**Proceedings of the ASME 2025 44th International Conference on Ocean, Offshore and Arctic Engineering**
**OMAE2025**
**June 22-27, 2025, Vancouver, British Columbia, Canada**

**OMAE2025-157263**

# ON THE REDUCTION OF DESIGN LOAD CASES FOR FATIGUE ASSESSMENT OF MOORING LINES FOR OFFSHORE RENEWABLE ENERGY SYSTEMS

**Ander Martinez-Perurena[1], Eguzkiñe Martinez-Puente[1], Iñigo Llavori[1], Markel Penalba[1,2,*], Gregorio Iglesias[3,4]**

[1]Mondragon Unibertsitatea, Faculty of Engineering, Mechanics and Industrial Production, Arrasate-Mondragon, Spain
[2]Ikerbasque, Basque Foundation for Science, Bilbao, Spain
[3]MaREI, Environmental Research Institute & School of Engineering, UCC, Cork, Ireland
[4]University of Plymouth, School of Engineering, Computing & Mathematics, Plymouth, UK

## ABSTRACT

*The design phase of offshore renewable energy systems requires considering numerous design load cases to meet standards. Long-term fatigue assessment, often the most time-consuming aspect, demands thousands of time-domain simulations to capture the combined effects of environmental conditions. This process becomes computationally expensive, contributing to the already high Levelized Cost of Energy (LCOE) for offshore renewables. To alleviate this computational burden, this study applies the K-means clustering technique, significantly reducing the number of environmental cases while maintaining fatigue estimation accuracy. A sensitivity analysis is conducted based on the number of clusters and statistical metrics to validate the approach. Results show that K-means effectively captures key resource characteristics and accurately estimates fatigue damage with 1000 clusters. This reduces the number of cases for fatigue analysis significantly, favorably impacting computational costs and enhancing the feasibility of large-scale studies in offshore renewable energy design.*

**Keywords: Metocean characterisation, Clustering techniques, Design Load Cases, Offshore Renewable Energies, Mooring lines design, Fatigue Assessment**

## 1. INTRODUCTION

Renewable energy has significantly reshaped the energy sector in recent years, with solar and wind energy achieving remarkable growth. In 2022, installed capacity for these technologies increased by 18.2 % and 8.3 % respectively compared to 2021, reaching a combined total of over 1,889 GW globally [1]. Offshore renewables, including floating wind, wave, current, and floating solar energy, are projected to play a vital role in achieving global emission reduction goals, with planned installed capacities expected to exceed 2350 GW by 2050 [2]. Despite their potential, offshore technologies face critical challenges—primarily high costs, technical complexities, and environmental constraints—that hinder their development and competitiveness compared to mature onshore wind and photovoltaic solar energy. Currently, only a limited number of offshore projects have reached the pre-commercial phase (e.g. [3] and [4]), highlighting the need for innovation to overcome these barriers.

A major challenge in Marine Energies lies in accurately modelling environmental loads during the design process. Engineers must consider numerous Design Load Cases (DLCs) to ensure the structural integrity of offshore systems under various operational and extreme conditions. In fact, standards from organizations like IEC [5] and DNV [6] guide the evaluation of these scenarios, requiring the combination of wind, wave, current, and sea level data to simulate real-world conditions. These DLCs account for [5]:

- **Ultimate loads**:maximum loads that can lead to structural failure.
- **Fatigue loads**: accumulated damage from repeated stresses over time.
- **Serviceability loads**: loads that, while staying within the load capacity, can cause deformations or vibrations that impair functionality.
- **Accidental loads**: loads that the structure must resist to ensure survival in damaged conditions or during unusual events.

Fatigue analysis is particularly demanding, as it involves modelling the joint probability distribution of metocean variables and performing thousands of time-domain simulations to account for nonlinear interactions. In some cases, this process can require

*Corresponding author: mpenalba@mondragon.edu
Documentation for `asmeconf.cls`: Version 1.38, March 20, 2025.

several tens of thousands of simulations or more [7], depending on site-specific conditions, making it computationally expensive and time-consuming.

To address these challenges, efforts focus on reducing the number of metoceanic conditions by selecting just the most representative ones for the full long term fatigue assessment. Several studies in the literature have demonstrated that machine learning techniques, particularly clustering methods, can be effectively applied to reduce fatigue bins by identifying patterns in large datasets. Paula Camus et al. [8] compared K-means, Self-Organizing Maps (SOM), and Maximum Dissimilarity Algorithm (MDA) for clustering wave climate data, finding all effective with 200 clusters, with MDA excelling at detecting unusual conditions. Samuel Kanner et al. [9] extended MDA to include wind data, achieving optimal results with 2000 clusters. Aitor Saenz-Agirre et al. [10] went a step further applying the Ward clustering for fatigue analysis of a floating turbine, using 20 clusters to model environmental conditions. This reduced number of conditions subsequently enabled the efficient computation of the equivalent fatigue damage loads corresponding to the turbine's 30-year lifecycle. However, it should be noted that no sensitivity analysis is conducted in [10] and the number of clusters is pre-selected randomly.

The studies conducted to date highlight the potential of clustering techniques to streamline the selection of representative metocean conditions. However, their efficacy in precisely capturing long-term fatigue assessments and resolving the uncertainties intrinsic to these methods remains insufficiently established.

