Relevance of Robustness and Uncertainties Analysis in the Optimal Design of Wave Energy Converters

F. Giorcelli, S. A. Sirigu, D. Basile

Abstract—**The optimisation design of Wave Energy Converters (WEC) to reduce the cost of energy of the technology is a widely investigated topic. In literature classical optimisation strategies have been presented and applied to identify the optimal system parameters of WECs to optimise specific techno-economic metrics. The performance of the optimal identified devices relies on these nominal parameters and it can be strongly affected by construction and modelling uncertainties. In this context, optimal solution robustness plays a relevant role in the identification of a device whose performance is affected as little as possible by uncertainties of various kinds. In the first part of this paper different declinations of robustness concept are derived from other fields of application and described. The identified robustness indexes are then applied to optimal solutions obtained via classical optimisation to evaluate its importance in the design process of WECs.**

Strictly related to this kind of methodology is the Sensitivity Analysis (SA) technique, it aims to investigate how the input variation (due to uncertainties or external noise or additional environmental parameters) influences the output results of a defined numerical model and highlight the relative input parameters relevance. SA, therefore, can be a valuable tool applicable in the uncertainty set estimation to identify the variables most subject to such uncertainties and their prominence.

The main objective of the work is to underline the importance of introduce the robustness evaluation of WECs during the optimisation process since classical optimisation techniques can lead to solutions that are affected by uncertainties.

Index Terms—**WEC Design, Uncertainty Analysis, Robust Design Optimization, Techno-Economic Optimization**

I. Introduction

THIS paper addresses and stress the importance of dealing with reliability and performance decline issues caused by the presence of uncertainties in real-world scenarios of WEC implementation and design.

For the successful development or commercialisation of a WEC, several aspects must be taken into account. In [1] (which in turn refers to [2]) authors outline the stakeholders and investors requirements for a WEC investment to be attractive: (a) having market-competitive cost of energy, (b) providing a secure investment opportunity, (c) being reliable for grid operations, (d) benefiting society, (e) being acceptable to permitting and certification; (f) being safe, and (g) being deployable globally. Already from this short list, the relevance of reliability and safety to the techno-economic aspects of WEC design is evident. In the same paper, Guo and Ringwood extensively examine the trajectories of technology development. Consistent with the requirements listed above, the two authors denote how TPL (Technology Performance Level) should take priority over TRL (Technology Readiness Level), especially for technologies in their early stages of development. Among the various performance's inidices, a broadly used techno-economic performance criteria is the Levelized Cost of Energy (LCoE), it is one of the main factors of choice for investors deciding whether or not to engage in a technology. In the conclusions of their work, authors list some possible options for reducing investor risk: e.g. reducing the LCoE and reducing LCoE uncertainty.

Different efforts have been made in order to cope with the necessity to minimize the LCoE both through the integration into already existing offshore structures [3] or during a device optimization process. In [4] the ratio between the delivered power and the capital expenditure is set as the first objective function in a multi-objective optimization problem, solved with through a genetic algorithm approach. In the paper the capture width ratio is chosen as a second parameter to optimize. Results of this work show that the device optimizing the two objective are substantially different and for this reason authors suggest that the techno-economic oriented metric should be preferred.

A detailed overview of the state of the art of geometric optimisation of WECs is given in [5]. In the paper the influence of several aspects (i.e. device concept, wave conditions, hydrodynamic modelling methods, control strategies) related to the WEC optimization process is investigated and the optimisation criteria relevance is emphasised. The paper groups the different possibilities of optimisation criteria to three types: economic-driven, technical and techno-economic criteria and he stress the difficult to handle as an objective function and evaluate the LCoE due to the high level of uncertainty in estimating this performance.

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From these few examples, the key role played by uncertainties in the field of WECs, both from a commercial and a design perspective, is already evident. In the literature there are several areas in which the uncertainties problem is addressed.

General recommended procedures and guidelines for Uncertainty Analysis (UA) during experimental tests in towing tank are given by ITTC (International Towing Tank Conference). In their directives, the ITTC considers various situations in which UA is required, some examples are: [6] in which suggests are given for handling uncertainty during the measurement of resistance tests in a towing tank, in [7] and [8] the purpose is to provide guidance to perform experimental UA of WECs and its implementation, considering a variety of uncertainties. A pratical example of UA in experimental WEC test is reported in [9], where authors highlights the importance of presenting experimental results with a description of the uncertainties involved. The case of study is the UA of an Oscillating Water Column (OWC) device experimental model test. The purpose is to evaluate the device's performance using probe's data of incident wave elevations, pressure and wave elevations inside the OWC chamber and quantifying their uncertainty with the phase-averaging data analysis technique. In the cases above mentioned is common to approach the uncertainty propagation problem with a classical partial derivative method. Instead, in [10], a Monte Carlo method is explored as a pratical alternative for complex models.

For what concern WECs array, the models physical validation presents some difficulities due to replicating numerical model characteristics complications. These obstacle in experiments and measurement repeatability are the uncertainties addressed in [11]. Remaning in WECs array field, another UA application is reported in [12]. In this work authors deal with the Wave Energy Converter Location Problem (WECLP) and study the optimal layout of WECs in an array under uncertainty, considering the latest arise from the ocean environment. In [13] authors present a new way to analyse a long-term simulation of WECs arrays. In their work a Monte Carlo technique has been used in order to perform the UA for the predictions of the wave energy resource available, stressing its utility for optimizing energy production.

