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Assessment of Wave Energy Converters Based on Historical Data from a Given Point in the Sea

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Abstract: The assessment of wave energy converters is a key issue for planning and managing the economic feasibility wave power plants. However, obtaining reliable assessments is a difficult goal due to the strong stochastic component of wave behaviour. This paper proposes a simple and straightforward assessment method based on empirical data to estimate not only the expected values of converted power, but also their confidence limits. The method combines Gaussian mixed models with the Monte Carlo method. The proposed approach was validated by assessing five converters with data obtained from two different buoys. The daily converted power values agree with the measured wave parameter patterns. Furthermore, all the observed values of monthly generated energy in the three years after the evaluation fell within the forecast intervals, supporting the validity of the proposed approach.

Keywords: wave buoy data; Canary Islands; wave energy converter assessment; Gaussian mixed models; stochastic modelling

1. Introduction

Renewable energy is one of the cornerstones of sustainable human development, with solar, wind and sea waves being the most popular due to their high energy capacity, although the latter is very far from achieving its exploitation objectives [1]. Within this field, wave energy has some important advantages, especially due to the continuous availability of the source, all day and year-round, and to its low environmental impact compared to other energy sources, since it does not generate emissions or pollution during its operation [2]. However, there are also challenges to consider, such as the technical complexity of designing and maintaining wave energy conversion systems, the high initial costs of implementing these technologies, and significant seasonal variability in wave energy [3,4].

The hypothetical global wave power energy per year has been estimated at 29,500 TW·h, enough to cover the world's annual energy demand. This high potential has led to a growing development of the marine sector for the exploitation of these marine resources, although a sufficiently mature technology for doing so has not been achieved [5]. Ocean Energy Europe states that the European Union (EU) has established renewable ocean energy deployment targets of 1.0 GW by 2030. This is an ambitious target, considering the total installed MW in the word in 2022 based on tidal and wave energy were around 66.1 MW (41.2 MW tidal and 24.9 MW wave energy). The tidal energy installed in the EU is 30.2 MW, and 12.7 MW of wave energy [6]. These statistics serve to show that wave energy is at the tail end of renewables, requiring adequate political support from governments, and more investment and research based on prototypes in order to determine how best to obtain the largest amount of energy at each point, with Artificial Intelligence (AI) being of great importance to achieving these goals.

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Spain is a European Union country with outermost regions that is very interested in developing renewable energies on its Atlantic islands. Despite all the efforts made, renewable energies supply less than 12% of the electricity mix in its outermost islands, in this case the Canary Islands [7], and work is ongoing to develop new and more advanced renewable energy projects, which are critical due to the inexistent electricity interconnection with any continent and their dependence on fuel for electricity generation [8]. This is largely due to the depth of the waters of the Atlantic Ocean, where the Canary Islands were formed millions of years ago, so the bathymetric gradient is very high [9]. To achieve these goals, it will be necessary to address promising new renewable energy sources involving the ocean, especially with the new energy scenario for Europe.

Many areas of the Canary Islands offer good wave potential, in excess of 25 kW/m in some points on the north and west coasts of all the islands, and higher on islands that are not affected by the shadow of other islands, such as the island of El Hierro. The seven islands of the archipelago are exposed to the waves generated on the Atlantic Ocean, and on the other hand, to the trade winds characteristic of these regions, which normally blow constantly throughout the year [5,9,10]. It is thus feasible to develop the wave energy industry in the marine waters around the islands, given that different industries and infrastructures such as ports, shipyards, shipping companies, etc., are already established in the archipelago, mainly on the islands of Tenerife and Gran Canaria [11]. The islands also have exceptional infrastructure for testing different types of wave energy capture (WEC) systems and ocean structures, such as the government's Oceanic Platform of the Canary Islands (PLOCAN) platform, located one mile northwest of the coast of Gran Canaria. This platform has all the necessary permits, such as environmental permits and military exclusions and protected areas, to conduct any type of research. It also has excellent bathymetry around it [12].

The effective use of wave energy converter devices depends on being able to reliably assess the energy conversion capacity at the installation site. Since this conversion depends on the wave parameters, it is essential to have a tool for modelling them in the period in question [13].

Several approaches for wave modelling have been proposed, which can be broadly classified into two major groups. First are the physics-based analytical and numerical models, which solve the complex equations that govern fluid dynamics and wave propagation [14–16]. Although this approach yields results with an interpretable physical meaning, it usually requires a high computational effort and suffers from significant errors due to idealization, discretization and numerical solution considerations. Ocean forecasts for practical applications must simultaneously consider predictions of sea level, waves, currents, temperature and salinity. However, solving for all these variables simultaneously was too difficult due to limited process knowledge and computational requirements [17].

