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Statistical Analysis of Wave Energy Resources Available for Conversion at Natural Caves of Cape-Verde Islands.

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Abstract

Using the time-series of significant wave height and the peak period between 1979 and 2009 generated by SOWFIA project, some relevant statistical information about energy content available in ocean waves in Cape-Verde is obtained. The monthly and annual time-series of the average power are analysed and the confidence intervals for their values are defined. Considering all of the 31 years of data, the results show that the most energetic month, from the average power point of view is January (23.49 kW/m) and the least energetic month is July (15.04 kW/m). In fact, the monthly average power decays from January to July and increases from July to December (21.21 kW/m). The annual average power exhibits a clear attenuation over the 31 years analysed, the reason for which is not yet clear to us. However, using the appropriate Autoregressive Integrated Moving Average (ARIMA) model it is possible to estimate that future values of the annual average power tend to oscillate around 18.2 kW/m. Through the Coefficient of Variation of Power (COVP), obtained by dividing the standard deviation of the power time-series by the average power, it is possible to conclude that the wave resource is stable, with COVP between 0.46 and 0.66. The values of the Monthly Variation Index (MVI), the maximum range of the monthly mean wave power relative to the yearly mean level, show that the resource is relatively stable, with MVI < 1.2. The present work calculates the available power input into the Natural Caves (NCs) in Cape Verde Islands, through a rigorous analysis of the wave climate that excites them. The minimum sampling size and the corresponding numbers of days of measurements per month,

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are also estimated.

1 Introduction

Ocean waves constitute one of the renewable sources of energy that are gradually entering the market of clean and sustainable energy worldwide. The global theoretical energy from ocean wave is estimated in 8 x10^6 Twh/year (Boyle, 2004). Many countries around world have been investing on this natural resource to produce useful and sustainable energy. Portugal (Pelamis and Pico Plant Projects.), Australia (CETO and OCEANLIX projects), France (SEAREV project), UK (OYSTER WEC and Limpet projects) and Holland (AWS project) are examples of some countries that have recognized the feasibility of harvesting this source of energy (ABP, 2004). According to the International Renewable Energy Agency (Monford et al., 2014), around 64 % of the Wave Energy Converters (WECs) has been projected for offshore application and 36% for near-shore and onshore operation. Some full-scale operational tests have been realized. These include the OYSTER device from Aquamarine Power, the Wave Roller from AW-Energy, Pelamis P2 from the Pelamis Wave Power, the Seabased and the Sea-Tricity devices. Magagna (2011) has identified, in 2011, over 100 wave energy developers. Yet, EMEC (2014) has listed 170 wave energy developers worldwide. About 45% of the wave energy developers are based in or are currently developing projects in the European Union (EU) regions. The global installed capacity of wave energy remains low and the technologies are still at an advanced R&D stage. Just a few machines have sustained long operational hours, such as the Aquamarine OYSTER (>20000 hours) and Pelamis (cumulative > 10000 hours) (Scottish Renewable, 2014). The growth of the wave energy sector is lower than expected and this situation may affect the confidence of investors in this area. Success in attracting future Original Equipment Manufacturer investments will depend on the capacity of the developers in improving performance, reducing cost and validating wave energy technologies. The long-term global wave energy is expected to become cost competitive and provide an alternative to other Renewable Energy Sources and conventional energy resources. Through a review of the existing data available, the different cost components in the Capital Expenditure (CAPEX) estimate for wave energy have been identified as follows (Table 1):

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Table1. Costs components estimate for wave energy extraction (JRC, 2014).

Civil and Structural costs	38%
Major Equipment costs	42%
Electrical and I&C supply and installation costs	8%
Project indirect cost	7%
Development cost	5%

Thus, the main contributors to the CAPEX are mechanical equipment, civil and structural costs. In this context, the developers of wave energy technologies must undertake efforts and strategies aimed at reducing mainly the two above mentioned costs.

SOWFIA-Streamlining of Ocean Wave Farm Impact Assessment is an EU Intelligent Energy European Project with the goal of sharing and consolidating pan-European experience and best practices for consenting processes and environmental and socio-economic impact assessment (IA) for offshore wave energy conversion developments. This project brings together ten partners across eight EU Member States actively involved in planned wave farm test centers and aims at providing recommendations for streamlining of IA approval processes with the purpose of removing legal, environmental and socio-economic barriers associated with development of the wave energy farms.

Cape-Verde is an archipelago of ten islands in the Atlantic Ocean, off the West Coast of Africa, with roughly half million people. The country is totally dependent on oil to produce electricity, having one of the most expensive cost of electricity in Africa, around 0.28 Euro/kWh (Electra, 2012) versus 0.17 Euro/kWh (Senelec, 2015) at Senegal, a continental neighbour. Some investments were made by the Government with the purpose of introducing renewable sources of energy in the country, basically solar and wind energy. The Government has defined an ambitious goal that consists in achieving 50% of Renewable Energy penetration in the country by 2020 (GESTO, 2011). Some research on using ocean energy through the OTEC – Ocean Thermal Energy Conversion system and WaveStar technology (Wave energy) was initiated in the country but these projects still lack feasibility studies.

