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An approach for evaluating the stochastic behaviour of wave energy converters

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ABSTRACT

Due to their random nature, obtaining reliable models that can describe the behaviour of waves is far from simple. This paper presents an approach for forecasting the capabilities of wave energy converters (WECs) for two points, one of them located offshore and the other nearshore. Bivariate Weibull distributions were fitted from spectral significant wave height and mean peak period data. Then, models relating the parameters of these distributions to the day of the year were obtained using mixture density networks, which give the distribution of the predicted variables instead of their expected value. Energy conversion capabilities were forecasted by generating a set of random values for the bivariate Weibull coefficients from the modelled distributions for the period in question. Predicted cumulative distributions for spectral significant wave heights and mean peak periods were then combined with the matrix of the converter in question, allowing the corresponding energy conversion capability to be computed. The proposed method was validated by considering data from the last three years, which were not used to train the models. The resulting predictions were consistent not only with the expected seasonal behaviour, but also with the expected differences between the offshore and nearshore points. It should be also noted that all the validation energy values fall into the forecasted 95% confidence intervals, showing the effectiveness of the approach.

1. Introduction

A common problem on Islands is their limited interconnection with other systems that could provide additional power. Because of that, a high dependence on imported fuels is common. This is the case of islands such as the Canary Islands. Moreover, land with a good potential for renewable energy is limited. Hence, it is necessary to look to the sea in the near future to meet the energy demand of islands, and especially to wave energy, which promises to be one of the most exploited oceanic sources of renewable energy in the future. Particularly in regions where favourable bathymetric conditions concentrate wave energy, such as the coasts of this archipelago (Iglesias and Carballo, 2011; Avila et al., 2021a; Yung Tay and Wei, 2020; Sheng, 2019).

Currently the outcast of all the renewable energies in the Atlantic islands is ocean energy, despite the fact that a great deal of research has shown the significance of waves, between (25–30 kW/m) in some regions of the Canarian archipelago (Avila et al., 2021a; Iglesias and Carballo, 2011) - as resource.

It is important to clarify that the scarce development of wave energy is not exclusive to isolated islands, because in the global renewable energy industry, the devices for transforming wave energy into useful energy are not mature enough to be used on a marketable scale. Nevertheless, a wide variety of demonstration prototypes of Wave Energy Converters (WECs) has been implemented around the world, with over 100 such experimental WEC projects being developed. These projects have been trialled in countries on different continents, such as America (USA), Asia (China), Europe (Spain, UK, Portugal, Norway, Sweden, Italy and France) and Oceania (Australia and New Zealand). The wave energy sector is not stationary and it will continue to grow with economic help from different governments and private investors, especially in developed countries, until a competitive commercial prototype is produced (Ahamed et al., 2020; Chen, 2016; Sheng, 2019; Yung Tay and Wei, 2020).

Researchers working on WECs experimental projects are conducting comprehensive analyses of the performance of their prototypes, including the power conversion capabilities (power matrix) for different sea states. In order to perform reliable forecasting of energy conversion capabilities, models describing the waves behaviour are needed. Some studies, such as those reported in Ahn et al. (2021, 2020), Azharul et al. (2020), Barstow et al. (2008), Gonçalves et al. (2014), Puscasu (2014), Sandvik et al. (2019), Swan Team (2020) and Group (1988) evaluate

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the importance of the third-generation (3G) wind-wave models, such as Wave Modelling (WAM) and Simulating Waves Nearshore (SWAN) for forecasting waves. Both models have been implemented in different important research projects around the world such as the WorldWaves (sea waves in the globe) and WERATLAS (European waters) projects. In the North Atlantic Ocean, several assessments have been carried out, also using 3G wind wave models, for example: Gonçalves et al. (2014), develop a numerical prediction of wave power distribution around the Canary Islands, and Bernardino et al. (2017) present a study of the wave energy resources of the Cape Verde Islands, using the Simulating Waves Nearshore (SWAN). Nevertheless, these analytical models still need more enhancements for achieving an accurate description of the non-linear and dynamical behaviour of the waves (Cavaleri et al., 2020).

Empirical models based on Artificial Intelligence are becoming stronger every day in dissimilar fields of science (Malekmohamadi et al., 2011), and wave simulation and prediction is not different. One such example of this is the application of different soft computing techniques (Fuzzy Logic, Artificial Neural Network, Genetic Algorithm and Support Vector Machine) in coastal studies in India (Dwarakish and Nithyapriya, 2016; Gopinath and Dwarakish, 2015). Artificial Neural Networks are being used to predict wave height in different places, like the west coast of Portugal (Makarynskyy et al., 2005), and on the Adriatic Sea off the shore of Croatia (Berbić et al., 2017). In the North Atlantic Ocean the Fuzzy Inference Models (FIS) was used to model wind and wave climatic simulations (Stefanakos and Vanem, 2018). Many other studies and implementations of soft computing (SC) techniques in wave energy potential assessment have been carried out, for example in Avila et al. (2020), Castro et al. (2014), Huang and Xu (2019), Huang et al. (2019), Sanaz et al. (2013) and Santos et al. (2018).

Mixture density networks (MDN) are a type of artificial neural networks whose output, instead of being a point value, is a probability density. Since it is represented by a mixture model, many probability distributions of different shapes can be adequately represented. Consequently, these networks can be used to model various phenomena with a strong random component (Hjorth and Nabney, 1999; Kevin, 2020).

MDNs have been used in various engineering investigations such as tomographic studies in marine oil fields (Earp et al., 2020), geolocation (Chen et al., 2020), autonomous driving cars (Baheri, 2022), quantifying the residential demand response potential (Shirsat and Tang, 2021), etc. In the field of renewable energies, they have been used mostly to forecast the energy production of wind turbines as discussed in Camal (2020), Men et al. (2016), Zhang et al. (2019) and Zhang et al. (2020), small-scale solar generation (Afrasiabi et al., 2020) and to forecast the power generated by wind and photovoltaic farms (Vallejo and Chaer, 2020). Therefore, the use of MDNs to forecast sea waves will be very effective to implement different WECs around the world in the future.