The second approach relies on empirical data for fitting forecasting models. For this purpose, different tools can be used, including statistical regressions [13,18] and time series [19,20]. Other machine learning tools, such as neural networks [21,22] and fuzzy inference systems [23,24] have been successfully applied to model wave behaviour and the corresponding converted energy. This approach is effective when reliable data are available, although collecting these data often requires long periods of time.

Combining both empirical and physics-based models can yield more robust predictions. By integrating historical data with the underlying physical principles governing wave energy conversion, hybrid models can offer a more comprehensive understanding of energy production potential [25]. Also, ensemble forecasting involves running multiple models with varying assumptions and inputs. This approach provides a range of potential outcomes and helps quantify the uncertainty associated with predictions [26]. Finally, incorporating real-time data from sensors on wave energy devices and buoys enhances the accuracy of forecasts [27].

Another important issue in wave converter assessment deals with the stochastic nature of the process and the consequent need to take into account this behaviour in the model outcomes [28]. Approaches such as the Weibull probability distribution [29,30] and Gaussian processes [31] have been effectively used to include randomness in the assessment.

This study focuses on a simple straightforward approach to assess the wave energy conversion capacity, based on historical wave data at a given point in the sea, and taking into account the stochastic nature of wave behaviour. The paper is divided into four sections. After this introduction, the approach is described, detailing every step. In the third section, five converters are assessed at two different points in the sea. Finally, concluding remarks and future works are outlined.

2. Materials and Methods

The proposed approach seeks to assess wave energy converters based on historical data of wave behaviour and the corresponding energy conversion matrix (see Figure 1).

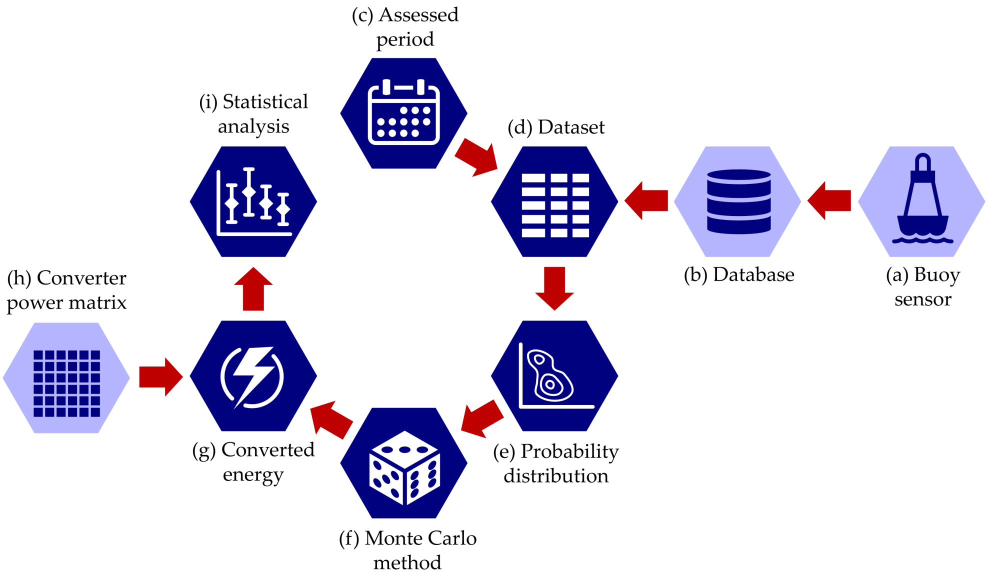

Figure 1. Graphical representation of the approach used.

The wave data are measured, over a period of several years, at the point to be assessed by using a buoy sensor, in order to have a sufficiently broad basis for modelling the wave behaviour, including its stochastic variability (see Figure 1a).

To describe the wave behaviour, the peak period, T_p, and significant wave height, $Hm0$, were chosen, as they are two key parameters for describing waves at sea. The significant wave height represents the average wave height in a swell field, while the peak period is the average time between successive peaks of the largest and most energetic waves. The relationship between them indicates whether the swell is more organized or agitated: when the peak period is higher, waves tend to be longer and more spaced out, indicating a less agitated swell, while a shorter peak period suggests shorter and closer waves, representing a more chaotic and agitated swell. These parameters are essential not only for navigation, maritime safety and the building of structures in the water, but also for the design of wave energy systems [12,32].

The data obtained are stored in a database, where they are pre-processed to eliminate corrupt or unreliable data (see Figure 1b).