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However, four projects for offshore wave energy conversion based on the Pelamis technology were proposed for four of the islands (GESTO, 2011): Sal (3.7 MW), S. Antão (3.7 MW), S.Vicente (3.7 MW) and Boavista (3.5 MW).

Being composed of islands, most of Cape-Verde's economic activities (around 90%) are concentrated on coastal areas (Carvalho, 2013). In this context, it makes sense to use wave energy for producing electricity locally. A clear alternative is harvesting Natural Caves existing just below the rocky shore, with fountain-like structures (Fig. 1).

NCs are caverns that form naturally under the rocky shorelines, inside of which there is an air layer. This air layer acts like an air pump as the wave enters and leaves these natural infrastructures. As a result, the air is forced to go in and out of the NCs, through surface holes that exist on top of the cave. Fig. 2 shows a Natural Caves with two holes in operation. Monteiro and Sarmento (2015) carried out a study aiming at characterizing the NCs in the context of wave energy extraction.

Figure 1. Activity in a Natural Cave.

Figure 2. Activity in a NCs with two holes.

The Principles of NCs operations are similar to the man-made Oscillating Water Column device, projected for onshore application.

The justification for the idea of using the NCs is the possible cost reduction on the Civil and Structural components, which are, as mentioned before, one of the most important costs associated with building wave energy devices to produce electricity, and also to minimize the risks of collapse, by taking advantage of the sturdiness of the natural rocky structure, time tested by the waves and storms.

To evaluate the potential of NCs for electricity production, it is necessary to estimate its output power. To do this, a set of experiments aimed at determining the values of some important physics parameters of NCs operations need to be conducted. Monteiro and Sarmento (2015) carried out the analytical modelling of the NCs operations as a function of their functioning physical parameters. The present study is part of a deeper work aimed at quantifying the output power of NCs and to project an adequate power take-off system to be adapted on their holes, for electricity production.

Since the excitation waves are irregular, non-linear and non-stationary phenomenon it is very important to determine beforehand the sampling size, i.e. how long it takes to carry out the experiments on NCs to guarantee the time representativeness of its output power. To achieve this goal, some statistical analysis has to be carried on the wave energy input regime.

2 Methodology

Calculation of the wave energy input regime is carried out using principles and parameters described below.

2.1 Average Power

In deep water, where the depth is greater than a half of the wavelength, the average wave power can be determined through the following equation, applied only for unidirectional Pierson-Moskowitz wave spectrum.

$$P = \frac{\rho g^2 H_S^2}{64\pi} T_e \tag{1}$$

Where, H_S is significant wave height, T_e is energy period, defined in terms of the spectral momentum by the following relation:

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$$T_e = \frac{m_{-1}}{m_0} = \frac{\int_0^{2\pi}\int_0^{\infty} f^{-1} S(f)\, df d\theta}{\int_0^{2\pi}\int_0^{\infty} S(f)\, df d\theta} \tag{2}$$

in which, m_{-1} is the spectral momentum of order -1, m_0 is the spectral momentum of order 0, f is the frequency, $S(f)$ is the spectral density function and θ is the direction of the energy propagation (Dean and Dalrymple, 1991).

The characterization of the wave climate is made by the combination of the significant wave height H_S and peak period T_P or the zero-crossing period T_Z parameters. The energy period determined by the Eq.(2) require the knowledge of the form of energy spectrum. When the form of the energy spectrum is unknown it can be approximated by the some model as for example, the Pierson-Moskowitz spectrum. This is the approximation used on the elaboration of the Marine Atlas of Renewable Resources in UK (ABP, 2004). Another approximation commonly used for T_e is represented by $T_e \approx \alpha T_P$, where α is an empirical parameter. For Pierson-Moskowitz spectrum, $\alpha = 0.86$ (Dean and Dalrymple, 1991). To evaluate the wave resource for South of New England, Hagernam (2001) used the approximation $T_e = T_P$ and considered this approximation very appropriate to make a preliminary analysis of wave energy resource.

Using the monthly series of the available power in waves it is possible to define the annual time-series of this parameter through the following expressions:

$$P_{aj} = \frac{\sum_{i=initial\ month}^{initial\ month+11} P_{ij}}{12} \tag{3}$$

In the above equation P_{aj} is the average power for year j, P_{ij} is the average power for the month i and year j. In this way, the monthly time-series begin on January and ends on December of each year.

It is important to note that there is no physical justification for wave power to be monthly periodic, but since the sun-cycle is the underlying cause for atmospheric pressure distribution and wind patterns over the ocean, most likely it will be yearly periodic.

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The reason to calculate monthly series of available power is just related to how data is collected and made available at SOWFIA.