Hence, this study introduces the use of K-Means clustering technique for synthesizing metocean conditions, with an initial evaluation of their efficiency based on resource-specific metrics, following the approach in [8] and [9], and a subsequent assessment using design parameters for fatigue. The focus is limited to a Wave Energy Converter (WEC) technology, with the potential for future application to other offshore technologies.

The structure of the paper is as follows: Section 2 provides an overview of the K-Means clustering technique used in this study and details the procedure for evaluating fatigue damage on the turbine. Section 3 introduces the case study, outlining the geographical locations, the offshore renewable energy (ORE) technology utilized, and the metocean variables considered. It also describes the test cases used to validate the K-Means clustering technique against other methods from the literature, assess its effectiveness in reducing metocean conditions, and evaluate its accuracy in estimating fatigue damage. The results for the case study are summarized in Section 4, and the conclusions are presented in Section 5.

## 2. METHODOLOGY

The approach used in this analysis involves two primary stages. The first stage in Section 2.1 will identify the clustering technique to be applied, which will help define a representative set of metocean conditions. The second stage in Section 2.2 will focus on incorporating these conditions into a fatigue analysis, where fatigue damage will be estimated using spectral models. The block diagram shown in Figure 1 illustrates the workflow followed in the development of this study.

### 2.1 Clustering technique

The analysis aims to demonstrate the potential of clustering techniques to reduce the computational cost when evaluating the long-term fatigue of ORE systems, while maintaining accuracy in damage estimation. To achieve this, the study focuses on a single clustering technique, synthesizing the results for better understanding and enabling a more comprehensive assessment of the clustering effectiveness for this type of application.

The selected technique for this task is the K-means algorithm, due to its high scalability and interpretability. The K-means method, based on partitioning the data into clusters, allows for direct identification of representative metocean conditions for each group. Additionally, it can efficiently handle large datasets with relatively low computational cost, as the computational complexity of K-means is linear with respect to the number of data points.

This technique, divides a dataset $N$ into $K$ distinct clusters. Each cluster is represented by the mean value $\mu_j$ of the data points assigned to that cluster, and these mean values are referred to as centroids. Although the centroids do not necessarily correspond to actual data points within the dataset $N$, they exist within the same feature space.

The algorithm works iteratively, adjusting the position of the centroids to minimize inertia, defined as the sum of squared Euclidean distances within each cluster, also known as the within-cluster sum of squares (WCSS). The objective is to minimize this value, which is mathematically expressed through the equation 1, aimed at reducing inertia.

$$WCSS = \sum_{i=1}^{K} \sum_{x_j \in C_i} \|x_j - \mu_i\|^2, \tag{1}$$

where $K$ is the number of clusters, $C_i$ represents the data points in the i-th cluster, $x_i$ represents a data point in cluster $C_i$, $\mu_i$ is the centroid of the $i$-th cluster and $\|x_j - \mu_i\|$ is the Euclidean distance between the data point $x_j$ and the centroid $\mu_i$.

The implementation of the K-means algorithm in the Python environment is carried out using the Scikit-learn library [11], which provides optimized clustering codes ready for direct application in various scenarios. The code allows for the external specification of the number of clusters to which the algorithm will converge, making it ideal for conducting sensitivity analyses with different cluster counts and identifying the optimal number of clusters. Additionally, K-Means code offers the flexibility to choose the initialization method for centroids. In this study, the k-means++ method has been selected, which, in contrast to the traditional k-means technique, optimizes centroid initialization by maximizing the distance between them and reducing the likelihood of the algorithm converging to a local optimum.

Once the clustering algorithm is set up, the metocean data is prepared for clustering. Given the focus on a WEC in this study, only wave-related variables are considered, specifically significant wave height ($H_s$), spectral peak period ($T_p$), and mean wave direction ($Mwd$). This selection results in a three-dimensional dataset comprising $N$ samples.The data is then processed using a custom-built code designed to perform sensitivity analysis on the number of clusters. This iterative methodology aims to identify

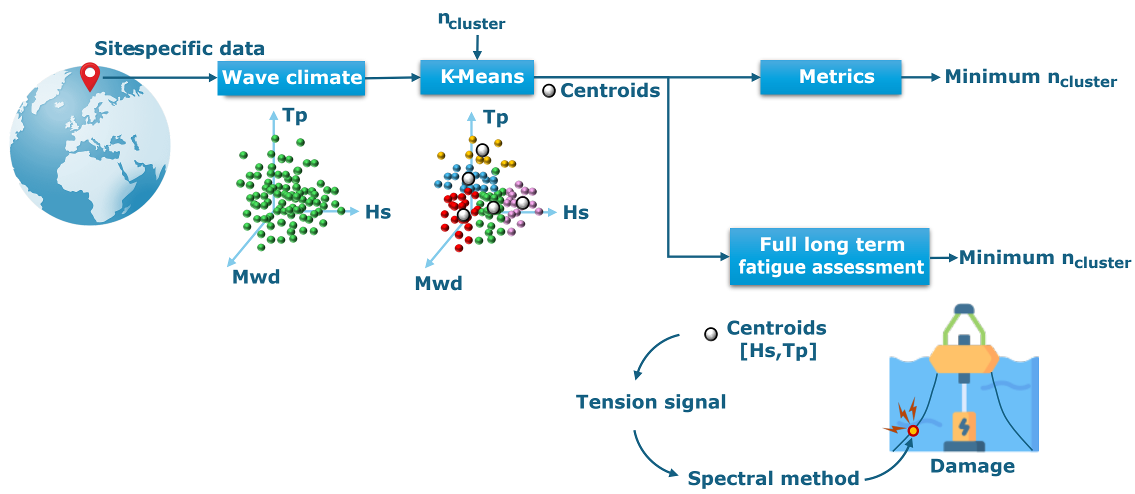



**FIGURE 1: FLOWCHART OF THE ASSESSMENT METHOD FOR K-MEANS ALGORITHM.**

the optimal number of clusters, ensuring the clustering method accurately captures the intrinsic patterns within the data.