The assessment process itself starts with the determination of the period of the year to be considered (see Figure 1c). This is performed by establishing the days of the year corresponding to the beginning and end of this interval. For example, if we want to evaluate the behaviour of a converter during the third week of the year, the start day would be the 15th and the end day would be the 21st. In another example, if we want to evaluate during the month of July, the interval would be from the 182nd to 212th day of the year. With the given period, the corresponding dataset is extracted (see Figure 1d) from the historical database (see Figure 1b).

The next step is the core of the proposed approach. In it, a Gaussian mixture model is fitted from the previously selected data set in order to describe the bivariate probability distribution of the significant wave height and the peak period (see Figure 1e).

The Gaussian mixture model (GMM) is one of the more recent algorithms for dealing with non-Gaussian data, and is classified as a linear non-Gaussian multivariate statistical method [33]. This Gaussian mixture model is composed of the weighted sum of several normal distributions, in the following form:

$$f(x) = \sum_{i=1}^{N} w_i \frac{\exp(-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_i)^{\mathrm{T}}\boldsymbol{\Sigma}_i^{-1})(\mathbf{x}-\boldsymbol{\mu}_i))}{\sqrt{(2\pi)^k|\boldsymbol{\Sigma}_i|}}; \tag{1}$$

where N is the number of the Gaussian functions involved; $\mathbf{x} = [H_{\mathrm{m0}}, T_{\mathrm{p}}]^{\mathrm{T}}$ is the distributed vector; mu_i is the mean vector of the i-th distribution; and $\boldsymbol{\Sigma}_i$ is the $k \times k$ covariance matrix of the i-th distribution [34].

The distribution parameters (i.e., weights mean vectors and covariance matrices) are fitted from the selected dataset by using the k-means algorithm, which is a popular unsupervised machine learning method that has been widely used in several investigations on data clustering [35].

Based on the fitted distribution, the converted power with a given converter can be estimated from a set of simulated points, generated though the Monte Carlo method (see Figure 1f). This is an approach for solving complex problems by using random numbers. The Monte Carlo method is not a set of ordered steps, like a recipe or an algorithm; on the contrary, it is just a simulation philosophy that is widely used for dealing with stochasticity in several branches of science and technology.

The Monte Carlo method relies on generating a usually large set of random numbers from the corresponding probability distributions. From each of these random numbers, the behaviour of the system is then modelled. Finally, the set of randomized states is statistically analysed to determine the expected values and probability distributions of the system response [10,36,37].

In spite of its high demand for computational resources, the Monte Carlo method has several remarkable advantages, including the straightforwardness of the analyses; the capability of dealing with real-world problems that involve complex, nonlinear, and noisy systems; and the ability to survey the complete search space of a problem, assuming the model is correctly parameterized [36,37].

With the wave values (i.e., significant wave height and peak period pairs) randomly generated from the previously fitted bivariate distribution, the converted power is determined for each of them (see Figure 1g), considering the power matrix of the evaluated converter (see Figure 1h). With these converted power values, then, its probability distribution is estimated using the kernel density estimation method [38]. Finally, by using this distribution, the expected value of the converted power and its confidence limits can be determined (see Figure 1i).

3. Case Study

In order both to illustrate the proposed approach and to validate its results under real conditions, a case study is presented consisting of evaluating five converters at two different locations at sea.

3.1. Data Source

The data used to train the models were taken from two buoys (see Figure 2). The first buoy is Las Palmas Este (1414), which is located at 28.05° N and 15.39° W. This buoy is less than 2 km from the shore, with a mooring depth of 30 m; consequently, it can be regarded as a nearshore point. The second buoy is Gran Canaria (2442) buoy, which is located at 28.20° N and 15.78° W, around 8 km away from shore, and with a mooring depth of 780 m.

The buoy models are: SeaWatch for Gran Canarias (2442) [39], for depth waters, i.e., more than 200 m of profundity, and Triaxys for Las Palmas Este (1414) [40] in swallow waters, i.e., less than 100 m of profundity. Both buoys are part of the Deep Water Network and Coastal Network of Harbors of State (Puertos del Estado) of Spain. Each measurement taken by the sensors is processed and stored on board the buoys and transferred via satellite on a temporary basis [41].