2.2 Monthly Variation Index (MVI)

The temporal variability of the wave resources is a key factor that affects decisively the feasibility of wave energy projects. In this sense, the regions of the ocean where the resources are stable are more attractive for all possible investors. Naturally, the level of the average power is another important factor for viability of wave energy harvesting. The Monthly Variation Index is defined as the ratio of the differences between the maximum and minimum values of the monthly average wave power in year j by the corresponding annual average wave power (Cornett, 2008). That is.

$$MVI_j = \frac{(P_{\max} - P_{\min})_j}{P_{aj}} \tag{4}$$

where $P_{\max}$ and $P_{\min}$ are, respectively, the maximum and minimum values of the monthly average power in year j.

2.3 Coefficient of Variation of Power (COVP)

COVP is another very important parameter used to evaluate the temporal variability of wave resources. This quantity is defined by the ratio between the standard deviation of the wave power and the respective annual average wave power in year j (Cornett, 2008).

$$(COVP)_j = \frac{\sigma(P(t))_j}{P_{aj}} \tag{5}$$

In the Eq.(5), $\sigma(P(t))_j$ represent the standard deviation of temporal series of wave power, $P(t)$, for year j, and P_{aj} is the respective annual average wave power. According to Cornett (2008), small values of COVP means that the wave resources are stable. For $0.8 \le COVP \le 0.9$ the wave resources can be considered moderately instable. Therefore, for $COVP > 0.9$ the resource is unstable.

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2.4 Statistical analysis

The wave climate at a certain location is well characterized by the time-series of significant wave height and the peak period. Through these parameters that are recorded for each 3 hour (time interval necessary for verifying significant change in wave spectrum) other parameters such as the time-series of the average available power in waves can be defined. To understand the time-series behavior of some important wave parameters, to calculate the confidence interval, the smoothing curves, and the forecast of its values, many statistics tools of analysis are used. In this context, some well known statistics software such as XLSTAT and Minitab are used. Aspects such as the trend analysis, stationarity and normality tests of the average power are here analysed. To perform the forecast of the average power in waves, the Autoregressive Integrated Moving Average (ARIMA) model is used. Non-seasonal ARIMA model is generally represented as ARIMA (p,d,q) where, p is the order of the Autoregressive Model, d is the degree of differencing and q is the order of the Moving Average Model (Bisgaard and Kulahci, 2011).

Finally, the wave histogram is a table that lists the occurrence of the sea-states in terms of significant wave height and peak period or mean up-crossing period. It is the long-term statistical representation of sea states. Using the information in the wave histogram it is possible to identify the most common sea states in a certain region.

2.5 Representativeness of the monthly average output power from the NCs

The energy that excites the NCs is a function of the local wave regime, while its output energy depends on the input energy (wave regime) and on the geometry of the NCs (Fig. 3). For each NC the geometry is fixed, hence the output energy is directly influenced by the local wave regime. This mean that the variation in the output energy content is just caused by the variation in the input energy content, that is by the variation of the local wave regime. In this context, it is reasonable to assume that the minimum sampling size necessary for characterizing the input energy content is equal to the minimum sampling size needed to characterize the output energy from the NCs. The calculation of the minimum sampling size for characterizing the input energy into the cave is done using the Minitab Software. For three hours time interval between successive readings, the total number of data points acquired during one day is eight. So, if this minimum sampling size is represented by N_{in}, the

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correspondent minimum time duration for data acquisition to achieve the representativeness of the input power is $N_{in}/8$ days. Therefore, to guarantee the representativeness of the output energy from the NCs the duration necessary to realize the experimental study on these natural infrastructure is equal to $N_{in}/8$ days.

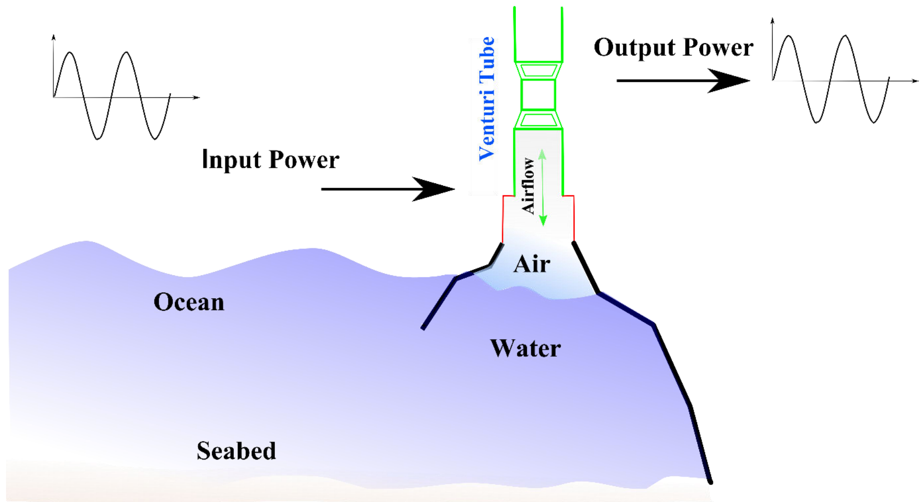

Figure 3. Energy production system by NCs.