The results are evaluated using metrics designed to determine an appropriate number of clusters. These metrics are classified into two categories, the first comprising standard clustering evaluation methods that assess inter-cluster distances:

- **Quantization Error**: Measures the average distance between data points and their assigned cluster centroids, indicating the quality of the cluster representation.

$$q = \left[1 - \frac{1}{n}\sum_{j=1}^{n}\frac{1}{p}\left(\sum_{k=1}^{p}\left|\hat{X}_k - X_{j,k}\right|\right)\right] \times 100, \quad (2)$$

  where $n$ corresponds to the number of samples, p represents the number of dimensions that compound the hyperspace, $\hat{X}_k$ the centroid of a cluster and $X_{j,k}$ the observations that correspond to the same cluster.

The second category encompasses metrics that evaluate the statistical distribution of the data. The metrics employed in [8] and [9] have been utilized as a reference for this analysis.

- $90^{th}$ **percentile error**: Focuses on the most common environmental conditions, evaluating the accuracy of clustering for values up to the $90^{th}$ percentile of the dataset.
- $99^{th}$ **percentile error**: Captures the error in the upper tail of the distribution, emphasizing extreme cases.
- **PDF score**: Quantifies discrepancies between the probability distribution functions of the clustered and original data, assessing representativeness [12].

$$PDF_{score} = \sum_{m=1}^{M} min(PDF(y_m^{obs}) - PDF(y_m^{as})), \quad (3)$$

  where $M$ is the number of bins used to represent the PDF.

Following the extraction of metrics for each iteratively defined number of clusters, the behaviour of these metrics is analysed through 2D visualizations to identify convergence points.

## 2.2 Spectral fatigue assessment

For the estimation of fatigue damage, centroids from each cluster are utilized as inputs in a frequency-domain fatigue life model, as outlined in [13]. Unlike traditional time-domain methods that rely on rainflow counting, spectral techniques substantially reduce computational effort while maintaining high accuracy, making them particularly suitable for assessing numerous environmental conditions.

Aligned with the benchmarking analysis by Eguzkine et al.[13], the Tovo-Benasciutti method is selected as the spectral approach to estimate cumulative fatigue damage in the mooring lines of a WEC, which is shown to overperform the Dual Narrow Banded spectrum approach recommended by DNVGL-OS-E301 [5]. The process begins with the transformation of $H_s$ and $T_p$ parameters into irregular wave fields using the JONSWAP spectrum, employing a peak enhancement factor of 3.3. The mean wave direction is excluded from the fatigue calculation for simplicity.To ensure the simulations' fidelity, IEC 61400 [6] standards require a minimum time series duration of 10 minutes for wave conditions in power production scenarios, capturing the system's essential dynamic behaviour. However, following [13], this period has been extended to 125 minutes in the present study to ensure fatigue estimation is consistent. Additionally, at least six random seeds are generated for each metocean condition to achieve statistical robustness.

Subsequently, the wave time series are converted into synthetic stress signals based on hydrodynamic simulations of the reference turbine described in Section 3.2.Mooring line stress responses are derived from WEC-Sim simulations of the reference WEC (see the wave energy converter in Section 3.2). This approach avoids the need for exhaustive simulations for each environmental condition, thereby expediting the calculations while accurately accounting for hydrodynamic effects.

Finally, the spectral model estimates the fatigue damage rate for the selected centroids. This facilitates an analysis of how the damage rate varies as the number of clusters increases, enabling the determination of the minimum number of clusters required to adequately represent long-term fatigue behaviour.

## 3. CASE STUDY

As part of the case study, metocean data from a site-specific location, detailed in Section 3.1, will be employed to evaluate the practical application of clustering techniques. A full long-term fatigue assessment will be carried out using the wave energy converter presented in Section 3.2 as the reference system. Furthermore, the test cases outlined in Section 3.3 will be examined to assess the effectiveness of clustering methods in reducing the complexity of metocean variables while ensuring accurate fatigue damage estimation.

### 3.1 Location and wave data

The study area focuses on the maritime region of the Bay of Biscay, specifically the Biscay Marine Energy Platform (BIMEP) area. It is located 1.5 km offshore, near the town of Armintza, where the sea depth ranges between 50 m and 90 m (see Figure 2).This site serves as a testing ground for prototypes of marine energy converters and is located off the Basque coast. BIMEP represents an optimal location for assessing the performance of clustering techniques due to its strategic position and its significant role in marine energy research. Situated in the Bay of Biscay, the area offers a wide range of metocean conditions, which are essential for evaluating the robustness and effectiveness of clustering algorithms. Moreover, as a dedicated testing site for marine energy prototypes, BIMEP provides a controlled yet realistic environment to analyse long-term fatigue assessments and validate clustering methods in scenarios that closely reflect real-world conditions. The site's established infrastructure and the availability of comprehensive metocean data further strengthen its suitability for this study.