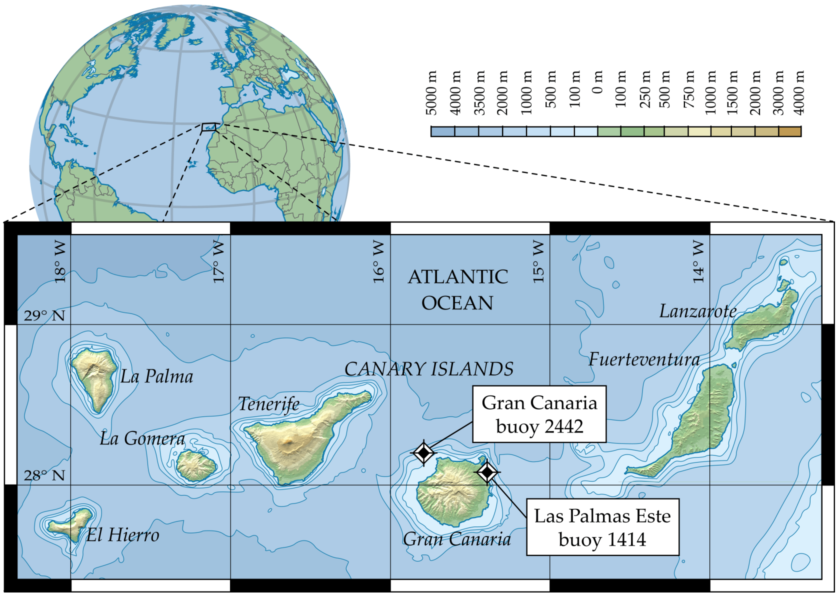

Figure 2. Geographic locations of the buoys.

The peak period, T_p, and significant wave height, H_{m0}, were recorded each hour, computed for a period of 20 min. The measurement accuracy was ±0.05 m for H_{m0} and ±0.05 s for T_p.

In total, 226,679 valid records were taken for the Las Palmas Este (1414) buoy and 151,824 for the Gran Canaria (2442) buoy (see Figure 3). As can be seen, the highest values of significant wave height correspond to the Gran Canaria (2442), which is an offshore buoy.

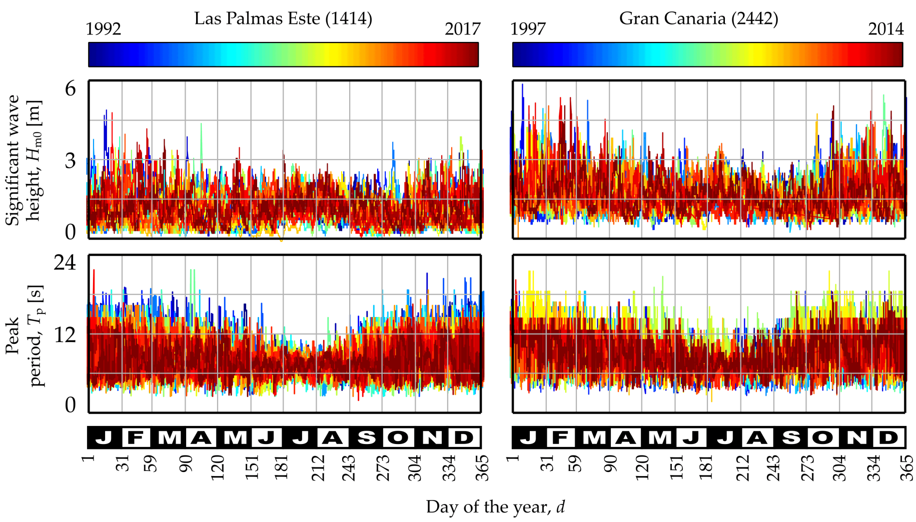

Figure 3. Measured values of significant wave height and peak period through the year.

Note also that the significant wave height varies throughout the year at the Gran Canaria (2442) and Las Palmas Este (1414) buoys, with the highest values in the period from October to March.

With respect to the peak period, the values measured at the two buoys span similar ranges, although at the Gran Canaria (2442) and Las Palmas Este (1414) buoys, a significant decrease is observed in the summer months (June to August).

3.2. Converters Studied

Five converters were assessed at the points in question: Aqua Buoy, Oyster, Pelamis, SSG and Wave Dragon [42]. They cover the full operability scale of the current energy converters. Aqua Buoy and Pelamis are regarded as offshore devices, Wave Dragon (which operates between 25 m and 40 m) and Oyster (which operates at about 15 m water depth) as intermediate water devices, while SSG is a typical shoreline conversion system.

The converters considered also differ in their dimensions and power capacities. Thus, SSG and Wave Dragon are large devices, Oyster and Pelamis are medium-sized, and Aqua Buoy is a smaller device. Their respective conversion matrices are graphically represented in Figure 4.

