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IEA Wind TCP Task 42

Lifetime Extension Assessment

Deliverable Report

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Deliverable Report D-1: Gap Analysis of Existing Procedures required for Life Extension

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Contents

1 Introduction 4

2 Methods of Lifetime Assessment 7

2.1. Structural reliability based methods 8

2.2. Measurement data based methods 10

2.3. Missing elements and required studies 13

3 Inspection Procedures 15

3.1. Visual Inspections 17

3.1.1 Case study – Enercon 18

3.2. Other NDT methods 19

3.3. Monitoring versus Inspections 21

3.4. Gaps and required studies 22

4 Summary of Gaps in the State of the Art for Further Investigations 23

References 25

Executive Summary:

This report documents the state-of-the-art procedures in the life assessment and life extension of wind turbines in a wind farm and thereby the missing elements required in the procedures used currently are delineated.

Recent literature on the topic of life extension, remaining life assessment, reliability and inspection methods is reviewed. Simulation based methods and inspection based methods are addressed separately. The specific topics covered in this document are:

- Assessment of remaining life of wind turbine structures, components
- Physics based methods in the design process to evaluate fatigue
- Type of measurement data, time duration of recording
- Types of simulations of the turbine possible
- Inspections methods and what to inspect
- Probability of detection of damage
- Remote monitoring versus physical inspections
- Uncertainties in the process of lifetime extension

The topics are explained briefly with the salient points found either in published literature or as a best practise in industry. The missing details that are needed to have a robust life extension process are thereafter summarized as potential focus points in this task.

1 Introduction

With a significant number of wind turbines reaching their planned design life (usually 20 years), it is essential that wind-farm owners need to take decisions regarding their viable options: life extension, repowering or decommissioning. The decision is taken based on the technical, legal and economic aspects. To enable life extension, the wind turbine components should have sufficient remaining useful life (RUL), for which they need to be assessed to ensure their integrity upon continued operation. This implies that the annual probability of failure of structural components is still acceptable, considering the maintenance history and component-failure modes.

In order to assess the RUL of a wind turbine, the DNV GL guideline (DNVGL-ST-0262, 2016) lists three assessment methods,

(i) analytical (simulation),
(ii) practical (inspection),
(iii) data-driven methods (measurements).

In the analytical assessment, updated aeroelastic load simulations (Galinos, Dimitrov, Larsen, Natarajan, & Hansen, 2016) are used for the estimation of the remaining useful life. Fatigue life assessments are made for both the original design basis and turbine's present state (using site specific environmental conditions). Differences in the fatigue damage between these assessments provides an estimate about the RUL of the major structures, based on which the life extension can be decided. For an accurate simulation based estimate, these models should include (Zieglera, Gonzalezc, Rubert, Smolka, & Melero, 2018)

- state of art for aeroelastic simulations
- appropriate representation of system dynamics
- inclusion of uncertainty assessments and safety factors.

Practical assessment is based on the detailed inspection and the maintenance records of the turbine. The practical assessment is a better approach than the analytical assessment in providing a realistic picture of the turbine's current health status and predict potential near future failures. Practical assessments usually are limited by: (i) inspection methods, (ii) challenges on inspections and its solutions. There are some research articles and patents available on the types of inspection. Some of them are (US Patentnr. 12/606,737, 2010) (U.S. Patentnr. 13/021,056, 2012) (Chady, et al., 2016) and review of existing methods such as (Drewry & Georgiou, 2007) (Raišutis, Jasiūnienė, Šliteris, & Vladišauskas, 2008) (Amenabar, Mendikute, López-Arraiza, Lizaranzu, & Aurrekoetxea, 2011). Many of them are focused on blade inspections. Inspection planning is one of the key challenges in reducing the levelized cost of energy (LCoE) and in order to address this, various optimisation techniques have been reported in the literature (Sørensen, 2009), (Andrawus, Watson, Kishk, & Gordon, 2008), (Nielsen & Sørensen, 2011), (Florian & Sørensen, 2015) and (Leanwind, 2017). Recently, machine and deep learning techniques have been introduced for drone based inspections in order to reduce the LCoE (Wang & Zhang, 2017), (Shihavuddin, Arefin, Ambia, Haque, & Ahammad, 2010) and (Shihavuddin, et al., 2019). Regarding the life extension, the Lifewind project (Lifewind, 2019) carried out a detailed inspection of several operating wind turbines onshore and offshore to recommend procedures for life extension beyond 20 years.

Design life is determined in the turbine design process based on an acceptable probability of failure to be reached after the planned lifetime. This process assumes several uncertainties in loads, material behaviour, which may be different during the operation of the wind turbine. Thus measured data from the wind turbine is required to assess the actual life consumption in relation to the design lifetime. Based on the availability of data, (Megavind, 2016) outlines four different measurement data driven assessments:

(i) no design basis or operational measurement available,
(ii) design basis without any operational measurements,
(iii) design basis with SCADA based measurements,
(iv) design basis with multilayer load and operational measurements.

Data driven assessments in categories (iii) and (iv) give the most accurate assessments about RUL than any other assessments. Lifewind (Lifewind, 2019) presented a detailed study on these categories in estimating the RUL. For this purpose, machine learning algorithms and inverse problem techniques have been used.

Several projects and publications focus on the different aspects (technical, legal and economic) of life extension: (i) (Zieglera, Gonzalezc, Rubert, Smolka, & Melero, 2018), and (ii) (Lifewind, 2019). The first reference is mainly a review article on investigating the current trends, challenges, and research needed relating to lifetime extension of wind turbines. Whereas the second one is a more detailed project that focusses on improving the state of art procedures for the lifetime extension. Followings are the main important outcomes of the work:

- It formulated the procedures for lifetime extension based on the inputs of several stakeholders.
- Based on inspection based assessments and simulation based methods, recommendations were given on extending the turbines design of life.
- A detailed review on the existing standards on the life extension were presented.
- Estimation of the remaining useful life from SCADA based measurements were presented.
- Reliability based approaches were presented for life extension.

