Journal of Physics: Conference Series

PAPER • OPEN ACCESS

O&M Cost-Based FMECA: Identification and Ranking of the Most Critical Components for 2-4 MW Geared Offshore Wind Turbines

To cite this article: D Cevasco *et al* 2018 *J. Phys.: Conf. Ser.* **1102** 012039

IOP Conf. Series: Journal of Physics: Conf. Series **1102** (2018) 012039 doi:10.1088/1742-6596/1102/1/012039

O&M Cost-Based FMECA: Identification and Ranking of the Most Critical Components for 2-4 MW Geared Offshore Wind Turbines

D Cevasco[1], M Collu[2] and Z Lin[2]

[1] Offshore Energy Engineering Centre, Cranfield University, Bedfordshire MK430AL, United Kingdom
[2] Naval Architecture, Ocean and Marine Engineering, University of Strathclyde, Glasgow G11XQ, United Kingdom

Email: d.cevasco@cranfield.ac.uk

Abstract. To date, the focus of the research on offshore wind turbines (WTs) has been mainly on how to minimise their capital cost, but Operation and Maintenance (O&M) can represent up to a third of the lifetime costs of an offshore wind farm. The cost for the assets repair/replacement and for the logistics of the maintenance operations are two of the biggest contributors to O&M expenses. While the first is going to rise with the employment of bigger structures, the latter can significantly increase dependently on the reliability of the components, and thus the necessity to performed unscheduled maintenance operations. Using the reliability data for a population of offshore WTs (representing the configurations most employed offshore), first, the share of the components failures to the O&M cost, together with an estimation of their dependency on some O&M parameters has been derived. Then, by following a cost-based Failure Modes Effects and Criticality Analysis (FMECA), and ranking the components through O&M cost priority number, the most critical components for O&M unplanned operations are identified.

1. Introduction

Over the past decades, the offshore wind energy sector has been growing significantly, with the employment of more than 1,500 units in UK only. Efforts are being made to minimize the overall cost of a wind farm (WF) from the capital cost point of view. On the contrary, to date, not enough attention has been given to the other cost driver of offshore structures: operation and maintenance (O&M). The two main contributors to O&M expenses are the cost for repairing/replacing the assets and the cost for logistics. It has been forecasted [1] that, with the employment of bigger power class turbines, installed further offshore, the share of the O&M expenses could reach the 39% of the lifetime costs of an offshore WF. Thus, it looks clear how much the understanding of when, where and how the wind turbine (WT) components fail is becoming crucial to improve current maintenance scheme and planning.

For this reason, and as a part of HOME Offshore project [2], the work of the authors first focused on the development of a methodology for identifying the components that are worth being further analyzed and developed in a holistic multiphysics modelling of the WT. A flowchart of the methodology applied for approaching this research questions is shown in Figure 1. In particular, the main contribution of this work is the ranking methodology, and the following identification, of the most critical components from an O&M point of view (for unplanned operations). By following a cost-based Failure Modes Effects and Criticality Analysis (FMECA), and using the reliability data for a population of offshore wind turbines (representing the offshore most installed configuration - see Figure 3), the share of the components failure to the O&M cost, together with an estimation of their dependency on some O&M parameters, is derived. In a parallel work [3], the advanced interpretation of the fault mechanisms for a specific failure mode, and its physics of failure, of the most critical component here identified, is presented, with the main aim of reducing the order of the WT model of dynamics (closing up with the last steps of the flowchart).