3 Results

The information about the significant wave height (Hs) and peak period (Tp) for the wave regime in Cape-Verde is obtained for the location characterized by the coordinate 16ºN-24ºW, where the water depth is around 3.7 km (NOAA, 2015), using the SOWFIA project and is presented in Fig. 4. Data was gathered for period between 1979 and 2009 and the values of Hs and Tp are recorded every 3 hours.

The histogram and the time-series of average power available in waves were calculated and shown in Table 2 and Fig. 5, respectively.

As the histogram shows, the largest number of occurrence is 18854, representing 20.81% of all occurrences and featuring peak period from 6-9 s and significant wave height from 1.5-2 m.

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Also, 78.03 % of the waves present significant wave height between 1-2 m.

The minimum and maximum values of significant wave height and peak period recorded are, respectively 0.59 m and 3.82 m and 2.85s and 22.12 s.

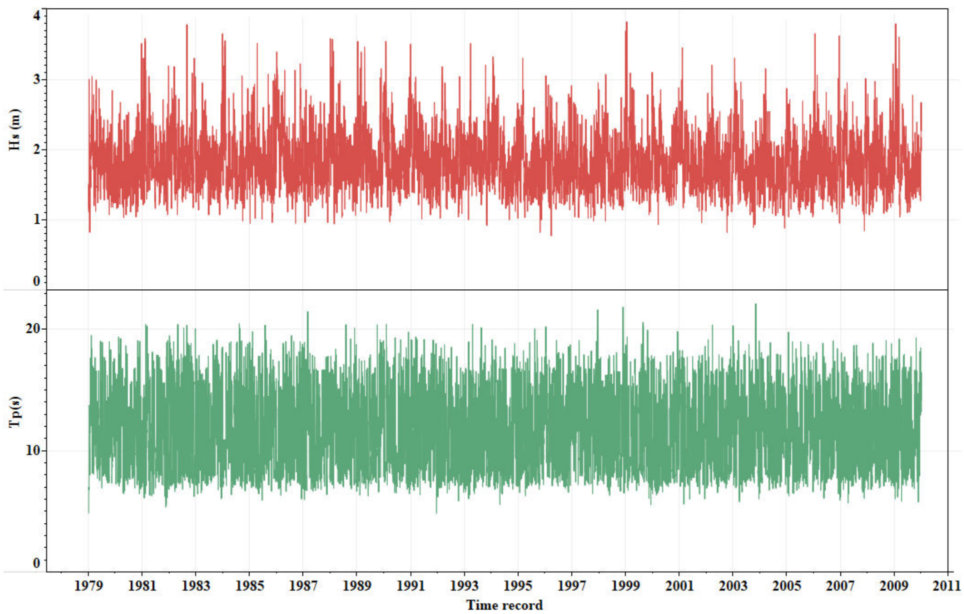

Figure 4. Time-series of significant wave height and peak period between 1979 and 2009 (SOWFIA Project).

The histogram presented in Table 2 shows two local maxima for the peak period, 6–9s and 12–15s, for significant wave height between 1.5–2.5 m. This bimodal distribution indicates a superposition of two distinct wave regime, the first with origin in a region of a shorter fetch (smaller period) and the second with origin in a region of longer fetch (longer period). We suspect that the former is generated during early-year (winter) storms in the North-Atlantic and the latter during the end-year (autumn) storms in the South-Atlantic.

This is consistent with later findings in this paper that January and December are the most energetic months and July is the least energetic month.

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Table 2.Histogram.

Significant Wave Height, Hs [m]	Peak Period, Tp[s]: 1-3	3-6	6-9	9-12	12-15	15-18	18-21	21-24	Occurrence of Hs	%Occurrence of Hs
0-0.5	0	0	0	0	0	0	0	0	0	0.00
0.5-1	**1**	**3**	**170**	**427**	**141**	**29**	**6**	0	777	0.86
1-1.5	0	**572**	**8307**	**9194**	**7288**	**1742**	**127**	**4**	27234	30.07
1.5-2	0	**730**	**18854**	**7590**	**12783**	**3315**	**171**	**2**	43445	47.96
2-2.5	0	**20**	**8482**	**2072**	**3329**	**1355**	**85**	0	15343	16.94
2.5-3	0	0	**1657**	**731**	**431**	**293**	**25**	0	3137	3.46
3-3.5	0	0	**254**	**219**	**51**	**47**	**7**	0	578	0.64
3.5-4	0	0	**28**	**29**	**3**	**8**	**1**	0	69	0.08
>4	0	0	0	0	0	0	0	0	0	0.00
Occurrence of Tp	**1**	**1325**	**37752**	**20262**	**24026**	**6789**	**422**	**6**	**90583**	100
%Occurrence of Tp	**0.00**	**1.46**	**41.68**	**22.37**	**26.52**	**7.49**	**0.47**	**0.01**	**100**	