This paper presents a new approach for forecasting the sea wave energy conversion based on MDNs that predict the values of bivariate Weibull distributions of wave significant spectral heights and mean peak periods. Through the Monte Carlo method, a number of simulations can be done and the corresponding converted energy values are computed, allowing estimating the confidence intervals of converted power. The models were fitted with the data set of the Las Palmas Este nearshore buoy (1414) and the Gran Canaria offshore buoy (2442), both in Gran Canaria Island. The two buoys used in the study belong to the Spanish State Ports network (Harbors of State of Spain, 2017).

This approach is new, to the best of our knowledge, not only due to the application of the MDN to the sea wave energy conversion forecasting, but also as it proposes a general methodology, which takes into account the stochastic behaviour of the waves, that could be applied, after the proper future validation, to other geographic regions with different sea conditions.

The paper is arranged into nine different sections. Having presented the introduction, the rest of the paper is organised as follows. Section 2 depicts the whole approach. Sections 3 and 4 discuss the geographic location and datasets used in the study, as well as the main features of the WECs considered. The modelling procedure for the Bivariate Weibull distribution is given in Section 5. The training of the MDNs and their evaluation are detailed in Section 6. Section 7 describes the predicted wave energy conversion capability of the different WECs at the study buoys. The proposed model is validated in Section 8, and conclusions are provided in Section 9.

2. Description of the approach

The proposed approach (Fig. 1) was designed to handle the stochastic nature of waves. This stochasticity was considered not only by using bivariate Weibull distributions to describe the behaviour of the spectral significant wave height and mean peak period, but also by reflecting the variation of the Weibull coefficients through the year.

Based on periodically measured data of spectral significant wave height and mean peak period over several years (Fig. 1a), bivariate Weibull distributions are fitted for every day of the year (Fig. 1b) and the corresponding coefficients are modelled by using mixed density networks (Fig. 1c). These are a kind of artificial neural networks that, instead of crisp values, predict probability distributions. In the proposed approach, the mixed density networks give a probability distribution for the bivariate Weibull distribution coefficients (output variables) for a given value of the day of the year (input variable). To estimate the generated power for a given converter, a set of coefficients is randomly generated by using the predicted probability distribution (Fig. 1d). With these coefficients, the predicted bivariate Weibull distributions (Fig. 1e) are combined with the power matrix (Fig. 1f) of the converter in question and the corresponding converted power is predicted.

Based on the set of predicted powers (Fig. 1g), the expected values and confidence limits of the converted power for each day of the year can be determined.

3. Geographic location and datasets

Avila et al. (2021a) state that five buoys are located in the Canary Islands that provide data on the behaviour of sea waves in real time. Three of these buoys are nearshore: Santa Cruz Buoy (1421) and Granadilla Buoy (7401) in Tenerife and Las Palmas Este Buoy (1414) in Gran Canaria. The other two are deep-water buoys: the Gran Canaria buoy (2442) in Gran Canarias and the Tenerife Sur buoy (2446) in Tenerife.

Two buoys were considered in this study (Fig. 2). The first one is the offshore Gran Canaria buoy (2442), located at 28.20°N and 15.78° W. This buoy is around 8.0 km away from shore, with a mooring depth of 780 m. The second one is the nearshore Las Palmas Este buoy (1414), whose position is 28.05°N and 15.39°W. This buoy is less than 2.0 km from the shore, with a mooring depth of 30 m (Harbors of State of Spain, 2017, 2018; PivotBuoy, 2019).

In this research, data were taken from the offshore buoy (2442) and the nearshore buoy (1414), because both buoys have different advantages compared to the other buoys, such as good and representative locations, high influence of the easterlies, and data from these buoys have been used in many technical and scientific studies. More information on these buoys and their advantages can be found at Harbors of State of Spain (2017, 2018) and PivotBuoy (2019).

Data from both buoys were accessed through the Spanish State Ports dataset, which, for the Gran Canaria buoy, ranges from 1997 to 2019, when the buoy (2442) was taken out of the seawater for maintenance works (22 years). In the case of the Las Palmas Este buoy, the data set covers a period of 27 years, from 1992 to 2019.

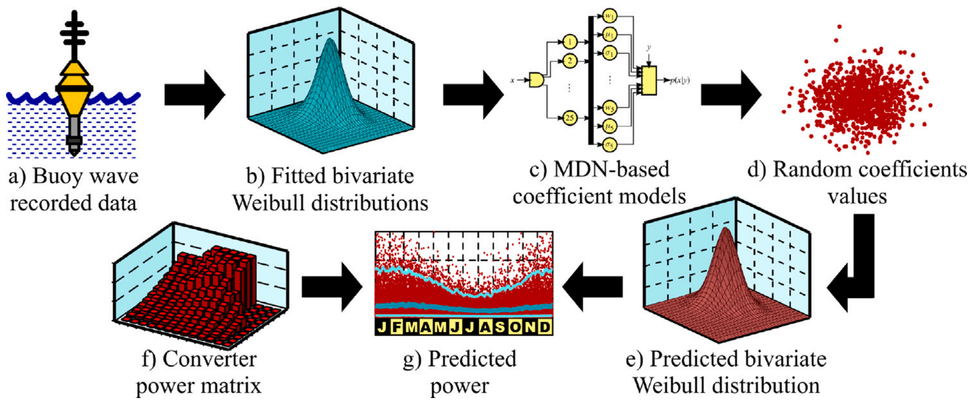

Fig. 1. Graphical description of the proposed approach.

