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A decision support model to optimise the operation and maintenance strategies of an offshore renewable energy farm

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ABSTRACT

In order to accelerate the access into the energy market for ocean renewables, the operation and maintenance (O&M) costs for these technologies must be reduced. In this paper a reliability-based simulation tool for the optimization of the management of an offshore renewable energy (ORE) farm is presented. The proposed tool takes into account the reliability data of the simulated devices and estimations on the energy produced to create a series of results in terms of availability and maintainability of the farm. The information produced supports operational and strategic decision making regarding the O&M for offshore farms. A case study simulating a conceptual tidal energy project, consisting of an array of two tidal turbines located off the north coast of Scotland, is presented to show some of the results achievable with this model. The proposed methodology, although adopted for a tidal farm here, is generally applicable to other kinds of ORE farms.

1. Introduction

Offshore renewables hold large potential to contribute to the future renewable energy mix. In order to do so, the costs associated with the deployment of offshore devices need to be strongly reduced and these have to become competitive in respect to other technologies. By definition, O&M is a combination of all those practical and administrative actions, undertaken in a complex decision-making process, which aim to keep a system, subsystem or single component as efficient and productive as possible during its life cycle. O&M represents a major share of the total unit energy cost (Nielsen and Sorensen, 2011), reaching peaks of 30% of the total cost of a project. Improving O&M practices and taking design choices that facilitate operational requirements has been therefore indicated as one of the most cost effective approaches for mitigating the financial risks of offshore infrastructures (Shafiee and Kolios, 2015). As can be expected, maintaining the considered system in an operating state for a longer time, increasing in this way the availability of the device, means a higher amount of energy produced and consequently greater revenue. However, an increase in availability is obtained through an increase in maintenance efforts and, as a consequence, in maintenance costs (Rinaldi et al., 2016a). Therefore, selecting the most appropriate maintenance strategy among the many options available is not a straightforward task. Comprehending the dynamics of the farm, taking into account the interactions among different components and all the unexpected events may be extremely challenging. In addition, planning and scheduling of the O&M activities are extremely dependent on the project and especially the technology considered. For example, the accessibility challenges to take into account for interventions on offshore wind turbines, where wave and wind conditions are fundamental, are different from those to consider for tidal turbines fixed to the sea bed, where tide level and water current are of primary importance. This, or other factors like the failure behaviour and the experience previously acquired with similar devices, have important repercussions on the choice of the proper assets, and as a consequence on the input set to consider for the effective modelling of the farm. Under these circumstances, a number of computational tools have been developed to address this problem and characterize the operational expenditures of an ORE farm, mainly for the offshore wind industry. Most of these models aim to estimate the costs related to the deployment of the farm exploring the different options available and investigating different maintenance regimes. One part of these tools has been developed exclusively as a commercial product, in order to assist farm operators in the monitoring of the O&M procedures and the control and optimization of the cost (Braam et al., 2011; Dinwoodie et al., 2015; Hofmann and Bakken, 2013). Other models have been proposed in the research literature to contribute to the general knowledge in this area and solve specific targeted problems. Among these, the assessment of the influence of weather forecast uncertainties (Ambühl et al., 2016), the applicability of these

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tools to combined offshore platforms (Mcauliffe et al., 2015), their integration with other techniques (Martin et al., 2016) and the accurate estimation of the charter rate for the access systems, i.e. vessels and workboats (Dalgic et al., 2013; Dalgic et al., 2015a). But operating conditions can be investigated also in more generic terms. For example these can be referred to device design choices, offshore locations, crew employed or, more in general, maintenance strategies (Dalgic et al., 2015b). A thorough review of the models for offshore wind farms belonging to both categories has been provided by Hofmann (Hofmann, 2011). Here, these are arranged in different categories depending on their central purpose, i.e. the main aspect or cost driver to characterize.

Thus, the objective of this paper is to provide a novel contribution to the existing range of computational O&M tools, showing the properties of the developed toolbox and especially how the results obtained with this can be used to support the decision-making process, as well as improve the cost efficiency, of offshore renewables. Focus is given towards the reliability characterization of the device, and the support this can provide in the effective planning and optimization of the power production, with the final aim of reducing the cost of the energy produced.

In the next section 2 the full methodology adopted will be introduced. A case study to show the modelling and optimization possibilities will be presented in the following Section 3. Results will be shown and discussed in Section 4. Future work and optimization proposals will be anticipated in Section 5. Finally, conclusions are drawn in the last Section 6.

2. Methodology

This section describes in detail the offshore O&M tool implemented. Specifics are provided on the input variables required to start the simulations, together with the mechanisms and constraints that regulate their evolution with time. In addition, a full description of the outputs obtained and their use in the strategy planning is presented.