WECs' control strategies is another field in which the UA is widley used. Two examples are [14] and [15]. The first work cope with device's uncertainty related to the energy conversion with an artificial neural-network-based predictive control strategy. Also uncertainties of the neural network are investigated and identified, i.e. the prediction deviation is quantified and its influence on WEC performance is examined. Then, in Fusco and Ringwood's paper a hierarchical robust control has been developed in order to reduce the controller sensitivity to modeling errors and nonlinear effects [15].

In this last work an application of the robustness concept is used, in particular the *Robust Control*. The robustness concept has a great relevance in control area. In this field of study, the definition relies on the control strategy insensitive to model uncertainties that guaranteeing both good output performance (e.g. maximizing energy harvesting) and stability of the controlled system [16]. The same last cited book introduces other areas of interest where the concept of robustness is articulated in different manners. E.g. *Robust Statistics* deals with the robustness concept observing the insensitivity to outliers; *Support Vector Machines* field (subset of the greater Machine Learning area) have been developed with the purpose to reduce the sensitivity to specific uncertainty.

From a more generic perspective, a context in which the concept of robustness plays a key role is in the realm of optimisation. Again in [16] a wide overview related the robust optimiziation paradigm is given, with a detailed focus on *Robust Linear and Conic Optimization* and the Robust Counterpart notion. Slightly changing the approach to the robust optimisation problem it is possible to identify the *Robust Design Optimization* (RDO) domain. Robust Design (RD) purpose is to obtain system design insensitive to uncertainty, external noises, perturbation, model sensitivities and tollerances [17], In their work [17], authors classified three RD methods: the Taguchi Method (developed for quality improvement), Robust Design Optimization (RDO, with the aim to exploit optimization techniques in order to perform RD) and robust design with the axiomatic approach.

In the area of simulation-based optimisation for engineering problems of which WEC design is a part, RDO certainly plays a major role. An extensive survey with a main focus on the different approaches used to account for the RDO is given in [18], including stochastic approximation and evolutionary computation. In light of the extensive use of evolutionary optimisation techniques, it is worth introducing two further pertinent topics in RDO processes: the Robust Multi-Objective Optimization (RMOO) and robustness measures. The first relies on the widly studied Multi-Objective Optimization framework, listing some of the most important ones [19]: methods minimizing the mean of the objective function, methods minimizing the mean-variance of the objective function, methods using an additional objective function related to robustness, methods using additional constraints related to robustness, method based on comparing the cumulative distribution functions. A robustness measure or robustness index (RI) is an advantageous way to identify and quantify the sensitivity (or insensitivity) of the system to those factors that can lead to poor performance; by quantifying and classifying this design property in such a way, it is also possible to manage it as a parameter within an optimisation (e.g. as an objective function in a genetic algorithm). A classical example can be the robustness (or risk) measure $R(F) = \mu(F) + k\sigma(F)$, where $\sigma(F)$ is the standard deviation of the response and $k > 0$ is a constant and is applied in RD paradigms named '3σ-design' and '6σ-design' [20]. An example of optimization under uncertainty applied to the WEC design using an evolutionary algorithm and two different RI (a symmetrical and an a-symmetrical one) is given in [21].

The proceeding is arranged as follows: after the above introduction to the work's topics a brief description to the system is given (*ISWEC case of study*), in the third section (*Sensitivity Analysis and Robustness Quantification Methodology*) the used uncertainty and robustness identification methodology and metrics are reported. The results obtained are than presented in the subsequent part of the paper (*Results*) and followed by a discussion of the achievements and open points in the final section (*Conclusions and Discussion*).

II. ISWEC CASE OF STUDY

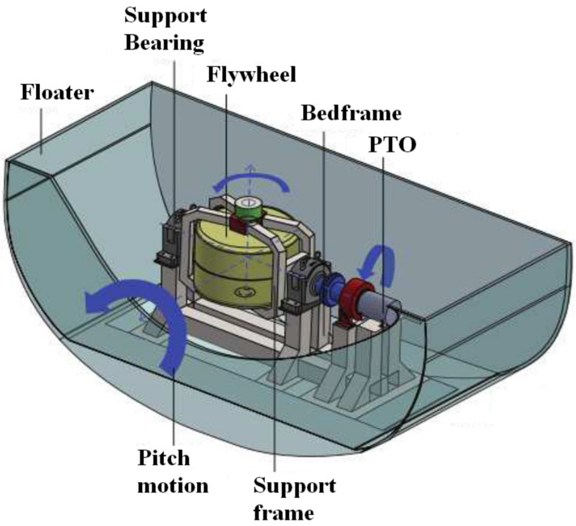

Fig. 1. ISWEC device components scheme [22].

This section provides a general introduction related to the WEC technology on which the uncertainty analysis covered in the paper was carried out. Moreover, also the mathematical model is presented.

The Inertial Sea Wave Energy Converter (ISWEC) is a well-known device conceived by the renewable energy group of the Department of Mechanical and Aerospace Engineering of the Polytechnic of Turin, which gave rise to the MOREnergyLab (Marine Offshore Renewable Energy Lab), that still continues to research this and other marine energy technologies. ISWEC, together with PEWEC [23], have been developed in order to be well suited for the Mediterranean Sea location and in August 2015 the device has been launched in the Island of Pantelleria for the first time together with the company Wave for Energy Srl [24]. Before exploring the mathematical model of the device, a brief and generic description of ISWEC and its operating principles is given below.