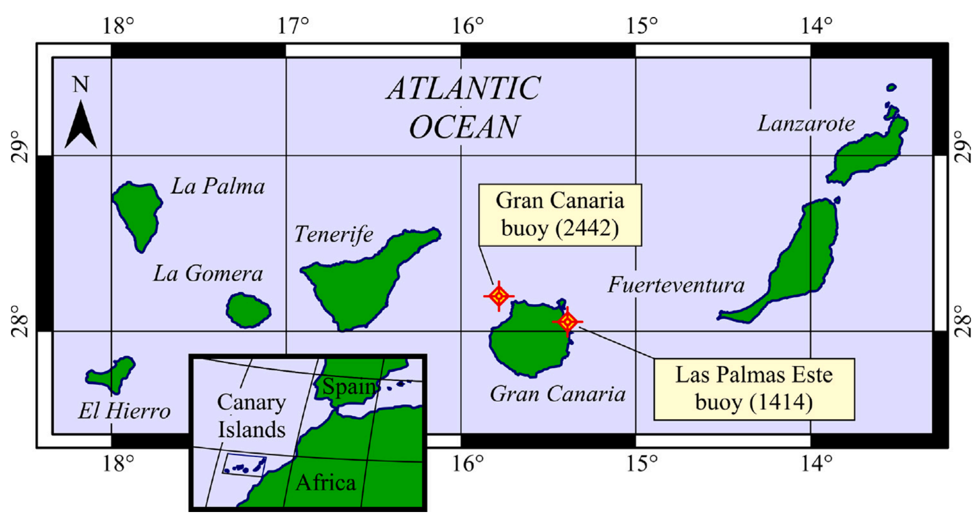

Fig. 2. Location of the buoys considered in the study.

The datasets used includes date and time of the measurement and the measured values of spectral significant wave height, H and mean peak period, T, which were recorded every three hours. For both cases, the measurement accuracy was $\pm$0.05 m for H and $\pm$0.05 s for T (Harbors of State of Spain, 2017, 2018; PivotBuoy, 2019), 151,824 valid records were taken for Gran Canaria (offshore) buoy, and 226,679 for Las Palmas Este (nearshore) buoy. The measured data were not pre-processed.

Table 1
Main features of the WECs considered (Silva et al., 2013).

WEC	Nominal Power [kW]	Classification	power matrix resolution [m × s]
Aqua buoy	250	Point absorber	0.5 × 1.0
Oyster converters	290	Terminator	0.5 × 1.0
Wave dragon	7000	Terminator	1.0 × 1.0
SSG	20,000	Terminator	0.5 × 0.5
Pelamis	750	Absorber	1.0 × 0.5

4. WEC systems

Sea waves are the most widely available renewable energy resource in coastal countries in continents and in isolated islands, called upon to cover a large share of the current global demand for electricity (Falcão and Henriques, 2019; Sheng, 2019). According to different authors (Bertram et al., 2020; Khan and Behera, 2021; Ulazia et al., 2019), the theoretical worldwide amount of energy available from waves alone is on the order of 32,000 TWh.

As Sheng discusses in (Sheng, 2019), the development of wave energy can yield great benefits for these countries such as: (i) an increase in the renewable and traditional energy mix; (ii) more independence in their energy supply; (iii) creation of jobs, (iv) reduced carbon dioxide emissions; and (v) less visual impact.

As mentioned before, the wave power industry does not have a commercial prototype yet, but the research and development work done in the last few decades will lead to a commercial model sooner rather than later (Robles et al., 2019). This makes it important to develop an efficient computer predictor to determine the behaviour of any kind of WEC in offshore and nearshore seawater.

Five WECs are considered on this study: Aqua Buoy, Oyster, Wave Dragon, SSG, and Pelamis. All these WECs have a different power take-off (PTO). When considering the mean peak period, T, and the spectral significant wave height, H, power matrices can be used to calculate the output power of WECs in various sea states. The five WECs used in the study rely on two operating principles to transform the oscillating motion of sea waves into useful energy: a hydro turbine in Wave Dragon, Oyster, SSG and Aqua Buoy, and a hydraulic motor in the case of Pelamis (Ahamed et al., 2020; Bertram et al., 2020) (see Table 1).

Fig. 3 shows a graphical representation of the five power matrices used in the calculations. Table 1 shows a few of the main features of the WECs considered in the study, such as nominal power and classification, taking into consideration the working principle and the