2.1. The offshore O&M tool

A number of probabilistic evaluation techniques exist to model the systems' reliability and provide an assessment of the maintenance procedures. However, if the modelling of random processes (e.g. unexpected failures) is the objective, Markov chains and Monte Carlo simulation are the most diffused approaches (Hofmann, 2011; Alexander, 2003) due to their degree of flexibility and level of understanding provided. Monte Carlo techniques are a set of non-deterministic mathematical models based on the random sampling of determined quantities. In reliability engineering, Monte Carlo analysis uses reliability data and statistical distributions to define the behaviour of the system over the considered period of time. A time domain approach based on this technique has been adopted to develop the O&M tool presented in this work. This exploits the generation of random numbers for a sufficient number of times (i.e. for each timestep and each component of the simulated lifecycle) in order to cover all the possibilities and provide unbiased results (Rinaldi et al., 2016b). The idea of this model is that by exploiting the metocean data (hindcast or synthetic) of the location where the offshore farm is or will be located, together with all the specifications of the projects in terms of devices, vessels and maintenance strategies, it is possible to obtain a series of results that can be analysed in an iterative procedure to characterize the dynamic of the farm and optimise the planning actions. To do so, the model takes into account a large number of inputs, mechanisms and constraints according to the Structured Analysis and Design Technique (SADT) (Karyotakis, 2011), a computational practice used to describe complex systems and which operates on the general basis shown in the diagram in Fig. 1.

All the inputs, constraints, mechanisms and outputs considered in this tool will be introduced in the following subsections.

2.1.1. Inputs

The main inputs that the model requires to perform the simulation are:

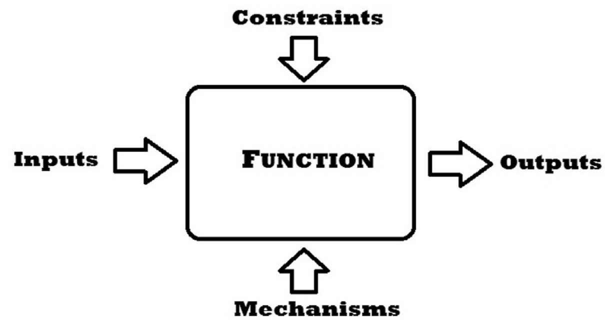

Fig. 1. Graphical representation of SADT.

Number and power rating of the devices. The number of devices that constitute the offshore farm, but not their disposition in the array, must be specified together with the energy converter reference power performance. This last is a power curve in the case of an offshore wind turbine (OWT) and a marine current turbine (MCT); conversely, it is a power matrix in the case of a wave energy converter (WEC).

Metocean data. The model uses the time-series of the resource data principally to produce the energy estimations of the farm and secondarily to calculate the accessibility of the maintenance vessels respecting their limits and weather windows length. These time-series can be either hindcast or synthetic forecast data, referred to wind, wave and current characteristic parameters. No restrictions exist on the maximum or minimum length of the timestep that separates two consecutive values.

Failure distributions. The occurrence of a failure is a probabilistic event whose likelihood depends on many factors, either intrinsic to the nature of the considered system (or single component) and due to external circumstances. The first somehow reflect the quality of the materials, engineering skills and manufacturing processes adopted to obtain the item; the second represent the effects of environmental factors, loads and usage conditions. The model takes into account both these kinds of mechanism that lead to a failure. In order to allow for the intrinsic aspects of a component its failure rate has to be considered, taken as the frequency of failures over a given period. This value has to be established with data obtained in previous experiences with the same component (Carroll et al., 2015) or, when this is not available, adapted from existing databases (Norske Veritas, 2002) or surrogate data using the engineering judgement. A combination of both methods is the most effective choice in order to adapt longstanding databases to a specific context. This is particularly important in the case of marine energy devices, which are generally characterized by limited experience. In addition, this value can be constant or variable depending on the age of the specific component in the considered system and the probabilistic distribution chosen to represent its failure behaviour. A classic example to show this concept is the well-known bathtub curve (Klutke et al., 2003), shown in Fig. 2, which gives a clear illustration of the variation of failure rate $\lambda(t)$ over time for a generic component.

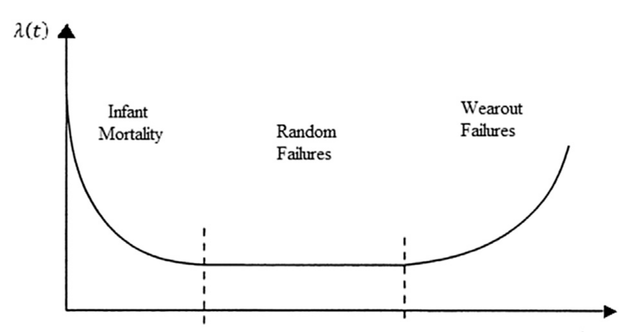

Fig. 2. Bathtub curve, representing the generic variation of the failure rate with time.