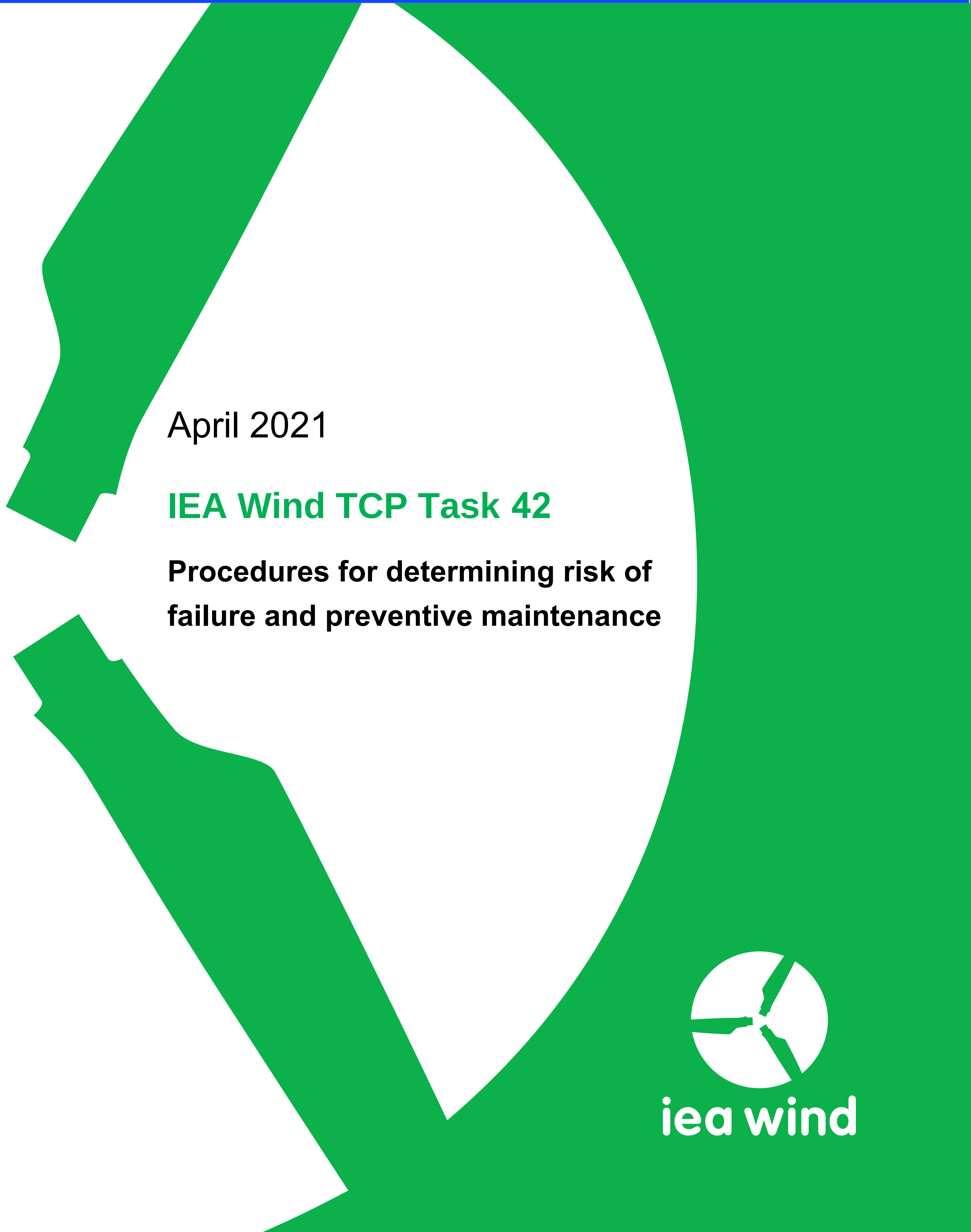
Technology Collaboration Programme
by iea



April 2021

IEA Wind TCP Task 42

Procedures for determining risk of failure and preventive maintenance

iea wind

IEA Wind Task 42

Lifetime Extension Assessment

Deliverable Report 2: Procedures for determining risk of failure and preventive maintenance

April 2021

Anand Natarajan, W. Dheelibun Remigius
Technical University of Denmark

Jannie S. Nielsen
Aalborg University

Clemens Hübler, Tanja Greissmann
University of Hannover

Contents

Executive Summary:

Minimizing operation and maintenance (O&M) costs for wind farms, offshore and onshore is feasible through the quantification of the risk of failure of the wind farm assets over time and addressing that risk through preventive maintenance. The risk is established using a risk priority number, which is also associated with the cost of failure. Accuracy in the risk priority can be achieved using failure mode effect analysis and root cause analysis of past failures. Monitoring and inspection of assets is also essential. This report outlines in brief these processes and the quantification of risk and remaining useful life evaluation. Monitoring of wind turbine structures for fatigue life consumption and the need for extrapolation of fatigue damage equivalent load is explained in brief, so that an accurate forecast of the remaining useful life of major structures such as blades can be obtained. Recommendations for implementing preventive maintenance and prognostics is provided.