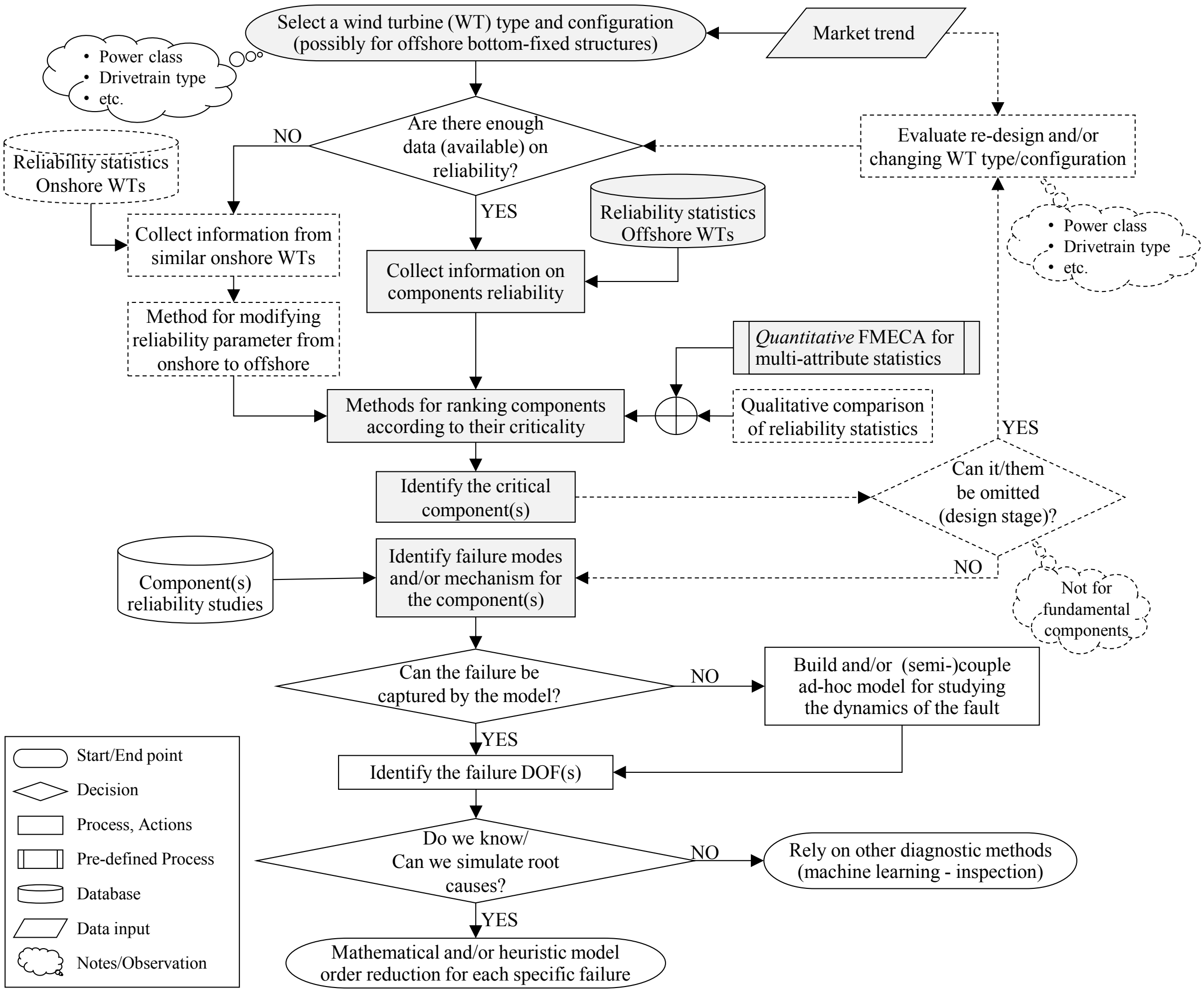

Figure 1. Overall methodology flowchart. In grey, the actions and processes presented in this work, while dashed is the loop for the additional review processes to include other drivetrain typologies.

2. Problem statement and aim

Reliability and maintainability data of WTs have been historically collected and analysed in databases, where maintenance logbooks, SCADA data and/or purchase/service bills, provided by owners and operators, are summarised in averaged results and statistics [4]. In particular, depending on the typology of data collected, more or less detailed analysis on the reliability of the components are possible.

Due to the lack of information available and/or accessible for offshore structures, the more comprehensive historical data for onshore WTs are first analysed (Figure 2). However, instead of answering the questions investigated, two main issues are identified:

- *Inconsistency of the statistics*. Due to either poorly documented collections or for confidentiality reasons, onshore databases generally report averaged results over broad populations, for varying characteristics of the units. By looking at Figure 2, where the most complete results for several onshore reliability sources are compared, a wide spread in both failure frequency and consequence (in terms of hour lost per failure) is observable.

- *Two-dimensional analysis only.* Frequencies and downtimes associated to the failure of the several components are the only information provided, at best. While they can be enough for the understanding of the criticality of onshore structure, offshore maintenance actions can be significantly affected by other logistic factors (such as number and typology of vessels and technicians required), as well as assets repair and replacement costs.

Therefore, despite the fact that drivetrain systems' faults are the highest contributors to the lost hours for the majority of the initiatives (Figure 2), it is not possible draw an immediate conclusion about its criticality when applied offshore, because of: the unjustified unlikely trend for others populations (e.g. Huandian statistics [5]), the possible influence of varying and disused typologies, and the lack of information about the severity of the maintenance action only over the time lost for the restoration of the system.

Learning from onshore databases shortcomings, recently launched offshore data collection international initiatives have been set up to obtain a more suitable and consistent set of data. The SPARTA (System Performance, Availability and Reliability Trend Analysis) initiative [6], initiated in 2013 by The Crown Estate, and under the supervision ORE Catapult, is gathering Key Performance Indicators (at the WF level) and reliability figures (at the subsystem level) from the participating operators. The output are monthly benchmark reports, of which, to date, only partial and incomplete results (from April 2015 to May 2016) have been published [7]. The German equivalent, WInD-Pool (Wind-Energy-Information-Data-Pool), with Fraunhofer IEE as trustee, is analysing and benchmarking operational and maintenance data based on minimum data requirement [8]. This initiative can be seen as the successor of WMEP [9], where additional (but never published) information on the cost of the maintenance services were collected. In particular, it continues and merge the EVW [8] and Offshore~WMEP [10] research projects, gathering historic and newly collected data for both onshore and offshore WTs. Unfortunately, neither this initiative has published complete results yet (additional information in [11]).

