A coupled Monte Carlo - Evolutionary Algorithm approach to optimise offshore renewables O&M

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Abstract — **Improving the reliability and survivability of wave and tidal energy converters, whilst minimising the perceived risks and reducing the deployment costs, are recognised as key priorities to further develop the marine energy market. Computational decision-making models for offshore renewables have demonstrated to be valuable tools in order to provide support in these strategic areas.**

In this paper, the authors propose an integrated approach of Monte Carlo simulation and Evolutionary Algorithms to address these challenges. A time-domain method based on the Monte Carlo technique, with specific consideration of marine renewable energy requirements, is used for the assessment of the devices and the characterization of the offshore farms. This permits the obtainment of energy predictions and indications on the reliability, availability, maintainability and profitability of the farm.

A multi-objective search, by means of a specifically designed Genetic Algorithm, is then used to determine the ideal variation of inputs set for the improvement of the results. Suitable objective functions aiming at the minimization of the maintenance costs and the maximization of the reliability are considered for this purpose. The outcomes obtainable for the assessment of an offshore farm, as well as suggested practices for the optimisation of the Operation and Maintenance (O&M) procedures, are introduced and discussed. Results on the ideal trade-off solutions between conflicting objectives are presented.

Keywords **- O&M, Reliability, Multi-Objective Optimisation, Monte Carlo, Genetic Algorithms.**

I. INTRODUCTION

Operational Expenditures (OpEx) have been recognised as major contributors to the final cost of the energy produced from offshore renewables, accounting for up to one third of the total amount [1]. Reduction of such costs, together with improvements on the reliability and survivability of ocean energy devices, are therefore fundamental in order to raise trust and investments on ocean energy devices. Under these circumstances, a number of computational models have been developed to support the strategic planning of the O&M activities for marine renewables. Even if the specific focus or type of outcome provided may vary from one tool to another, the main goal of such tools is to capture the mutual interactions between the internal components of the device, as well as between the device and the access systems selected for its maintenance. This, in turn, leads to improvements in the design choices, selection of the most appropriate O&M assets, planning of the ideal maintenance schedule and mitigation of the economic and technical risks.

Due to the higher maturity of the offshore wind industry with respect to other marine renewables, specific O&M tools have so far been focused mainly on this sector. Being in a more advanced stage of development, the faster spread and growth of this technology has augmented the needs for methodical ways of managing the assets of the farm, providing at the same time greater possibilities of application to developers who wanted to generate and calibrate their models. A thorough review of available modelling tools for offshore wind turbines is provided in [2]. Most of these models ~~permit to estimate~~allow for the estimation of different aspects of the offshore farm (e.g. lifetime costs, energy production, losses, etc.), and more generally in terms of reliability, availability and maintainability (RAM) analysis [3]. These, allow for the characterization of available assets and capabilities, permitting ~~to identify~~the identification of possible weaknesses of the management strategy andto consider alternatives. The eventual improvement of the O&M procedures is left to the decision maker, who uses the information acquired during the modelling phase to propose changes or variation to the current strategy. The effectiveness of the proposed improvements can then be assessed repeating the simulations, comparing the outputs with those previously obtained. Two considerations are important to note. Firstly this approach requires a deep understanding of the dynamics of the offshore farm, a strong knowledge of its practical aspects and some degree of experience with the computational tool. Secondly, effective solutions may still remain unexplored if for any reason not all the possible combinations of assets and strategies are considered. For this reason, in this work the use of multi-objective optimisation and genetic algorithms is proposed in order to automate the optimisation procedure and explore a wider range of possible solutions.

In the next section II, the Monte Carlo tool developed for the characterisation of an offshore farm, together with examples of the information obtainable and possible use for improvement of the farm will be introduced. Similarly, in section III, the evolutionary algorithm techniques used to promote the automated optimisation of the O&M procedures will be presented, together with the outcomes of such implementation. Finally, in section IV, the achievements of this combined approach as well as proposals for future developments of the procedure will be discussed.

II. CHARACTERISATION – MONTE CARLO TOOL

The O&M modelling tool developed by the authors has been conceived specifically for ocean energy devices, in such a way to deal exclusively with the information valuable to owners or operators for the effective management of an offshore renewable farm. The model is flexible regarding technologies, including most wave energy converters (WECs), tidal and marine current turbines (MCTs) and offshore wind turbines (OWTs).