This WEC consists of a pitch-floating hull with an all-enclosed configuration. The wave energy collection system is positioned inside the floater. The latter is composed of a Power Take Off (PTO) which exploit the precession motion of a gyroscope system in order to harvest the mechanical energy produced. The precession motion is induced by the dynamic copuling between two of the 7 degree of freedom of the device: the first is the pitch motion, the second the flywheel rotation. In order to avoid the gyroscope stabilization, a eccentric mass is designed with the function to induce a elastic recall [25]. In order to gain the resonance tuning and increase the energy harvested, a proper PTO control logic can be implemented also with the integration of a Pitch Resonance Tuning Tanks (PRTT) [26]. For this work, the only PTO case is studied and its general mathematical description is reported next.

Several simulation based numerical experiments need to be performed in order to investigate the uncertainty relevance during a WEC design process. Therefore, attention should be paid to the choice of the numerical model employed. A first possibility is to implement a time domain simulation with the purpose to consider non-linearities in the model [27], in this case the main drawback is the high computational cost that can be unaffordable. Whereas, frequency and spectral domain models involute lighter computational efforts and despite a reduction in accuracy they are suggested in analysis that are looking for the comparison between different devices and design solutions [25] [22] [28].

A. Spectral-domain model

This subsection will discuss the general idea of the spectral-domain model (SDM) for the ISWEC device, this will be next used in the procedure of this work. This introductory overview refers to more in-depth work, in particular [25], [22] and [28].

Before introducing the SD is useful to give a generic time-domain description of the system. Therefore, the non-linear state-space equation can be written as:

$$\mathbf{M}\ddot{\mathbf{X}} + \mathbf{B}\dot{\mathbf{X}} + \mathbf{K}\mathbf{X} + \boldsymbol{\Theta}(\ddot{\mathbf{X}}, \dot{\mathbf{X}}, \mathbf{X}) = \mathbf{f(t)} \tag{1}$$

where the state variable of interest $\mathbf{X}$, the mass, damping and stiffnes matrix $\mathbf{M,B,K}$, the non-linear function $\Theta(\ddot{\mathbf{X}}, \dot{\mathbf{X}}, \mathbf{X})$ and the external forces $\mathbf{f(t)}$ are given. It is from those non-linear equations, which treatment is similar to the one discussed in [29], that the formulation of the spectral-domain counterpart of the system in question is derived.

The purpose of the SDM is to obtain an approximate solution of the generic time-domain one (1). This is done describing the system as probabilistic, considering its inputs as stochastic ergodic process [30]. An equivalent to (1) linear system can be written as

$$\mathbf{M}_S\ddot{\mathbf{X}} + \mathbf{B}_S\dot{\mathbf{X}} + \mathbf{K}_S\mathbf{X} = \mathbf{f(t)} \tag{2}$$

where the $\mathbf{X}$ vector collects hulls ($\mathbf{X}_f$) and radiation states (ζ) with the precession angle of the gyroscope ε. Moreover:

$$\mathbf{M}_S = \mathbf{M} + \mathbf{M}_{eq} \tag{3}$$

$$\mathbf{B}_S = \mathbf{B} + \mathbf{B}_{eq} \tag{4}$$

$$\mathbf{K}_S = \mathbf{K} + \mathbf{K}_{eq} \tag{5}$$

These matrices are composed by a first linear part related to the linear terms of (1) and a second part that represents the statistical time-varying behaviour of the time-domain system non-linear terms. Therefore, this second part of each matrix is defined using the gradient and the "expected value" operator as follow:

$$\mathbf{M}_{eq} = \langle \nabla_{\ddot{\mathbf{X}}} \boldsymbol{\Theta} \rangle \tag{6}$$

$$\mathbf{B}_{eq} = \langle \nabla_{\dot{\mathbf{X}}} \mathbf{\Theta} \rangle \tag{7}$$

$$\mathbf{K}_{eq} = \langle \nabla_{\mathbf{X}} \mathbf{\Theta} \rangle \tag{8}$$

Now, it is possible to obtain a "wave forces to ISWEC states" transfer function ($\mathbf{I}$ is an identity matrix of appropriate dimension):

$$\mathbf{H}_{f\mathbf{X}}(\omega) = \frac{\mathbf{I}}{-\omega^2 \mathbf{M}_S + i\omega \mathbf{B}_S + \mathbf{K}_S} \tag{9}$$

Exploiting this statistical linearization of non-linear effects it is possible to procede with the WEC output evaluation as in a frequency domain model, trough the power spectral density (PSD) of the input wave force and the linear transfer function of the WEC, as follows [22]:

$$\mathbf{S}_{\mathbf{XX}}(\omega) = \mathbf{H}_{\mathbf{fX}}(\omega) S_{\mathbf{ff}}(\omega) \mathbf{H}^*_{\mathbf{fX}}(\omega) \tag{10}$$

where: $\mathbf{H}_{\mathbf{fX}}$ is the numerical SDM for ISWEC, $S_{\mathbf{ff}}(\omega)$ is the PSD of the input wave force and the complex-conjugate transpose operation is denoted with the operator $*$ [22].