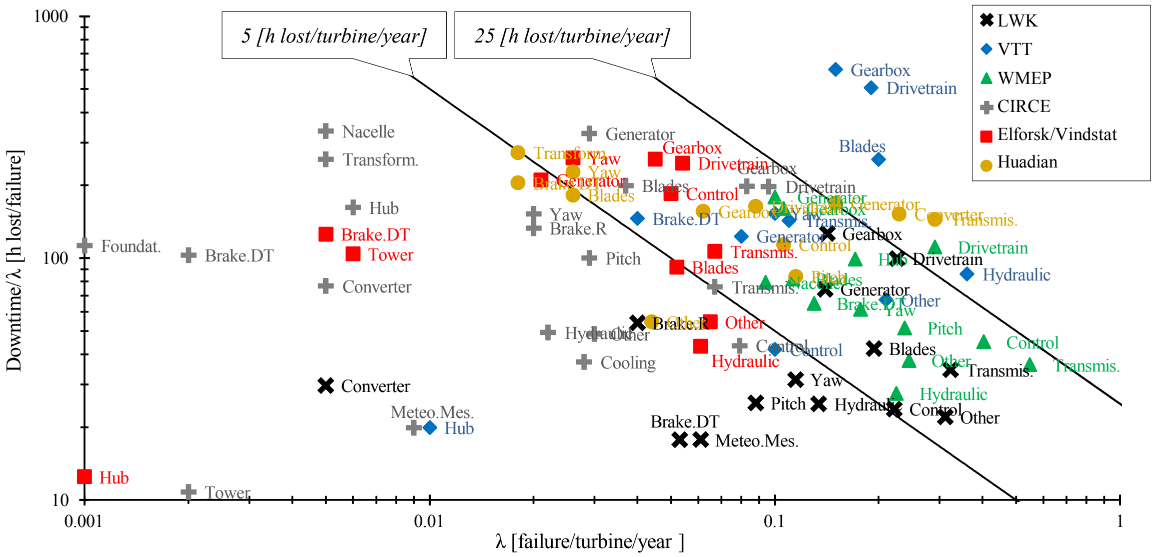

Figure 2. Comparison of the onshore initiatives based on the statistics reported by [11].

Consequently, publications from other independent authors are reviewed as well, giving a hint on the experience for various offshore WFs installed around Europe. Performance for UK offshore round 1 and 2, with evidences of WFs availability and/or capacity factor, are reported in [12], whilst maintenance records and operating issues of some specific WFs can be found in [13,14]. Outstanding among these "secondary" data collections, are the reliability and maintainability data, published by Carroll et al. [15], for a population of 350 offshore WTs. Despite the results presented are from a single manufacturer, the detailed definition of the failure and the maintenance statistics for the repair time (indicating the minimum downtime of the WT), material costs, and required technicians, per subassembly, are provided. For this reason and being representative for the majority of WTs installed offshore to date, these results - called from now on “Strathclyde” statistics - will be used in this paper.

Once accessed to this level details, however, another issues arises: how can we summarise this multi-attribute description of maintenance action, to identify the most critical failure modes? To answer this question, first reliability methods and/or O&M analysis tools, already applied for the wind sector, are briefly reviewed (section 3.1). Nonetheless, needing for a simple method, able to deal with a higher number of parameters in a consistent and systematic way, an ad-hoc FMECA approach is proposed, allowing to gather both performance and maintenance parameters.

3. Approach and methods

3.1. Methods to prioritise the failures

As suggested by the authors in [15], the purpose of reliability and maintainability data collection is to contribute to offshore wind O&M cost and resource modelling. Multi-agent systems simulation and modelling of O&M activities are continuously developed, to aid O&M planners and managers in decision making [16]. Although these tools (e.g. ECN O&M Tool [17]) are able to simulate both scheduled and unscheduled maintenance activities, eventually allowing to outline the most critical components from a cost point of view, they are generally employed for WF cost estimations. An application of the Strathclyde statistics for evaluating how the drivetrain technology choice, and the wind farm distance from shore influence availability and O&M costs, have been recently published by [18]. However, being usually based on several assumptions for both system reliability and maintenance actions, the semi-qualitative character of these tools does not match to the need of this analysis.

On the other hand, lower order analysis, by applying well-known reliability-based methods (and/or tools), can come to help in identifying, in a more straightforward way, the most critical failure modes for a given system. The several methods and approaches have been extensively reviewed by [19], with focus on the ones already applied to the offshore wind industry. In particular, a FMECA approach is selected for the purpose of this paper, not being interested, at this stage, in analyzing the sequences of events leading to failure and/or possible dependencies between the failure mechanisms.

Among the various examples of FMEA applied to WT systems, it is worth citing the work of [20] and [21]. While the first is a pioneer in the application of the FMEA approach to a wind energy converter, the latter presents a detailed breakdown of the possible failure mode and maintenance scheme for the 5 MW REpower turbine. To be able to extend these analyses to different WTs structures, FMECA software were then created. Among these programs, it is worth mentioning the Relex Reliability Studio software, selected for analyzing the ReliaWind project’s WT models (R80 and R100) [22,23] due to its high flexibility. On the other hand, as noted by [24], although it is theoretically possible to find all failure modes and insert them into the model, this would necessitate excessive calculation work. For this reason, other authors suggested to employed of the so called correlation-FMEA [19,24].

Despite the different implementations, all the FME(C)A methods and tools above mentioned, are related to qualitative judgements of the authors. In a FMECA, indeed, the failures ranking is performed by the use of a risk priority number (RPN), which is derived from the multiplication of biased and unweighted risk factors. The RPN, difficult to be accurately determined for each single failure mode, has additionally a very little informative character when comparing different wind turbine. While, in [25], Braglia suggested a method to cope with the prioritization of the attributes, Kahrobaee and Asgarpoor [26] first, and Shafiee [27] after, proposed a semi-unbiased approach, by the use of a cost priority number (CPN). Computed based on the probability of failure, its consequences (in terms of cost), and the probability of non-detectability, this methods still includes both qualitative and quantitative measures. However, the economic measure given by the CPN allows a more realistic and quantitative comparison, with respect to criticality, of the different WTs systems.