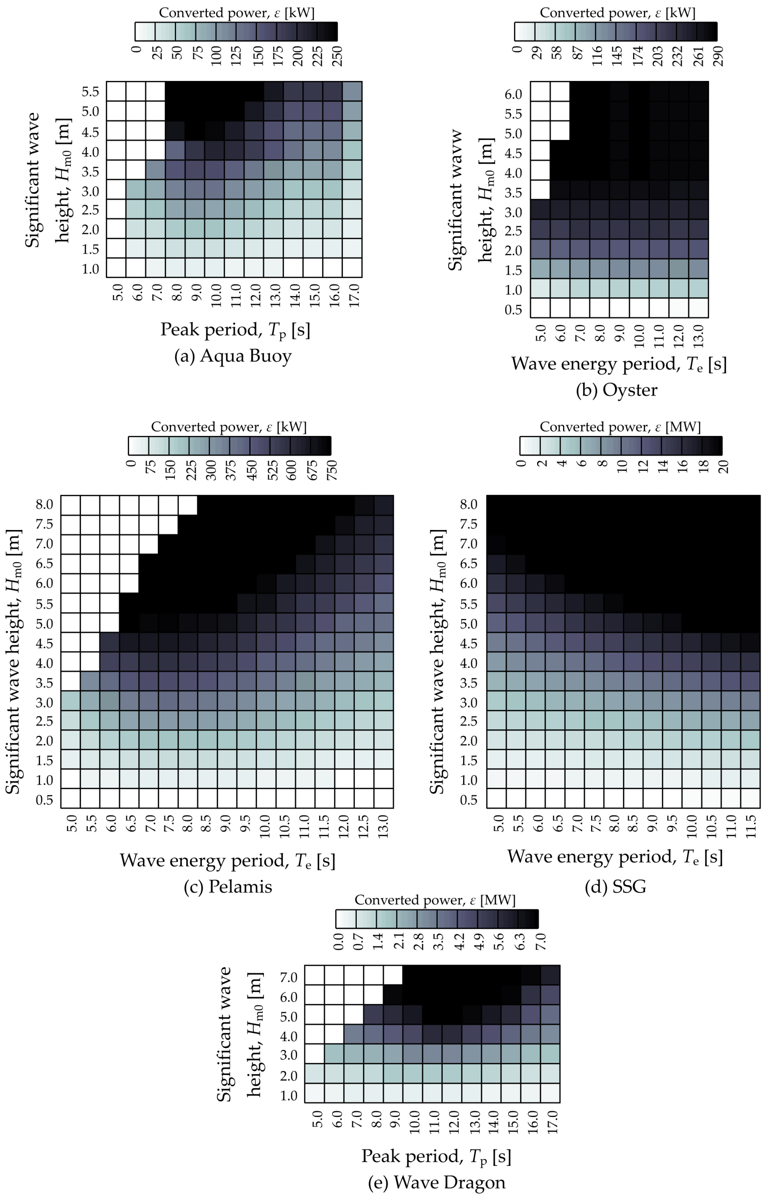

Figure 4. Graphical representation of power matrices.

Since the matrices of some of the converters are a function of the wave energy period, T_e, rather than the peak period, T_p, the evaluation is carried out through the expression:

$$T_e = 0.86T_p; \tag{2}$$

which is based on empirical observations [32].

3.3. Assessment of the Daily Converted Power

Firstly, the converters considered were assessed every day of the year. In order to exemplify the results obtained, Figure 5 shows the fitted probability distributions for the 15th day of four representative months (March, June, October and December). As we can see, the probability distributions (contour lines) closely match the observed values of significant wave heights and peak periods (blue points).