- Based on the complete study, a detailed list of recommendations was formulated as an input to the IEC 61400-28 standard.

The remainder of the report is organised as follows. Section 2 presents the detailed study on the methods for lifetime assessment. Inspection procedures and its types are given in section 3. A resulting summary on the gaps in the current state of art procedures on lifetime assessments is presented in section 4.

2 Methods of Lifetime Assessment

Modern wind turbines are typically designed to IEC 61400 series (IEC 61400-1, 2019) type classes and it is further verified that the site specific fatigue life is larger or equal to the planned lifetime of the wind turbines, typically 20-25 years, on a given site. The design is made using characteristic values of load and strength parameters. Aeroelastic simulations are performed to obtain load times series using input wind mean speed bins with a characteristic value of the turbulence intensity. Post processing of the loads allows the computation of load cycles in each critical location during the lifetime, which in turn can be processed to obtain stress/strain cycles. Using characteristic SN curves and partial safety factors it is verified that the design fatigue life is at least equal to the planned lifetime.

Site assessment is made to verify that a turbine of a given IEC class is appropriate for a specific site. This can be verified in a simple way, if all conditions on the site are more benign than the IEC class, or more advanced assessments using aeroelastic simulations can be made to verify that the design fatigue life is sufficient for a given site (considering also wake effects).The impact of the effect of wakes inside wind farms on the fatigue damage of wind turbine structures needs to be assessed such as shown in (Karlina-Barber, S., Mechler, S. & Nitschke, M. (2016)). Standard design calculations of fatigue lifetimes of wind turbines are based on a set of aero-elastic simulations (see for example (IEC 61400-1, 2019)). If lifetime extensions are planned, these calculations can be updated (see (DNVGL-ST-0262, 2016)) using more accurate descriptions of the site environmental and operational conditions (EOCs). These are available, for example, from continuous measurements (e.g. SCADA data) or through met-masts or lidars on the site. These simulations can be made by the OEM using a type specific aeroelastic model, or by a third party using a generic aeroelastic model. If a generic model is used, the verification is done in a relative manner. It is assumed that the original design gives a design fatigue life T_{design} equal to the planned lifetime, and it is verified whether the specific site conditions will result in longer or shorter assessed “design” lifetime T_{site}. Often an “intermediate” linear SN curve is used for this purpose which is constructed based on more realistic bi-linear models. Here the choice of slope coefficient *m* must reflect the fatigue sensitivity of the material.

Higher partial safety factors should be used, when the estimate of fatigue life is more uncertain, and vice versa. The partial safety factors used in design are calibrated for an annual probability of failure in the last year of operation of $\Delta P_{F,t} = 5 \cdot 10^{-4}$ corresponding to an annual reliability index $\beta_t = 3.3$. This target reliability level is given in IEC61400-1 ed. 4.

As such, a lifetime assessment in relation to lifetime extension is an exercise similar to the site assessment exercise. However, there are several differences:

- The remaining design fatigue life is of interest, thus the exact choice of slope coefficient for a generic analysis becomes significant.
- Often operational data is available: SCADA, met-mast, maintenance records, fault logs, information on component replacements.
- The economic situation is different from the situation at the design stage, and the optimal target reliability will typically be lower.

While the assessment of fatigue life is possible without including operational data, use of operational measurements in the estimation of fatigue life could lead to a more accurate prediction. For life extension projects with narrow profit margins, requirements for advanced analyses could be the tipping factor making life extension computations infeasible. If sufficient fatigue life can be verified without use of advanced data based methods, this could be optimal for some projects, especially with small wind turbines (< 1MW).

2.1. Structural reliability based methods

As described above, the remaining lifetime assessment of a wind farm requires fairly high computational power, due to the number of aero-elastic simulations to be conducted, the analysis of operational measurements and reliability evaluations. Normally, the selection of aeroelastic simulations is based on a definition of different design load cases (DLCs) and the use of combinations of environmental conditions (IEC 61400-1, 2019). For example, a grid is applied so that several simulations are conducted for wind speeds of 4 m/s, 6 m/s, etc. It was shown that such an approach is numerically inefficient ((Graf, Stewart, Lackner, Dykes, & Veers, 2016), (Chian, Zhao, Lin, Nelson, & Huang, 2018)) and more advanced sampling techniques can help to reduce the computational effort (Hübler, Gebhardt, & Rolfes, 2018). Although sampling techniques were partly validated using real measurement data (Hübler, Weijtjens, Gebhardt, Raimund, & Devriendt, 2019) comprehensive assessments of available methods are missing.

The current analytical approaches to lifetime extension analysis in FLS are primarily based on either:

1. A comparison of the design fatigue load effect and the site-specific fatigue load effect.
2. Probabilistic methods where the structural integrity is verified by direct reference to the target reliability level.

For a linear SN curve, method 1 estimates the theoretical fatigue lifetime (T_{fat}) by:

$$T_{fat} = T_L \left(\frac{F_{site}}{F_{IEC}}\right)^{-m} \qquad \text{- (1)}$$

Where, F_{site} and F_{IEC} are the site-specific and design fatigue load level respectively, and T_L is the intended lifetime of the wind turbine using the design fatigue load. In method 2, a limit state equation g (Nielsen & Sørensen, 2011) is used to estimate the fatigue life. A typical limit state equation for a linear SN curve is given as:

$$g(z,t) = \boldsymbol{\Delta} - \frac{N_{eq} \cdot t}{\boldsymbol{K}} \left(\boldsymbol{X_{Wind}} \boldsymbol{X_{SCF}} \frac{F_{g,site}}{z} \right)^m \qquad -(2)$$

where,

- $\boldsymbol{\Delta}$ is a stochastic variables for the model uncertainty on Miners rule
- $\boldsymbol{K}$ is a stochastic variable for the SN curve intercept parameter
- $\boldsymbol{X_{Wind}}$ and $\boldsymbol{X_{SCF}}$ are stochastic variables modelling the uncertainty on the fatigue load effect
- N_{eq} is the annual equivalent number of fatigue cycles
- t is time in years
- z is a design parameter
- $F_{g,site}$ is the site-specific fatigue load effect estimated by simulation of bins of wind speeds and turbulence intensities, and integration over their distributions, or by using surrogate models.