A. Methodology

The main concept of this tool is hereinafter described. Starting from the relevant Metocean data of the offshore location where the devices will be deployed, it is possible to simulate the lifecycle of the offshore farm (or a different pre-established amount of time) by adding the specifications of the project. These, are primarily intended as information on the structure of the device (subassemblies and components) and correspondent reliability data, as well as the device's power performance (power curve or power matrix depending on the technology). In addition, specifics of the access systems that will be used for the maintenance of the farm can be exploited to analyse the effects of planned and unplanned interventions during the simulated period. Therefore, analysing the results obtained from the simulation it is possible to attain the complete characterisation of the operational aspects of the offshore farm. This permits the achievement of significant insights on the functioning of the devices, in particular in terms of generated yield, revenue, expenses, availability and reliability of the farm. As a consequence, the presence of eventual underlying problems, as well as cost drivers, can be directly identified.

The tool can be divided in four main sub-modules. These, within the workflow of the whole model, are illustrated in Figure 1.

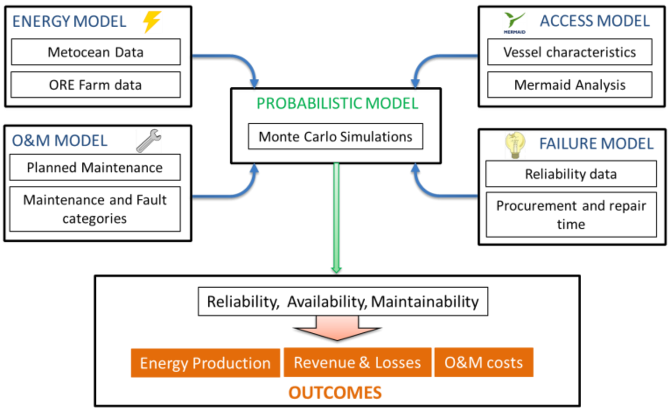

Fig. 1 Workflow Diagram of the O&M characterisation tool.

The first sub-module is the 'Energy module'. This uses the Metocean information on wave, wind and water currents and the power characteristics of the devices, in order to provide an estimation of the energetic yield produced in ideal conditions, i.e. lack of failures and scheduled or unexpected disruptions. The length of the individual timestep in the timeseries, as well as the interval between two consecutive values of generated power in the power curve (or power matrix) of the device, is variable depending on the information available to the tool user. The second is the 'Access module'. This exploits again the Metocean data available, but this time in conjunction with the capabilities of the access systems considered (vessels, workboats, helicopters, etc.) to assess the accessibility of the offshore farm. If available, this module relies on the use of Mojo Maritime's proprietary offshore operations planning software Mermaid [4] in order to reduce the assumptions concerning the accessibility of the devices and obtain a detailed daily range for the time required for each offshore operation. A 'Failure module' is then used to generate a statistical distribution of unexpected failures or degradation of the devices according to the reliability data provided (failure rates, redundancies, criticalities, dependencies, etc.). These figures, together with procurement and repair time of each component, availability of eventual spare parts in stock and availability of the required access systems, are used to calculate the downtime of the farm and the consequent energetic (and economical) loss. The last sub-module is the 'O&M module', which is used to manage both corrective and scheduled maintenance interventions. The former are verified by analysing and comparing the maintenance categories of components and access systems, allowing the intervention only if there is a match between these categories. The latter, besides being subject to the same check, account for all the pre-established and timetabled inspections, repairs and replacements. In addition, this module considers fault categories and consequence classes [5] to assess the consequences of each intervention in terms of required crew, extent of the operation and economic aspects.

These four sub-modules interact in a single probabilistic model, which uses Monte Carlo simulation techniques [6] to calculate the empirical statistical distribution of results to characterise the key performance parameters of the offshore farm.

B. Outcomes

The outputs produced at the end of the simulation analyse and compare the various options and access systems in terms of reliability, availability and maintainability of the farm. These include estimations of the yield generated and lost as a consequence of the failures, economic production and losses, reliability of the components, availability of the farm and probability distributions of the results obtained. Some examples of these results, shown below, have been extracted from previous works of the same authors [7,8].

In Figures 2 and 3 the power delivered to the grid and the availability (time-based and energy-based) of a WECs farm are compared for two different access systems (a workboat and a multicat vessel). These figures ~~permit to assess~~allow for the assessment of which access system is the most effective in operating on the farm, as well as the relative differences in productivity due to higher or lower effectivity in the overall maintenance of the farm. However, final results must always be weighed against the direct and indirect costs (e.g. standby rate, mobilisation, crew, etc.) related to the choice of an individual access system, or a combination of these in an eventual mixed fleet.