In this paper no more detailed informations will be given of the formal ISWEC spectral-domain treatment and we refer to works more oriented to this purpose [25] [22] [28] [31] [30].

III. Sensitivity analysis and robustness quantification methodology

In this section, the uncertainty analysis framework performed and two possible robustness metrics are presented.

With this purpose, a preliminary SA was carried out. The first step of this analysis is the identification of the parameters to be analysed, which were selected on the basis of previous experience. With regard to the hydrodynamics of the ISWEC device also taking mooring into account, experimental campaigns have already been carried out previously [32]. In this earlier work, non-linearities and differences between theoretical results and data obtained in real-world applications havce been discussed.

- I_s: gyroscope inertia with respect to the ϵ axis;
- $M_{5,5}$: pitch device inertia;
- $\gamma = \frac{T_{5,Mooring}}{T_{5,NoMooring}}$: the ratio between the two resonance periods at the device's pitch considering and not considering the mooring effects. This parameter will impact the stiffness of the system on the relative degree of freedom ($K_{5,5}$).

The output investigated was identified in the Annual Energy Production AEP in [MWh/y]. The analysis can be accomplished using a classic tornado method, this techniques investigates the impact of one variable at a time (thus belonging to the once-at-a-time methods) on a predefined output.

A possible second framework is the so called "*Elementary Effect Test*" (EET) which investigates two different parameters: μ_{EET} and σ_{EET} that represent the impact on the output performance and the dependency between the investigated parameters, respectively. The results will then be represented on a plane and the greater the distance of μ_{EET} from the origin then the greater its impact on the output, while the greater σ_{EET} the more dependent on each other the variables under examination will be.

Amongst these two methodologies, we chose to direct our work towards the first one listed. That is, the first type is much clearer than the EET and RSA methods, it is easy to implement and yet complete in terms of the information we wish to extrapolate in our work at this stage. In [33] an helpful application of the EET method is disclosed in the procedure for a surrogate model building.

The following cases of interest were selected:

1) *Case 1*: test parameters are varied with a fixed sensitivity and each time the hull control parameters are re-optimised;
2) *Case 2*: test parameters are varied with a fixed sensitivity and each time the PTO control parameters are not re-optimised compared to those of the nominal case without perturbations of the input variables.

For a first round of analysis, three different devices have been chosen: *ISWEC A01*, *ISWEC A02* and *ISWEC A03* for two different sensitivity values (positive and negative).

Thereafter, a classic Monte Carlo (MC) analysis is useful to delineate the WEC's outputs probability density function (PDF) as the inspection parameters change. The criticalities of this method are mainly the computational cost (around 7 h for each device analysed with 1000 samples) and the need to make an assumption related to the distribution of parameters considered uncertain if there is no clear knowledge of their real PDF behaviour. Concerning the latter necessity, in the work, the assumed test parameters distributions are shown in table I. For the variables considered to be affected by uncertainty, a Gaussian probability distribution has been assumed for each of them. It is worth paying particular attention to the choice of the γ distribution. The latter does not directly represent the change in pitch stiffness, but the disturbance of the relative DOF resonance period due to the mooring. Thanks to previous experience, we are able to quantify the variation of this parameter more easily than the direct value of the $K_{5,5}$ stiffness, we choose to analyze how to set up the γ distribution. For the following analyses, the assumed distributions are set up such that at thier tails corresponds a variation (positive or negative) from the mean design value around 10%.

From a general perspective, the attention has been then directed towards finding possible trends trough which to preliminary relate certain device characteristics with sensitivity measurements.

With this purpose, the following sensitivity indices are initially proposed:

- $R^+ = max[|\Delta_{\%,PositiveVariation}|]$ the maximum deviation from the output nominal value due to a positive change in the variables under consideration;
- $R^- = max[|\Delta_{\%,NegativeVariation}|]$: the maximum deviation from the output nominal value due to a

negative change in the variables under consideration;

- $Q^+ = min[\Delta_{\%,PositiveVariation}]$ the minimum increase or the maximum reduction from the output nominal value due to a positive change in the variables under consideration;
- $Q^- = min[\Delta_{\%,NegativeVariation}]$ the minimum increase or the maximum reduction from the output nominal value due to a negative change in the variables under consideration.

A sufficiently large and significant set of devices need to be identified in order to perform this overview, in this way a SA could be carried out for each individual and indices calculated. For this work the chosen set is part of the outcomes of a genetic optimization process 8. In order to highlight the difference in robustness between devices characterised by comparable performance, 9 individuals have been individuated and employed in the analysis. Investigations with more global relevance could be carried out and a hint of such possibilities is given in the conclusions of the paper. The robustness measurement mentioned above can be quantified using the following robustness indices [21]:

$$R = \sqrt{\sum_{i=1}^{m} \left(\frac{s_{f_i} + |\mu_{f_i} - f_{i,0}|}{f_{i,0}} \right)^2} \tag{11}$$