1 Introduction

Wind farm operational and maintenance (O&M) costs are primarily a result of necessary costs for operating the wind farm, planned maintenance, unplanned maintenance and due to failures. The planned maintenance costs include regular maintenance needs such as gearbox oil change, greasing bearings and other items ensuring optimal wind turbine performance. These maintenance tasks are usually mandated through a maintenance contract and also planned through remote monitoring of the wind turbines. Such planned maintenance is cost effective and is not a major concern. Unplanned maintenance makes up for the vast majority of maintenance costs, especially offshore (Nielsen, 2013) and this is even more exacerbated when failures occur. Examples of causes of unplanned maintenance include pitch bearing erosion, blade leading edge erosion, converter failures etc. For replacing failed wind turbine components, the supply chain for the replacement must be in place, otherwise this leads to large downtime of the wind turbine and loss of production. Offshore, replacement of large wind turbine components can require the need for larger ships such as jack-up vessels, which can lead to large downtime dependent on the availability of these vessels.

The above economic consequences of unplanned maintenance can result in large costs of wind energy to the wind farm owner and thereby the risk of failure needs to be sufficiently reduced to ensure profitability and safe operation. Further, when wind farms come out of their warranty period, there is a strong need to quantify the remaining lifetime of their assets, and make informed decisions about replacements and repairs so as to avoid costly downtime and to plan replacements to minimize the cost involved. Therefore, there is the need to reduce the risk of failure through improved forecasting of various aspects, not only of weather and environmental conditions for maintenance access offshore, but also in terms of component maintenance needs and supply chain inventory.

Offshore wind farm maintenance requires careful safety and financial planning, due to the harsh, complex and variable environment. It is required to remove the need for wind farm operators to plan daily maintenance schedules without intelligent forecasts being available. The maintenance process includes planning the logistics, forecasting weather windows, travelling to the site and actual repair time (Le B. and Andrews, J.). Balancing large fleets of vessels, spares, technicians and turbines, with planned maintenance activities, in order to deliver the greatest net income over the year is to be achieved through the use of data analytics and decision making. By providing data-driven schedule optimization techniques designed specifically for the farm manager, long periods of unnecessary downtime and missed weather windows can be avoided offshore.

It is also required to reduce the need for human inspection of turbines, which is not only risky and costly, but also implies that inspection data - for example from blades or foundations - is infrequently gathered. By the use aerial drones, underwater autonomous vehicles offshore designed specifically for wind farm inspection tasks and intelligent sensors mounted on turbines will provide essential regular data input for component degradation and predictive maintenance systems, such that human inspection is needed only when the remote monitoring systems show the need for it.

Risk-based O&M will ensure that decision on maintenance is made to minimize expected costs, considering also how the availability of the turbines is affected by the maintenance strategy. Choosing an optimal strategy, will contribute to increasing the net capacity factor and reducing the maintenance costs.

2 Methods of Risk Assessment

According to IEC/ISO 31010, risk assessment is the overall process of risk identification, risk analysis and risk evaluation. The first step is to identify events that are associated with risk. In the risk analysis, the consequences and the probability that the consequences occur are combined to determine a level of risk. This risk level can be qualitative, semi-quantitative and quantitative. In the risk evaluation, it is determined whether the risks are acceptable, or whether risk treatment measures should be taken to reduce risks. Risk assessment therefore is the basis for decisions on risk treatment. Various methods can be applied in the process of risk analysis; IEC/ISO 31010 describes 31 methods.

2.1. Root Cause Analysis

Root cause analysis details the reasons for unexpected behavior, faults and failures in wind farms, based on measured field data, inspections and numerical models. Conducting Root Cause Analysis helps wind farm owners reduce the risk of future failure and improve their wind farm future performance. The findings can also lead to continuous improved design standards such as the IEC 61400-4 on gearbox design or IEC 61400-5 on blade design.

Examples of inspection base root cause analysis can be the analysis of the failure of a bearing that requires that bearing grease and segments from the bearing are sent to a laboratory for chemical analysis and microscopy to understand the metals in the bearing grease/oil and mode of bearing failure that was suffered. Figure 1 shows a visual grease examination from a pitch bearing that shows macroscopic small metal particles, which are mostly normal after several years of operation. The results of such analysis will let the wind farm owner know whether the bearing is degraded, requiring replacement or if more turbines in the wind farm can have bearing problems, prompting a large scale maintenance planning or if there needs to be a change in the operation of the wind turbines to mitigate the probability of future failures. The same bearing failure root causes may also be discerned using field measurements if the bearing was equipped with temperature or vibration measurement sensors. The readings of these sensors when correlated with turbine operational measurements as a function of the location of the turbine within a wind farm can provide valuable information on the reasons for the failure.

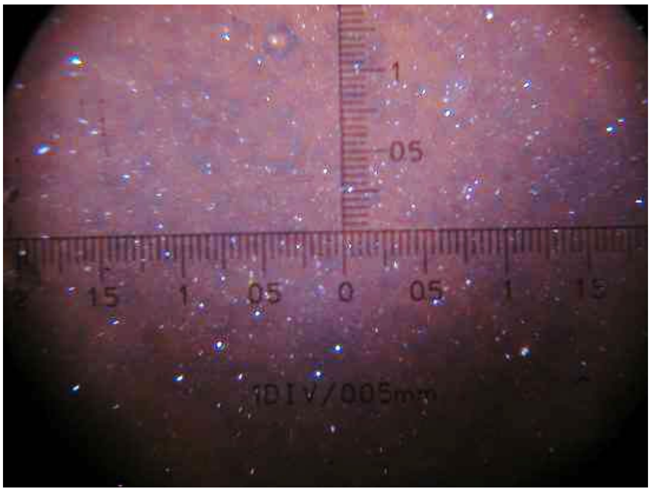


Figure 1: Grease from a pitch bearing showing white particulates less than 0.5 mm in size. (Natarajan, et.al.)