The annual probability of failure in year t given survival up to time t is given by:

$$\Delta P_{F,t} = \frac{P(g(z,t) \leq 0) - P(g(z,t-1) \leq 0)}{P(g(z,t-1) > 0)} \qquad -(3)$$

The annual reliability index is then found using the inverse standard normal distribution:

$$\beta_t = -\Phi^{-1}(\Delta P_{F,t})$$

For linear SN curves, and if the stochastic variables are assumed log-normally distributed, the limit state equation is linear in the normalized U-space. Consequently, direct exact solution of the annual reliability index is possible. For bi-linear SN curves, structural reliability methods can still be used.

If the structural components in existing wind turbines are required to fulfil the reliability requirement for new turbines of $\beta_t = 3.3$, then a lifetime extension can be verified using the procedure summarized above. Here it is possible to take into consideration directly the influence of changes in uncertainties, as this will affect the reliability. The change in reliability needs to be ascertained by potential inspections to ensure that the component integrity is indeed within allowed limits.

Further, a risk-based assessment can be applied to estimate the target reliability for existing wind turbines, which due to differences in the economic situation can be different than for new wind turbines. If a reliability level of $\beta_t = 3.1$ ($\Delta P_{F,t} = 10^{-3}$) can be accepted for life extension, a probabilistic analysis can show that this alone can increase the assessed lifetime by almost a factor of two.

Even when using advanced sampling techniques, the computational effort of lifetime extensions using aero-elastic simulations – especially if probabilistic approaches are used – is fairly high. An alternative, being recently investigated extensively, are meta-model-based approaches ((Dimitrov, Kelly, Vignaroli, & Berg, 2018), (Slot, Sørensen, Sudret, Svenningsen, & Thøgersen, 2019)). For such approaches, classic aero-elastic models are replaced by mathematical meta-models that are calibrated using a limited number of aero-elastic simulations. Although, there has been some effort to find suitable meta-models, concluding evaluations of the various potentially applicable meta-models are missing.

2.2. Measurement data based methods

An alternative or complement to simulation-based lifetime assessments are pure measurement-based approaches. Measurement data methods for calculation of the life time extension potential of a machine involves a lot of different types of measurement but also turbine/model data as well as certification data and maintenance log data. Depending on the availability and quality of these data, the fatigue life time of each component can be evaluated in a deterministic manner. According to the relevant uncertainty associated to the quality of models and data, safety factors can be applied to the deterministic values of the calculation according to reliability levels or uncertainty quantification probabilistic methods similar to what is currently done with the turbine design standards. Failures due to extreme loads (e.g. deteriorated material properties) or production deficits cannot be evaluated with such methods. Hence, measurement data methods need to complement inspection methods and should not be seen as distinct methods but rather different aspects of the same procedure.

The type of data that would be used in such a procedure can be categorized in measurement data and turbine/model data. The first category includes wind, SCADA and loads measurements and the second category includes the aeroelastic model (including the controller which is crucial), the certification loads and the certification method. The availability, quality and resolution of these data can be used to classify the methods based on which life time extension can be calculated as well as assign the appropriate safety factor. One way would be to create a list classifying the possible combinations based on which safety factors for each case can be defined as well as the specify the procedures per case.

The introduction chapter earlier suggested 4 classifications of data availability, for example having wind data only from a near met mast but not SCADA or load data and no aeroelastic model available. Even then, aeroelastic simulations can be performed with a reverse engineered model of a generic reference turbine to obtain some reference loads. The actual wind data from the met mast can be used then to create a wind distribution and simulate the loads. Comparing these loads to the reference one can estimate roughly the life time of each component.

As an example, load data (e.g. strain measurements) and data of environmental conditions (e.g. SCADA data) can be required. If high quality measurement data for a sufficient time period is available, such an approach can be very accurate. Nonetheless, the “measured damages” (e.g. strain cycles are converted to short term damages using Palmgren-Miner rule, S-N curves, etc.) have to be extrapolated to the entire remaining lifetime. Another approach is directly creating surrogate models from measurements without using any aeroelastic model, using machine learning or statistical approaches. A load map per component (given there is sufficient data) can then be created. For this approach we need to know the certification loads. In case these don’t exist, they have to be either assumed by generic simulations or derived by the surrogate models based on the turbine class. These last two approaches will be associated with a highly conservative safety factor.

In the previous approaches the main challenge would be to define the appropriate safety levels that are present per component, as at the end of the intended life, the turbine must still be safe for operators to de-commission it. Further extrapolation to future long term is an uncertain process due to limited data of the past and unknown data for the future. Probabilistic approaches such as bootstrapping for the estimation of the stochastic uncertainty may be utilized (see for example (Hübler, Wout, Raimund, & Christof, 2018)).

2.2.1. Statistical data based methods

Wind farm operators can also get a sense of the reliability of a population of major components across a farm with an application of appropriate statistical measures. This can provide insights into how to optimize the life and value of their farm assets. The success of these measures is critically reliant on the type and amount of data available. Common SCADA packages will often maintain sufficient data to perform such statistical evaluations.

Nonparametric life data analysis, Weibull Standard Folio life data analysis, and ALTA Standard Folio life data analysis component (Rezamand, Carriveau, Ting, Davison, & Davis, 2019) can be used to predict the reliability of groups of major components. The naive prediction interval procedure can also be leveraged to provide an approximate range for the remaining life of each major. These analyses can provide some insight into how reliable a subset of major turbine components is and the lifetime distribution of individual major components. Outcomes from these analyses may be leveraged further by the research community for companion applications like prognostic maintenance and investment decision support systems. Here Figure 2-1 reveals the relative frailty of an existing wind turbine generator population with a roughly 77% probability of failure by the tenth year of operation.