Where the number of goals on wich the robustness want to be optimized has been denoted as m (e.g., device annual energy production, AEP). The terms s_{f_i} and $|\mu_{f_i} - f_{i,0}|$ represent the dispersion around the nominal value and the difference between the mean (μ) obtained from simulations and the nominal value ($f_{i,0}$) for the i-th robustness goal. These terms quantify the measure of device robustness, indicating the deviation between the nominal value and the system response. To ensure comparability across different devices, the nominal value $f_{i,0}$ is used for normalization purposes in the index. This enables the results to be compared effectively. The Monte Carlo method is employed to calculate the mean and dispersion around the nominal value for the i-th goal in the following manner:

$$\mu_{f_i} = \frac{1}{N} \sum_{j=1}^{N} f(x_j)_i \tag{12}$$

$$s_{f_i} = \sqrt{\frac{\sum_{j=1}^{N} \left[f(x_j)_i - f_{i,0} \right]^2}{N-1}} \tag{13}$$

In the given context, $f(x_j)_i$ represents the value of the i-th goal obtained from the j-th simulation out of N simulations. Here, x_j corresponds to the j-th set of perturbed design parameters. A smaller value of R indicates a higher level of robustness in the system being considered. On the other hand, the index associated with the second approach is defined as an asymmetric value. It penalizes only the deviations from the nominal value that result in poorer performance and consequently worse values of the objective function in question. As a result, the risk measure for this approach is evaluated as follows (where m still represents the number of objective functions):

$$Q = \sqrt{\sum_{i=1}^{m} \left(\frac{Q_{i,0}}{f_{i,0}} \right)^2} \tag{14}$$

In the case where the i-th performance needs to be minimized, $Q_{i,0}$ represents the objective function value at which the q% (typically greater than 90%) of occurrences are observed. In this scenario, a smaller value of Q indicates a better risk measure. Conversely, if the i-th performance needs to be maximized, $Q_{i,0}$ is the objective function value at which the (100-q)% (typically greater than 90%) of occurrences are observed. In this case, a larger value of Q indicates a better risk measure. To enable comparison across different devices, the nominal value $f_{i,0}$ is used in the index for normalization purposes. The Q_i index provides us with more than just an asymmetric risk measure based on a fixed percentage threshold, q. It also offers insights into the quality of the device's functioning with respect to the i-th objective function.

IV. Results

The results for each step of the work are presented in this section. The work will focuses only on the AEP as performance under investigation, this choice has been made considering the costs as fixed and therefore the only variable affecting the cost of energy is the device energy production. High values of $\Delta_{AEP}\%$ ($\Delta_{AEP}\% = \frac{(AEP - AEP_0)}{AEP_0} 100$) related in particular to the variations of the parameter γ are obtained.

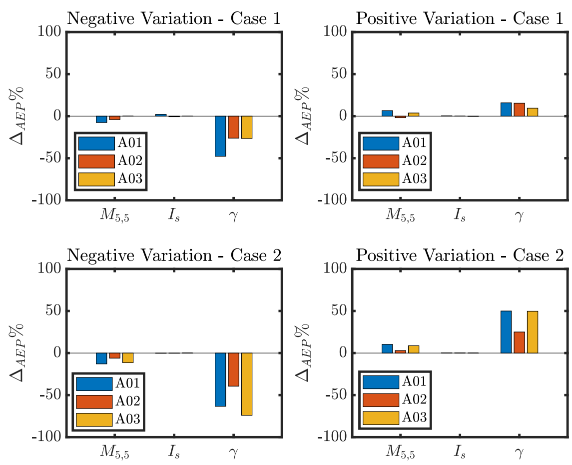

Fig. 2. Results with sensitivity 10%.

These findings makes it interesting to investigate the RAO variation related to the pitch DOF for the three different devices. Fig 4, 5 and 6 show three

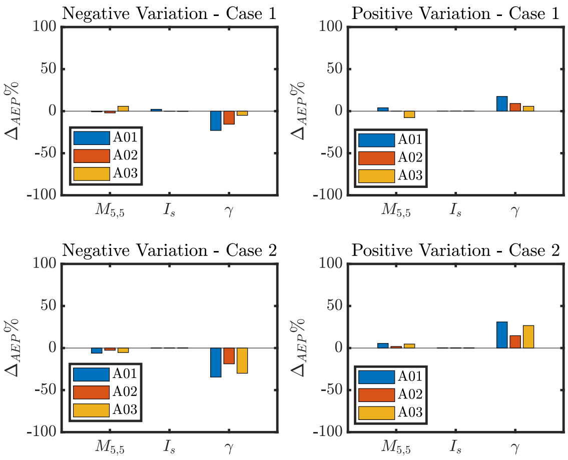

Fig. 3. Results with sensitivity 5%.

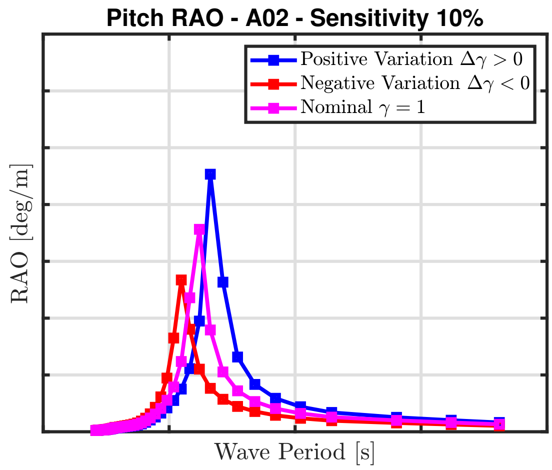

Fig. 5. *ISWEC A02 RAO*, with sensitivity 10%.