It is also possible to make simulation based root cause analysis, such as through the use of calibrated aeroelastic models of the wind turbine or other digital twins of the wind turbine/wind farm. Such models can use measured site environmental conditions to reproduce with sufficient accuracy the mechanical loading on different turbine components as seen on the wind farm. This may then suggest overloading or improper operation scenarios that lead to a particular component failure or the probability of that component failing in a given time. However these type of software models usually assume that cause of failure is loads or environmental condition or operation driven. Such correlations between failures and operating conditions or loads is not always discernable. Many a time the cause of failure is due to manufacturing defects which will not be detected through software simulations.

2.2. Failure mode and effects analysis

Failure mode and effects analysis (FMEA) is a widely used reliability engineering technique for designing, identifying and eliminating potential/known system failures. It has emerged as a powerful tool for risk and reliability analysis of systems in a wide range of industries including automotive, nuclear, construction, etc. FMEA is a structured, bottom-up approach that starts with potential/known failure modes at lowest level (i.e., component level) and investigates the effect of the component level failure on the next sub-system level and then this process continues until the system level. The way in which a component, sub-system or system could potentially fail to perform its desired task is known as the failure mode and a cause that leads to the failure is known as a failure cause. Upon identifying the failure modes, for each failure modes, it’s ultimate effects need to be determined by the experts of the cross-functional team. A failure effect is defined as the result of a failure mode on the function of the system as perceived by the user.

D2 Procedures for determining risk of failure and preventive maintenance

Pillay and Wang (Pillay & Wang, 2003) outlined the process for carrying out an FMEA can be divided into several steps as briefly explained here (Mahmood Shafiee & Dinmohammadi, 2014):

1. Collect the system function information: develop a good understanding of the system functionalities and then, divide the system into sub-divisions and use schematics and flow charts to identify relations among sub-assemblies; lastly, prepare a complete part list for each sub-assembly.

2. Identify the failure modes of each sub-assembly.

3. Consider how the failure modes might affect the performance of sub-assemblies, sub-divisions, and the entire system.

4. Identify the operational and environmental stresses that cause failures.

5. Estimate the probability of failure occurrence, and find the occurrence ranking (O) using the 10-point scale.

6. Categorize the hazard level of each failure, and find the severity ranking (S) using the 10-point scale.

7. Identify the current control schemes to detect or prevent a given cause of failure, and find the detection ranking (D) using the 10-point scale.

8. Calculate the risk-priority-number (RPN) which is defined as the product of the occurrence (O), severity (S) and detection (D) of a failure, i.e., $RPN = O \times S \times D$.

