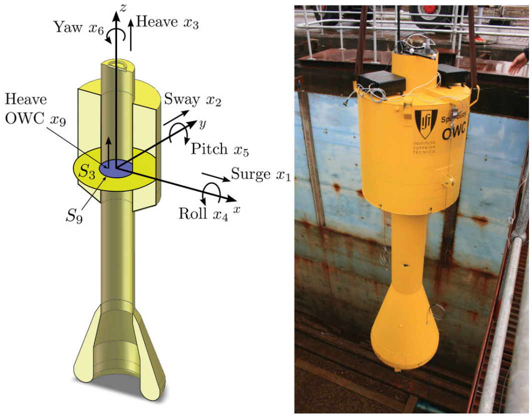
c) T_p [s].

Fig. 1. Geographical location, and Taylor diagrams and bias of the different BC techniques: (b) H_s and (c) T_p [19]

A. Wave data

The present study analyses a single geographical location among the four locations studied in [19]: Gulf of Biscay, as illustrated in Fig. 1 (a). This location represents a sheltered area in the North-East Atlantic Ocean that is primarily influenced by swell waves ($\hat{H}_s = 1.9$ m and $\hat{T}_p = 9.6$ s). Although sheltered, this area is considered to be highly interesting for the implementation of diverse ORE technologies, as demonstrated by the Mutriku Wave Power Plant continuously supplying electricity to the grid since 2011 [23] and the pre-commercial FOWT farm promoted by Saitec Offshore Technologies [24].

In this study, re-analysis data is obtained from the ERA5 product by the European Centre for Medium-Range Weather Forecasts, while observations data is provided by the Spanish Port Authorities coordination agency, Puertos del Estado. Both datasets are publicly available. Although the temporal resolution is identical, the observation dataset provided by Puertos del Estado includes several missing points, meaning that a pre-processing is necessary for comparability. The pre-processing addresses irregularities and temporal gaps in the observation data, either by interpolating single-sample gaps or omitting data for longer gaps. These actions ensure that the datasets have the same length



a) Illustration of the Sparbuoy WEC.

		Wave peak period (s)															
		6	6.5	7	7.5	8	8.5	9	9.5	10	10.5	11	11.5	12	12.5	13	14
Significant wave height (m)	1	7	8	8	9	9	10	10	10	9	9	9	8	8	8	7	7
	1.5	10	10.5	14	14.5	17	17.5	19	19	17.5	17	16.5	16	14.5	14	12.5	12
	2	11	15	25	28	34	35.5	36	35.5	34	33	30	25	23	20	17	16
	2.5	16	25	38	48	55	59	61	60	54	51	48	44	37	34	29	22
	3	24	34	54	68	81	85	85	85	80	75	68	62	57	51	45	34
	3.5	32	51	75	89	106	115	118	115	107	102	95	85	79	68	62	50
	4	48	51	97	112	131	138	139	138	136	124	119	111	98	91	78	66

b) Power matrix of the Sparbuoy WEC.

Fig. 2. (a) Illustration of the Sparbuoy OWC device, including the cut section indicating the fixed reference frame and the 1:16 scale of the device [25]), and (b) the power matrix of the Sparbuoy [26].

and discretisation for the computation of correction factors in the bias correction techniques.

The improvement of data quality due to different BC techniques are evaluated in [19] and illustrated in Figures 1 (b) and (c) by means of Taylor diagrams. Three aspects can be highlighted here:

- The quality of the raw ERA5 dataset is rather poor, particularly for T_p,
- The Delta and FDM BC techniques barely provide any improvement,
- The QM and GQM techniques, especially the QM, significantly improve the quality, considerably reducing the bias.

The results of the present study assesses the impact of such an uncertainty of the wave data on the different crucial aspects of the WEC design process.

B. *Sparbuoy WEC*

The Sparbuoy is a floating OWC (Oscillating Water Column) device that consists of a semi-cylindrical hollow floater moored to the seabed. As in any other floating OWC device, ocean waves induce the motion of the floater and the water column, enabling the compression and expansion of the air in the chamber. This air flows out and in the chamber from the top of the floater, driving an air-turbine with the flow and generating energy via the electric generator coupled to the turbine. Fig. 2 illustrates the cut section of the device indicating the fixed reference frame and the 1:16 prototype of the device [25]. Oscillating water column WECs are one of the most robust and reliable technologies, demonstrated both in reference onshore wave plants, such as the Biscay Marine Energy Platform (BiMEP) test-site [23] and offshore floating prototypes, like the MARMOK-A-5 [27] developed by IDOM.