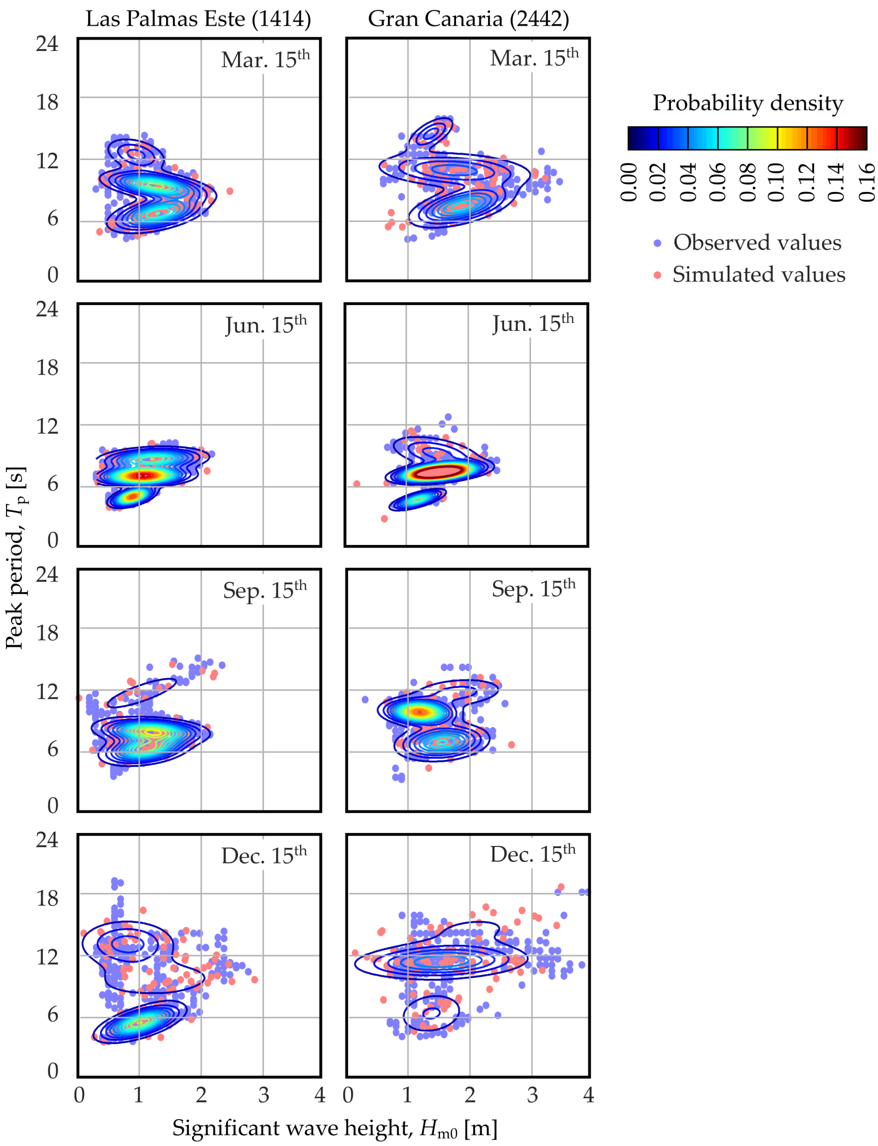

Figure 5. Recorded wave data for the 15th day of four months.

These distributions change significantly over the seasons, with a higher probability of large significant wave height values in the winter months for both buoys.

Figure 5 also represents the data generated randomly from the previously fitted probability distributions, simulated using the Monte Carlo method. Note the coincidence of these data (pink points) not only with the respective probability distributions but also with the measured wave data (blue points).

With the simulated data, the daily converted power is computed. Figure 6 shows the resulting values and the corresponding expected values and 95% confidence limits. Two main facts emerge from these outcomes. In the first place, the converted power is highest for the Gran Canaria buoy (2442) for all the converters evaluated, which agrees with the measured wave parameter patterns.