9. Rank the RPN values that are between 1 and 1000 to find out the failures with higher risks for correction.

10. Develop recommendations (preventive or corrective actions) to enhance the system performance.

11. Prepare FMEA report by summarizing the analysis in a tabular form.

FMEA was applied for the risk analysis of a 2 MW wind turbine in (Arabian-Hoseynabadi et al., 2010) to prioritize the failure modes using the field data and then comparison was made between the quantitative results of the FMEA and reliability field data from real wind turbine systems and their assemblies. Tavner et al. (Tavner et al., 2010) focused on the reliability analysis of a wind turbine as a single, complex system, consisting of several mechanical, electrical, and auxiliary assemblies at its design stage. They applied FMEA to the design of availability of a 2 MW geared R80 wind turbine. By comparing the prospective reliabilities of three versions of geared wind turbine, they proposed solutions to reduce the overall failure rate of the turbine and raise its availability. Das et al., (Das et al., 2011) presented a FMEA on a 2 MW doubly fed induction generator (DFIG) based on data collected from field experts. Kahrobaee and Asgarpoor (Kahrobaee & Asgarpoor, 2011) presented a quantitative approach called Risk-Based-FMEA of the wind turbines based on their failures modes contributions to the total failure cost. To evaluate the risk of the failure mode, a new quantity called cost priority number (CPN) was introduced. The CPN is obtained by multiplying the probability of occurrence, the probability of not detecting the failure and the cost consequence of the failure. The CPN was introduced to overcome the drawback of the RPN that it is not informative enough to assess the component criticality. They demonstrated the proposed method to a 3MW direct drive wind turbine. Shafiee and Dinmohammadi (Mahmood Shafiee & Dinmohammadi, 2014) performed a comparative study using the traditional RPN based FEMA and the CPN based FEMA on two same type of onshore and offshore wind turbines and showed the effectiveness of the CPN based FEMA. They also developed a fuzzy-FMEA model to analyze risk and failure mode in offshore wind turbines (M Shafiee & Dinmohammadi, 2013). They used a fuzzy version of traditional FMEA to combine the qualitative (expert experience) and quantitative data. The proposed approach was applied to an offshore wind turbine and the results are compared with the traditional FMEA. Sinha and Steel (Sinha & Steel, 2015) applied Failure Modes Effects and Criticality Analysis (FMECA) as a structured failure analysis tool to evaluate the risk and priority number of a failure and thereby assist in prioritizing maintenance works for wind turbines. By proposing modifications to the RPN estimation procedures, they showed that better evaluations of the wind turbine critical failures can be obtained and also illustrated the usefulness of the RPN number in identifying and prioritizing failures, and consequently designing a cost effective maintenance plan. Zhou et al., (Zhou et al., 2015) proposed a framework for fault diagnosis of wind turbines on the basis of ontology and FEMCA. Tazi et al. (Tazi et al., 2017) proposed a hybrid cost-FEMA to overcome the limitations of the RPN by combining the following indicators: failure rates, expected failure costs and loss of production costs to identify the failure modes. All these three indicators are evaluated by making use of the available field data and hence it does not require any probability assessments. Ozturk et al. (Ozturk et al., 2018) applied FMECA to study the reliability and availability behavior of wind turbines by considering different weather conditions or climatic regions. Different climatic regions of Germany were investigated and differences in the behavior of the wind turbines were listed out. Further, they applied the FMECA to compare the criticalities of geared and direct drive wind turbine subsystems controlling climatic conditions. The main outcome of the study was that downtime and cost criticalities of sub systems depend on the locations and types of wind turbines. Catelani et al., (Catelani et al., 2020) regulated the FMECA technique by proposing a method to identify the risk threshold and consequently to categorize the failure modes as critical modes and negligible modes. By means of the statistical parameters and box plot of the RPN set, the risk threshold was defined. Accordingly, the critical modes are the failure modes with RPNs above the 75th percentile and the negligible modes are with RPNs below the median value. The modes with RPNs falls between the median and 75th percentile are quantifies as ALARP (as low as reasonably practicable) modes.

2.3. Probabilistic risk analysis

A coherent framework for risk assessment is described in the JCSS document “Risk Assessment in Engineering” (JCSS 2008). Other risk analysis methods can be considered as simplifications or parts of this framework. If methods not in line with this framework are applied, it will generally not lead to rational allocation of resources within risk management. All models are simplifications of the reality, but the impact of simplifications should be critically assessed. Risk assessment can be seen in the context of decision making for management of risks. The risk R_E associated with an event is the product of the probability p_E of the hazardous event and the consequences c_E of the hazardous event:

$$R_E = p_E \cdot c_E \tag{1}$$

For decision making in the context of risk assessment, decisions can be seen as either commitment of resources to limit the probability or severity of hazards or commitment of resources to obtain knowledge of the state of the system.

If no clear conclusion on the probability of failure of a structure or component can be made based on the preliminary risk assessment, a detailed risk assessment is recommended. The detailed assessment includes detailed review of past inspection documents, new inspections, testing in a lab, and detailed structural analysis based on updated models.

Decision making can be seen as an optimization problem, where the decision maker seeks to optimize an objective function, under some constraints. Two levels are relevant to consider: Societal decision making, and decision making from a private stakeholder. Examples of societal decision making are the rules in standards, national regulations, and decisions made by governmental organizations. The decision problem should be described from the point of view of the decision maker, with focus on the decisions that the decision maker has mandate to make. The space of possible decisions is constrained due to rules, regulations, contracts, and practicalities caused by decisions made by other decision makers in the organization. If only costs and consequences are considered, the objective function can be formulated as the total risk, which equals the total expected costs, and should be minimized. If also benefits are affected by the decisions, the objective function will typically be formulated as the total expected utility, which should be maximized.

The preferences of the decision maker are modeled by the utility function. Contributions to the utility are the benefits, costs, and potential direct and indirect consequences associated with hazards, which occurrence are affected by the decisions – seen from the perspective of the decision maker. Some contributors to utility are in monetary value; this will often be the case for some benefits, costs, and direct consequences. Indirect consequences include consequences that are not caused directly by hazards, but instead are caused by the failure of the system due to the hazard, such as loss of benefit or loss of reputation.

The total expected utility can be found by summation of all contributions to risk within the considered timeframe. The considered timeframe can be infinite, if a portfolio of assets is considered, where the same decisions strategies on renewals and maintenance are applied repeatedly. The considered timeframe can also be the remaining operational lifetime, which might be uncertain. All contributions to the total expected utility should be transformed to a common utility measure by net present value calculations. Risk-informed decision making following ISO 2394: 2015 can be applied for fleets of structures through standardization, by deriving risk-based target reliability levels specifically for life extension of wind turbines, as done in (Nielsen & Sørensen 2021). Alternatively, the approach can be applied directly by asset owners.

2.4. Risk Priority numbering

Risk priority numbering is a widely used technique, which allows for simple semi-quantitative risk analysis. It is included in the standard DS/EN IEC 60812:2018. The risk priority number (RPN) is calculated as follows:

$$RPN = S \cdot O \cdot D \tag{1}$$

where ordinal rating scales 1 to 10 are used for severity rating (S), occurrence rating (O), and detectability rating (D). The RPN will therefore be an integer value in the interval 1 to 1000. As the scales are ordinal, numerical ratios have no specific meaning. The RPN can be compared between different failure modes, but two failure modes with same RPN does not necessarily impose the same risk as introduced in section 2.3. RPN numbers cannot be aggregated from sub components to a component. A high RPN should be considered as a qualitative indication of risk, and could indicate where to focus qualitative analyses. Decision making based on RPI will generally not lead to rational allocation of resources within risk management.