C. *WEC design process*

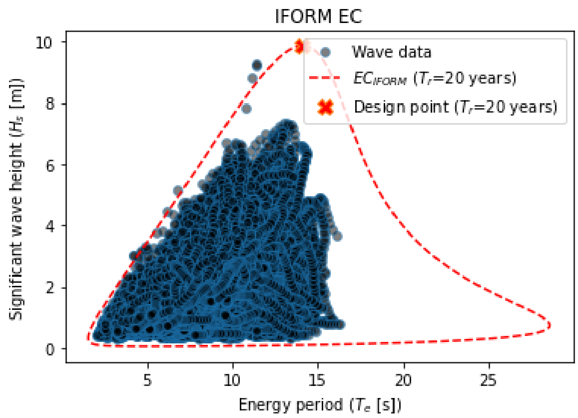
The design process of ORE technologies, including WECs and FOWTs, consider three main aspects defined in Section I: (i) power production capabilities, (ii) SI and (iii.) O&M. For each of these aspects, one metric is considered, so that the impact of resource uncertainties can be assessed.

1) Power production capabilities: In the case of power production capabilities, the AMPP is the estimation of the WEC's energy production, which is commonly evaluated by means of a power matrix [28], where the average power production from each wave conditions or sea states (combination of H_s and T_p) is estimated in a matrix. Fig. 2 (b) illustrates the power matrix for the Sparbuoy WEC provided in [26]. Combining the power matrix and the wave resource information, the annual mean power production (AMPP) can be computed as follows,

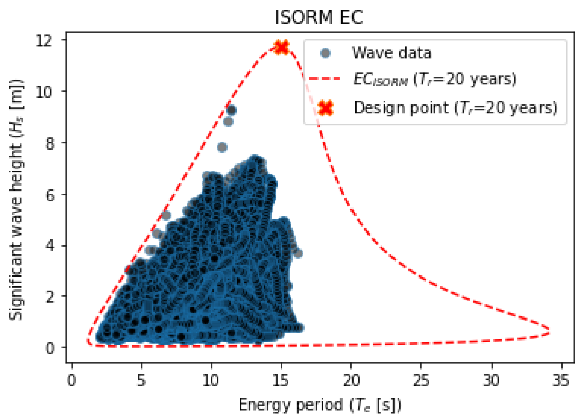
$$AMPP = \sum_{i=1}^{N_{H_s}} \sum_{j=1}^{N_{T_p}} P_{ss}\left(H_S(i), T_p(j)\right) \mathrm{PDF}\left(H_s(i), T_p(j)\right) \tag{7}$$

where the N_{H_s} and N_{T_p} are the number of H_s and T_p values considered in the power matrix.

2) Structural integrity: The assessment of the SI is commonly divided into fatigue and extreme loads, each of which have different consequences. In any case, the WEC needs to be able to reliably bear with the fatigue from cyclic loads and extreme loads occurred in extreme wave conditions. The former requires the computation of the damage by means of a fatigue model over the whole operational regions as in [29], while the latter is estimated by a single point in terms of H_s. Hence, the design point to be considered for considering extreme events is the limiting H_s value that is assumed to be the most extreme wave condition that a ORE technology will encounter [30]. This design point is commonly evaluated by means of environmental contours [9], [10], although other approaches have also been suggested [8]. Two of the most relevant environmental contours have been selected in this study: the inverse first-order reliability method (IFORM) and the inverse second-order reliability method (ISORM) [10]. The SI analysis in the present study is restricted to the evaluation of the extreme design point by computing the environmental contours via the Virocon toolbox [31] and identifying the limiting wave condition of the contour. Due to the uncertainty of the environmental contours [10], two different approaches have been used, as illustrated in Fig. 3.



a) IFORM-based environmental contour.



b) ISORM-based environmental contour.

Fig. 3. Environmental contour and extreme design point identification for the (a) IFORM and (b) ISORM techniques.

The environmental contours illustrated in Fig. 3 can be computed for different return periods, which represents the horizon for which the environmental contour is defined. As the return period increases, more frequent and harsher extreme events become more statistically more likely, which results in larger environmental contours and greater extreme design points. Therefore, the present study considers three different commonly used return periods: 20-year, 50-year and 100-year return periods.