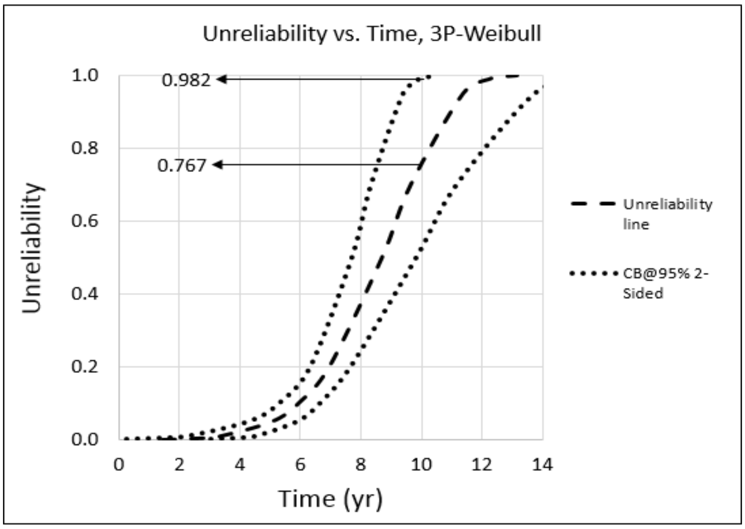

Figure 2-1: Sample unreliability plot of wind turbine generators. Weibull standard folio life data analysis (3P-Weibull) (Rezamand, Carriveau, Ting, Davison, & Davis, 2019).

2.2.2. Data visualization and usage ranking methods

Condition monitoring and prognostic reliability modeling is regularly used in maintenance and life extension decisions. These often resource intensive, sophisticated techniques are frequently administered by third parties and can be black boxes to wind farm stakeholders. Recent experience has highlighted the importance of broad engagement across wind farm teams in maintenance and planning discussions. The utilization of Geographic Information Systems (GIS) to illustrate data trends across wind farms proved to be a valuable tool in fostering fundamental understanding of an operation's signature performance characteristics. Graphical representations of farms provide a useful visualization of the operation's best and worst performers in terms of, power produced, wind speeds experienced, total revolutions, or highest gear box temperature, etc. These transparent representations of the data represent valuable starting points for discussion of performance or potential maintenance issues across farms. In some cases it can reveal unexpected trends that may raise bigger questions about how the farm is operating in general. Finally, these simple figures can serve as complementary inputs to larger, more complex data driven decision systems. In the example of Figure 2-2, the obvious relationship between wind speed and power production is illustrated, though close inspection reveals some outliers. These results are helpful in locating high and low performers across the farm. Furthermore, they prompt investigation when counterintuitive results are uncovered. Finally, such analysis reveals usage trends across the farm. This can be a useful companion analysis to statistical approaches that may indicate a particular number of components are due to fail. Usage investigations may inform which of the failure population are the most likely to fail first.

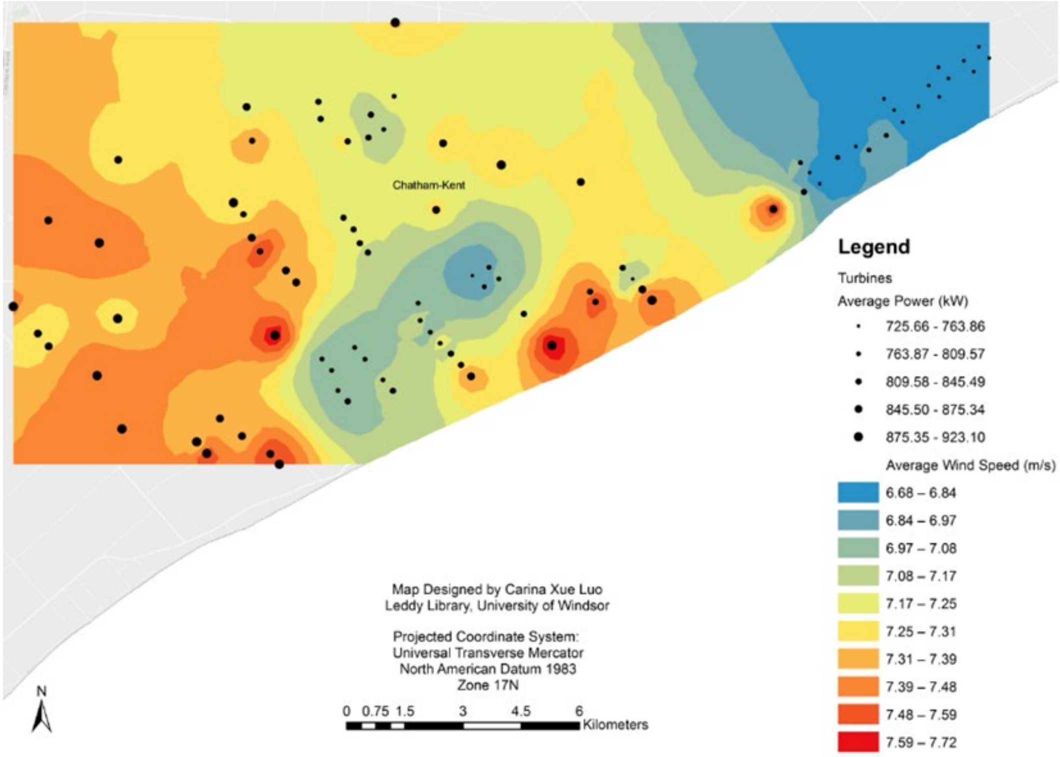

Figure 2-2: Sample Data Visualization Plot of Average Wind Speed (Contours) and Average Turbine Power Production (Dot Size) (Shen, et al., 2019).

2.3. Missing elements and required studies

Studies are required to quantify the uncertainty in each data-based procedure used in life estimation. Numerical and experimental studies have to be carried out to identify partial safety factors required to be used with the aforementioned procedure. These analysis become more complex as inspections result based uncertainty should be added on top of the uncertainty estimation to validate the required safety factors. Further the correlation between mechanical loading and observed damage on a structure needs to be made as it is also possible that damage or wear occurs due to other reasons such as faulty operation, lightning, rain etc.