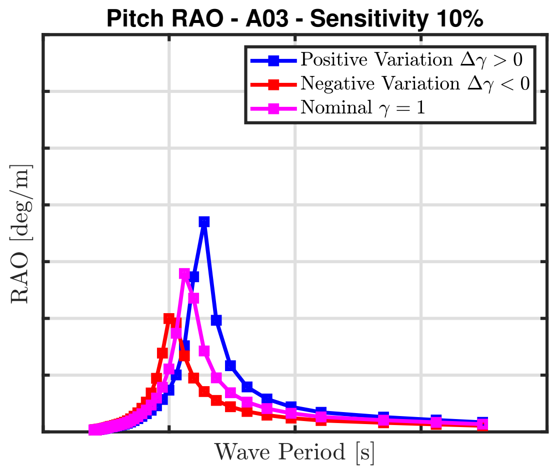

Fig. 6. *ISWEC A03 RAO*, with sensitivity 10%.

representative results. In these images it is possible to notice a marked reduction in the peak of the pitch RAO for negative perturbations.

The uncertainties distributions set-up is summarized in table I and the results of the first MC round have been reported in table II. The MC analysis has been performed with 1000 samples. Looking to the PDFs in Fig 7-1, 7-2 and 7-3 the investigation could be focus on three main aspects: the distance of the mean value from the expected nominal design one, the correlation with the previous identified SA outcomes and with the robusnstess measures Q and R. The PDFs' spread is more marked in ISWEC A01 and ISWEC A02 distributions than the A03 one. This is clear looking to the shapes of the three devices' PDF, i.e. the A03 distribution is narrower (and consequently also higher given a smaller neighbourhood within which an equal number of samples lie) than that of the other two devices, whose edges are less inclined. This aspect can be described by the value of $\frac{s_{AEP}}{AEP_0}$. Moreover, the A01 WEC is also distinguished by a mean value of the distribution more shifted than the expected value in comparison with that of the A02 and A03 cases. The lack of consistency of these last results with the ones obtained via SA point out the importance to always accompany it with a statistical one, e.g. MC.

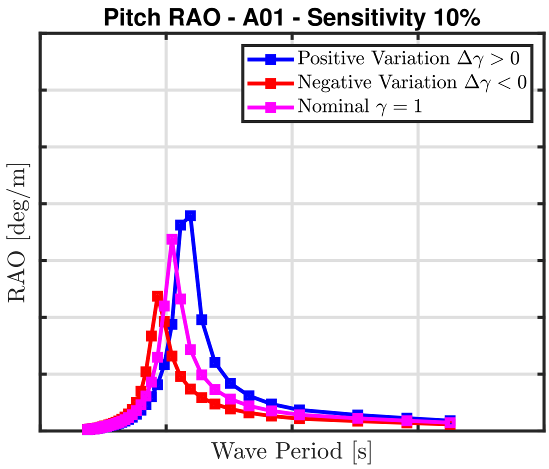

Fig. 4. *ISWEC A01 RAO*, with sensitivity 10%.

In order to quantify each device robustness the two RI have been evaluated for the three WECs, the measures obtained are reported in the relatives columns of table II.
From this perspective, previous PDF findings turn out to be consistent with the relative Q and R outputs obtained. The lowest R index is the ISWEC A03 one and this is another way to reach the conclusions above, i.e. the PDF is less spread than the other two cases. Moreover, the most unbalanced distributions toward higher values of AEP (parameter that we wants to maximize) are the ISWEC A02 and A03 PDF and this is consistent with the Q-index results. This results show us that the devices AEPs are described by a probability distribution such that in 90% of cases the number of produced MW will be greater than $67,5\%$ (A01), $82,2\%$ (A02) and $90,1\%$ (A03) of the relative nominal expected value. Those three measures clearly highlight a different behaviour for the three WECs, especially for A01 which is characterized by a low Q value that instead we want to maximize.

The set chosen in order to perform the general analysis part of the framework is composed by 1000 in-