3) Operation and maintenance: Finally, wave conditions can have a significant impact on O&M aspects by limiting the accessibility to the device/farms and, thus, the availability of the system. The availability reduction has a direct impact on the final energy generation and, as a consequence, the Operational Expenditure (OpEx) and levelised cost of Energy (LCOE). The accessibility and availability assessment are carried out based on the wave conditions and the O&M requirements of the device, where these requirements vary depending on the type of vessel used in the operation and the weather window (WW) required for the repair/replacement task [32]. The combination of the WW and the operational limits of the O&M vessels provides the mean waiting time (mWT), which represents the mean time to wait for executing the O&M task. Hence, each waiting time is defined as the time between two consecutive WWs, as illustrated in Fig. 4, which can be averaged over the whole lifetime to compute the mWT [33].

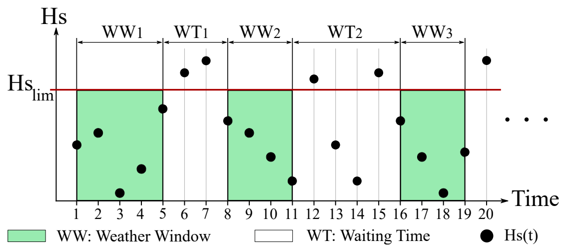


Fig. 4. Weather Window [33].

For the sake of simplicity, the O&M requirements of the device are fixed with an operational limit of $H_{s_{lim}} = 2m$, which represents O&M vessel characteristics between a Crew Transfer Vessel ($H_{s_{lim}} = 2.5m$) and a Field Support Vessel ($H_{s_{lim}} = 1.8m$). Additionally, the WW is also fixed for a duration of 8 hours, which represents the time required to perform a minor repair [32]. That way, each BC technique analysed in this study will provide a single mWT estimate for each environmental contour approach.

IV. Results and Discussion

Assuming that the Delta and FDM BC techniques barely improve the quality of the wave data, the design parameters are only computed for the datasets obtained via QM and GQM techniques, comparing them against the design parameters calculated based on the observation and raw ERA5 datasets. This comparison is carried out for the three WEC design aspects, showing the inappropriateness of the raw ERA5 datasets, on the one hand, and the suitability of each BC technique, on the other.

A. Power production

The estimation of the AMPP is crucial, since it is commonly used for the assessment of the different WEC technologies and/or geographical locations. Fig. 5 illustrates the AMPP estimates based on the different wave datasets, showing that the AMPP estimated based on raw ERA5 dataset (13kW) underestimates the power production capabilities in almost 50% of the AMPP estimated based on observations (21kW). Such a difference becomes almost negligible when computing the AMPP based on the QM- and GQM-corrected datasets, showing an improvement of over 70% with respect to the estimate based on the raw ERA5 dataset. In this sense, the QM technique seems to provide slightly better results, although the absolute deviation in both cases is below 1%.

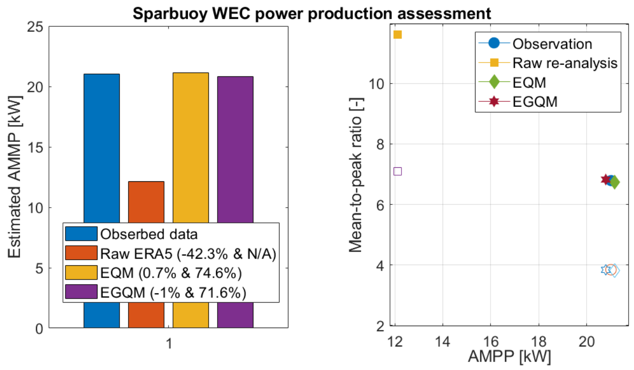


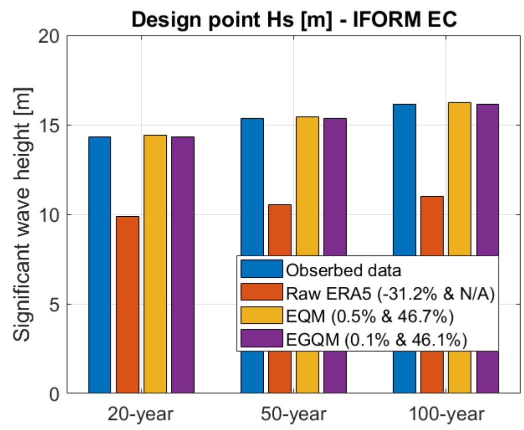
Fig. 5. Power production estimation based on the wave conditions from the different BC techniques.