The environmental data utilized in this study are sourced from ERA5, an atmospheric reanalysis product developed by the

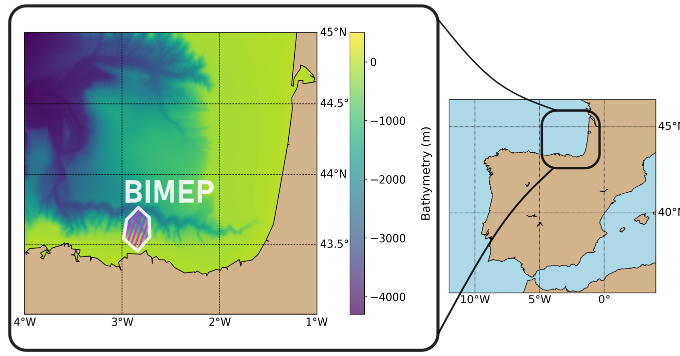
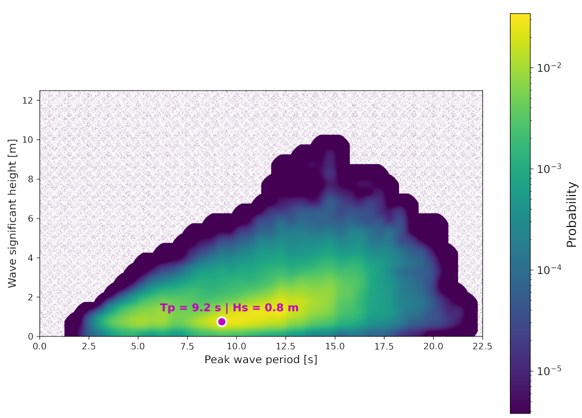



**FIGURE 2: BIMEP AREA FOR METOCEAN DATA EXTRACTION.**

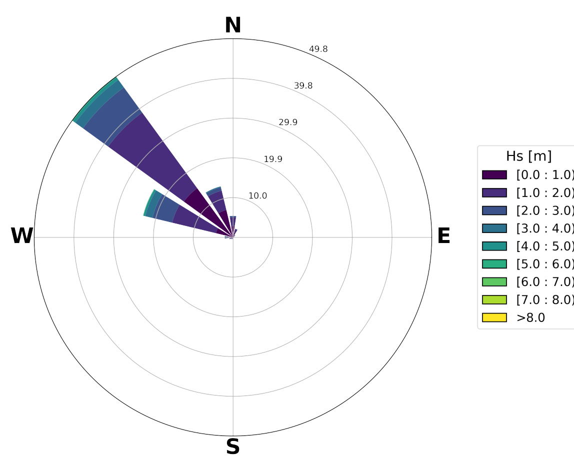
Copernicus Climate Change Service [14], which is extensively recognized within the offshore sector. ERA5 provides oceanic data at a spatiotemporal resolution of 1 hour and 0.5° for the variables Hs, Tp, and Mwd. Additionally, it offers global coverage with a temporal range spanning from 1940 to the present, rendering it an optimal resource for conducting long-term analyses of this nature.

The ERA5 coordinate closest to the BIMEP area, located at 43.5°N and 2.5°W, is selected for this analysis. In accordance with IMAREST guidelines [15], 30 years of hourly data are collected to accurately capture the temporal variations of the resource and extreme events. The $H_s$, $T_p$, and $M_{wd}$ data are then organized into scatter and rose diagrams to represent joint probabilities. These diagrams illustrate regions with the highest frequencies of occurrence, as well as the boundaries of the dataset corresponding to extreme values. The features represented in these diagrams encapsulate critical dynamics directly linked to accumulated fatigue damage.

The joint probability distribution represented in the scatter diagram in Figure 3a indicates that the most frequent sea state corresponds to a peak wave period $T_p$ = 9.2 s and significant wave height $H_s$ = 0.8 m. Extreme values with $H_s$ = 9 m are also




**(a) Hs and Tp scatter diagram.**




**(b) Wave rose.**

**FIGURE 3: SCATTER AND ROSE DIAGRAMS FOR BIMEP SITE.**

observed. However, in general, it can be noted that the metocean conditions in the BIMEP area are mild. This can be attributed to the specific coastal topography in this region, which mitigates wave heights. Additionally, the Galician coast extends into the Atlantic Ocean and lies directly in the path of intense storms originating from the west. This configuration reduces the severity of waves reaching BIMEP. Both effects are clearly represented in the rose diagram in Figure 3b, which shows a pronounced predominance of waves from the northwest—the direction where BIMEP is exposed to waves generated in the North Atlantic.

### 3.2 Wave energy converter: RM3

The fatigue analysis conducted in this study focuses on a WEC, specifically the RM3 point absorber. The reference model used for the simulations is the one developed by Sandia National Laboratories.