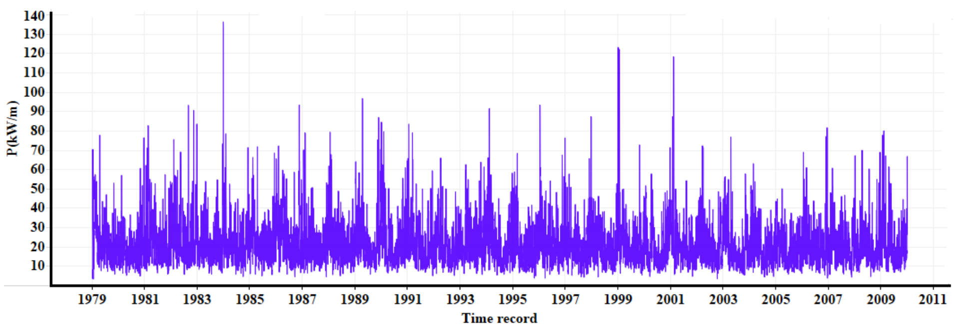

Figure 5. Time-series of mean power available on waves between 1979 and 2009.

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The curves on Fig. 6 show no clear trend on the time-series of the monthly average power, over the years. This fact is confirmed by the Mann-Kendal test (Mann, 1945) whose results are presented at Table 3. The Mann-Kendal test (at 5% level of significance) was done using a commercially available software (XLSTAT, 2015). The results show that these monthly time-series can be considered trendless over the years, except for September and October with low p-values of 3.8% (September) and 1.8% (October) implying a trend.

Table 3. The Mann-Kendall Trend test for monthly average time-series.

Months	**J**	**F**	**M**	**A**	**M**	**J**	**J**	**A**	**S**	**O**	**N**	**D**
p-values	0.946	0.176	0.696	0.311	0.825	0.302	0.424	0.199	0.038	0.018	0.866	0.176
Decision	Without Trend	Without Trend	Without Trend	Without Trend	Without Trend	Without Trend	Without Trend	Without Trend	With Trend	With Trend	Without Trend	Without Trend

Fig. 7 shows the minimum, average and maximum power available on waves which has been calculated for each month of the 31 year long record. The graph clearly shows that the most energetic month is January (23.49 kW/m) and the least energetic month is July (15.04 kW/m). In fact the average power decays from January to July and increases from July to December (21.21 kW/m).

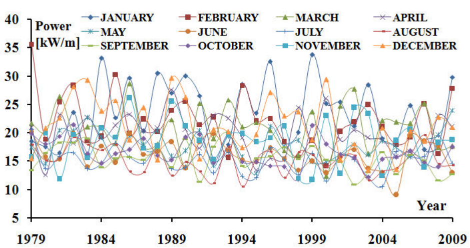

Figure 6. Time-series of monthly average power.

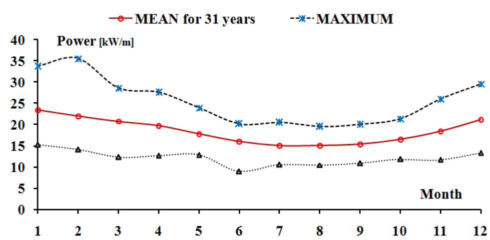

Figure 7. Statistics of monthly average power for 31 years of data.

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The increase of the annual average power, between 1979 and 2009 is shown in Fig. 8, together with its exponential and linear smoothing curves (Hyndmann et al., 2008). The Dickey-Fuller test helps us to verify if there are upward or downward trends in the time-series of the annual average power (Kirchgassner and Wolters, 2008). According to this statistical test (p- values equal to 0.475 and significance level of 5 %), the time-series of the annual average power is a non-stationary time-series and presents a downward trend, as it is possible to see by the two smoothing curves . We could not find any plausible explanation for this downward trend. In this context, it is worth making a forecast of the annual increase of average power for the next 15 years to see the trend for its predictable values. To achieve this goal, it is necessary to calculate the best ARIMA model.

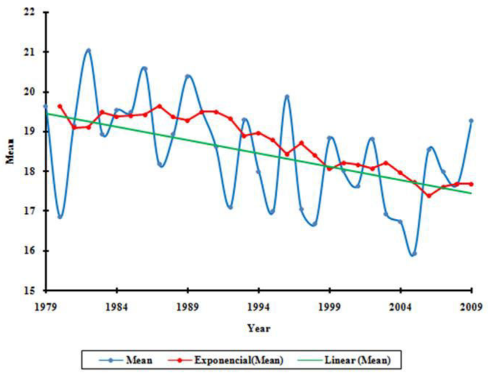

Figure 8. Time-series of annual average power, between 1979 and 2009.