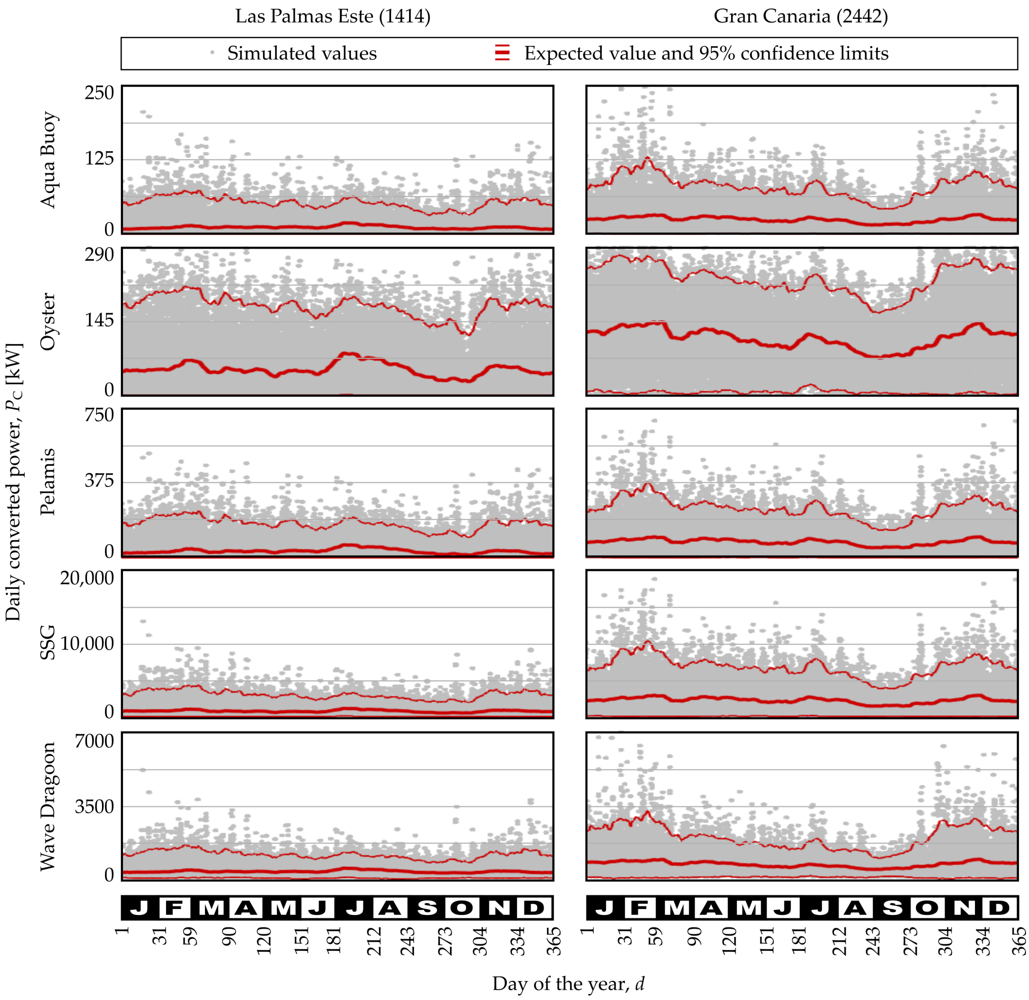

Figure 6. Daily converted power.

Another interesting fact arises from comparing the converted power to the maximum power that each converter can generate. As the figure shows, Oyster offers the highest performance for the two points evaluated, even the ones offshore, despite being an intermediate water device.

Considering that Wave Dragon, Oyster, SSG and Aqua Buoy are devices that operate under the operating principle of a hydraulic turbine, and Pelamis under the principle of a hydraulic motor [8,43,44], it is possible to affirm that the hydro-turbine used in Oyster and its engineering design is the best for this region.

3.4. Assessment of the Monthly Converted Energy

To validate the proposed approach, the monthly converted power was evaluated for the five converters in question (see Figure 7). The first thing that is striking about the expected values and the corresponding reliability intervals over the year is that they have similar shapes for the various converters applied to the same point, although the values of energy produced change depending on the converter's capacity. That is, the values of energy converted at Las Palmas Este buoy (1441) are higher than at Gran Canaria (2442). This is in complete correspondence with the observed values of significant wave height and peak period.