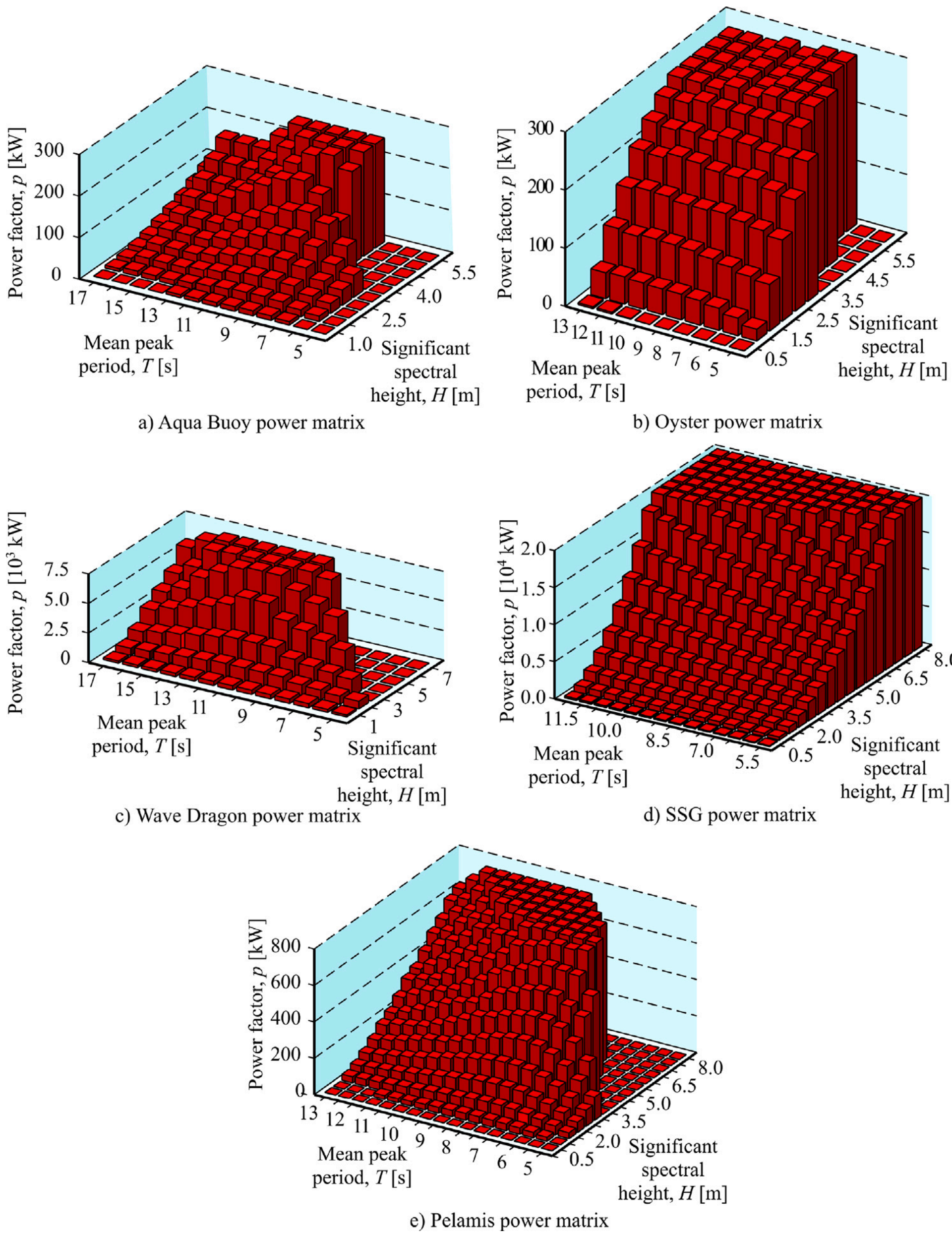

Fig. 3. Power matrices of the WECs considered (Silva et al., 2013, data source).

bin resolution of the power matrix (Avila et al., 2021a; Majidi et al., 2021; Sheng, 2019; Silva et al., 2013).

5. Bivariate Weibull distributions fitting

The first step in predicting the wave energy conversion capability is to model the wave behaviour, which was done by representing the joint probability distribution of spectral significant wave height, H, and mean peak period, T, through a bivariate Weibull distribution:

$$f(H,T) = \frac{k_1 k_2 \left(\frac{H}{c_1}\right)^{k_1-1}\left(\frac{T}{c_2}\right)^{k_2-1}}{c_1 c_2 (1-c_{12}^2)} \exp\left[-\frac{\left(\frac{H}{c_1}\right)^{k_1}+\left(\frac{T}{c_2}\right)^{k_2}}{1-c_{12}^2}\right] \dots$$
$$\dots \mathrm{B}_0\left[\frac{2c_{12}\left(\frac{H}{c_1}\right)^{k_1}\left(\frac{T}{c_2}\right)^{k_2}}{1-c_{12}^2}\right]; \quad (1)$$

where c_1, k_1, c_2, k_2, and c_{12} are the distribution parameters, and B_0 is the zero-order Bessel function. The corresponding parameters are obtained using the Simultaneous Maximum Likelihood Estimate method (Avila et al., 2021b; Barstow et al., 2008; Desouky and Abdelkhalik, 2019; Sorensen, 2006).

Numerous investigations on two-dimensional distributions reaffirm that they can be an effective tool in the characterisation of the state of the sea. One of the first theoretical approaches about bivariate distribution was suggested by Ochi (1978). In the next decade many others researchers working in this thematic, such is the case as Haver (1985) and Mathisen and Bitner-Gregersen (1990) that study among others thing the application of the Bivariate Weibull distributions, obtaining satisfactory results. More recently others academics studies were carry out about the application two-dimensional distributions in the prediction of the sea state such as Iglesias (2018), Lucas and Guedes Soares (2016) and Lucas and Guedes Soares (2015).

In order to fit the corresponding bivariate Weibull distributions, the datasets were split into a validation set, composed of data from the last three years (i.e., from 2017 to 2019, for the Gran Canaria and Las Palmas Este buoys), and a training set comprising the remaining data

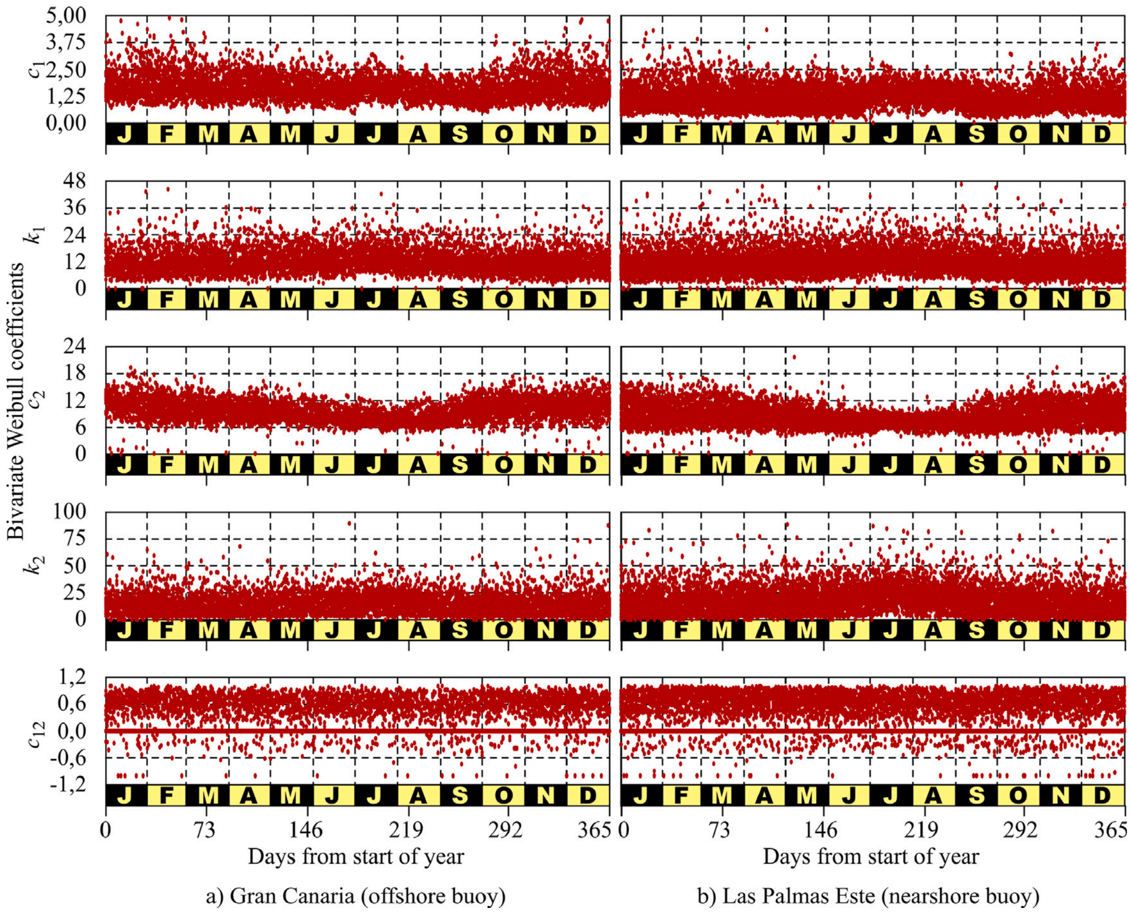

Fig. 4. Bivariate Weibull coefficients.