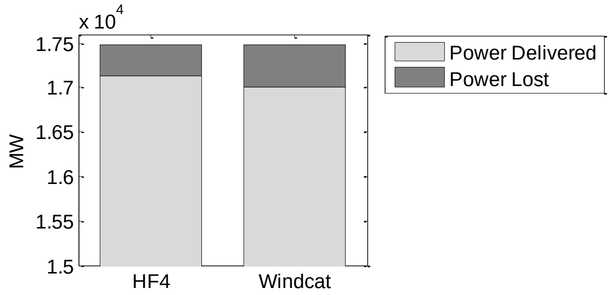

Fig. 2 Example of power delivered and power lost due to unexpected failures using a workboat (Windcat) and a multicat vessel (HF4) for a WECs farm [8].

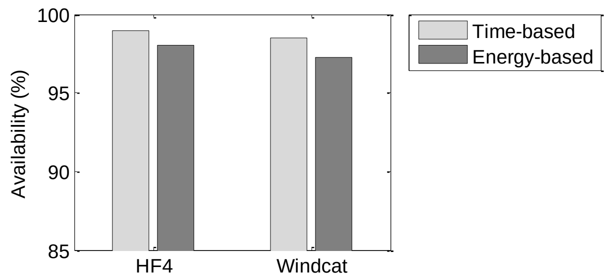

Fig. 3 Example of time-based and energy-based availability calculation using the two access systems for a WECs farm [8].

An example of results on the reliability of the devices is illustrated in Figure 4. Here, each component of the device is analysed in terms of its percentage contribution to the total number of failures and to the respective downtime caused as a consequence of the failure. A component can be classified as any element of the device's infrastructure (e.g. subassembly, subsystem or individual item).

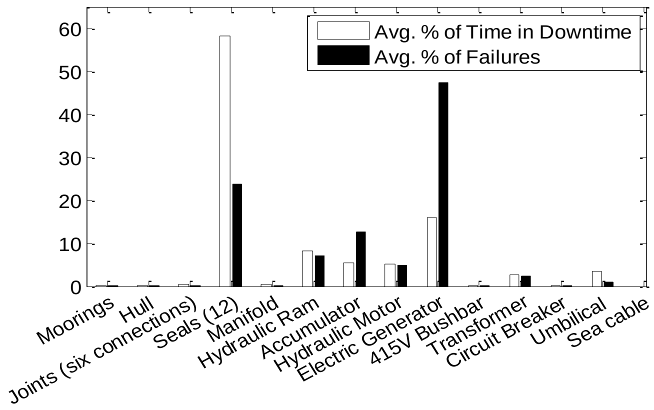

Fig. 4 Example of calculation of percentage contribution to total number of failures and total downtime caused for each component of the WEC [7].

This information permits not only ~~to identify~~the identification of the most sensitive components (those that fail more often), but also and especially those that cause the major amounts of downtime in the event of failure. This allows the decision-maker to focus the maintenance strategies on these components, or, if possible, replace them for more reliable or easier to repair products. Likewise, this information can be used to rank the components according to their failure occurrence and severity, in order to gain insights for the improvement of future designs of the same device and adopt appropriate risk mitigation measures.

Other results include the analysis of the resource available (wind, wave or water current), the taxonomy of the device according to the Reliability Block Diagram (RBD) technique [9], and monthly and annual statistics, as well as probability exceedances, on power produced, power lost, revenue and economic losses.

III. Optimisation – Evolutionary Algorithms

Once the characterisation is completed and a clearer picture of the operability of the farm has been obtained, a number of adjustments can be put in place in order to improve the productiveness and/or other aspects of the farm. Examples of possible improvements include, but are not limited to [7]: choice of a different access system with higher capabilities or lower running costs, introduction of preventive maintenance activities on the targeted components, replacement of sensitive components with more reliable counterparts, introduction of redundant elements. However, in order to explore the full range of possible alternatives for the optimisation of the maintenance assets, a systematic approach is required.

The task of improving the O&M procedures of an offshore farm is not trivial, since various and often contradictory aspects, weighed on several parameters and decision variables, have to be optimised. For instance, a solution that maximizes the reliability or the availability of the farm, may not be the most cost effective if the maintenance efforts and the associated cost are too high. In other words, it is highly unlikely that a solution is optimal with respect to all of the objectives. Hence, a suitable trade-off according to the requirements of the farm or to the preferences of the decision-maker has to be sought. Generally, situations like this are known as *multi-objective optimisation problems*, defined as those circumstances in which the goals are generally conflicting preventing simultaneous optimization of each objective [10].