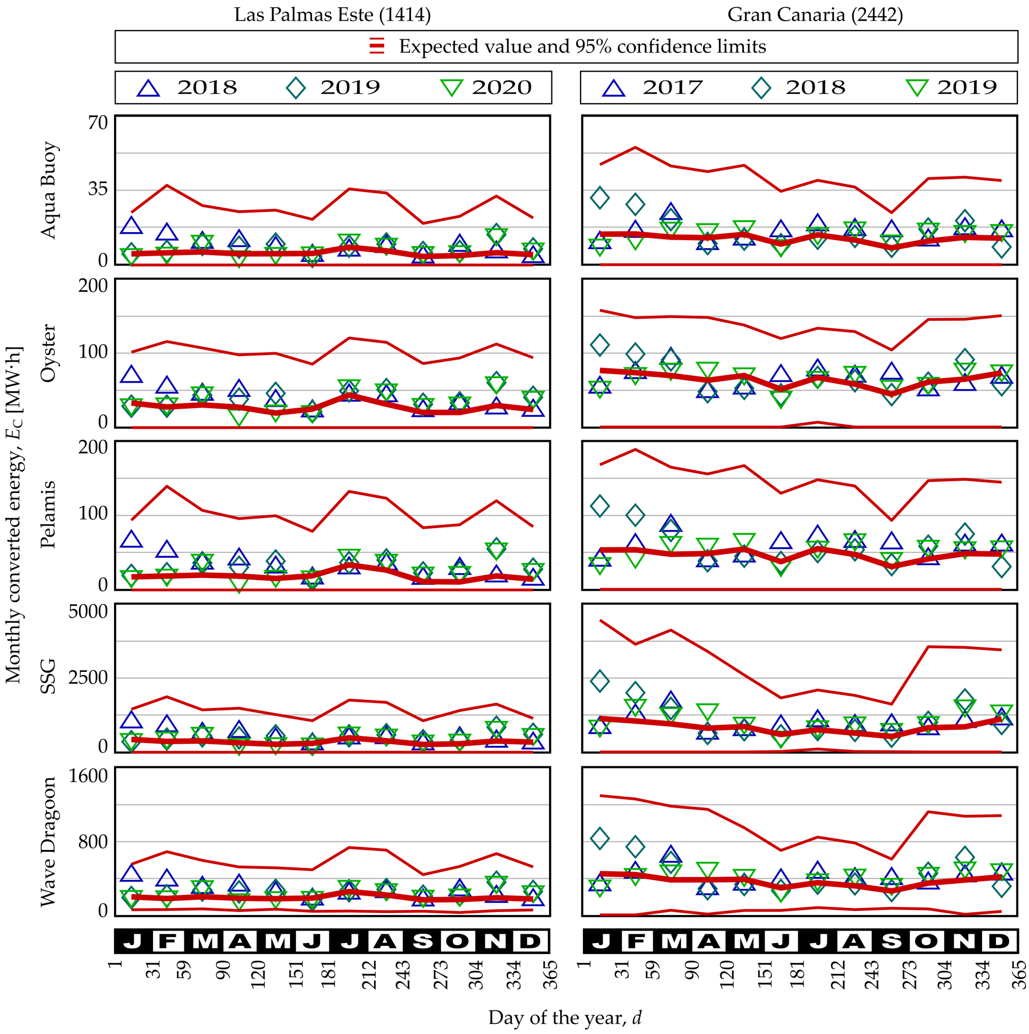

Figure 7. Monthly converted energy.

In contrast, the form of the energy converted, over the course of the year, varies significantly from buoy to buoy. For example, Las Palmas Este (1414) shows a more variable behaviour, with more marked peaks in the periods mentioned above. Also, the Gran Canaria buoy (2442) shows a significant difference between the summer months, with less energy generated, and the winter months, with higher generation values.

Finally, to validate the monthly converted energy assessments, values were calculated for the last three years for each buoy, which were not used to fit the Gaussian mixed models. As can be seen, all the monthly converted energy values, for the validation periods, fell within the predicted ranges. There is also a remarkable coincidence between the trend in these values over the year and that seen in the assessments.

4. Concluding Remarks

At the end of the research, we can conclude that the method proposed yields a simple and direct evaluation of wave energy converters at different points for which historical wave data are available. Particularly noteworthy is its capability to make predictions for various time periods.

The use of Gaussian mixed models gives special flexibility to the method, as it allows it to fit the probability distribution of significant wave height and peak period from the actual shape of the data, without relying on a predefined probability distribution. The probability distributions fitted in this way showed a remarkable agreement with the observed data for the two case studies considered.

Moreover, the Monte Carlo method has been shown to be an effective tool to analyse the effect of the probability distributions of some stochastic variables (such as significant wave height and peak period) on others (such as daily power or monthly converted energy), determining not only their expected values, but also their respective confidence intervals.

As concerns these confidence intervals, we note the asymmetric positions of the lower and upper confidence limits. Since this fact agrees well with the observed behaviour of the significant wave height and peak period, it can be considered an important indication supporting the effectiveness of the proposed approach.

The large predicted confidence intervals of converted power and energy are another important outcome. Notice that the lower value of the confidence interval is, in many cases, significantly smaller than the expected value. This is a fact of undoubted practical significance, as it implies that if conversion systems are designed based on the expected values, backup systems will be needed to make up for the shortfall in energy generated for a considerable part of the year.

The validation of the model, carried out by using data excluded from the model fitting, shows excellent predictability, with all the observed values falling within the predicted intervals. The assessed wave energy conversion values for the various converters show the usefulness of the proposed approach and its effectiveness, since they match the power data used for the validation.

From a theoretical point of view, the main finding of the work is the confirmation of the need to take into account the stochastic nature of waves when predicting the power generated by a given wave energy converter located at a certain point in the ocean. The effectiveness of the Monte Carlo method, when based on reliable probability distributions, also shows, once again, its ability to solve problems involving complex, non-linear and stochastic systems related to weather phenomena, such as waves.

It should be noted that the simplicity of the proposed modelling approach facilitates reassessment during the operation of the converters, which would allow for greater precision as the amount of available data grows. One potential expansion of this work in the future could involve cloud implementation, which would allow extending the method to other buoys quickly and easily.

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