(i.e., from 1997 to 2016 for the Gran Canaria buoy, and from 1992 to 2016 for the Las Palmas Este buoy). Bivariate Weibull distributions were fitted for data from every day of the year, starting from January 1 (day 1) to December 31 (day 365).

In this study, a daily time frame was assumed to evaluate the stochastic behaviour of different WECs, which was proposed in a recent study by Jamei et al. (2022) in predicting ocean wave energy using intelligent systems. The time scale of our model in the evaluation can be reduced if necessary, for example: to a timeframe of three hours or less.

Fig. 4a shows the values of the coefficients throughout the year for the Gran Canaria buoy (i.e., the offshore case). As the graphs show, there is a small variation in the values of these coefficients for different days of the year. Note the decrease between May and September in the values of coefficients c1 and c2, which represent the point where the spectral significant wave height and the mean peak period, respectively, reach their corresponding maximum probability.

Fig. 4b shows the behaviour of the bivariate Weibull coefficients for the Las Palmas Este buoy (i.e., the nearshore case). Despite exhibiting similar behaviour, there is a noticeable seasonal variation, not only for c_1 and c_2, but also for k_1 and k_2, with a small but perceptible increment in the summer.

6. Training and evaluating the mixture density network

In order to model the probability distribution density of each coefficient for any day of the year, the corresponding MDNs were trained. This probability distribution was computed by the so-called mixture density models, which can be considered as the weighted sum of five normal density distributions:

$$p(y|d) = \sum_{i=1}^{5} \frac{w_i}{\sqrt{2\pi}\sigma_i(d)} \exp\left\{ -\frac{[\mu_i(d) - y]^2}{2[\sigma_i(d)]^2} \right\}; \tag{2}$$

where y represents the values of the coefficients, d is the day of the year, μ_i and σ_i are the means and standard deviations of the ith NDD and w_i are the corresponding weights.

The MDNs used (Fig. 5) consist of a combination of a feed-forward network and a mixture density model. The feed-forward network is composed of an input layer, which receives the value for the day of the year but has not effect from a mathematical processing point of view, a 25 nodes-hidden layer with a sigmoid activation function, and a linear output layer, which returns the values of the five weights, means and standard deviations used by the mixture density model to predict the probability density distribution, $p(y|d)$, at d.

The training process was carried out through 500 training cycles, with a value of inverse variance for weight initialisation equal to 100, and 5 iterations of K means. All these parameters were chosen through a try-and-error process, where different combinations were tried until reaching the lowest values of predicted error. Fig. 6 depicts the mean values (thick line) and the 95% confidence limits (thin lines) for each predicted coefficient, for Gran Canaria (Fig. 6a) and Las Palmas Este (Fig. 6b). As the figures show, the maximum values of spectral significant height and mean peak period, given by coefficients c_1 and c_2, are higher for Gran Canaria (offshore) than for Las Palmas Este (nearshore), which can be explained by the stronger energy of offshore waves. Note that both coefficients exhibit a seasonal behaviour for Gran Canarias while, for Las Palmas Este, only c_2 shows a significant seasonal performance.

By contrast, coefficients k_1 and k_2, which determine the bell-shape of the distributions, show analogous behaviour for both buoys, not

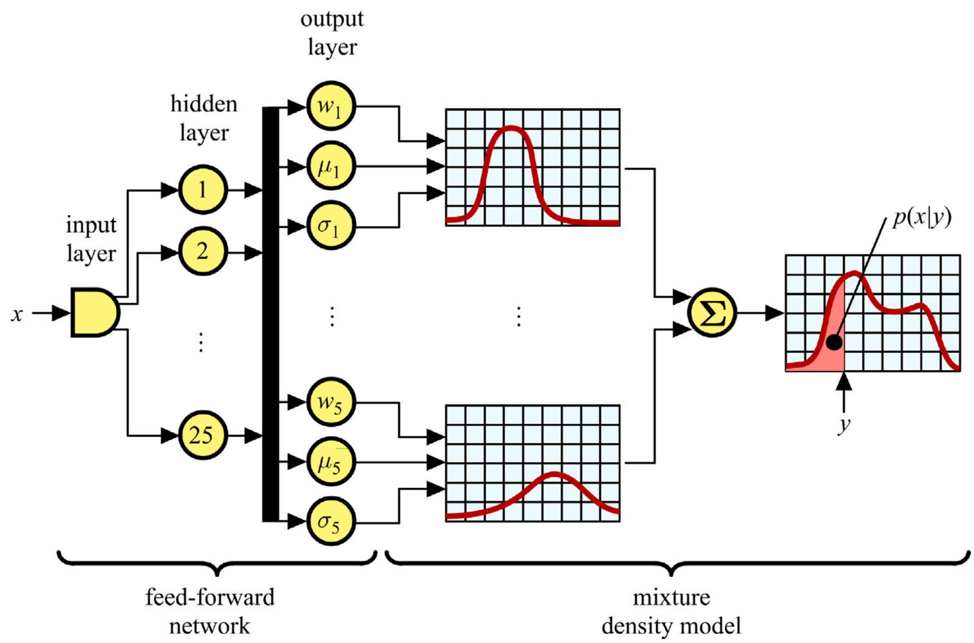

Fig. 5. Representation of the used MDNs.