A. Methodology

Evolutionary algorithms, so named because of their adaptation from biological evolution processes, are traditionally recognised as well-suited to solve both single-objective and multi-objective optimisation problems. Within this class of optimisation methods, Genetic Algorithms (GAs) [11] are the most popular, thanks to their remarkable applicability to the most varied types of problem. GAs are based on a direct analogy with the process of natural selection and evolution, and work according to the scheme showed in Figure 5. A population, intended as a group of individuals, is created at random. In this, each individual represents a candidate solution to the problem, and it is encoded using binary code or other representations. The individuals are evaluated according to their fitness with respect to a pre-defined objective, and then selected and crossovered proportionally to their fitness score. Finally, each new generated individual is randomly mutated to preserve diversity in the population. This process is repeated until certain conditions are met or the maximum number of generations is reached. In this way, over successive generations, the population is evolved toward a range of optimal solutions.

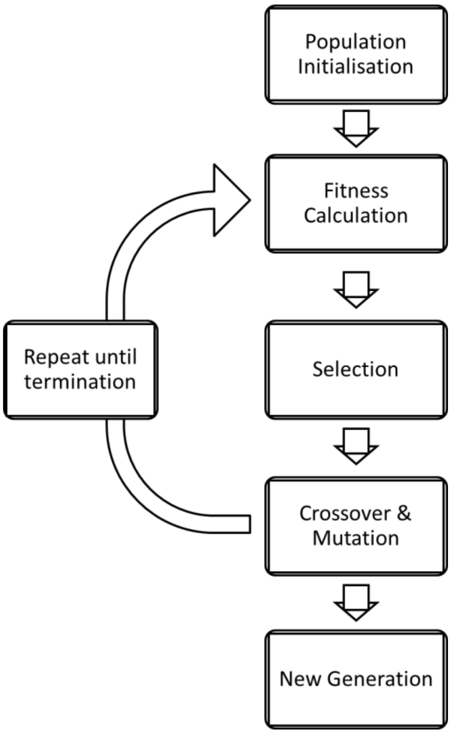

Fig. 5 Workflow of a Genetic Algorithm.

To address the challenges in planning a reliable and cost effective management procedure for a marine farm, the objectives considered in this work were the minimisation of the maintenance costs and the maximisation of the reliability of the devices. The binary representation has been chosen to encode the individuals, due to its high adaptability to the functions and operators implemented in the GA. Each individual is represented by its chromosome, which contains the information about the available assets of the offshore farm and their respective utilisation in binary digits of 0 and 1. These values encase the number, type and respective properties of the access systems of the farm, as well as information and reliability properties of the components of the device. Thus, the information contained in each chromosome represents the decision variables of the stated problem. An example of this representation is illustrated in Figure 6. A population containing different combinations of these values is generated at the beginning of the optimisations procedure. Appropriate relationships between parameters, decision variables and fitness scores are then needed to evaluate each candidate solution and establish a ranking of the best individuals. Such relationships have been established thanks to the modelling experiences gained with the O&M characterisation tool described in the previous section, and provide a direct link between the digits of the chromosome and the values of maintenance costs and reliability of the farm.

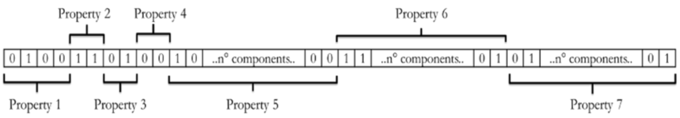

Fig. 6 Example of representation in binary code for individuals (candidate solutions) in the GA.

The selection of the individuals is operated using the *roulette wheel method* [12], which gives to each individual a probability of being selected for crossover proportionally to its fitness score. A crossover rate is specified, and compared against a randomly generated number to establish whether the generation of a new individual using two selected parent solutions should occur or not. In the first case the 'child' chromosome is generated by mixing two different parts of the selected parents, otherwise two new individuals are selected for crossover. Similarly, each new generated individual is altered through the mutation operator, meaning that a certain number of bits are randomly 'flipped' from 0 to 1 or vice versa. Analogously to crossover, a mutation rate has to be specified for this operator to establish whether the alteration will happen or not. In addition, in order to avoid that the best solutions disappear between one generation and the next one, a certain number of individuals among those that have obtained the highest score during the evaluation are preserved as they are through the process. In this way, their genetic heritage is not lost in case they are not selected for crossover. This mechanism is called *elitism*, and those automatically preserved are called *elite individuals*. Finally, once that the best individuals have been found, these can be re-converted in terms of offshore assets and properties of the device through decoding functions expressly implemented for this purpose.

B. Outcomes

1) *Single-objective optimisation*: At first, only one objective is considered: the minimisation of the maintenance costs. This allows for the calibration of the parameters and confirmation of the effective functioning of the GA, permitting ~~to verify~~the verification of the evolution of the population,~~if~~ generation by generation, ~~the population evolves~~ towards those solutions that satisfy the objective, i.e. provide lower maintenance costs. The main parameters for the execution of the implemented GA, adjusted from [13] in order to effectively explore candidate solutions, are given in next Table I.