Apart from the mean power production, precisely estimating the variability of the power production is crucial in WEC design, since the mean-to-peak ratio is considered, for example, when designing power take-off systems or control strategies. Fig. 5 on the right depicts the relationship between this mean-to-peak ratio and the AMPP. The figure clearly shows that the raw ERA5 dataset results in a great misestimation of both the mean-to-peak ratio and AMPP. In contrast, both the QM and the GQM show their capacity to accurately estimate the realistic power production capabilities, including a very good estimation of the mean-to-peak ratio.

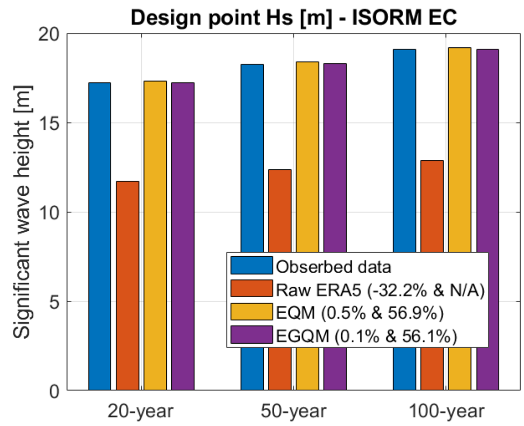
B. *Structural integrity*

The extreme design point for the assessment of the SI in extreme loads is analysed in this section. Figures 6 (a) and (b) illustrate the H_s corresponding to that extreme design point computed via IFORM and ISORM environmental contour approaches, respectively. In addition, Fig. 6 provide the information on the design point for three different return periods.

First of all, it can be observed that, for the observations wave data, the results based on the ISORM approach provides more conservative design points (above 17m for all the return periods) than the IFORM approach (below 16m for all return periods). However, the sensitivity of the design points with the wave data seems to be consistent regardless of the environmental contour approach. Hence, on the one hand, the raw ERA5 dataset is shown to significantly underestimate (over 30%) the extreme design point for all return periods. Such an underestimation can have dramatic consequences, since the WEC would be design to withstand wave condition of up to 10-12m, while the statistical analysis carried out with observations results in the need of up to 15m. On the other hand, it can be noted that both QM and GQM BC techniques provide very similar design point estimations for all the return



a) IFORM-based environmental contour.



b) ISORM-based environmental contour.

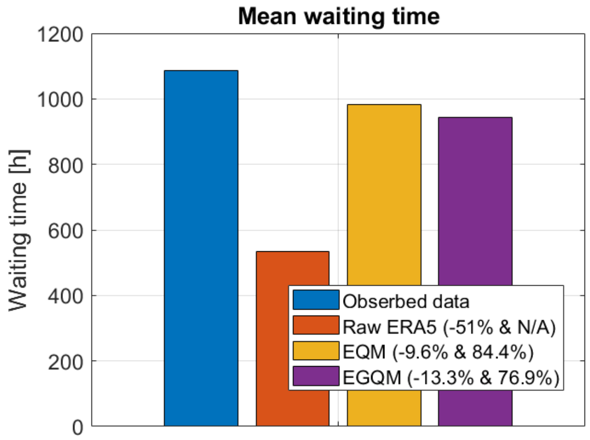
Fig. 6. Comparison of the extreme design points for different return periods and wave data: (a) IFORM and (b) ISORM environmental contour approaches.

periods, with GQM showing slightly better results. This is to be expected, since the GQM techniques focuses on the highest quantiles, considerably reducing the bias of the extreme conditions.