As stated in the standard from DNVGL (DNVGL-ST-0262, 2016), it is important to have information on what the turbine components have experienced from the very beginning of their operation life. Therefore access to commissioning records, maintenance records, reports from inspections, failure reports/reports on extraordinary maintenance activities and documentation on exchange of components are needed. Further these records should be digitized. In our experience it can happen often that this data is not centralized and digitalized. Different organizations have different types of records and the final decision maker, usually the farm owner, does not have a concrete basis. Inspections done later in the farm also should digitize the results and correlate with earlier maintenance records so that there is a correlation. This is presently almost impossible to verify.

In the same context, changes in operation of the turbines, for example long curtailment periods, downtime periods or controller settings play a very important role in remaining life estimation. For example advanced controls can mitigate loads on wind turbine structures (Abdallah, Natarajan, & Sørensen, 2016) These changes can have a big impact on the overall accumulated fatigue and fatigue consumption rate for each component and can lead to large over- or underestimates. Moreover, a standard procedure has to be identified on how one can consider these uncertainties but also how to include this information in fatigue calculations.

The timing of decision making for life time extension is also an important aspect that needs to be evaluated. The earlier in the life of a park life time extension (LTE) is considered the more solid can the decision be. Knowing the condition and limitation of the assets can lead to preventive maintenance conditions, replacement of parts or modified operation in order to increase LTE margins or if this is not possible to reduce operating costs or increase profitability by increasing fatigue consumption. Legislation is a very important aspect aside from the technical one. As there is no standardized process on how LTE should be evaluated, and the permitting procedures for both LTE and repowering are not concrete, the decision making can be very hard. In this sense it is urgent to create a standard on life time extension (IEC 61400-28) and clear legislations.

3 Inspection Procedures

Inspecting the conditions of wind turbines is crucial at various stages of wind turbine operation. It provides information about the integrity of the turbine components, maintenance needs and any potential performance degradation (Picciotto, u.d.). Also, it provides an independent assessment on the condition of wind turbines & assets and the effectiveness of maintenance & repairs. Inspection procedures are also used to perform a risk analysis that is required to assess the remaining life of a turbine, to quantify the likelihood of a failure and the possibility of detecting the failure before it occurs.

Megavind (Megavind, 2016) stated that the remaining useful life of wind turbines should be assessed in light of life extension and failure modes. Megavind listed out several possible failure modes of all major components of a wind turbines, potential mitigating actions and recommendations for further developments. Here, the critical failure modes of a wind turbine components given by Megavind are summarized in Table 3-1.

Table 3-1: Critical failure modes of a wind turbine components.

Component	Possible failure modes
Rotor	• Broken and/or loose bolts in between various interfaces • Fatigue of hub structure • Failure of turbine safety system components • Parts that fall to the ground • Rust and corrosion of bolts • Cracks and debonding of blades • Blade tower strike • Failures from lightning strikes and tip brakes • Leading edge erosion
Nacelle	• Gearbox/bearing failure • Fatigue failure • Failure of turbine safety system components • Failures due to blades falling off • Fretting corrosion • Electrical faults • Wear and tear • Yaw misalignment
Tower	• Fatigue failure
Offshore structures	• Joint between monopole and transition piece • Wear and tear

	• Fatigue failure • Scour

Most of these failure modes can be mitigated by suitable inspection procedures. For some cases, mitigation of failure requires combining inspections with data analyses and/or condition monitoring system. Similar kind of list is also given in (DNVGL-ST-0262, 2016).

Inspection activities can result in considerable savings in cost by preventing impending failures through preventive repairs. However, the frequency at which the inspections has to be carried out also plays a role in maintenance cost. If the inspections is carried out often, it leads to unnecessary maintenance costs. At the same time, inspections with larger time intervals may increase the chances of failure and lead to revenue loss. So, choosing the optimal time interval between inspections is crucial. In order to determine the optimal inspection time interval, there are two methods suggested in literature, namely, risk-based approach and reliability-based approach. In the risk based approach, the optimal time interval between inspections is the time interval at which the total expected preventive and corrective maintenance cost is minimized (Sørensen, 2009) (Nielsen & Sørensen, 2011) (Florian & Sørensen, 2015). This method is based on prior-posterior decision theory. On the other hand, when there is a minimum level of reliability required upon life extension, one needs to go for reliability-based inspection planning (Lifewind, 2019). In this approach, the reliability of inspections is modelled by POD (probability of detection) curves. Based on the required reliability level upon life extension, the inspection interval, inspection methods and repair strategy are chosen/optimized. Also, the LEANWIND project (Leanwind, 2017) proposed a simulation based model to optimise strategic decisions relating to timings and methods for inspections, repairs and condition monitoring of offshore wind turbines. Two decision models were used for this purpose: (i) decision rules based on time or on inspection or condition monitoring, and (ii) decision rules based on probability of failure. The reliability of inspection methods can be modelled by POD (Probability Of Detection) curves and if cracks are detected by the measurement accuracy. Such models should be developed for relevant inspection methods.

Based on the technique that is being used for the inspection, non-destructive testing (NDT) inspection methods are classified into:

I. Visual inspection
II. Infra-red thermography
III. Ultrasonic testing
IV. Digital radiography
V. Acoustic emission

VI. Tap testing
VII. Vibration analysis
VIII. Eddy current
IX. Infra-red scanning
X. microwave and terahertz techniques

3.1. Visual Inspections

Visual inspection is the simplest inspection technique by which the present conditions of the wind turbine components in outer lever can be evaluated using miniature cameras or endoscopes. Wind assets have to be powered down for prolonged amounts of time, for these types of inspections to be completed. In addition to the long downtime, images captured may not be as complete and clear as needed. Due to the height of the turbine and the shape of the blades, the angle looking up at the blades is very large, and some parts of the blades are in shadows while the other parts are under bright light. This naturally makes it difficult for ground-based scopes and cameras to identify all the defects and capture high-resolution photos of them. Small defects might be overlooked, and the picture quality might not be high enough for further severity diagnosis and damage analysis. There are three acknowledged visual inspection methods available for the inspection of wind turbines (Bladena, 2018), which are,

(i) Rope inspection: In this technique, a technician will be able to investigate the surface damage. Also, the technician can repair lower level damages whilst inspecting. Disadvantage of this method is that this is highly weather dependent, and documentation of the inspection can only done using images. Also, the associated cost is high.