An alternative risk priority number (ARPN) to overcome these flaws was proposed by Braband (2003). The alternative risk priority number is based on a consistent risk quantification, such that same ARPN means same risk. It uses that the risk of failure can simply be calculated by:

$$R = s \cdot o \cdot d \tag{2}$$

where s is the consequence of failure, o is the probability of failure, and d is the probability that consequences are not avoided by early detection. To retain the simplicity of the RPN number, it is convenient to define ratings as integer numbers, e.g. 1 to 10. However, the ratings will typically not correspond to a linear increase in severity, occurrence, and detectability. Often it is more appropriate to describe the ratings on a logarithmic scale. Taking the logarithm with base *b* of (2) yields:

$$\log_b(R) = \log_b(s \cdot o \cdot d) = \log_b(s) + \log_b(o) + \log_b(d) \tag{3}$$

The alternative risk priority number is therefore defined as $ARPN = \log_b(R)$:

$$ARPN = S + O + D \tag{4}$$

where severity rating (S), occurrence rating (O), and detectability rating (D) are all defined on logarithmic scales with same base *b*.

It is possible to aggregate failure mode risks R_i as given in (2) by simple summation:

$$R = \sum_{i=1}^{n} R_i \tag{5}$$

For failure modes with risk priority numbers $ARPN_i$, aggregation can therefore be performed by:

$$ARPN = \log_b(R) = \log_b\left(\sum_{i=1}^{n} R_i\right) = \log_b\left(\sum_{i=1}^{n} b^{\log_b(R_i)}\right) = \log_b\left(\sum_{i=1}^{n} b^{ARPN_i}\right) \tag{6}$$

2.5. Strain measurement-based fatigue assessment

The previously described procedures for determining the risk of failure are quite general ones, which are applicable to different types of structures and/or failures. In this section, a specific method for determining the risk of fatigue failure especially for wind turbine steel components is presented. The importance of such methods becomes apparent when considering the latest DNVGL standard for lifetime extensions of wind turbines (DNVGL-ST-0262). This standard states: “The focus of the assessment is the fatigue limit state.“ Assessments are normally based on aero-elastic simulations. However, the standard also states: “Measurements – both of the turbine response (e.g. component load measurements) and of the local site conditions (e.g. from met-mast) – may also be considered in the assessment”. Hence, measurement-based fatigue assessments are recommended. Nonetheless, these methods are not further specified. Moreover, it is not clear whether they can replace aero-elastic simulations or at least how exactly they can be used to support these simulations. A main reason for this vaguely formulated recommendation to also use measurement-based approaches is that these procedures are neither harmonized nor verified or validated. That is why in the following, some of these methods are presented. Their verification and validation and the following harmonization are current research for example in this IEA wind task 42 – wind turbine lifetime extension.

To analyze the risk of fatigue failure using strain measurements, first, short-term (10 min) damages have to be calculated. The calculation of short-term damages is a relatively standardized procedure, especially, if strain measurements at the position of interest are available. This means that no spatial extrapolation is required. This fact is assumed here, since spatial extrapolation is a different topic. Approaches for spatial extrapolation are, for example, static extrapolation (Hübler et al., 2018) or virtual sensing (Maes et al, 2016). If strain measurements are available at the position of interest, short-term damages can be calculated as follows:

a) Calculate stresses using $\sigma = E\epsilon$ and the measured strain signals (ϵ)
b) Apply stress concentration factors (SCF), safety factors, and other corrections to the stress signals
c) Apply Rainflow counting to the corrected stress signals to determine the number of cycles for all stress bins
d) Use linear damage accumulation (Palmgren-Minor-Rule) and S-N curves to determine equivalent short-term damages

It is unrealistic that strain measurements are available for the entire lifetime of a turbine, so that some kind of extrapolation in time is necessary. For this extrapolation, four possible approaches are briefly presented here. For further information, it is referred to Hübler et al. (2018).

a) Simple deterministic extrapolation:

The mean value of all available short-term damages is calculated. Subsequently, this value is multiplied by the number of 10 min-intervals (short-term damages) in the entire lifetime. The main disadvantage of this approach is that it does not take into account that environmental conditions might vary in the long-term during the lifetime. Hence, if all available measurements are from years with benign environmental conditions, the extrapolation will underestimate the actual fatigue damage.