According to the Dickey-Fuller test, the original time-series of the annual average power is non stationary. The first difference (P-1) is stationary as its possible to see through the values of the Autocorrelation Factor (ACF) and of Partial Autocorrelation Factor (PACF), that are statistically equal to zero, as they are less than 0.35, after Lag = 1 (for ACF) and Lag = 2 (for PACF). ACF and PACF are two statistical measures that show how the observations in a time-series are related to each other. Thus, to determine a proper model for a given time-series, it is necessary to carry out the analysis of these parameters (Frain,1999). Table 4 shows the values of these quantities under analysis. In the present case, the original time-series is converted into stationary time-series after the first differencing (d = 1).

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Table 4. The ACF and PACF values for P-1 (generated by NCSS10 Software)

ACF							
Lag	**Correlation**	**Lag**	**Correlation**	**Lag**	**Correlation**	**Lag**	**Correlation**
1	-0.41	8	-0.02	15	-0.02	22	-0.11
2	-0.28	9	-0.25	16	-0.17	23	-0.00
3	0.33	10	0.17	17	0.15	24	0.05
4	-0.04	11	0.02	18	0.09	25	0.10
5	-0.06	12	-0.06	19	-0.27	26	-0.15
6	-0.14	13	0.01	20	0.17	27	0.04
7	0.27	14	0.06	21	0.01	28	0.05
PACF							
1	-0.41	8	0.07	15	0.03	22	-0.03
2	-0.55	9	-0.00	16	-0.18	23	-0.10
3	-0.13	10	-0.08	17	-0.08	24	-0.05
4	-0.08	11	-0.09	18	0.09	25	-0.04
5	0.08	12	-0.02	19	-0.11	26	0.04
6	-0.27	13	0.08	20	0.00	27	0.09
7	0.09	14	0.12	21	-0.13	28	0.02

Significant if |Correlation|> 0.35

Accornding to Hintze (2007) the value of p is determined from the PACF of the appropriate differenced time-series. If the PACF cuts off after a few Lags, the last Lag with a large value would be the estimate for p. Therefore, p is equal to 2 (Table 4). The value of q is estimated, following the same procedure, using the values of the ACF parameter shown in Table 4. So, q=1 and, the best ARIMA model to make the forecast is ARIMA (2, 1, 1).

The following table shows the results of the forecast for the annual average power, achieved using the NCSS Software (NCSSLLS,1981) . According to the forecast, the predicted time-series of the annual average power oscillates, without any trend, around its average value

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(18.2 kW/m). This value is very close to the one presented by Falnes. J. (2007), for the most tropical waters, where Cape-Verde Island is located.

Table 5. Forecast of Annual Average Power (generated by NCSS10 Software)

Forecast

Row	Date	Forecast	Lower 95% Limit	Upper 95% Limit
33	2011	18.05	15.69	20.41
34	2012	17.75	15.40	20.11
35	2013	18.53	15.87	21.18
36	2014	18.33	15.55	21.11
37	2015	18.01	15.20	20.82
38	2016	18.26	15.35	21.18
39	2017	18.32	15.28	21.35
40	2018	18.16	15.07	21.25
41	2019	18.20	15.04	21.36
42	2020	18.27	15.01	21.52
43	2021	18.21	14.89	21.54
44	2022	18.20	14.81	21.60
45	2023	18.24	14.77	21.70
46	2024	18.23	14.69	21.77
47	2025	18.21	14.61	21.82

According to the Portmanteau Test (Hintze, 2007), for a significance level of 5%, the ARIMA model used to carry out the forecast is adequate, with p-value between 0.179 and 0.641, implying the acceptation of the forecast, as the p-values are higher than the significance level.

The normality test of Anderson-Darling (Thode, 2002) shows that the annual average power follows a normal distribution with p-value equal to 51.5% (Fig. 9). As this p-value is higher than the significance level of 5%, the hypothesis of the normality distribution is accepted. Fig.9 was generated by Minitab software and represents a summary report of the annual

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average power time-series. It shows, with a significance level equal to 0.05, the confidence intervals for the annual mean (17.981 kW/m – 18.924 kW/m), for the annual median (17.879 kW/m – 19.186 kW/m) and for the annual Standard Deviation (1.028 kW/m – 1.719 kW/m). Fig. 10 shows the normal probability plot for the annual average power. As it is possible to note in this figure, in general, the data follow the normal line. However, some deviataion from this normal line is registed between 16.99 kW/m and 17.09 kW/m.

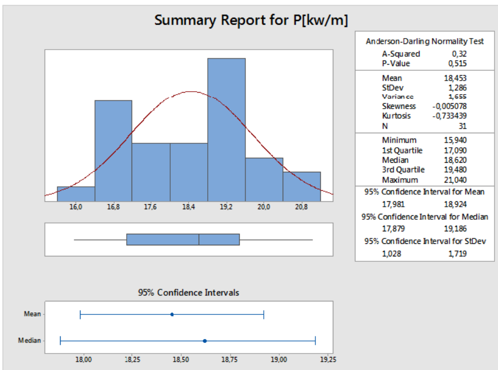

Figure 9. Summary report of annual average power, between 1979 and 2009.