TABLE I
INPUT VALUES FOR THE GA

Parameter	Value
Generations	40
Population size	30
Elite individuals	3
Crossover rate	0.7
Mutation rate	0.01

In Figure 7 the values of the maintenance cost associated to the best individual and the average of the population are shown for each generation. The best individual is considered the one providing the minimum maintenance costs in the population. Despite acceptable fluctuations in the mean value of the cost functions for each population, it can be seen how both the value of the best individual and population average improve (get lower) over successive generations. In order to verify if there are more solutions providing the same value of the cost function, as well as to vet the diversity of the population, the distribution of the maintenance costs for all the individuals of the final population is plotted in Figure 8. Here, a certain variety within the pool of individuals can be observed, confirming the effective search of the implemented algorithm in the objective space containing all the possible solutions for this first problem.

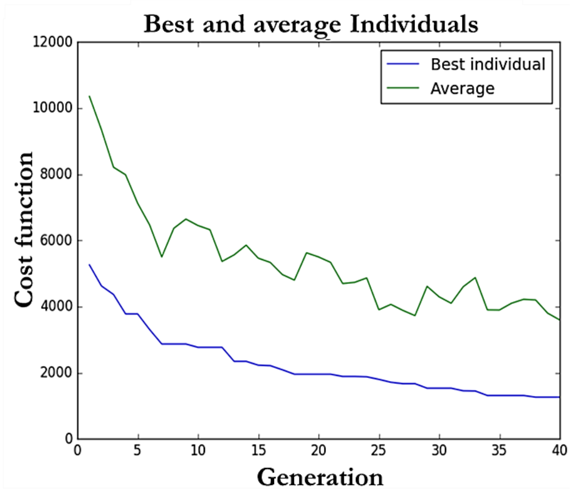

Fig. 7 Trend of best (lowest) and mean cost function values over the generations.

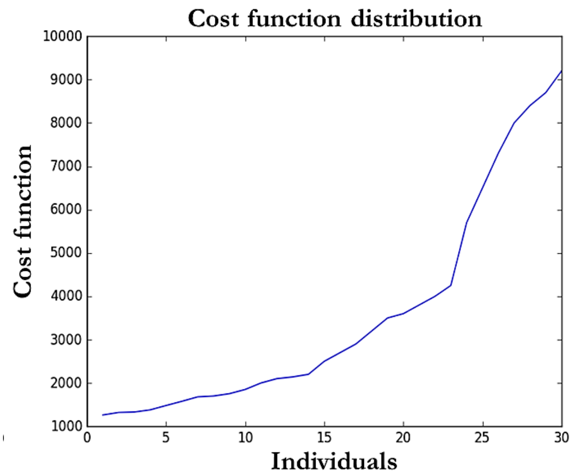

Fig. 8 Distribution of the cost function over all the individuals of the last generation.

2) *Multi-objective optimisation:* When also the second objective, the maximisation of the reliability of the farm, is included, the problem becomes a multi-objective optimisation of the inputs set. Each solution is now evaluated according to two different criteria (minimisation of the costs and maximisation of the reliability). While a number of suitable methods exist to solve multi-objective optimisation problems [10], the approach proposed in this work consists of combining the individual optimisations (and corresponding searches) of three separate objectives: minimisation of the costs, maximisation of the reliability, minimisation of the cost/reliability ratio. Figure A1 in the appendix shows the result of the first optimisation. The individuals of all the generations are plotted in function of their values of reliability and maintenance cost. The individuals of the last generation are highlighted to prove that the search moves towards those solutions that satisfy the objective, in this case minimise the

cost. Analogously, in Figures A2 and A3Fig. the same plots are reproduced for the other two objectives, the maximisation of the reliability and the minimisation of the cost / reliability ration respectively. Also in this case the individuals of the last generation are highlighted to check the correct directionality of the search, which varies moving towards different areas of the plot depending on the objective considered. This can be inferred also looking at the density of the solutions for the distinct objectives. The three separate optimisations identify a large set of possible solutions to the proposed problem, providing the corresponding values of cost and reliability for each. The complete range of such possibilities can be visualised when the results of the different searches are merged into a single plot. Figure 9 shows how the full objective space explored in this way is much larger with respect to that explored in each individual optimisation, providing a comprehensive assortment of solutions to define the best arrangements for the offshore farm. In all these figures both the cost and reliability functions are represented in arbitrary units in order to compare the different solutions relatively to each other.