3.2. Suggested approach: O&M cost-based FMECA
Starting from the work of these latter [26,27], but aiming to get rid of the last qualitative aspect of their risk-based FMECA analysis, an ad-hoc cost-based FMECA for offshore WTs is developed (section 3.2.1 to 3.2.4). In particular, relying on data statistics, the analysis of the failure modes is modified in an analysis of the components criticality first. The detailed study of the modes and mechanisms of failure will happen in a second phase (see flowchart in Figure 1,), based on additional information and details from the statistics, and/or by accessing components reliability studies.

3.2.1. Occurrence. The probability of failure is represented by the failure frequency or rate (λ). Differently from [26,27], who used the dimensionless ratio between the specific component failure and the total amount of failure of the turbine in statistics time period, this attribute has been kept with its dimensions (number of failures per turbine year).

3.2.2. Severity. The severity term accounts for the effect and consequences of the failure, in term of downtime (and/or repair time) and by considering all the other possible informative statistics provided by the database (average number of technicians, type of vessel employed etc.). To deal with all these different nature attributes the severity is translated in terms of cost.

3.2.3. Detectability. Considered only if detailed information are provided, it is defined by [26,27] as a probability of non-detection, ranging 0 to 1 (ratio of the number of failures and total number of occurred and potential failures). Similarly, it is here suggested to integrate this factor as a percentage curtailment in the failure rate. However, information on detected possible failures (usually achieved only after inspection) are difficult to access and/to hardly ever reported. For this reason, and due to the broader application of SCADA system/alarms, an approach based on the ratio between number of effective failures and number of SCADA alarm could be applied, in line with the detection analysis in [28].

3.2.4. O&M Cost Priority Number. As for the well-known RPN, the CPN (here specifically called O&M CPN) is derived by the multiplication of the occurrence, severity and detectability attributes. In particular, by maintaining the dimension of the failure attributes, the O&M CPN will provide information on the total annual cost, per turbine, for unplanned O&M actions (with details on the share per component).

4. Case study

4.1. Reliability and maintainability database
As anticipated in section 2, Strathclyde statistics [15] are the most complete data on offshore structures available to date. Although the WTs in the population have varying power class of 2-4 MW, and the average dimension of the EU installed offshore WTs is over 4 MW (weighted on the projects capacity), their characteristics can be related to the two currently most employed offshore configurations in Europe (Figure 3): geared WTs with an induction machine.

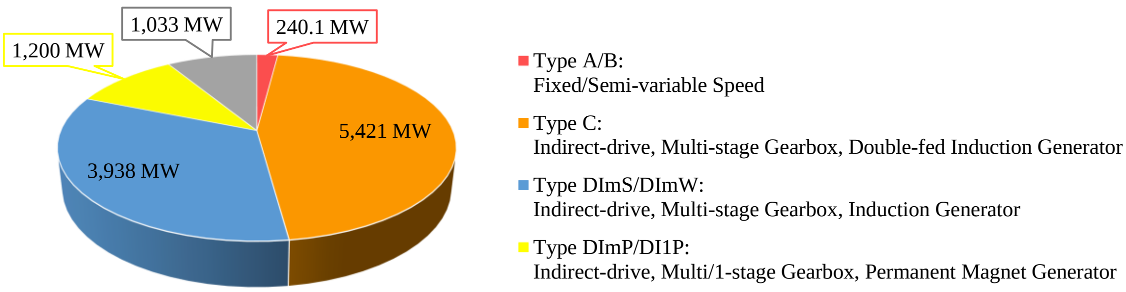

Figure 3. Drivetrain types, total EU installed capacity (for fully grid-connected wind farms, as estimated in [29]). The drivetrain types are described in [30]

Even though the taxonomy used by the authors do not conform to other internationally recognized [31], it has been judged clear enough for the purpose of this analysis. Additional details on the failure type are given by organizing the statistics in cost classes, either if no cost (*NC*) information were recorded, or according to the cost of the material for performing major replacements (*MR*), major and minor repairs (*Mr* and *mr*).

4.2. FMECA approach applied to the case study

Built on provided data, and aiming to maintain the analysis as unbiased as possible, the contributions of unknown possible cost is neglected (e.g. cost to equip the crew and the vessels, time to travel, and other possible logistic delays). Therefore, ignoring the cost of the service and the possible influence of weather days, the *O&M CPN* derived represents, for each component, a minimum forecast of the potential one. Furthermore, although Strathclyde statistics seem to be based on operational data coming from the collection of maintenance logs, no information are reported on potential vulnerabilities and near hit. Thus, to avoid adding qualitative judgement to the analysis, the detectability contribution is not considered either.

To not lose the details on the failure typology given by the division into classes of (material) cost to repair, the cost for O&M unplanned actions ($C_{O\&M}$) is defined per component (i-indexed) and cost classes (j-indexed), as from equation (1), weighting their contribution on the respective failure rate for determining the total averaged $\mathrm{C_{O\&M}}$ per component, as shown in equation (2).

$$\begin{aligned}(C_{O\&M})_{ij} &= (C_M)_{ij}+(C_P)_{ij}+(C_L)_{ij} \\ &= (C_M)_{ij}+\overline{P}\cdot CoE\cdot \mathrm{MART}_{ij}+(N_{tech})_{ij}\cdot c_{tech}\cdot \mathrm{MART}_{ij}\end{aligned} \tag{1}$$

$$(C_{O\&M})_i = \frac{\sum_j (C_{O\&M})_{ij}\cdot\lambda_{ij}}{\sum_j \lambda_{ij}} \tag{2}$$

The C_M, C_P and C_L are, respectively, the cost for the repair/replacement material, the loss of revenue for the production loss, and the cost for the labor. While the first is given by reference [15], the latter are estimated as in shown equation (1). The $\overline{P}$, CoE and c_{tech} represent, respectively, the assumed average power output of the WTs population - as product of average capacity factor (CF) and power class -, the cost of energy and the cost hour per technician. The Mean Active Repair Time (MART) and the average number of technicians required to repair (N_{tech}) are taken from [15].