The RM3 consists of a toroidal floater connected to a reaction plate via a spar, as illustrated in Figure 4. The device is moored to the seabed using three mooring lines. In terms of dynamics, the device primarily experiences oscillatory heave motion, which is induced by wave excitation. The reaction plate acts as a motion damper, enhancing the relative motion between the floater and the wave, thereby optimizing energy generation.

The geometric and physical specifications of the device are presented in Table 1.

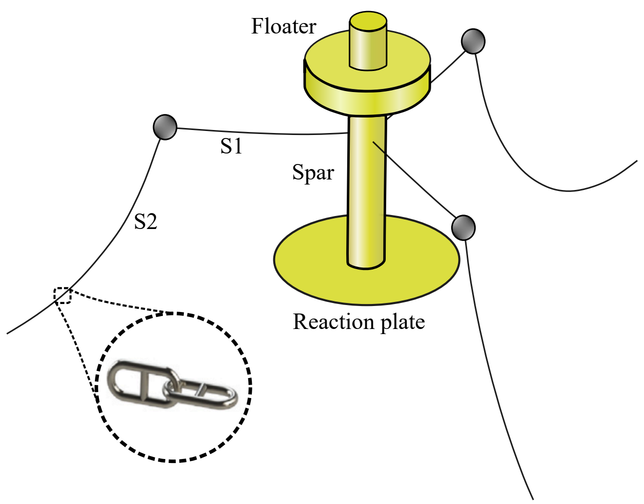



**FIGURE 4: REFERENCE RM3 MODEL REPRESENTATION AND MOORING SYSTEM [13].**

### 3.3 Test cases

The performance of the K-means clustering method in simplifying metocean conditions and accurately capturing cumulative fatigue damage has been assessed through a structured series of tests divided into three stages.

The initial stage in Section Section 3.3.1 involves validating the clustering quality by comparing it with other methods discussed in the literature. The second stage evaluates the method's ability to identify key resource features, such as the most frequent states and extreme conditions. Lastly, the third stage includes tests aimed at assessing the algorithm's effectiveness in reliably estimating cumulative fatigue damage.

**TABLE 1: TECHNICAL SPECIFICATIONS OF THE REFERENCE RM3 MODEL [13].**

| Parameter | Units | Value |
|---|---|---|
| *Floater mass* | kg | $7.27{\cdot}10^5$ |
| *Submerged buoy mass* | kg | 16755 |
| *Floater inertia* | kg·m$^2$ | |
| | Ixx | 20907301 |
| | Iyy | 21306091 |
| | Izz | 37085481 |
| *Spar inertia* | kg·m$^2$ | |
| | Ixx | 94419615 |
| | Iyy | 94407091 |
| | Izz | 28542225 |
| *Chain Nominal Diameter* | mm | 144 |
| *S1 length* | m | 40 |
| *S2 length* | m | 240 |
| *Linear density* | kg/m | 126 |
| *Line stiffness (EA)* | N | $583.38{\cdot}10^6$ |

#### 3.3.1 Verification case.

The clustering quality of K-means is evaluated through a sensitivity analysis based on the number of clusters. Iteratively, metocean data, consisting of 30 years of samples for Hs, Tp and Mwd, is fed into the algorithm along with the desired number of clusters for convergence.

Once all the cases for the sensitivity analysis are compiled, the clustering quality is assessed using the quality measure, silhouette score, and inertia metrics. Additionally, [9] is used as a reference to validate the obtained results. Unlike this study, [9] employs the Maximum Dissimilarity Algorithm and also includes wind speed and direction, increasing the dimensionality of the space to five. The data in [9] corresponds to a different location in the Borssele Wind Farm Zone.

Despite the differences, this reference serves as a benchmark for evaluating the effectiveness of K-means. To create a unified framework for comparing the clustering quality of both techniques, the clustering results for the specified number of clusters will be compared using the quality measure metric, as originally employed in [9].

#### 3.3.2 Metocean-based analysis.

The centroids extracted from the sensitivity analysis conducted in Section Section 3.3.1 are subsequently used to evaluate their accuracy in capturing relevant characteristics of metocean conditions. On one hand, the $90^{th}$ percentile and mean flux energy metrics will be implemented to ensure that the K-means algorithm adequately represents frequently occurring conditions that significantly impact fatigue. On the other hand, the $99^{th}$ percentile will be applied to assess the algorithm's efficiency in representing extreme conditions. Finally, a PDF score index will be included to evaluate the effectiveness of K-means in capturing the full range of metocean conditions distributed along the cumulative distribution function. The results obtained for each metric are visualized in Cartesian plots as a function of the number of clusters, enabling the identification of convergences and the determination of the optimal number of clusters.

**3.3.3 Damage-based analysis.** Similar to the tests described in the previous sections, a sensitivity analysis will also be conducted for fatigue analysis as a function of the number of clusters. In each iteration, the centroids corresponding to each number of clusters will be determined, and the average damage will be calculated using the Tovo-Benasciutti spectral model. The trend of the damage as a function of the number of clusters will then be visualized to identify the point at which the damage converges.

## 4. RESULTS

This section presents the results of evaluating the performance of clustering techniques in reducing the number of environmental conditions, as well as the fatigue analysis performed using the reduced set of environmental cases. Accordingly, the section is divided into three main chapters: Sections Section 4.1 ,Section 4.2 and Section 4.3.