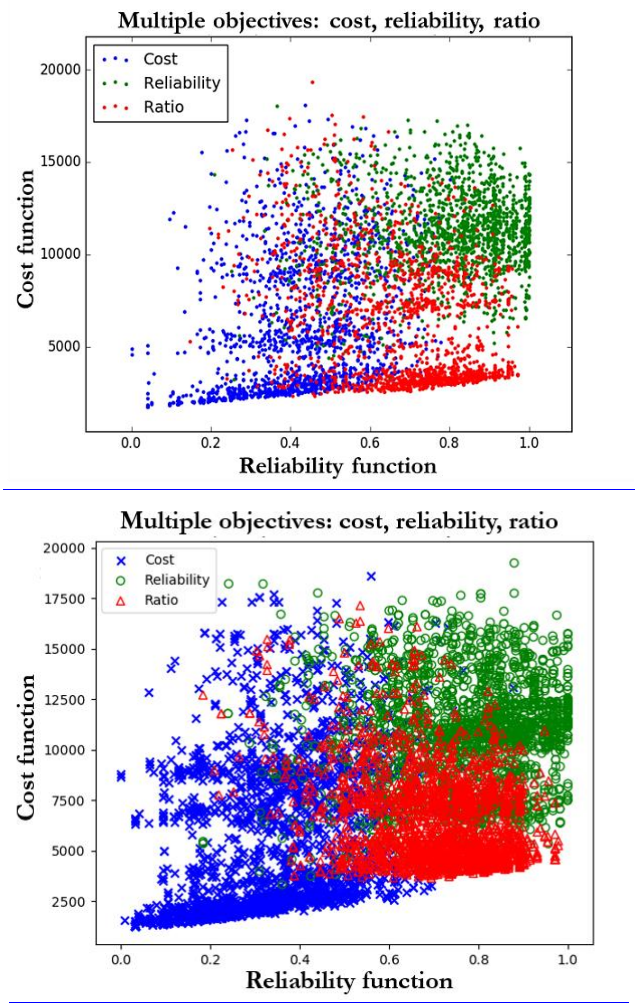

Fig. 9 Reliability / Cost scatter plot for the three objectives combined: minimisation of the costs, maximisation of the reliability and minimisation of the cost / reliability ratio.

Further information can be extracted from the merged objective space by isolating those solutions that cannot be improved without worsening at least one of the objectives, as shown in Figure 10. These solutions constitute a frontier known as Pareto optimal, and represent the ideal set of trade-offs for the defined constraints. In this case, moving from one solution in the Pareto front to its neighbouring one would mean either to achieve a higher reliability at a higher cost, or reduce the maintenance costs at a lower reliability. This allows the decision-maker to get a complete picture of the different options available, and select the solution that satisfies the needed requirements or preferences. In other words, the wanted input set of assets and properties of the farm, which guarantees the desired balance between reliability and costs, can be found immediately without the need of repeating the simulation for many different combinations.

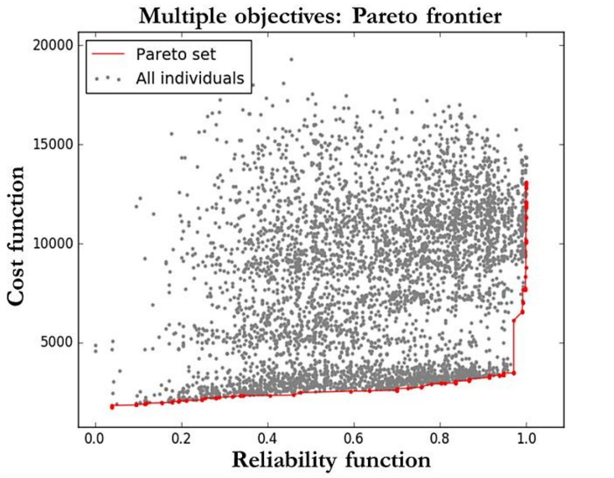

Fig. 10 Pareto frontier showing the best trade-off solutions for the three objectives combined.