(ii) Ground based camera inspection: With a ground based high resolution cameras, series of shots have to be taken from ground and finally merged for complete picture. These images have to be used for inspection purposes. This process is expensive and requires a lot of storage facilities as there are many high resolution photos. Also, some aspects like shadow side of blade cannot be captured accurately and works well only upto wind speed of 18 m/s.

(iii) Drone (UAV) inspection: By utilizing this method it is possible to have both video and still pictures, however the image size tend to be large and hence require a larger storage capacity. The main advantage of this method is that its shorter duration. The down sides are wind speed (14 m/s) and temperature limitations.

Among these three inspection techniques, drone based inspections have gained a lot of attention (Wang & Zhang, 2017). The effectiveness of drone inspections depends highly on the drone operator and type of drone. During an inspection, the operator needs to know exactly when and how to adjust the drone to accommodate its current wind speed and direction, so that the drone is able to gather sufficiently high resolution images without any danger of accidently crashing into the wind turbine. Therefore, the operator of the drone needs to be a highly trained professional. This dependency on highly-trained drone operators prevents wind farms from using manual drone inspection as frequently as they would like. Recent developments use fully autonomous drone inspections or deep learning aided drone inspections for the subsequent analysis of drone inspection images (Shihavuddin, et al., 2019).

Further, visual inspections are not only used to examine the present condition of a wind turbine, it is also used to evaluate the quality of service work. Lifewind (Lifewind, 2019) project carried out a visual inspection of 8 different wind turbines, which ages are ranging from 4 to 24 years. Based on the thorough visual inspection, the following key observations were made:

Table 3-2: Observations of visual inspection on 8 wind turbines.

Component	Observation
Rotor	• Leading edge erosion on blades • Blade bolts and blade bearing bolts look good • No cracks or corrosion on hub and bolts
Main shaft and main bearings	• No cracks or major corrosion on the main shaft and main bearings • Leakages found in seals
Nacelle frame	• No cracks or major corrosion
Yaw system	• No major problems found • More focus needed on wear and tear on the brake pads.
Tower	• No cracks on tower welding. • Bolt elongations are good • Bolt protection system is working fine
Foundation	• Corrosion on foundation bolt presents for one particular turbine.

Also, regarding the quality of service, it was found that a high degree of correlation between independent service providers doing maintenance and inspection reports must be found, so as to verify that problems identified during inspections are indeed resolved. Further, using the visual inspections most failure modes on the outer surface presented in Table 3-1 can be identified.

3.1.1 Case study – Enercon

Visual inspections are carried out on the wind turbines of ENERCON GmbH at a distance of ~1m from the object to be inspected. The visual inspection is divided into 5 groups.

- Visual inspection (without aids with the naked eye at a distance of approx. 1m from the object to be inspected)
- Visual inspection with optical magnification (e.g. magnifying glass, endoscope, mirror)
- Visual inspection with hand lamp (~300lx at a distance of approx. 1m from the inspection object)
- Indirect visual control (with camera, videoscope, etc.)
- Close to hand visual control

In principle, all components are subjected to a visual inspection. In most cases the inspection is carried out with a hand lamp. A very common inspection is the visual inspection of moving marks on screwed connections and components. Lubricant samples are subjected to a visual inspection on site in the WTG in order to decide, based on appearance, consistency and odour, whether a larger quantity must be removed and analyzed in the laboratory.

Video endoscopic inspections or even boroscopic inspections are usually performed only if previous inspections have revealed possible irregularities in the area of the main bearings.

The rotor blades are subjected to a visual inspection from inside and outside. Attention is paid to signs of wear and impacts from lightning, for example. The tower in its various designs with its internals is also subjected to a precise visual inspection and documented. However, there are no specifications or instructions as to what should be subjected to visual inspections of wind turbines.

However, for failure modes that may be present inside the structure, one needs go for other inspection techniques which will be discussed in the following sub sections.

3.2. Other NDT methods

NDT methods are effective methods that do not require any destructive treatment of the components of the wind turbine. Some of the NDT methods used to inspect components such as blades include:

Ultrasonic NDT inspection: It is used to investigate damages that are present inside the wind turbine components. It reveals the defects quickly, reliably and effectively (Drewry & Georgiou, 2007). The main advantage of this method is that it enables us to see beneath the surface. The main application of this method is to inspect bolt cracks, delamination in the blade, and cracks in mainframes. Ultrasonic methods can be combined with advances such as phased array, and automatic inspection for data acquisition and storage.

Tap test: This method is based on the fact that there is a change in sound emitted from a structure when tapped if there are any changes in structural thickness or material and if any porosities present. Also, the disbond between the skin laminate and the main spar also causes the change in sound. There are three types of tap testing equipment: a manual tapping hammer, the ‘Woodpecker’ portable bond tester and the Computer Aided Tap Tester (CATT) system (Drewry & Georgiou, 2007). This method is generally used to verify the results from the ultrasonic NDT. The automated tap methods are very good in printing the damaged area. Also, the tap method is better suited for composite structures of thin size and not so effective on thicker parts.

Infrared thermography: This method is better suited for inspecting the adhesive joints of the blade structure. Using infrared scanners, the blade is examined throughout its length, measuring same points each time to check the laminate and the adhesive joints. Also, it records the temperature differences in the adhesive, based on that defects are identified. Further details about this method can be found in (Chady, et al., 2016).

Terahertz Imaging: It is a non-invasive, non-ionizing and non-contact examination method (Chady, et al., 2016). The electromagnetic waves in terahertz frequency band are sensitive for changes of refractive index, and the changes in the refractive index happen due to one of the following,

- void,
- delamination,
- inclusion,
- material inhomogeneities (fiber/matrix distribution),
- surface roughness,
- fiber waviness.