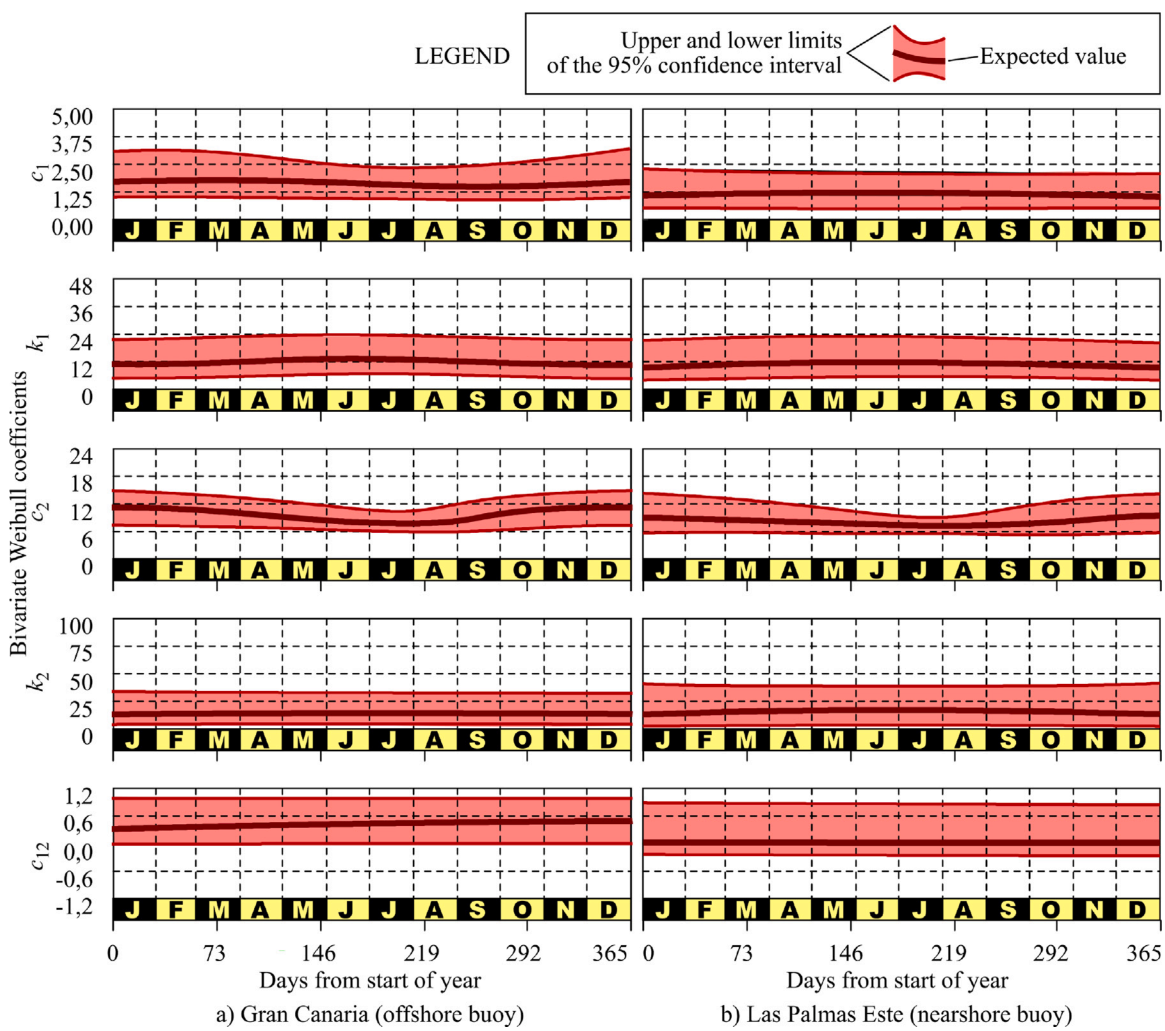

Fig. 6. Probability predictions for the bivariate Weibull distribution coefficients.