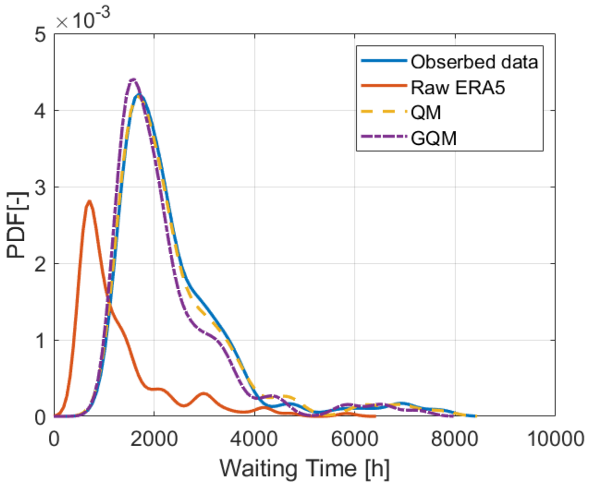
C. *Operation and maintenance*

Overall, similar trends are also observed when analysing O&M aspects for WEC design. Indeed, the WTs computed based on the raw ERA5 wave dataset shows to underestimate the real WTs in 50%, as illustrated in Fig. 7 (a). Hence, the impact of the bias of the ERA5 re-analysis dataset is largest when analysing O&M aspects. Fig. 7 (b) illustrates the PDFs of the estimated WTs for each dataset, clearly showing that, besides the mean WT, the difference in the WT estimates is remarkably poor.

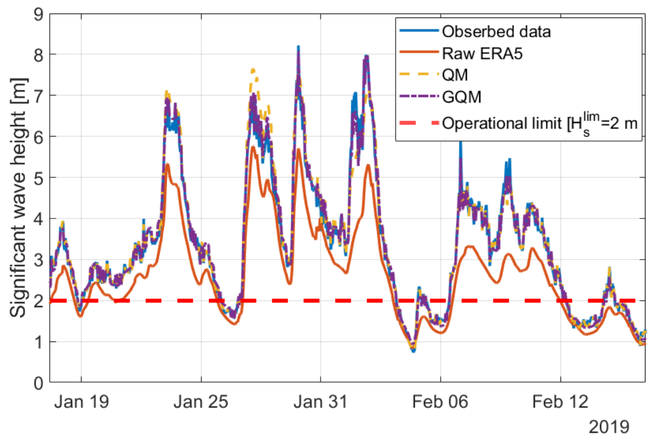
As in other design aspects, the use of BC techniques can correct this underestimation, although the WTs computed on the corrected datasets also show higher deviations for O&M aspects: almost 10% and 15% underestimation for the QM and the GQM, respectively. However, the WT PDFs for the QM and GQM techniques shown in Fig. 7 (b) demonstrate that the improvement with respect to the raw ERA5 dataset is outstanding, especially for the QM approach. This is also to be expected, as the QM technique provides a



a) Mean waiting time.



b) PDF of the waiting times.



c) H_s series compared to the O&M vessel operational limit.

Fig. 7. O&M design aspects.

better correction for average H_s values ($H_{s_{lim}} = 2m$ is considered). This is clearly illustrated in Fig. 7 (c), where the hourly H_s signal is illustrated.

V. Conclusions

Resource assessment is well known to be crucial for site selection and evaluating the interest of different geographical locations. Hence, policymakers and governments make decisions based on the resource characteristics of specific geographical areas, for example, to define the areas offered in auction. Beyond the political level, resource assessment is also critical in the design of offshore renewable energy (ORE) technologies. Some of the key aspects in the design process of Wave Energy Converters (WECs), such as power production capabilities, structural integrity and Operation and Maintenance (O&M) aspects are highly sensitive to the resource characteristics. However, precise metocean data is not always available, because wave monitoring technologies are expensive and delicate, while climate models and/or re-analysis datasets are still not fully reliable.

In this sense, statistical bias correction techniques are commonly used in meteorological applications, but not that frequent in the ORE industry. The present paper analyses the sensitivity of some of the most critical design parameters (annual mean power production, extreme design point and waiting time between weather windows) to wave conditions. To that end, these design parameters are computed based on four different wave datasets: observations, raw ERA5 re-analysis, and re-analysis data corrected via the quantile-mapping (QM) and Gumble quantile-mapping (GQM) techniques.

Results show two main conclusions. On the one hand, it is demonstrated that the raw re-analysis wave datasets are unreliable to be used in the design of WEC systems. In fact, the raw ERA5 dataset is shown to be unreliable for all the three design aspects, with underestimations of up to 50%. However, the use of bias correction techniques can significantly improve the quality of the wave data, reducing the misestimation to up to 10% and providing reliable estimates for all the different WEC design aspects. In fact, both QM and GQM techniques show similar results, the QM being more appropriate for power production and O&M aspects, and the GQM more adequate for the extreme design points.

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