Acoustic emission: It is based on the principle that when a component is stressed, the built-up stress spontaneously discharges at a crack, thereby generating sound impulses. This method is mainly used to identify the cracks that are formed during the blade certification test.

Apart from these methods, Eddy current is a good method for inspecting welded joints and HAZ inspection method is better suited for cracks and also, without the necessity of removing the surface coating.

Typical and still widely used maintenance activities include preventive maintenance with routine inspections, and reactive (corrective) maintenance after failure (Tchakoua, et al., 2014). The health status of wind turbines depends on both site environmental conditions and maintenance strategy. Maintenance of wind turbines is either performed by the original turbine manufacturer, a maintenance provider or directly in-house by the operator. Maintenance contracts may consist of full or partial coverage. No clear trend towards either type could be identified between the interview participants (Zieglera, Gonzalezc, Rubert, Smolka, & Melero, 2018).

Only few operators regularly use SCADA data with a sampling interval between 1-10 s. When SCADA data is used, normally 10-min statistics are the basis for trend analysis- ((Fischer & Coronado, 2015), (Zieglera, Gonzalezc, Rubert, Smolka, & Melero, 2018)). Predictive maintenance based on operational data is desirable, but still in the early stages of commercialization. A good database of O & M including failure occurrences is understood as an advantage for faster, cheaper and more reliable lifetime extension assessment. But such databases are usually not available for research purposes.

Today's commercially available CMS and SHM are predominately vibration-based systems monitoring the rotating drivetrain, namely the main bearing, the gearbox and the generator bearings, rotor blades, tower and foundation (Fischer & Coronado, 2015). The sensors used for vibration based monitoring of rotor blades, tower and foundation are mainly accelerometers. Velocity and displacement transducers, electrical and fibre optical strain gauges are also used, but not so often.

The combination of vibration-based monitoring from measured time series with SCADA data can be achieved by using Artificial Neural Networks (ANN) (Rolfes, R., Achmus, M., Albiker, J., Dubois, J., Eichstädt, R., & Häfele, J. (2018)).

3.3. Monitoring versus Inspections

Condition monitoring (CM) is a process of monitoring the system parameters that represents the condition of a system in order to identify indications of a developing fault. It is a major part of preventive maintenance. CM systems are installed in modern wind turbines for systematic data collection and evaluation to identify changes in the turbine's behaviour. By doing this, remedial actions including preventive maintenance, inspection and repair could be planned to maintain reliability in a cost-effective manner. Many failure modes have measurable responses and develop over time. These are the ideal applications for condition-based maintenance (CBM). CM can provide early warning of potential failure, if the measurement parameters are correctly chosen and measured with accurate sensors (Megavind, 2016). Information from inspections and condition monitoring are useful in updating the turbine's reliability in its remaining lifetime.

When compared to the inspection procedures, the CM has the following advantages:

- Unlike most of inspection procedures, CM can work well even when the turbine is running.
- CM is independent of weather conditions and wind speeds.

- Inspections can only identify defects or any damage related information, whereas CM in addition to that, can provide performance related information.
- Cost of CM can be lower than the cost involved in inspections (Leanwind, 2017).
- Also, when there is no design basis available, one can estimate system loads and fatigue life from CM data (SCADA) (Lifewind, 2019).
- Using CM data with new retrofitted control systems, service costs can be reduced by optimizing the daily operation and avoiding increased unscheduled maintenance of older turbines, which also results in increased lifetime.

On the other hand, CM typically provides indirect information on damage and faults of the components, whereas inspections can provide direct information with less uncertainty (Leanwind, 2017) . Also, many of the older turbines for which the decision on life extension has to be taken, do not have such CM systems.

3.4. Gaps and required studies

Based on the literature survey, the existing gaps and areas in inspections for further research are listed below.

- For bolt inspections/testing, cost effective methods have to be developed to determine its condition without dismounting them.
- NDT methods have to be developed further to detect pre-stress and crack formation.
- Drone inspections have to be improved by installing NDT sensors and thermal cameras. Also, the working conditions and battery performance of the drones have to be improved as per needs of wind industry.
- More focus needed on the application of machine and deep learning algorithms on damage detection from inspections.
- Both risk based and reliability based inspection planning methods have to be improved not only for optimal inspection planning and also for efficient damage detection.
- More detailed study has to be performed with sufficiently larger sample size of inspected turbines for a reliable recommendation on life extension from only inspection methods.

4 Summary of Gaps in the State of the Art for Further Investigations

Relevant studies to evaluate the wind turbines remaining life potential through specific experiments and benchmark studies is necessary. Studies that provide new insights on variation in predicted remaining lifetime between different models is necessary. This study would be to compare different methods reliability based, probabilistic, measurement based etc. on specific cases. Such a verification exercise can give an initial understanding of the differences between the methods and serve as a starting point for standardizing the LTE estimation procedure. It is also necessary using experimental tests to determine the important fatigue failure modes for a specific design type, which can then be used to reinforce the decision making process for life extension on different types of sites.

For pure measurement-based approaches (Hübler, Wout, Raimund, & Christof, 2018), there is the need of further developments that first, determine the uncertainty of these approaches. In this context, the amount of measurement data (i.e. how long do we have to measure) that is required to achieve reliable estimates is especially interesting. And second, the spatial extrapolation of measurements to other positions is limited so far. This means that according to the state of the art, lifetime estimations based on strain measurements are only possible for locations where strain data is available. Hence, for the application of these approaches, a large amount of sensors per turbine is needed. Extrapolations to other positions on the turbine are subject of current research (Iliopoulos, Weijtjens, Hemelrijck, & Devriendt, 2015) and quite relevant in this context.

Regarding the use of simulation-based meta-models for lifetime assessments, a comprehensive comparison or cross-verification is still missing. Certainty, by different researchers, work was conducted, which is intended to assess the performance and/or uncertainty of different meta-models, e.g. (Dimitrov, Kelly, Vignaroli, & Berg, 2018) and (Slot, Sørensen, Sudret, Svenningsen, & Thøgersen, 2019). Nonetheless, first, these investigations are only based on single turbines. Hence, general validity was not proven. And secondly, there are no comprehensive studies incorporating meta-models of different institutions/research groups, so that the different implementations, etc. cannot be compared. Hence, real benchmarks are missing.