IV. Discussion and Conclusions

Due to their high unpredictability, O&M expenses still constitute a substantial portion of the total costs of a marine renewable project. As a consequence, an effective O&M planning prior to the deployment of the devices could deliver high value to offshore farm owners and, in the long term, be one of the most effective approaches to foster and consolidate the marine energy market. In order to achieve this result innovative, specific and adaptable computational tools are required for the characterisation and optimisation of the O&M procedures for marine renewable farms. In fact, although the relatively restricted availability of real data limits the verification and validation of these tools against real cases, computational simulation remains the preferable approach to mitigate the risks of offshore renewables. In this work, a combined approach based on Monte Carlo simulation and multi-objective optimisation via evolutionary algorithms, is proposed to face this challenge and offer new methodologies for the sensible management of the maintenance assets of an offshore farm. On one hand, the Monte Carlo tool permits the characterisation of all the reliability, availability and maintainability related aspects of the farm, allowing for the identification of major weaknesses and ideas of improvement in these areas. Figures on energy production, generated revenue, maintenance expenses, repair and replacement costs, access systems accessibility and other reliability related parameters can be immediately estimated to get a comprehensive overview of the farm viability. In addition, different choices, planning strategies and maintenance schedules can be directly evaluated using the comparison tools integrated in the model. A major shortcoming of this approach is that the results obtained strongly depend on the quality of the inputs provided, i.e. are more accurate if the data on reliability of the devices and capabilities of the access systems are specific for the analysed offshore farm. These, especially for wave and tidal devices, often rely on data approximated or adjusted from other sectors, due to the limited experience with these technologies and the restricted availability of information due to commercial confidentiality reasons. As more data will become available the computational tools may be adapted in response. ~~Besides, the alternatives and variations to the original input set which defines farm assets and maintenance strategy, is limited to the user proposals, hence subject to his/her personal experience and engineering judgment.~~ On the other hand, the multi-objective optimisation by means of evolutionary algorithms permits the exploration of a large range of suitable alternatives in a short time, providing valuable, timely support at the moment of taking the most adequate decisions for the management of the farm. The process of proposing corrective measures for the previously identified areas of amelioration is thus systematic, automated and improved.

The drawback of this method is that direct relationships between the decision variables of the problem (the input set representing both the assets of the farm and the reliability adjustments of the devices) and the value of the objective functions, have to be established in order to evaluate the individuals during the GA. These, despite being useful shortcuts when limited information on the expected outcomes of a problem is available, are still educated guesses, which, according to the definition of heuristics, narrows the search in a domain that it is not well defined and understood but do not guarantee optimal solutions if poorly implemented. Although many objectives can be proposed to improve the O&M aspects of the farm, the minimisation of the costs and the maximisation of the reliability are proposed in this work as they cover two of the most important aspects of the farm administration. Depending on the preferences of the farm stakeholders, or as an input for future work, other aspects, like availability, maintainability, profit and others, could be included among the objectives to consider for the optimisation of the farm logistics. As advised above, additional functions, appropriate to establish a direct link between the parameters of the candidate solutions and the assets of the farm, should be determined for this scope. Similarly, other evolutionary formulations, that exploit different search techniques and optimisation methods [14], can be implemented with the aim of extending the investigated space and find previously unexplored solutions.

Acknowledgments

The work in this paper has been conducted within the multinational Initial Training Network (ITN) OceaNET, funded under the People Programme (Marie Curie Actions) of the European Union's Seventh Framework Programme FP7/2007-2013/ under REA grant agreement n° 607656. Mojo Maritime (JFMS) have provided access to Mermaid to support, and for integration with, this research.

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APPENDIX

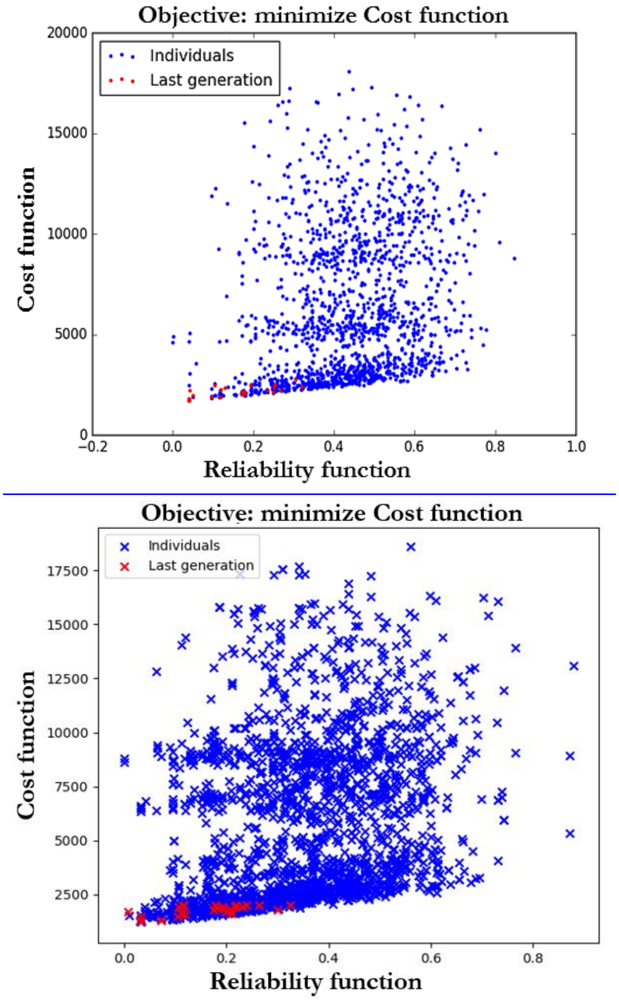

Fig. A1 Reliability / Cost scatter plot for the first objective: minimisation of the costs.