To understand the influence of the unknown parameters on the $C_{O\&M}$ and, consequently, the sensitivity of the *O&M CPN*, these constants are varied in a range compatible with the data of [12,32]: the CF is varied between 0.2÷0.6, the CoE between 30÷80 €/MWh, and c_{tech} between 50÷100 €/h.

5. Results and discussion

5.1. Sensitivity analysis: influence of performance and cost parameters

Although, as in [26], this analysis can be easily implemented in a spreadsheet, a preliminary study on the dependency of the results on the assumed parameters was performed in MATLAB. In the specific, a script was developed to calculate the $C_{O\&M}$ for varying scenarios (combinations of power class, averaged performance, and energy and labor cost) with respect to the several components and for the different cost class and types assigned. As stated in equation (1), linear relations between the $C_{O\&M}$ and the performance and cost parameters are expected.

Analyzing the scattered results of the total cost, it emerged that the effect of the CoE is significant only for high power rating, whilst the c_{tech} seems to be the biggest cost driver for major replacement and repair classes. In particular, the highest averaged cost is observed for major replacement actions, where the generally high cost of the material and long repair times lead to about €250,000 to €450,000 per failure. Investigating the share of the components to the total cost, its variation throughout the minimum, maximum and average *O&M CPN* scenarios is plotted in Table 1-2, preliminary neglecting the division in the *MR*, *Mr*, *mr* and *NC* cost classes.

Table 1. Percentage share of the components failure to the *O&M CPN*, and to the cost types identified (C_P, C_L and C_M) - graphical presentation - for the minimum, average and maximum possible scenarios.

	Case	*Gearbox*	*Generator*	*Pitch/Hydraulic Systems*	*Blades*	*Other Structural/ Mech. Components*
Share to the total cost	*Min*	75.27%	13.17%	2.46%	1.36%	1.09%
	Ave	71.49%	13.26%	3.37%	1.86%	1.56%
	Max	69.52%	13.16%	3.88%	2.16%	1.83%

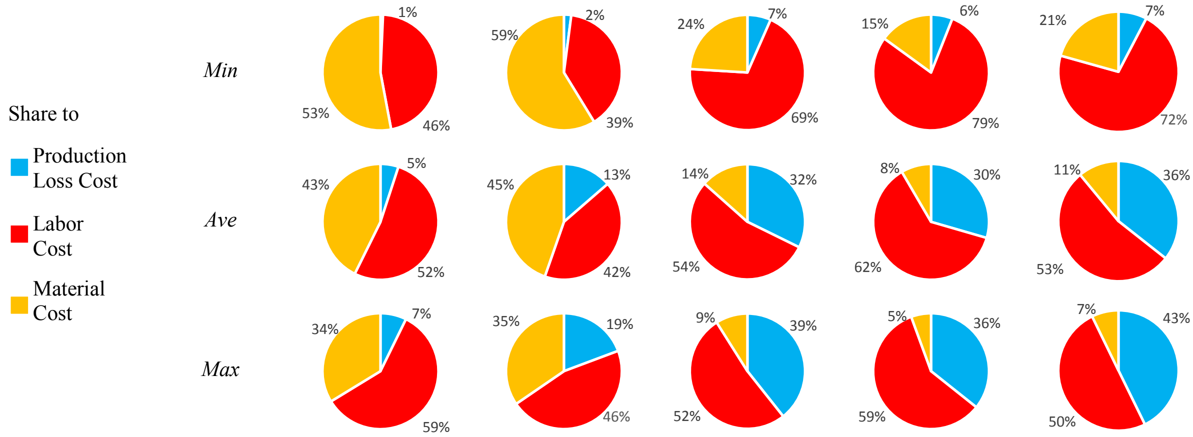

Table 2. Continuation of Table 1.

	Case	*Hub*	*Power Supply/ Converter*	*Controls*	*Breaker/Relay*	**O&M CPN (€/turbine/year)**
Share to the total cost	*Min*	1.03%	0.94%	0.81%	0.80%	**89,212**
	Ave	1.32%	0.99%	1.09%	1.00%	**116,533**
	Max	1.51%	1.00%	1.25%	1.11%	**151,667**

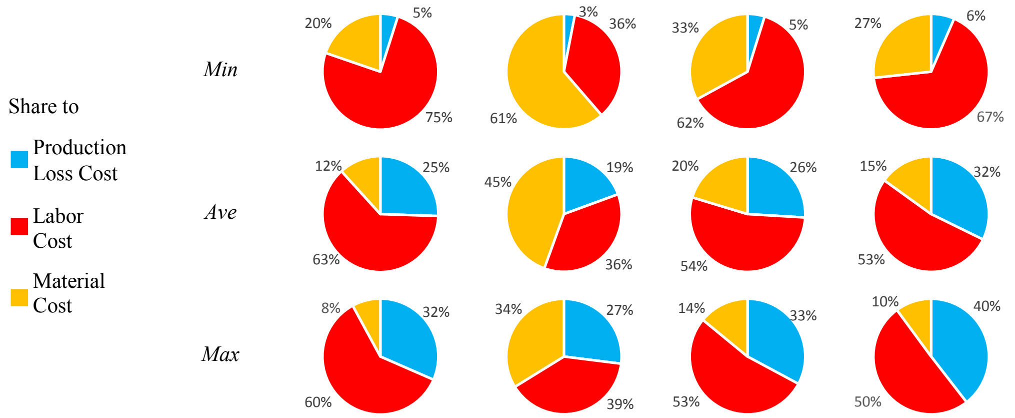

Table 3. Loss of production and technician cost factors for the O&M CPN minimum, average and maximum scenario