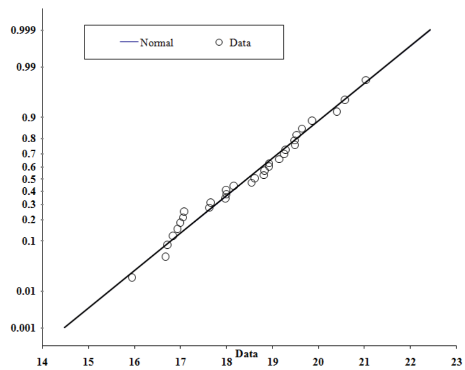

Figure 10. Normal probability plot.

The wave energy resources are stable with COVP less than 0.8, as it is possible to see in Fig. 10, which represents the time-series of the annual values of COVP. The MVI parameter shows that the monthly wave energy resources can be considered relatively stable with MVI values less than 1.2 (Fig. 11). This is a very attractive aspect associated with the utilization of wave energy to produce electricity in Cape-Verde since it affects the useful life cycle of ocean wave conversion equipment.

Defining a set of samples using all values of the significant wave height, peak period and the average power obtained for each month during the 31 years of data, the confidence intervals for all of these parameters were calculated, using the Minitab software and admitting a significance level of 5% . Before defining the referred confidence intervals the normality tests for all of these parameters were performed. Table 6 summarizes the statistical information

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about the normality tests, average values and confidence intervals for each month. The data are non-normal, as it is possible to see through the values of the A-squared parameter. According to D'Agostino (1986), the cricital value of the A-squared parameter, for a 95% confidence level, is 0.752. The values of this parameter presented in Table 6 are higher than this critical value. That is, there is a very strong evidency that the data is non-normal. This result is confirmed by the p-values that are, in all cases, lower than 0.05 (significance level) implying the rejection of the normality hypothesis. The Minitab software has a option to calculate the confidence intervals for non-normal data. The reseults are presented in Table 6.

Table 6. Monthly statistical reports.

	Variable	Simple size. N	Anderson-Darling Normality Test		Mean	StDev	SE Mean	95% CI
J	**Hs[m]**	7687	A-Squared: 40.63	p-value <0.005	1.92191	0.50899	0.00581	(1.91053; 1.93329)
	Tp[s]	7687	A-Squared: 170.24	p-value <0.005	10.7142	3.1631	0.0361	(10.6435; 10.7849)
	P [kW/m]	7687	A-Squared: 202.38	p-value <0.005	23.513	13.783	0.157	(23.205; 23.821)
F	**Hs [m]**	7008	A-Squared: 15.53	p-value <0.005	1.87711	0.46451	0.00555	(1.86623; 1.88798)
	Tp[s]	7008	A-Squared: 145.66	p-value <0.005	10.4387	3.0192	0.0361	(10.3680;10.5094)
	P [kW/m]	7008	A-Squared: 208.03	p-value <0.005	21.897	12.716	0.152	(21.599; 22.195)
M	**Hs [m]**	7689	A-Squared: 21.63	p-value <0.005	1.80126	0.43902	0.00501	(1.79144; 1.81107)
	Tp[s]	7689	A-Squared: 70.03	p-value <0.005	10.8515	2.8814	0.0329	(10.7871; 10.9159)
	P [kW/m]	7689	A-Squared: 131.79	p-value <0.005	20.780	10.801	0.123	(20.538; 21.021)
A	**Hs[m]**	7440	A-Squared: 36.30	p-value <0.005	1.80543	0.38490	0.00446	(1.79668; 1.81417)
	Tp[s]	7440	A-Squared: 118.55	p-value <0.005	10.3233	2.7986	0.0324	(10.2597;