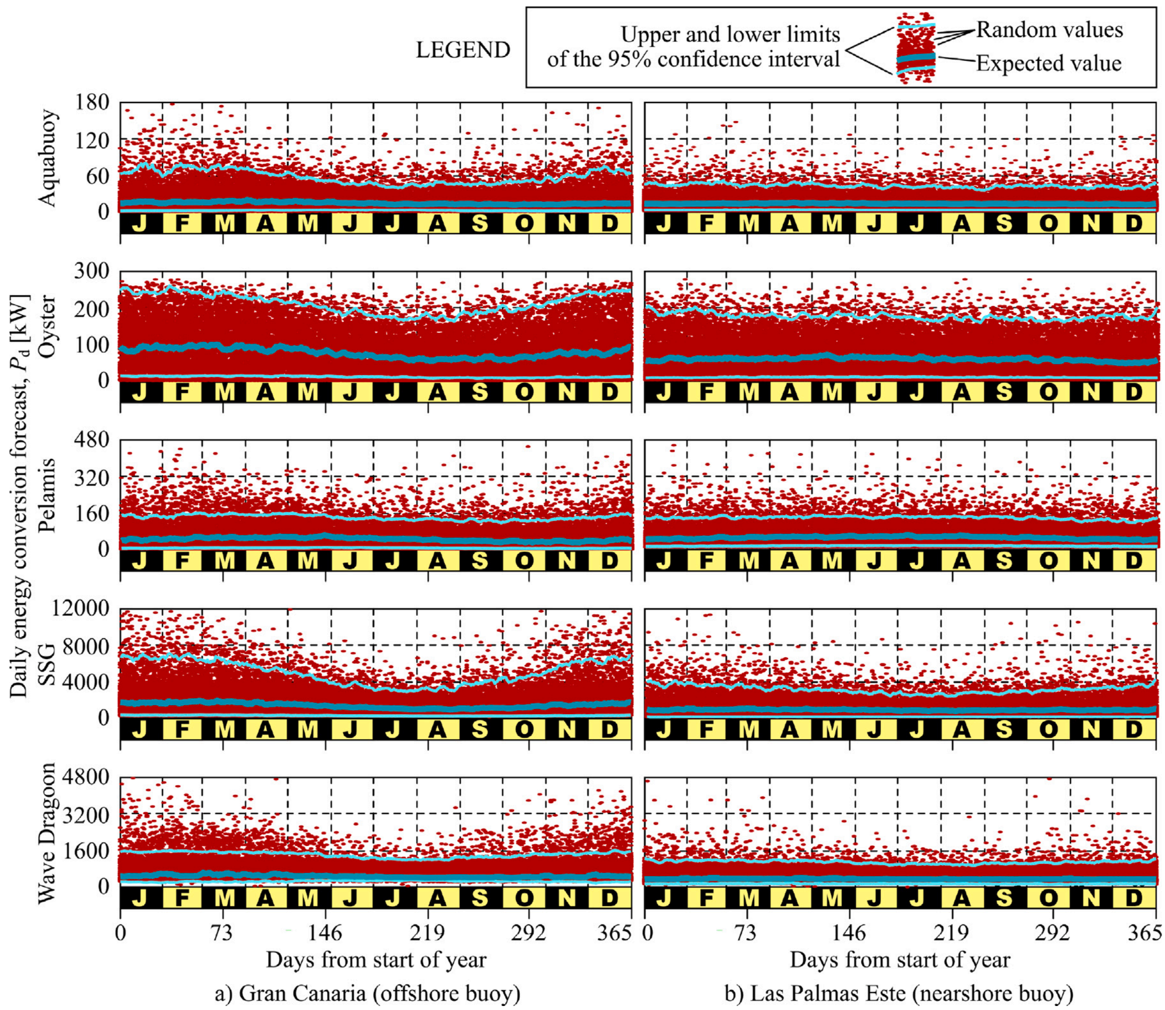

Fig. 7. Daily energy conversion forecasting.

only because their values are very similar but also because there is a noticeable non-seasonal pattern in both cases.

Finally, the c_{12} coefficient, which represent the interaction between the spectral significant height and the mean peak period, shows a remarkable non-seasonal behaviour, but with higher values for Gran Canaria (offshore) than for Las Palmas Este (nearshore).

7. Forecasting wave energy conversion capability

Based on the MDN models fitted as explained in the previous section, the energy conversion capability forecasts were obtained for each buoy and converted. In order to obtain the wave energy conversion forecast, 100 analysis points were considered for each day of the year. For every point, the values of the five parameters of the corresponding bivariate Weibull distribution were randomly generated by following the mixture probability distributions obtained from the MDN models:

$$c_1^i = \varphi_1(d), i = 1, \ldots, 100; \tag{3a}$$

$$k_1^i = \varphi_2(d), i = 1, \ldots, 100; \tag{3b}$$

$$c_2^i = \varphi_3(d), i = 1, \ldots, 100; \tag{3c}$$

$$k_2^i = \varphi_4(d), i = 1, \ldots, 100; \tag{3d}$$

$$c_{12}^i = \varphi_5(d), i = 1, \ldots, 100; \tag{3e}$$

where $\varphi_j, j = 1, \ldots, 5$, are the mixture density probability given by the MDN models, for a given value of day of the year, d.

Then, the expected wave energy conversion, P_d, for a given converter, can be computed by the expression:

$$P_d = \sum_{r=1}^{m} \sum_{s=1}^{n} \xi_{r,s} p_{r,s}; \tag{4}$$

where $\xi_{r,s}$ is the energy conversion factor for the rth row and the sth column of the power matrix, and $p_{r,s}$, is the cumulative probability in the corresponding interval ($H_r^l \leq H_r \leq H_r^u, T_s^l \leq T_s \leq T_s^u$):

$$p_{r,s} = p|_{H_r^l \leq H_r \leq H_r^u, T_s^l \leq T_s \leq T_s^u} = \int_{H_r^l}^{H_r^u} \int_{T_s^l}^{T_s^u} f(H,T) dT\, dH; \tag{5}$$

where $f(H,T)$ is the bivariate Weibull probability distribution function, given by Eq. (1). This probability is computed numerically by using the fifth-order Gauss–Legendre quadrature for double integrals:

$$p_{r,s} = \frac{(H_r^u - H_r^l)(T_s^u - T_s^l)}{4} \sum_{i=1}^{5} \sum_{j=1}^{5} \omega_i \omega_j f(H_i, T_j); \tag{6}$$

where H_i and T_j can be computed by the expressions:

$$H_i = \frac{H_r^u + H_r^l}{2} + \frac{H_r^u - H_r^l}{2} \zeta_i \tag{7a}$$

$$T_j = \frac{T_s^u + T_s^l}{2} + \frac{T_s^u - T_s^l}{2} \zeta_j; \tag{7b}$$

and $\omega_{i|j}$ and $\zeta_{i|j}$ the corresponding weights and evaluation points of the interpolation polynomial see Table 2 (Kiusalaas, 2005).