Scenario	$\overline{P} \cdot CoE$ **(€/h)**	c_{tech} **(€/h)**
Min	12	50
Ave	105	70
Max	192	100

It has to be noted that the average *O&M CPN* does not correspond to the midrange between the minimum and maximum value, being the *P* varied between 2-4 MW according to the actual capacity of the European installed offshore WTs [29]. The combinations of the performance and cost factors in the "*min*", "*ave*", and "*max*" scenarios are reported in Table 3.

Looking at Table 1-2, it is first noticeable that the top-six components do not change their ranking among the various scenarios. In agreement with what observed by [13], for the UK offshore round 1 structures, and tackled by the Gearbox Reliability Collaborative (GRC) project [33], the gearbox has the highest percentage of the total annual cost for unplanned maintenance operation. Its steady 70% share is caused by the elevated average cost of the material to repair, in the "*min*" scenario, and it is then overtaken by the cost of labor in the high cost scenario. The generator follows, with an almost constant 13% of the total cost, despite of the significant increase of the loss of production cost, among the scenarios. On the other hand, all the other top-10 components participate with values lower than 4% to the total cost. For this reason, despite of the reverse ranking of power supply (or converter), controls and breaker/relay, the average scenario is used for the final FMECA.

To understand, then, what type of failures are the main responsible for their high cost, the share per cost class for the top-three components is plotted in Figure 4. It is observable that both gearbox and generator cost are driven by major replacement cost. However, while the first show and additional high variance with the cost of the technicians, as a consequence of long average repair time, the latter is mainly affected by the high cost of the material for replacement.

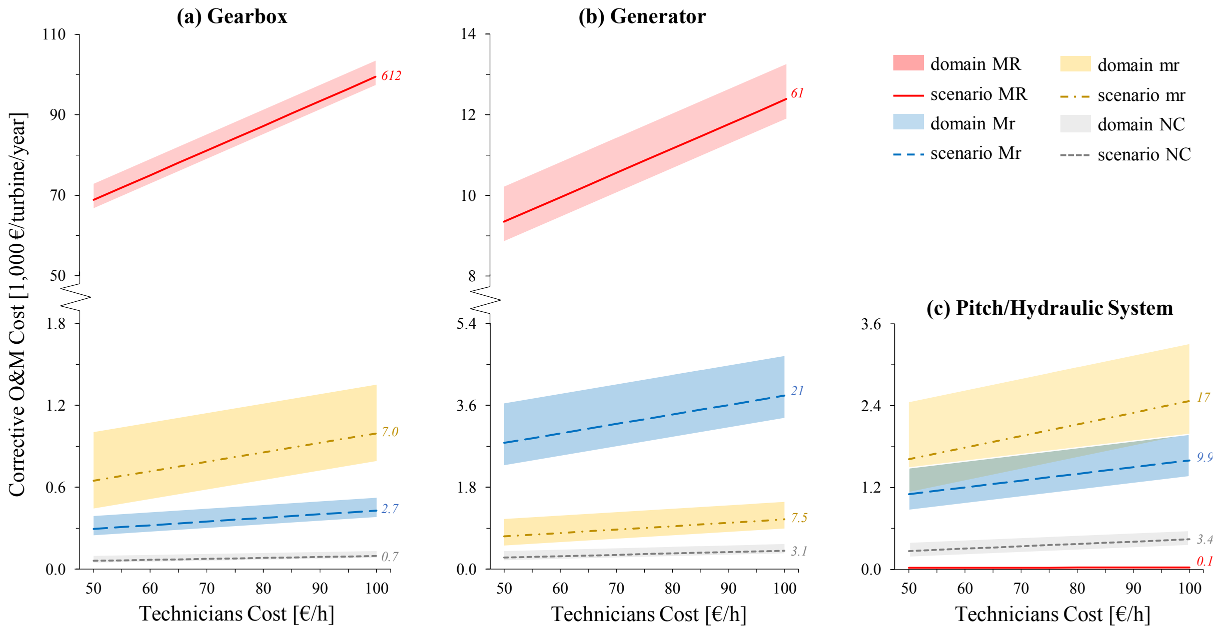

Figure 4. *O&M CPN* (in thousand € per turbine and year) vs c_{tech}, for the top-three ranked components: (a) gearbox, (b) generator, and (c) pitch/hydraulic system. The shaded areas represents the domain of the variation between the assumed *min* and *max* scenarios, whilst lines and the slopes show the trend against the c_{tech} for exemplificative scenario: P = 3.6 MW, CF = 0.36, CoE = 80 €/MWh.