An example assessment consists of analytical load assessment through an aero-elastic simulation performed with an appropriate software. The aero-elastic simulation is made considering wake effects, based on all wind turbines in the wind farm within a radius of *10* Rotor Diameters of the turbine being assessed. The effective turbulence intensity TI_{eff} is calculated taking the ambient turbulence intensity and the turbulence generated by wakes. The total life of a turbine structure is obtained by multiplying the life time factor F by the design life time (TD)

$$TD = F \cdot 20\ years$$

F is found by computing the annual Damage Equivalent Loads (DEL) for the site specific wind conditions DEL_{ss} and for the reference wind conditions that the turbine was designed for, DEL_{ref}. Lifetime factor, *F* is computed as:

$$F = \left(\frac{DEL_{ref}}{DEL_{ss}}\right)^{m}.$$

Where *m* is the material Wöhler Exponent,

The assessment results in a total life time for each of the turbines in the wind farm, from which the remaining life can be computed.

b) Simple probabilistic extrapolation:

Since the "simple deterministic extrapolation" is based on a limited amount of data, for example, aeroelastic simulations over one year, it features a significant amount of uncertainty. To estimate the uncertainty, a probabilistic approach based on bootstrapping can be applied. In case of the "simple probabilistic extrapolation", not the mean value of all available short-term damages is calculated, but the mean value of N randomly drawn short-term damages (with replacement). N represents the number of available short-term damages. This means that each short-term damage can be drawn once, but it may be chosen more than once or not be selected at all. In a second step, the calculated mean of the N samples is multiplied by the number of 10 min-intervals in the entire lifetime. If this is repeated several times, e.g. 10.000 times, a statistical distribution of lifetime values the result. This distribution represents the uncertainty of the extrapolation based on limited data.

c) Deterministic extrapolation based on wind speed correlations:

Simple extrapolations are based on the assumption that the available strain data is representative for the entire lifetime of the turbine. However, this is not always the case. For example, if all measurements were conducted during benign environmental conditions, simple extrapolations (deterministic and probabilistic ones) yield too low fatigue damages. Hence, a more advanced approach is to consider correlations of short-term fatigue damages and environmental conditions. Here, only wind speed correlations are considered, but correlations with other environmental and operational conditions (EOCs) are possible as well (Hübler et al., 2016). To consider wind speed correlations, first, all short-term damages are sorted into wind speed bins. For example, if there was a mean wind speed of 5.7ms^{-1} during a 10 min-interval, the corresponding short-term damage is put into the wind speed bin 4 to 6ms^{-1}. The precise size of the bin depends on the amount of available data. Second, in each bin, the mean damage is calculated. Third, the mean damage of each bin is multiplied by the occurrence probability of this wind speed bin. There are different possibilities how this probability can be determined (Hübler et al., 2016). The most common ones are the use of long-term distributions, which were used during the design, and the use of empirical distributions based on SCADA data. The latter one has the advantage that data of the precise site and correct time period is used. Moreover, in most cases, SCADA data of several years or even the entire lifetime is available, whereas strain data is only available for a limited time period. The last step is – as before – the multiplication by the number of 10 min-intervals in the entire lifetime.

d) Probabilistic extrapolation based on wind speed correlations:

Similar to the simple extrapolation, the extrapolation based on wind speed correlations still features a significant amount on uncertainty due to limited data. Short-term damage values in each bin are scattering and might not cover all possible combinations of environmental conditions. For example, during the covered measurement period, most of the time the wind came from western directions leading to different fatigue damages compared to eastern wind conditions that might occur more frequently during all other (non-covered) years. Hence, a probabilistic approach estimating the uncertainty of the extrapolation is useful. For the "probabilistic extrapolation based on wind speed correlations", bootstrapping, i.e. random selection with replacement, is conducted within each wind speed bin. This means that step 2 of the "deterministic extrapolation based on wind speed correlations" Is repeated N times. This yields a statistical distribution of fatigue lifetime values.

e) Probabilistic extrapolation of Damage Equivalent loads

The DELs computed using aeroelastic simulations or measured on the wind turbine components are over finite time. Therefore it is required to determine the lifetime DEL based on limited simulations using site wind conditions or through load measurements over a year and compare that with the DELs obtained using the turbine design basis. This comparison can be realistically achieved through probabilistic extrapolation of the DEL to low probabilities of exceedance. Figure 2 shows the probability of exceeding the magnitude of the 10-minute damage equivalent flap moment at the blade root at two different mean wind speeds. Such an extrapolation allows the selection of an appropriate probability of exceedance of the DEL that should be used in remaining life assessment, that is what is the acceptable exceedance probability above which, the component is said to have reached its intended lifetime.

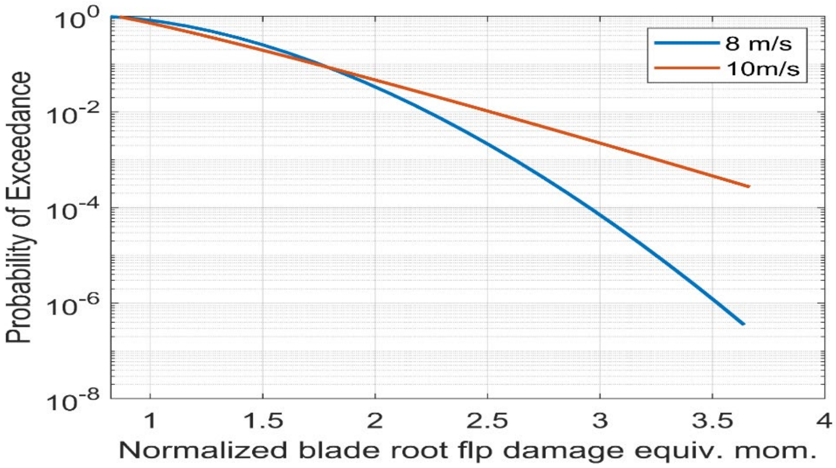


Figure 2: Probability of exceedance of the 10-minute blade root damage equivalent moment determined using extrapolation methods

3 Maintenance procedures

Maintenance is broadly classified as planned maintenance, unplanned maintenance and preventive maintenance. We do not focus on unplanned maintenance here, as the objective is avoid unplanned maintenance through the use of predictive techniques.