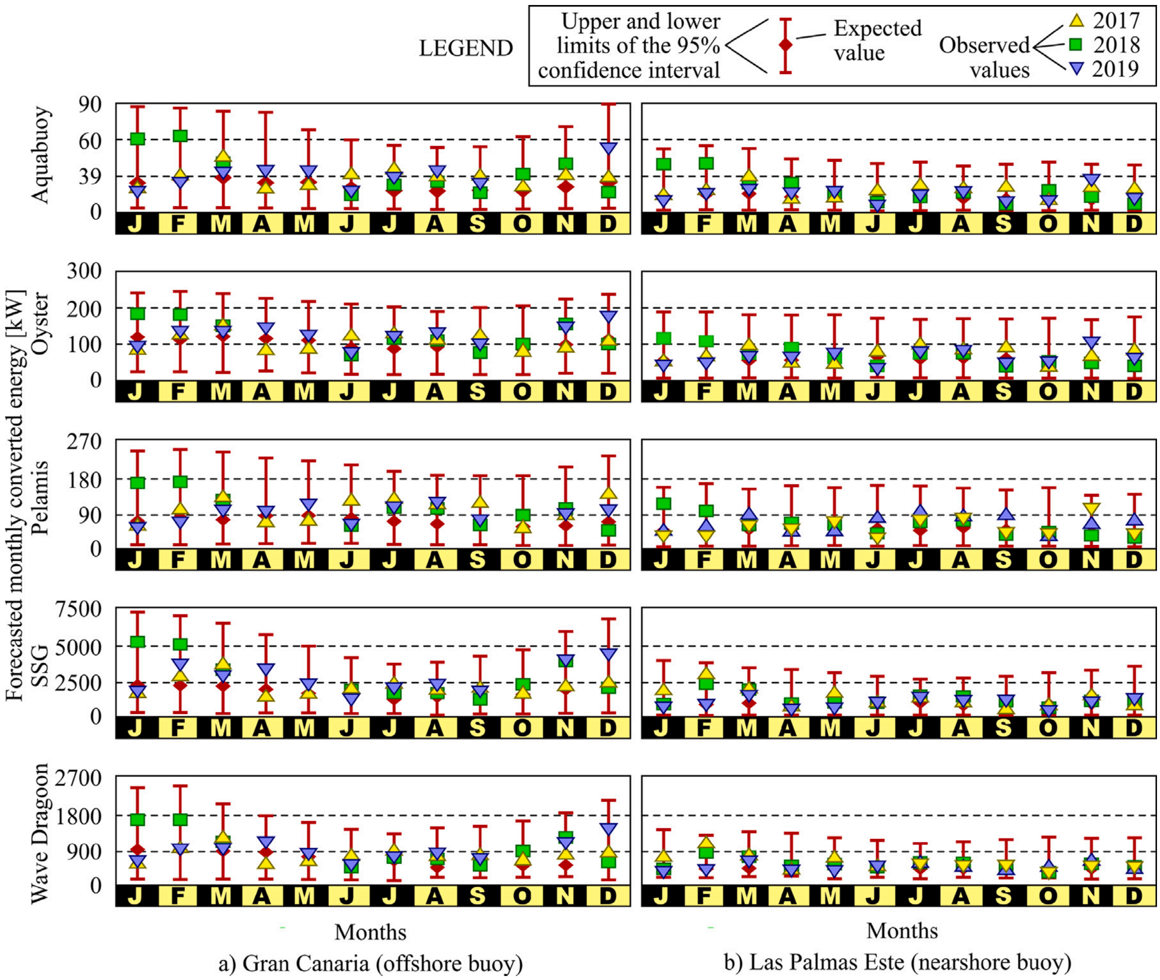

Fig. 8. Validation through the monthly converted power.

Table 2
Gauss–Legendre weights and positions.

$i\|j$	$\omega_{i\|j}$	$\zeta_{i\|j}$
1	0.236927	−0.906180
2	0.478629	−0.538469
3	0.568889	0.000000
4	0.478629	0.538469
5	0.236927	0.906180

Fig. 7 depicts the 100 random values of predicted power (black points) with the corresponding expected value (thick white line) and the lower and upper limits for the 95%-confidence interval (thin white lines). These confidence intervals were obtained by fitting a five-term mixture density probability distribution.

The number of 100 predicted power values was selected as a reasonable trade-off between the probability for estimating the expected value (based on the law of large numbers) and the computational cost.

As the graph shows, there are two main differences between the energy conversion forecast for the Gran Canaria (offshore) and Las Palmas Estes (nearshore) buoys. In the first place, Gran Canaria exhibits higher energy conversion values than Las Palmas Este. This is especially so for the Aquabuoy, Oyster and SSG converters. Another important observation is the seasonal behaviour, which is more pronounced in the Gran Canaria (offshore) buoy than in Las Palmas Este (nearshore).

This difference between the two buoys in terms of the energy conversion forecast and the seasonal behaviour can be explained if we consider Fig. 2. On this map, it is easy to identify the difference between the Gran Canaria marine buoy (2442) and the Las Palmas Este buoy (1414), near the coast. For example, buoy 2442 receives the full influence of the waves coming from the North in the Atlantic Ocean, which are only tapered by the distant influence of the Island of Tenerife to the northwest. Buoy 1414, which is located near the coast, is highly influenced by the shadow of the island of Gran Canaria, which hampers high wave potentials in this position. As a result of its location, however, buoy 1414 is more protected from the effects of inclement weather in the region.

8. Validation

In order to validate the forecasting capabilities of the proposed approach, the power for each month of the year was predicted. The corresponding expected value and confidence intervals were obtained by fitting a five-term mixture density model from forecasted power data corresponding to the monthly period. By contrast, the power for the validation, which considered those years that were not used for training, was directly computed from the experimental data.

A graphical representation of the resulting values (see Fig. 8) shows that all the computed power values, for the validation years, fall into the predicted 95% confidence intervals, showing the reliability of the predictor.

9. Conclusions

As a practical contribution to the field of Ocean Engineering, the work presented a predictor of wave energy conversion capabilities. The model developed in the research could provide a useful computational tool to evaluate the power take-off (PTO) of different WECs at any position in the ocean, in both nearshore and offshore waters, preferably on isolated islands. In a future study, the model could be tested with data from buoys located near the European continent.

The main conclusion that can be drawn from this study is the suitability of the proposed methodology for forecasting the energy conversion capability from measured historical wave data. Also of note is the model's ability to deal with the confidence intervals despite the expected values, which is more suitable for the intrinsically random wave behaviour.

MDNs can be used to deal with the non-symmetric probability distribution show not only by the bivariate Weibull coefficients but also by the predicted converted power. The MDNs exhibit a remarkable capability for modelling the behaviour of the wave parameters (i.e., spectral significant wave height and mean peak period).

The forecasted energy conversion values for the different converters show the effectiveness of the proposed approach, as they not only reflect the expected behaviour for both the offshore and nearshore buoys, but they also match the power data used for the validation.

As a future continuation of this work, several lines can be identified. In the first place, the proposed approach should be validated with data from other geographic regions, in order to verify its applicability in different climatic conditions and sea wave behaviour. The use of a more general bivariate distribution for modelling the behaviour of spectral significant wave height and mean peak period could be also considered. In this sense, using MDNs to directly predict the probability distribution of spectral significant wave height and mean peak period, could be an interesting option. Finally, hybrid models that combine theoretical models and empirical data can also be considered.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Deivis Avila Prats reports financial support was provided by University of La Laguna. Deivis Avila Prats reports a relationship with University of La Laguna that includes: employment. The authors declare no conflict of interest. The founding sponsors had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, and in the decision to publish the results.

Data availability

The authors do not have permission to share data.

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