5.2. Cost-based FMECA

The FMECA ranked results, already briefly and visually presented in [3], are shown in Table 4. In that first work the values of failure frequency and cost consequences are converted in dimensionless factor (ranged from 1 to 10), to obtain an expectable ranging of the final values. However, the authors following decided to keep the analysis in dimensional quantities, not to lose the sensitivity on the actual cost to repair, and to easily allow future comparisons between different WT systems. On the other hand, the use of average cost, instead of prioritising by distinguishing per cost class, ease the possible future integration of detectability factor.

Despite the relative long downtime for the reparation of the gearbox (with a weighted average MART of about 63 hours per failure), the share of the loss of production cost, compared to the material and the technicians' expenses, seems to be underestimated. More in general, a small contribution of the cost of energy loss to the total is observable for all the components. The following shortcomings of the presented analysis can possibly justify this trend:

- The use of the *CF* for calculating the lost energy might be appropriate for long downtimes, but it underestimates it for short downtimes. It has been already shown, indeed, that the λ can be related to the wind speed, and failures generally appear in periods with rather high winds [34].
- The logistics, technical and weather-day delays, not yet integrated in these results, can considerably stretch of both long and short downtimes.

Once identified the most critical component(s), a more in-depth analysis of the critical modes of failure has to be performed, following the approach suggested in Figure 1: by accessing the results of specific studies on the components reliability ([33,35]), and, if necessary, updating and completing the ranking by adding component failure-specific detection. A hint on the more likely frequency failure of the generator (either wound rotor or a caged one) and of the pitch/hydraulic systems are reported by [15], while the one for the gearbox have been investigated more in details by the GRC project [33].

Table 4. O&M Cost-based FMECA results (ordered) for the average scenario.

Systems and Sub-System	**λ (failure/turbine/year)**	**Cost Severity (€/failure)**				***O&M CPN* (€/turbine/year)**
		C_M	C_P	C_L	$C_{O\&M}$	
Gearbox	0.633	56,184	6,534	68,807	131,524	83,255
Generator	0.999	6,908	2,083	6,455	15,445	15,430
Pitch/hydraulic system	1.076	490	1,163	1,981	3,633	3,909
Blades	0.52	351	1,213	2,587	4,151	2,159
Other components	1.005	199	637	967	1,803	1,812
Hub	0.235	771	1,654	4,116	6,541	1,537
Controls	0.428	449	948	1,569	2,966	1,269
Contactor/circuit/breaker/relay	0.43	549	692	1,452	2,692	1,158
Power supply/converter	0.18	2,847	1,227	2,312	6,387	1,150
Sensors	0.346	613	787	1,233	2,633	911
Electrical components	0.435	211	587	918	1,716	746
Pumps/motors	0.346	514	515	733	1,762	610
Grease/oil/cooling liquid	0.471	164	420	587	1,171	552
Heaters/coolers	0.213	458	549	886	1,892	403
Yaw system	0.189	281	636	1,026	1,943	367
Tower/foundation	0.185	599	371	568	1,538	284
Transformer	0.065	1,259	979	1,782	4,021	261
Safety	0.392	148	213	267	628	246
Service items	0.125	79	746	1,109	1,934	242

6. Conclusion

In this work, an unbiased approach for the ranking and identification of the most critical components of a population of currently installed WT systems has been proposed, based on an O&M cost estimation.

The main advantages of the proposed methodology are:

- Elimination of the qualitative nature of the severity and detection criticalities, opting for a quantitative conversion of reliability and maintenance statistics;
- Then, elimination of additional "weighting factors" for integrating the relative importance of the criteria.

On the other hand, the areas of improvement are:

- The need to add a second-stage FMEA, to complete the analysis with the components-specific failure modes and failures-specific detection criticality;
- This method can only be used when enough reliability data and/or cost information are provided.

As regards the results from the components ranking, it is clear that further effort is needed to improve the reliability and maintenance of the gearbox, the induction generator, and the pitch system, and to understand the root cause(s) and physics of failure of both their major and minor failures modes. However, the analysis still need to be completed with sensitivity on the service cost (component-dependent attribute, for the type of technicians and unit required) and possible weather day effect.

Acknowledgements
This work is supported by the UK Engineering and Physical Sciences Research Council (EPSRC) HOME-Offshore project (EPSRC Reference: EP/P009743/1). The first author is supported by grant EP/L016303/1 for Cranfield University and the University of Oxford, Centre for Doctoral Training in Renewable Energy Marine Structures - REMS (http://www.rems-cdt.ac.uk/) from the UK Engineering and Physical Sciences Research Council (EPSRC).