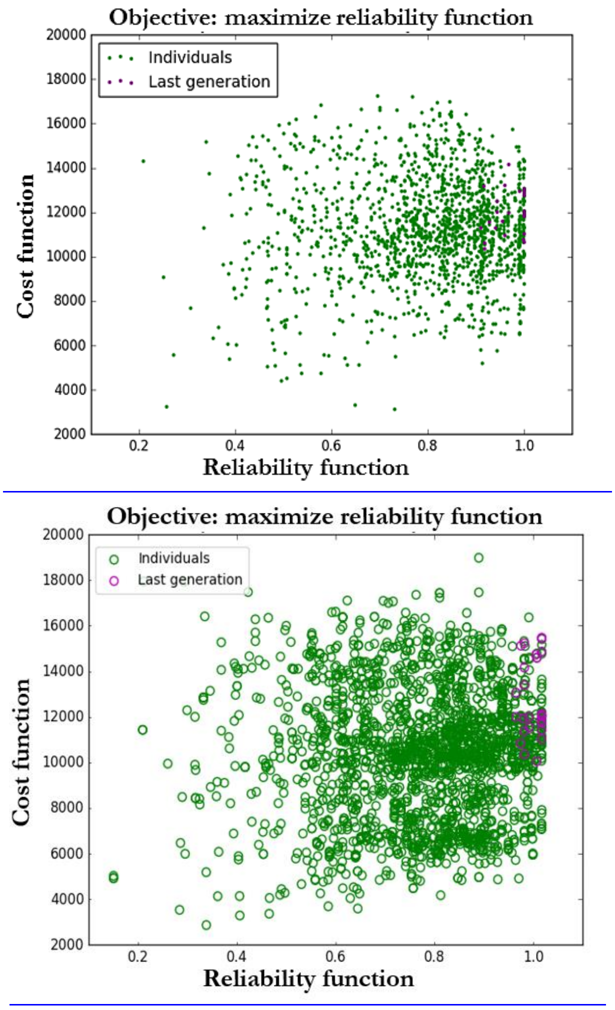

Fig. A2 Reliability / Cost scatter plot for the second objective: maximisation of the reliability.

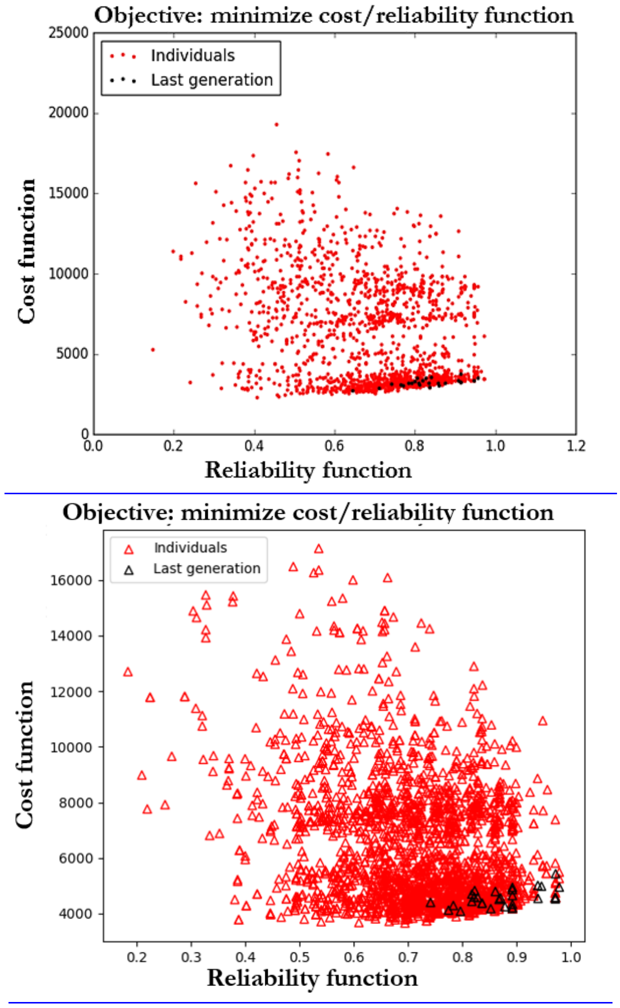

Fig. A3 Reliability / Cost scatter plot for the third objective: minimisation of the cost / reliability ratio.