### 4.1 Verification case

Taking as a reference the completion of the tests proposed in Section Section 3.3.1, this section presents the results obtained in the validation of the K-Means algorithm. As previously mentioned, the analysis focuses on the metrics: quality measure, silhouette score, and inertia. Additionally, to corroborate the results, the quality measure values are compared with those reported in the literature for the MDA algorithm [9].

It can be observed in Figure 5 that K-Means technique consistently demonstrates an improvement in clustering quality as the number of clusters increases, indicating that more observations are positioned closer to their respective cluster centroids. With as few as 50 clusters, K-Means achieves high-quality values, and beyond 2000 clusters, the variation becomes negligible.

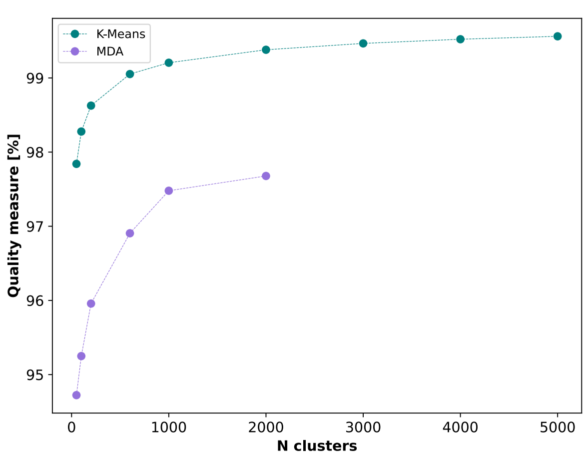



**FIGURE 5: K-MEANS AND MDA QUALITY MEASURE AS A FUNCTION OF THE NUMBER OF CLUSTERS. MDA RESULTS ARE EXTRACTED FROM [9].**

The MDA algorithm achieves slightly lower values compared to K-Means and appears to converge within the range of 1000–2000 clusters. This slight difference may be attributed to MDA's need to handle higher-dimensional data, which makes it more challenging to distinguish clusters accurately. Nevertheless, it can be noted that both methods exhibit analogous behaviour as a function of the number of clusters and approximately align in terms of clustering quality.

### 4.2 Metocean-based DLC reduction

The analysis is further enriched by incorporating metrics that compare the statistical distribution of the original environmental data with that of the clustered data. These metrics assess the ability of the clustering algorithms to represent the most frequent and moderate conditions, as well as extreme values located in the tails of the distribution.

As an initial step, errors at the $90^{th}$ and $99^{th}$ percentiles for $H_s$, a key indicator of wave climate, are evaluated (see Figure 6). Figure 6a reveal that increasing the number of clusters significantly reduces the error at the $90^{th}$ percentile, effectively capturing the distribution of the most frequent environmental conditions. Notably, beyond 2000 clusters, the error stabilizes below 1 %.

For extreme conditions (Figures 6b), the error initially presents significant values, highlighting the algorithms' inability to capture outliers with a small number of clusters. However, as the number of clusters increases to 600, the error decreases sharply, eventually stabilizing around 1 %.

The $90^{th}$ and $99^{th}$ percentile error analysis, while valuable, focuses on specific ranges within the data distribution. To provide a broader perspective, the PDF score metric is introduced. This metric enables a direct comparison of the cumulative distribution functions (CDFs) of the original and clustered data. The PDF score values presented in Figure 6c confirms that the centroids estimated by the clustering techniques poorly approximate the original data distribution with cluster numbers below 600. But acceptable $PDF_{score}$ values are attained from 1000 clusters onward. However, it is observed that the metric does not fully converge, even at 5000 clusters.

### 4.3 Damage-based DLC reduction

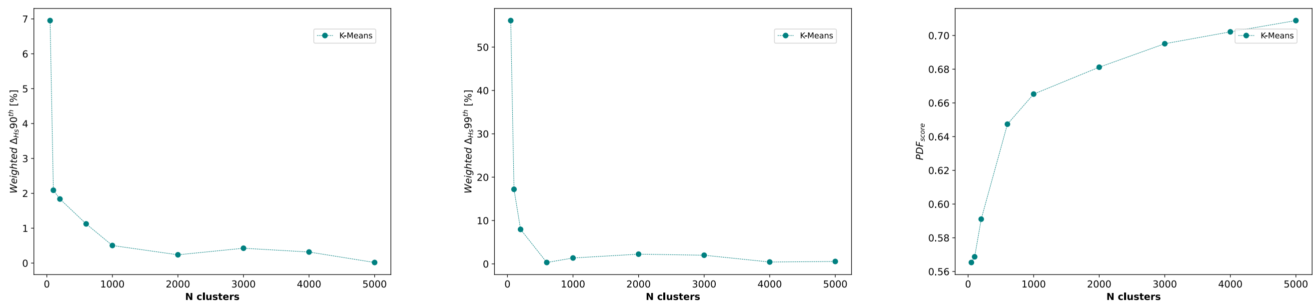
In this section, the main results of the fatigue assessment performed on the RM3 device are synthesized. Specifically, the accumulated fatigue damage in the chain of mooring system bolts has been evaluated.

As explained in previous sections, the fatigue analysis employed in this study is based on the Tovo-Benasciutti spectral model and utilizes synthetic signals [13]. These synthetic signals simulate the tensions generated in the mooring systems due to the hydrodynamic response of the RM3 device. The tensions are composed of two components [13]: a wave-frequency component (WF) and a low-frequency component (LF). The WF captures wave-induced dynamics, resulting in high-frequency oscillations of short duration. In contrast, the LF component reflects longer-term stress variations caused by factors such as currents and tides.