3.1. Planned Maintenance

Planned maintenance is usually the main approach used by wind farm owners, wherein the guidance from the turbine manufacturer or expertise of the technicians in the company are used to predict which turbine components required maintenance and at what time intervals. This is based on the built-up knowledge over time by the wind farm owner, which enables them to “predict” when manual intervention in a wind farm is necessary. These planned maintenance schedules are also validated through visual inspections of the wind turbines. However since inspection reports are usually hand-written and made by personnel different than those performing maintenance, there may not be a good correlation between problems identified in inspection reports and those fixed during maintenance (Natarajan, A. et.al.). Therefore digitalization of inspection and maintenance records to ensure a good correlation between problems identified and repairs implemented is essential for planned maintenance to be effective. If the wind farm life is extended, the objective should be to be able to keep the same level of inspections/maintenance after life extension of a turbine as during the original design life of the turbine.

3.2. Prognostics

Prognostics is the basis by which predictive maintenance can be made, that is to be able to predict which turbine components in a wind farm need repair, servicing so as to prevent failures or to predict the remaining life of the wind farm conditional on the operational conditions. Wind farm that farms have complex interactions amongst its constituent wind turbines and therefore the performance and operation of the wind farm is strongly correlated to operational set points of the individual turbines. For example the effects of wakes on downstream turbines results in higher fatigue damage and lower energy production, so much so that under some conditions, the overall energy production from the farm may increase if some of the upstream turbines are shut-down or curtailed. The effect of the type of wind farm operation on the health of its constituent wind turbines can be predicted using prognostic methods.

Prognostics can be broadly classified into data-driven methods and model driven methods (Rezamand , M., Kordestani, M., Carriveau, R., Ting. D.S.K., et.al.). Data-drive methods use the measurements from the wind turbines actively, such as through machine learning algorithms to quantify the health of wind turbine components and structures and thereby predict the need for maintenance. Model-driven methods utilize physics based models to predict the degradation in wind turbine structures and components. In practice a combination of data-driven and model-driven methods can be more effective and link the wind turbine integrity to its original design basis.

The output of a prognosis model should communicate to the wind farm owner the remaining useful life of several wind turbine components, levels of degradation over time, future output forecasts from the wind farm, the time window available for performing maintenance and the suitability of wind farm operational change to maximize performance (Le B. and Andrews, J.).

3.3. Preventive Maintenance

Preventive maintenance is the maintenance performed to keep a turbine in satisfactory operating condition, thereby preventing failures or major defects. Decision support models in the literature have considered various factors on wind farm maintenance, e.g. the availability of various resources, spare parts, and appropriate skilled personnel. Preventive maintenance should be planned during periods when shutdown of turbines will have the least impact on the net energy production, for example during low wind speeds or during periods when the grid demand is low. Accessibility of offshore wind farms is significantly affected by site weather conditions and the availability of appropriate maintenance vessels. The weather conditions offshore that determine maintenance operations are mainly the wind speed and significant wave height. If weather conditions are appropriate, required vessels are available and the component supply chain is sufficient, preventive maintenance of all turbines in the wind farm can be performed at the same time to minimize costs. Experience has shown that the downtime energy loss and maintenance cost is minimize using a maintenance scheduling approach that had correctly determined:

1) Feasible Weather conditions time window
2) Ship availability
3) Component supply chain
4) Available labor force

4 Recommendations for implementation in practice

A comprehensive risk assessment of wind farm assets is required at regular intervals to provide minimal maintenance costs. This paves the way for preventive maintenance and optimal power production. A readily implementable risk measure is the risk priority number, which is the product of severity of failure, occurrence and detectability. The risk quantification can also lead to a decision making framework that seeks to minimize the cost associated with the risk. To ensure accurate RPN, analysis of potential failure modes and their impact must be made. Such FMEA, may involve inspections, monitoring and review of past incidents. Prognostics based methods of predicting future faults and the probability of failure of components based on present data and models can be implemented, which can lead to predictive maintenance. Remaining life of wind turbine structures needs to be determined using a combination of monitoring and modeling strategies with extrapolation. The following actions are essential for these risk based decisions to be accurate and effective:

1) Digitalization of inspection and maintenance reports, so that a correlation and tracking mechanism is possible between issues detected during inspections with those resolved during maintenance.
2) Correlations of short-term fatigue damage estimations using measurements or simulations with measured environmental conditions is required to determine the reasons for specific damage equivalent load measures and to be able to predict the trend in damage equivalent loads in the future, given a variation in met-ocean conditions.
3) Measurement based fatigue assessment is preferred, but extrapolation for fatigue damage using different techniques is essential for remaining life assessment.
4) The RPN number should be complemented with a cost quantity in terms of the consequence of failure, given that the failure is not detected.
5) Decision support models for maintenance planning is essential that takes into account a combination of factors such as weather windows, fleet availability, labor cost and supply chain.