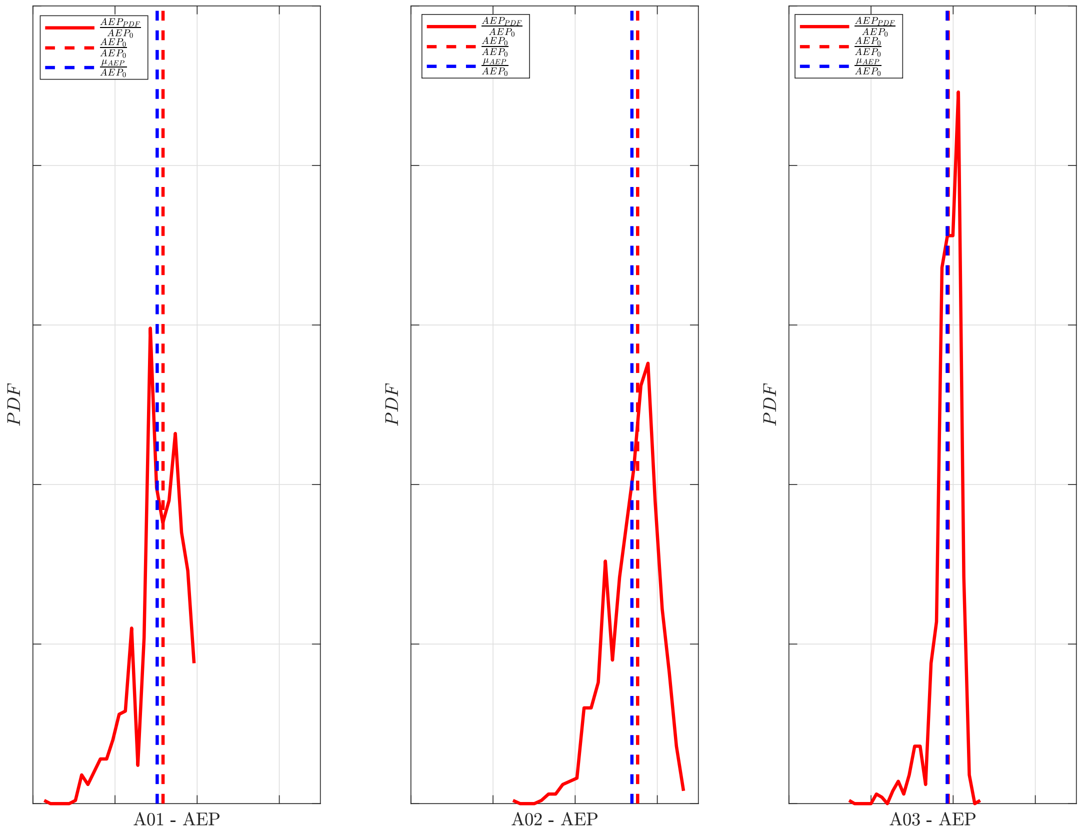

Fig. 7. *ISWEC A01*, *ISWEC A02* and *ISWEC A03* PDFs outcomes from the MC analysis.

TABLE I
INPUT DISTRIBUTIONS

Input	μ	σ
γ	γ_{nom}	$0.05\gamma_{nom}$
$M_{5,5}$	$M_{5,5,nom}$	$0.05M_{5,5,nom}$
I_s	$I_{s,nom}$	$0.05I_{s,nom}$

TABLE II
OUTPUT DISTRIBUTIONS

Device	Q	R	$\frac{s_{AEP}}{AEP_0}$	$\frac{\lvert\mu_{AEP}-AEP_0\rvert}{AEP_0}$
ISWEC A01	0.675	0.241	0.196	0.045
ISWEC A02	0.822	0.140	0.115	0.025
ISWEC A03	0.901	0.094	0.088	0.006

dividuals extracts from a neighbourhood of the pareto set (Fig. 8) obtained from a GA. The trends highlighted after the set analysis were then obtained by means of a classical quadratic regression. The results are shown in Fig. 9 10. In these two pictures the Q^- trends related to the pitch resonance period and to the total device mass are highlighted. Observing Q^- is found to be interesting among the others SA-indices because in the SA results its value is related to the most negative outcome for a performance that designers want to maximize. That is, in our analysis Q^- accounts for the most significant effects associated to a negative perturbation $\Delta\gamma < 0$. The asymmetric index give us back a sensitivity measure without losing the sign information and with the last an indication of whether the disturbance is improving or worsening the performance analysed. The two highlighted tendencies describe that, subject to some dispersion of results, increased masses and resonance periods lead to a reduction in the AEP maximum percentage decrease.

Then, devices with comparable AEP are identified and a new MC analysis round is performed with the same tuning parameters in order to evaluate the two robustness measure. In Fig. 10, 9 and 8 the selected devices are highlighted in magenta and their characteristics are shown in table III. They are sorted with ascending T_{res}. It is evident from the results that there is no correspondence between an accurate measure of the robustness of a specific device and its Q^- index. This is due to the dependence of that index on a specific value of uncertainty starting from which it is calculated and not on a PDF associated with such uncertainty. Q^- (like the other SIs) can instead be interpreted as a quantification of how severe the variation of a specific parameter can be in respect to deviation from the nominal value of a chosen performance.

For the chosen devices, the outcomes describe a 20.7% maximum variation between the higher and lower values of Q and a 12.3% one for the R index.

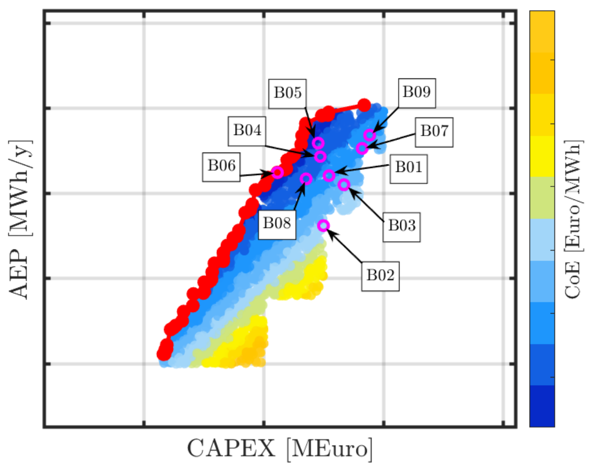

Fig. 8. Total GA outcomes set in gray and the chosen subset coloured, the relative pareto front in red.