Both components are derived for each sea state represented by the centroids, producing the total tension visualized in Figure 7. For each sea state, six realizations of 7500 seconds each are






**(a) $90^{th}$ percentile error of $H_s$.** **(b) $99^{th}$ percentile error of $H_s$** **(c) PDFscore_K-Means.**

**FIGURE 6: SENSITIVITY ANALYSIS OF RESOURCE BASED METRICS RESPECT TO THE NUMBER OF CLUSTERS.**

generated. This process is repeated for all centroids included in each iteration of the sensitivity analysis, which is conducted as a function of the number of clusters. For instance, in the first iteration, 50 clusters are analysed, resulting in a total of 6 × 50 synthetic signals being generated.

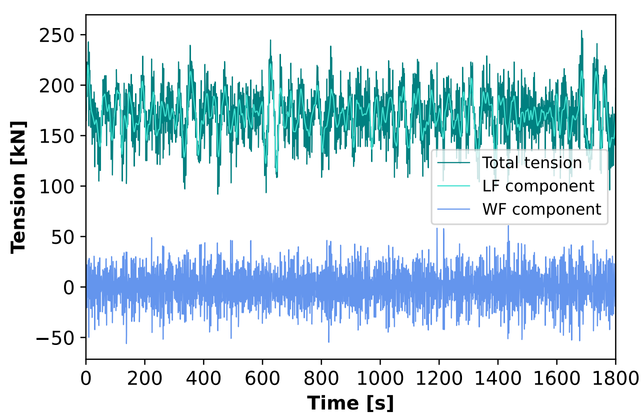



**FIGURE 7: TENSION COMPONENTS OF THE SYNTHETICALLY GENERATED RESPONSE.**

Following the generation of synthetic signals, the spectral model is applied, and the mean damage is obtained, as presented in Figure 8.

Similarly, Figure 8 illustrates that the mean damage increases rapidly over the first four cases before stabilizing around $3.0{\cdot}10^{-5}$ upon reaching 1000 clusters. Beyond this point, the damage remains essentially constant, suggesting that selecting 1000 clusters is sufficient for an accurate estimation of the accumulated fatigue damage. Consequently, the metocean conditions considered for the fatigue study are significantly reduced, from approximately 30 years of data (8760 samples per year) to 1000 representative clusters.

Additionally, it can be observed that during the 30 years of metocean data and the RM3's exposure to these conditions, no fatigue failure will occur in the mooring lines. This conclusion is supported by the mean damage remaining well below 1, indicating that the system is deemed safe in terms of fatigue, with a margin of durability under the specified conditions.

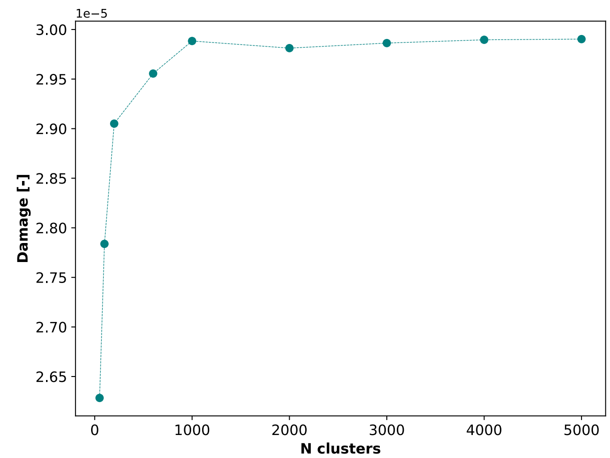



**FIGURE 8: MEAN DAMAGE EVOLUTION RESPECT TO NUMBER OF CLUSTERS.**

## 5. CONCLUSION

Addressing the current needs of the offshore renewable energy sector, this study proposes an effective tool to reduce workload during design processes. Specifically, the study alleviates the computational burden faced by designers when performing fatigue analyses for Offshore Renewable Energy (ORE) devices. As demonstrated throughout the analysis, clustering techniques significantly and effectively reduce the metocean conditions typically considered in design practices.

Based on the results obtained using the k-means algorithm, it has been shown that this technique can efficiently handle large, multidimensional datasets, achieving clustering quality values of 99 % with only 1000 clusters. Furthermore, the method accurately captures the most frequent meteorological conditions, critical for subsequent fatigue assessments, and extreme events.

Finally, the accuracy of clustering techniques for estimating accumulated fatigue damage has been verified. It is observed that 1000 clusters are sufficient to capture the full long-term fatigue. Consequently, the number of study cases is reduced by 99.62 %, favorably impacting the computational cost engineers face when conducting analyses of this scale. Nevertheless, it should be noted that, the uncertainty of the data source (*i.e.* ERA5) can affect the accuracy of the selected 1000 cluster.

## ACKNOWLEDGMENTS

This publication is part of the research project PID2021-124245OA-I00 funded by MCIN/AEI/10.13039/501100011033 and by ERDF A way of making Europe, the European Union Horizon Europe programme under the agreement 101136087 (INF4INITY Project), and the research project funded by the Basque Government's ELKARTEK 2024 program under the grant No. KK-2024/00086. Finally, the authors from the Fluid Mechanics research group at Mondragon University are also supported by the Basque Government's Research Group Program under the grant No. IT1505-22.