References

Arabian-Hoseynabadi, H., Oraee, H., & Tavner, P. J. (2010). Failure Modes and Effects Analysis (FMEA) for wind turbines. *International Journal of Electrical Power and Energy Systems*, *32*(7), 817–824. https://doi.org/10.1016/j.ijepes.2010.01.019

Braband, J. (2003), Improving the Risk Priority Number concept, Journal of System Safety, 3, p. 21-23

Catelani, M., Ciani, L., Galar, D., & Patrizi, G. (2020). Risk assessment of a wind turbine: A New FMECA-Based tool with RPN threshold estimation. *IEEE Access*, *8*. https://doi.org/10.1109/ACCESS.2020.2968812

DS/EN IEC 60812:2018: Failure modes and effects analysis (FMEA and FMECA)

Das, M. K., Panja, S. C., Chowdhury, S., Chowdhury, S. P., & Elombo, A. I. (2011). Expert-based FMEA of wind turbine system. In *Ieee International Conference on Industrial Engineering and Engineering Management*. IEEE. https://doi.org/10.1109/IEEM.2011.6118183

Hübler, C., Weijtjens, W., Rolfes, R., & Devriendt, C. (2018). Reliability analysis of fatigue damage extrapolations of wind turbines using offshore strain measurements. J. Phys. Conf. Ser, 1037, 032035.

IEC/ISO 31010:2009: Risk management – Risk assessment techniques.

ISO 2394:2015 General principles on reliability for structures

JCSS, Risk Assessment in Engineering: Principles, System Representation & Risk Criteria, 2008, ISBN 978-3-909386-78-9

Kahrobaee, S., & Asgarpoor, S. (2011). Risk-based failure mode and effect analysis for wind turbines (RB-FMEA). In *Naps 2011 - 43rd North American Power Symposium*. IEEE Computer Society. https://doi.org/10.1109/NAPS.2011.6025116

Le B. and Andrews, J. (2016) " Modelling wind turbine degradation and maintenance", Wind Energy; Vol. 19, 571–591

Maes, K., Iliopoulos, A., Weijtjens,W., Devriendt, C. & Lombaert, G. (2016). Dynamic strain estimation for fatigue assessment of an offshore monopile wind turbine using filtering and modal expansion algorithms. Mech. Syst. Signal Process, 76–77, 592–611.

Natarajan, A., Dimitrov, N. K., William Peter, D. R., Bergami, L., Madsen, J.(2020), et. al. “Demonstration of Requirements for Life Extension of Wind Turbines Beyond Their Design Life”, DTU Wind Energy Report No. E-0196,

Nielsen, J.S. (2013) " Risk-Based Operation and Maintenance of Offshore Wind Turbines", Ph.D. Thesis, Aalborg University.

Nielsen, J. S., & Sørensen, J. D. (2021). Risk-based derivation of target reliability levels for life extension of wind turbine structural components. Wind energy, https://doi.org/10.1002/we.2610

Ozturk, S., Fthenakis, V., & Faulstich, S. (2018). Failure modes, effects and criticality analysis for wind turbines considering climatic regions and comparing geared and direct drive wind turbines. *Energies*, *11*(9). https://doi.org/10.3390/en11092317

Pillay, A., & Wang, J. (2003). Modified failure mode and effects analysis using approximate reasoning. *Reliability Engineering and System Safety*, *79*(1), 69–85. https://doi.org/10.1016/S0951-8320(02)00179-5

Rezamand , M., Kordestani, M., Carriveau, R., Ting. D.S.K., et.al. (2020), "Critical Wind Turbine Components Prognostics: A Comprehensive Review", IEEE Transactions On Instrumentation And Measurement, Vol. 69(12), 9306-9328.

Shafiee, M, & Dinmohammadi, F. (2013). A Fuzzy-FMEA Risk Assessment Approach for Offshore Wind Turbines. *International Journal of Prognostics and Health Management*.

Shafiee, Mahmood, & Dinmohammadi, F. (2014). An FMEA-based risk assessment approach for wind turbine systems: A comparative study of onshore and offshore. *Energies*, *7*(2), 619–642. https://doi.org/10.3390/en7020619

Sinha, Y., & Steel, J. A. (2015). A progressive study into offshore wind farm maintenance optimisation using risk based failure analysis. *Renewable and Sustainable Energy Reviews*, *42*, 735–742. https://doi.org/https://doi.org/10.1016/j.rser.2014.10.087

Tavner, P. J., Higgins, A., Arabian, H., Long, H., & Feng, Y. (2010). Using an FMEA method to compare prospective wind turbine design reliabilities. In *European Wind Energy Conference and Exhibition 2010, Ewec 2010* (Vol. 4, pp. 2501–2537). European Wind Energy Association.

Tazi, N., Châtelet, E., & Bouzidi, Y. (2017). Using a hybrid cost-FMEA analysis for wind turbine reliability analysis. *Energies*, *10*(3). https://doi.org/10.3390/en10030276

Zhou, A., Yu, D., & Zhang, W. (2015). A research on intelligent fault diagnosis of wind turbines based on ontology and FMECA. *Advanced Engineering Informatics*, *29*(1), 115–125. https://doi.org/10.1016/j.aei.2014.10.001