References
[1] GL Garrad Hassan 2013 *A guide to UK offshore wind operations and maintenance*
[2] EPSRC 2018 HOME Offshore: Holistic Operation and Maintenance for Energy from Offshore Wind Farms
[3] Lin Z, Cevasco D and Collu M 2018 Progress on the development of a holistic coupled model of dynamics for offshore wind farms, phase I: Aero-Hydro-Servo-Elastic Model, with drive train model, for a single wind turbine *Proceedings of the ASME 2018 37th International Conference on Ocean, Offshore and Arctic Engineering (OMAE2018)* Madrid (Spain) pp 1–9
[4] Kaidis C, Uzunoglu B and Amoiralis F 2015 Wind turbine reliability estimation for different assemblies and failure severity categories *IET Renew. Power Gener.* **9** 892–9
[5] Ma Z, An G, Sun X and Chai J 2015 A study of fault statistical analysis and maintenance policy of wind turbine system *International Conference on Renewable Power Generation (RPG)* p 4
[6] CATAPULT Offshore Renewable Energy 2018 SPARTA: A UK offshore wind performance data benchmarking platform, transforming wind turbine operational performance
[7] Fox A and Hill C 2017 *System Performance, Availability and Reliability Trend Analysis: Portfolio Review 2016*
[8] Fraunhofer IEE and Dresden IZP 2018 WInD-Pool (Windenergie-Informations-Datenpool)
[9] Faulstich S, Hahn B and Tavner P J 2011 Wind turbine downtime and its importance for offshore deployment *Wind Energy* **14** 327–37
[10] Faulstich S, Pfaffel S, Kühn P and Lyding P 2012 Monitoring offshore wind energy use in Europe - Offshore~WMEP *Energy Procedia* **24** 322–7
[11] Pfaffel S, Faulstich S and Rohrig K 2017 Performance and reliability of wind turbines: A review *Energies* **10** 1–27
[12] Crabtree C J, Zappalá D and Hogg S I 2015 Wind energy: UK experiences and offshore operational challenges *Proc. Inst. Mech. Eng. Part A J. Power Energy* **229** 727–46
[13] Feng Y, Tavner P J and Long H 2010 Early experiences with UK Round 1 offshore wind farms *Proc. Inst. Civ. Eng. Energy* **163** 167–81
[14] NoordzeeWind 2008 *Operations Report 2007-2009*
[15] Carroll J, McDonald A and McMillan D 2016 Failure rate, repair time and unscheduled O&M cost analysis of offshore wind turbines *Wind Energy* **19** 1107–1119
[16] Sahnoun M, Baudry D, Mustafee N, Louis A, Smart P A, Godsiff P and Mazari B 2015 Modelling and simulation of operation and maintenance strategy for offshore wind farms based on multi-agent system *J. Intell. Manuf.* 1–17
[17] Rademakers L W M M, Braam H, Obdam T S and Pietermen R P v. d. 2009 *Operation and Maintenance Cost Estimator (OMCE)*
[18] Carroll J, McDonald A, Dinwoodie I, McMillan D, Revie M and Lazakis I 2017 Availability, operation and maintenance costs of offshore wind turbines with different drive train configuration *Wind Energy* **20** 361–78

[19] Leimeister M and Kolios A 2018 A review of reliability-based methods for risk analysis and their application in the offshore wind industry *Renew. Sustain. Energy Rev.* **91** 1065–76
[20] General Electric Company 1979 *Mod 1 Wind Turbine Generator Failure Modes and Effects Analysis*
[21] Bharatbhai M G 2015 Failure Mode and Effect Analysis of Repower 5M Wind Turbine *Int. J. Adv. Res. Eng. Sci. Technol.* **2** 2394–444
[22] Hoseynabadi H A, Oraee H and Tavner P 2010 Failure Modes and Effect Analysis (FMEA) for Wind Turbines *Int. J. Electr. Power Energy Syst.* **32** 817–24
[23] Bueno Gayo J 2011 Final Publishable Summary of Results of Project ReliaWind 1–62
[24] Kang J, Sun L, Sun H and Wu C 2017 Risk assessment of floating offshore wind turbine based on correlation-FMEA *Ocean Eng.* **129** 382–8
[25] Braglia M 2000 MAFMA: multi- attribute failure mode analysis *Int. J. Qual. Reliab. Manag.* **17** 1017–33
[26] Kahrobaee S and Asgarpoor S 2011 Risk-based Failure Mode and Effect Analysis for wind turbines (RB-FMEA) *North American Power Symposium (NAPS)* pp 1–7
[27] Shafiee M and Dinmohammadi F 2014 An FMEA-based risk assessment approach for wind turbine systems: A comparative study of onshore and offshore *Energies* **7** 619–42
[28] Reder M D, Gonzalez E and Melero J J 2016 Wind Turbine Failures - Tackling current Problems in Failure Data Analysis *J. Phys. Conf. Ser.* **753**
[29] Cevasco D and Collu M 2018 Dataset for European Installed Offshore Wind Turbines (until year end 2017)
[30] Pinar Pérez J M, García Márquez F P, Tobias A and Papaelias M 2013 Wind turbine reliability analysis *Renew. Sustain. Energy Rev.* **23** 463–72
[31] Hahn B, Welte T, Faulstich S, Bangalore P, Boussion C, Harrison K, Miguelanez-Martin E, O'Connor F, Pettersson L, Soraghan C, Stock-Williams C, Dalsgaard Sørensen J, Van Bussel G and Vatn J 2017 Recommended practices for wind farm data collection and reliability assessment for O&M optimization *14th Deep Sea Offshore Wind R&D Conference, EERA DeepWind'2017* vol 137 (Trondheim, Norway: Elsevier B.V.) pp 358–65
[32] Maples B, Saur G, Hand M, van de Pietermen R and Obdam T 2013 Installation, Operation, and Maintenance Strategies to Reduce the Cost of Offshore Wind Energy *Tech. Rep. Nrel/Tp-5000-57403* 1–106
[33] Link H, Lacava W, Dam J Van, Mcniff B, Sheng S, Wallen R, McDade M, Lambert S, Butterfield S and Oyague F 2011 *Gearbox Reliability Collaborative Project Report : Findings from Phase 1 and Phase 2 Testing* 85
[34] Tavner P, Edwards C, Brinkman A and Spinato F 2006 Influence of Wind Speed on Wind Turbine Reliability *Wind Eng.* **30** 55–72
[35] Sandia National Laboratories 2015 Blade Reliability Collaborative