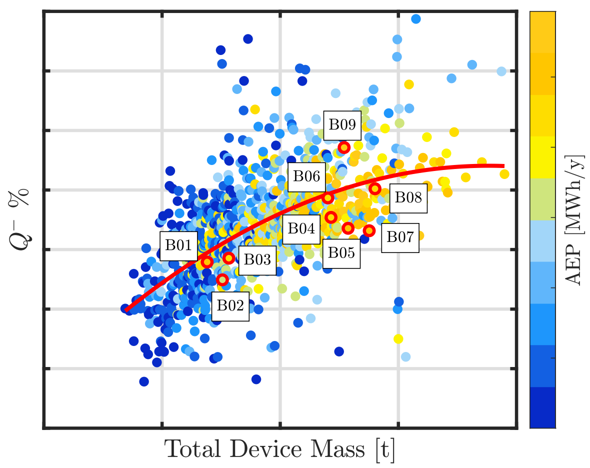

Fig. 9. Q^- - $TotalDeviceMass$ trend.

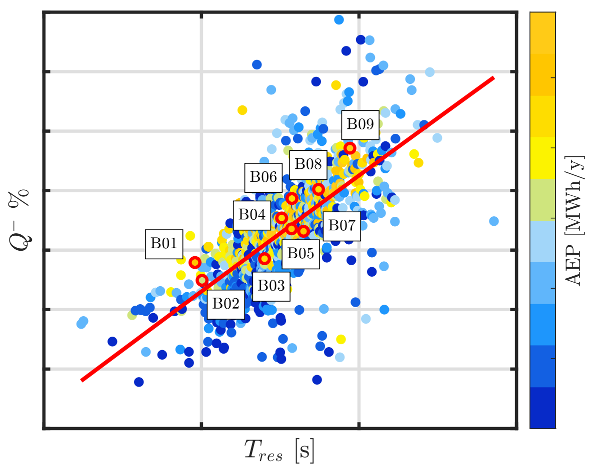

Fig. 10. Q^- - T_{res} trend.

V. Conclusions and Discussion

In this work a preliminary study about the uncertainty effects on the design process of a WEC has been presented. The paper proposes some possibilities for the uncertainties quantification and robustness measurement for a device via two indices and SA.

From a broader perspective, the results show the impact that the presence of uncertainties has on the performance of the system under investigation. Therefore, those achievements highlight that can be useful to continue explore this area of study in order to obtain robust devices in real-world operating conditions. Moreover, those presented RI can be useful in decision making. Among the analyzed devices, the best from a statistical performance point of view are B06, B08 and B09 but looking on Fig 8, only one of them relies on the Pareto front of the optimization's individuals. These all are information that may be beneficial in order to target one. This emphasises once again the usefulness of considering robustness aspects during a WEC design optimisation process and points out that classical optimisation techniques can be greatly affected by uncertainties. Furthermore, it is also worth to direct research towards the definition and implementation of new robust optimisation frameworks.
Analysis was carried out on a set of interest obtained from a sub-set of individuals produced during an genetic algorithm optimisation process. The trends obtained describe a correlation between T_{res} and the device sensitivity.

Outcomes also leave some open points.
In this preliminary study a MC approach with 1000 samples has been applied. For a more accurate analysis maybe the use of a larger number of samples could be taken into account, assessing the impact of this parameter on the robustness measure.
However, the main ongoing issue is the design of an appropriate uncertainty distribution for each parameter considered to be affected by them. Results describe inconsistent behaviours for the same device (e.g. ISWEC A03) if we refer to the SA outcomes and the MC analysis ones. That is, a only SA is not sufficient to fully describe the performance characteristics of the device and needs to be complemented by a statistical analysis such as MC. In this work a SA is performed with two different sensitivity values, 5% and 10%. Focus our attention on the device A03, which from the MC turns out to be the most robust one among the first three WEC analysed, it is possible to clearly see that increasing the magnitude of the perturbation we reach different robustness relationship between A02 and A03. In *Case 1*, for a 5% perturbation A03 is more robust than

TABLE III
Selected Devices Output Distributions

Device	Q	R	$\frac{s_{AEP}}{AEP_0}$	$\frac{\lvert\mu_{AEP}-AEP_0\rvert}{AEP_0}$
ISWEC B01	0.716	0.219	0.206	0.012
ISWEC B02	0.684	0.227	0.224	0.003
ISWEC B03	0.731	0.213	0.159	0.054
ISWEC B04	0.788	0.163	0.149	0.014
ISWEC B05	0.773	0.182	0.097	0.024
ISWEC B06	0.832	0.139	0.104	0.035
ISWEC B07	0.751	0.194	0.153	0.041
ISWEC B08	0.847	0.113	0.102	0.011
ISWEC B09	0.891	0.104	0.097	0.007

A02 but if we increase the sensitivity intensity their robustness appear comparable. Therefore, it can be concluded that attention must be paid on an adequate modelling study of the uncertainties' distribution to be applied to each parameter that we consider to be affected by such uncertainties.

Possible future developments of this work may be the more systematic investigation of the parameter space subject to uncertainties, going on to define a Worst Case Scenario (WCS) uncertainties and the quantification of them by exploiting more computationally efficient techniques. That is, makes it possible both to increase the number of samples with the same computational budget and to achieve a speed-up of the framework. E.g. Polynomial Chaos Expansion (PCS), Support Vector Machine (SVM) or even Gaussian Process Regression. Thus, a robust optimization framework can be designed focusing now on more techno-economic parameters, i.e. the LCoE, including uncertainties affecting also the WECs' costs parameters.

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