## REFERENCES

[1] IRENA. "RENEWABLE ENERGY STATISTICS 2023." Technical report no. International Renewable Energy Agency, Abu Dhabi. 2022. URL https://www.irena.org/Publications/2023/Mar/Renewable-capacity-statistics-2023?utm_source=chatgpt.com.

[2] IRENA. "Offshore Renewables: An Action Agenda for Deployment." Technical report no. International Renewable Energy Agency, Abu Dhabi. 2021. URL https://www.irena.org/publications/2021/Jul/Offshore-Renewables-An-Action-Agenda-for-Deployment?utm_source=chatgpt.com.

[3] Equinor. "Hywind Tampen." Online (2024). URL https://www.equinor.com/energy/hywind-tampen. Last accessed: 29/09/2024.

[4] Large, Provence Grand. "Provence Grand Large." Online (2024). URL https://provencegrandlarge.fr/. Last accessed: 29/09/2024.

[5] GL, DNV. "DNV-ST-0119 Floating wind turbine structures." (2021). Edition July 2021.

[6] (IEC), International Electrotechnical Commission. "UNE-EN IEC 61400-1:2020: Wind Turbines – Part 1: Design Requirements." Standard (2020). Spanish version of IEC 61400-1:2020, Published by UNE.

[7] Katsikogiannis, George. "Estimation of Long-Term Fatigue and Extreme Responses of Large-Diameter Monopiles for Offshore Wind Turbines." Ph.D. Thesis, Norwegian University of Science and Technology, Trondheim, Norway. 2024. URL https://ntnuopen.ntnu.no/ntnu-xmlui/handle/11250/3116766. PhD dissertation, Department of Marine Technology.

[8] Camus, Paula, Mendez, Fernando J., Medina, Raul and Cofiño, Antonio S. "Analysis of clustering and selection algorithms for the study of multivariate wave climate." Vol. 58 No. 6 : pp. 453–462. DOI 10.1016/j.coastaleng.2011.02.003. Accessed 2024-09-24, URL https://linkinghub.elsevier.com/retrieve/pii/S0378383911000354.

[9] Kanner, Samuel, Aubault, Alexia, Peiffer, Antoine and Yu, Bingbin. "Maximum dissimilarity-based algorithm for discretization of metocean data into clusters of arbitrary size and dimension." *Proceedings of the International Conference on Offshore Mechanics and Arctic Engineering - OMAE* Vol. 10 (2018): pp. 1–9. DOI 10.1115/OMAE2018-77977.

[10] Saenz-Aguirre, Aitor, Ulazia, Alain, Ibarra-Berastegi, Gabriel and Saenz, Jon. "Floating wind turbine energy and fatigue loads estimation according to climate period scaled wind and waves." Vol. 271 : p. 116303. DOI 10.1016/j.enconman.2022.116303. Accessed 2024-09-24, URL https://linkinghub.elsevier.com/retrieve/pii/S0196890422010810.

[11] scikit-learn developers. "Clustering." Online (2024). URL https://scikit-learn.org/stable/modules/clustering.html. Last accessed: 29/09/2024.

[12] Penalba, Markel, Guo, Chao, Zarketa-Astigarraga, Ander, Cervelli, Giulia, Giorgi, Giuseppe and Robertson, Bryson. "Bias correction techniques for uncertainty reduction of long-term metocean data for ocean renewable energy systems." *Renewable Energy* Vol. 219 (2023): p. 119404. DOI https://doi.org/10.1016/j.renene.2023.119404. URL https://www.sciencedirect.com/science/article/pii/S0960148123013198.

[13] Martinez-Puente, Eguzkiñe, Zarketa-Astigarraga, Ander, Martinez-Agirre, Manex, Zabala, Alaitz, Esnaola, Jon Ander, Muñiz-Calvente, Miguel, Llavori, Iñigo and Penalba, Markel. "Benchmarking of spectral methods for fatigue assessment of mooring systems and dynamic cables in offshore renewable energy technologies." *Ocean Engineering* Vol. 308 (2024): p. 118311. DOI https://doi.org/10.1016/j.oceaneng.2024.118311. URL https://www.sciencedirect.com/science/article/pii/S0029801824016494.

[14] ECMWF. "Browse reanalysis datasets." Online (2024). URL https://www.ecmwf.int/en/forecasts/datasets/browse-reanalysis-datasets. Last accessed: 29/09/2024.

[15] IMAREST. "Metocean procedures guide for offshore renewables." Technical report no. Institute of Marine Engineering, Science & Technology (Offshore Renewables Special Interest Group. 2018.

[16] Okpokparoro, Salem and Sriramula, Srinivas. "Reliability analysis of floating wind turbine dynamic cables under realistic environmental loads." *Ocean Engineering* Vol. 278 (2023): p. 114594. DOI https://doi.org/10.1016/j.oceaneng.2023.114594. URL https://www.sciencedirect.com/science/article/pii/S0029801823009782.

[17] for Standardization, International Organization. "ISO 9001: Quality Management Systems – Requirements." Standard (2015). URL https://www.iso.org/standard/62085.html. Last accessed: 09/01/2025.