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					10.3869)
	P[kW/m]	7440	A-Squared: 161.64	p-value <0.005	19.763 9.983 0.116 (19.536; 19.990)
	Hs[m]	15376	A-Squared: 29.32	p-value <0.005	1.73386 0.31984 0.00258 (1.72881; 1.73892)
M	**Tp [s]**	15376	A-Squared: 491.92	p-value <0.005	10.2287 3.0524 0.0246 (10.1804; 10.2769)
	P[kW/m]	15376	A-Squared: 258.45	p-value <0.005	17.8068 7.9966 0.0645 (17.6804; 17.9332)
	Hs[m]	14880	A-Squared: 29.78	p-value <0.005	1.64809 0.30307 0.00248 (1.64322; 1.65296)
J	**Tp [s]**	14880	A-Squared: 618.05	p-value <0.005	10.1125 3.0069 0.0246 (10.0642; 10.1608)
	P[kW/m]	14880	A-Squared: 291.89	p-value <0.005	16.0597 7.4576 0.0611 (15.9399; 16.1795)
	Hs[m]	15376	A-Squared: 46.52	p-value <0.005	1.59065 0.26830 0.00216 (1.58640; 1.59489)
J	**Tp [s]**	15376	A-Squared: 849.41	p-value <0.005	10.1592 2.8717 0.0232 (10.1138; 10.2046)
	P[kW/m]	15376	A-Squared: 254.08	p-value <0.005	15.0375 6.6470 0.0536 (14.9324; 15.1425)
	Hs[m]	7688	A-Squared: 27.43	p-value <0.005	1.57631 0.26316 0.00300 (1.57043; 1.58219)
A	**Tp[s]**	7688	A-Squared: 337.55	p-value <0.005	10.2906 2.9649 0.0338 (10.2243; 10.3569)
	P[kW/m]	7688	A-Squared: 174.44	p-value <0.005	15.1119 7.2471 0.0827 (14.9499; 15.2740)
	Hs[m]	7440	A-Squared: 13.53	p-value <0.005	1.59887 0.27965 0.00324 (1.59251; 1.60522)
S	**Tp[s]**	7440	A-Squared: 204.76	p-value <0.005	10.2960 2.8409 0.0329 (10.2315; 10.3606)
	P[kW/m]	7440	A-Squared: 143.42	p-value <0.005	15.4316 7.0104 0.0813 (15.2723; 15.5910)
O	**Hs[m]**	7687	A-Squared: 24.60	p-value <0.005	1.60069 0.33400 0.00381 (1.59322; 1.60816)

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	Tp[s]	7687	A-Squared: 61.21	p-value <0.005	10.8908	2.8969	0.0330	(10.8261; 10.9556)
	P[kW/m]	7687	A-Squared: 188.74	p-value <0.005	16.5502	8.6290	0.0984	(16.3573; 16.7431)
	Hs[m]	7440	A-Squared: 45.13	p-value <0.005	1.65678	0.39347	0.00456	(1.64784; 1.66573)
N	**Tp[s]**	7440	A-Squared: 47.37	p-value <0.005	11.0808	2.9679	0.0344	(11.0133; 11.1482)
	P[kW/m]	7440	A-Squared: 212.76	p-value <0.005	18.439	11.008	0.128	(18.189; 18.689)
	Hs[m]	7688	A-Squared: 65.15	p-value <0.005	1.80871	0.45569	0.00520	(1.79852; 1.81890)
D	**Tp[s]**	7688	A-Squared: 110.55	p-value <0.005	10.7810	3.1661	0.0361	(10.7102; 10.8518)
	P[kW/m]	7688	A-Squared: 298.54	p-value <0.005	21.213	13.252	0.151	(20.917; 21.509)

Using the Minitab software, the minimum number of sample points, for average monthly power, was calculated admitting a 0.85 power factor, a significance level equal to 0.05 and a value of 3kW/m for margin of error. This margin of error was assumed taking into account the possibility of completing all measurements in one year. In this context, lower margin of error implies higher number of sample points. Table 7 show the standard deviations, the minimum sampling size to guarantee the representativeness of the values of the monthly average power and, consequently, the number of days to carry out the experiments on the Natural Caves in order to ensure the correct values of the average power extracted from these natural infrastructures.

Table 7. Minimum sampling size and the corresponding numbers of days of measurements

Power Factor: 0.85; Margin of Error: 3 kW/m; Significance level: α = 0.05			
Months	**Standard deviation, σ**	**Minimum sampling size, n**	**Numbers of days (for 3 h time step)**
J	13.25	178	23
F	11.01	123	16

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M	8.63	77	10
A	7.01	51	7
M	7.25	55	7
J	6.65	47	6
J	7.46	58	8
A	7.99	66	9
S	9.98	102	13
O	10.80	119	15
N	12.78	165	21
D	13.78	192	24

Conclusion

The most common sea state in Cape-Verde occurs 20.81% of time, featuring peak periods from 6-9 s and significant wave height from 1.5-2 m. For period between 1979 and 2009, 78.03% of the waves present wave height between 1 and 2 m.

January and December are the most energetic months and July is the least energetic month. The monthly wave power decreases from January to July and increases again to December.

Through the Coefficient of Variation of Power (COVP) it is possible to conclude that the wave resource is stable, with COVP between 0.46 and 0.66.

The MVI parameter shows that the wave resource can be considered relatively stable (MVI <1.2) from monthly average power point of view.

The monthly average time-series is stationary and has no trend over time. The confidence intervals for all months were calculated using the Minitab software.

The time-series of annual average wave power is non-stationary and presents a visible attenuation over the years. However, by the use of an appropriate ARIMA model it was possible to verify that its values oscillate around its average (18.2 kW/m).

The minimum time recording of physical parameters associated with the NC operation are determined, for each month, under the assumption that the minimum sampling size necessary to characterize the monthly average power on waves is equal to the minimum sampling size to characterize the monthly average power emanating from the NC. In this context and for the Cape-Verde Wave Regime, the minimum sampling size and the corresponding numbers of days of measurements are given in table 6.

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