In addition to benchmarks for simulation-based meta-models, there is also a lack of measurement-based meta-models. When measuring environmental conditions and acting loads (i.e. strains), it should be possible to use more or less the same meta-models compared to simulation-based concepts. However, this has not been tested so far. Still, such an approach could also be understood as a validation of the meta-models. A comparison between purely measurement-based approaches and simulation-based methods (fully or partly, e.g. the use of real SCADA data in aero-elastic simulations) is missing so far.

Most estimations of turbine lifetimes, and therefore, also most analyses of lifetime extensions focus either on technical aspects only or are pure economic considerations (not focus of this task). However, the inclusion of economic effects within technical lifetime assessments is still rarely conducted. An exception is, for example, (Hübler, C., Piel., J.H., Stetter, C., Gebhardt, C. G., Breitner, M. H., & Raimund, R. (2020)). Nonetheless, for a profound evaluation of the potential of lifetime extensions, economic issue may not be neglected. The challenge in this context is, inter alia, the lack of cost data (e.g. how do O&M costs change, if lifetime extensions are conducted).

In summary, the following topics requires further work in order to perform accurate lifetime extension analysis:

- Decisions on the target failure probability for existing wind turbines upon lifetime extension.
- A computationally feasible approach to propagate uncertainties from wind assessments to wind turbine loads.
- A quantification of the uncertainties that are related to the available wind data used for lifetime extension.
- Verified uncertainty models for fatigue load effects e.g. stress concentration factors, aero-elastic simulation, surrogate models, etc.
- Verified uncertainty models for fatigue strength in terms of Miner's rule and SN-curves.
- An efficient and accurate framework to estimate failure probabilities and assess the sensitivities towards each uncertainty.
- Quantification of the variation in predicted lifetime for various methods for lifetime extension.
- Guidance on selection of appropriate SN curves for estimation of fatigue life.
- Cost effective methods to determine wind farm condition.
- NDT methods developed further to detect pre-stress and crack formation.
- Drone inspections have to be improved with possible thermal imaging cameras and correlated to NDT.
- Digitization of inspection reports and maintenance records
- More focus need on the application of machine and deep learning algorithms on damage detection from inspections.
- The stochastic modelling in IEC61400-1 ed. 4 is for welded details in steel. For other fatigue critical details similar models should be developed.

References

Abdallah, I., Natarajan, A., & Sørensen, J. D. (2016). Influence of the control system on wind turbine loads during power production in extreme turbulence: Structural reliability. *Renewable Energy, 87*, 467-477.

Amenabar, I., Mendikute, A., López-Arraiza, A., Lizaranzu, M., & Aurrekoetxea, J. (2011). Comparison and analysis of non-destructive testing techniques suitable for delamination inspection in wind turbine blades. *Composites Part B: Engineering, 42*(5), 1298-1305.

Andrawus, J., Watson, J., Kishk, M., & Gordon, H. (2008). Optimisation of wind turbine inspection intervals. *Wind Engineering, 32*(5), 477-490.

Bladena. (2018). *Instruction- Blade Inspections.* Vattenfall.

BWE. (2017). *BWE Grundsätze zum Weiterbetrieb. Für die Durchführung einer Bewertung.*

Chady, T., Sikora, R., Lopato, P., Psuj, G., Szymanik, B., Balasubramaniam, K., & Rajagopal, P. (2016). Wind Turbine Blades Inspection Techniques. *Przeglad Elektrotechniczny*.

Chian, C. Y., Zhao, Y. Q., Lin, T. Y., Nelson, B., & Huang, H. H. (2018). Comparative study of time-domain fatigue assessments for an offshore wind turbine jacket substructure by using conventional grid-based and monte carlo sampling methods. *Energies, 11*(11), 3112.

Dimitrov, N., Kelly, M. C., Vignaroli, A., & Berg, J. (2018). From wind to loads: wind turbine site-specific load estimation with surrogate models trained on high-fidelity load databases. *Wind Energy Science, 3*(2), 767-790.

DNV GL AS. (2016). *Lifetime extension of wind turbines.* DNV GL.

DNVGL-ST-0262. (2016). *Lifetime extension of wind turbines.*

Drewry, M. A., & Georgiou, G. (2007). A review of NDT techniques for wind turbines. *Insight-Non-Destructive Testing and Condition Monitoring, 49*(3), 137-141.

Fischer, K., & Coronado, D. (2015). *Condition Monitoring of Wind turbines: State of the Art, User Experience and Recommendations.* Bremerhaven: Fraunhofer-IWES.

Florian, M., & Sørensen, J. D. (2015). Wind Turbine Blade Life-Time Assessment Model for Preventive Planning. *Journal of Marine Science and Engineering, 3*(3), 1027-1040.

Galinos, C., Dimitrov, N., Larsen, T. J., Natarajan, A., & Hansen, K. S. (2016). Mapping wind farm loads and power production-a case study on horns rev 1. *Journal of Physics: Conference Series, 753*(3), 032010.

Graf, P. A., Stewart, G., Lackner, M., Dykes, K., & Veers, P. (2016). High-throughput computation and the applicability of Monte Carlo integration in fatigue load estimation of floating offshore wind turbines. *Wind Energy, 19*(5), 861-872.

Holzmüller, J. (2016). Analysing the lifetime of a wind turbine – operation past design life. *Proceedings of Wind Europe Summit 2016.* Hamburg, Germany.

Hübler, C., Gebhardt, C. G., & Rolfes, R. (2018). Methodologies for fatigue assessment of offshore wind turbines considering scattering environmental conditions and the uncertainty due to finite sampling. *Wind Energy, 21*(11), 1092-1105.

Hübler, C., Piel., J.H., Stetter, C., Gebhardt, C. G., Breitner, M. H., & Raimund, R. (2020). Influence of structural design variations on economic viability of offshore wind turbines: An interdisciplinary analysis. Renewable Energy, 145, 1348-1360.

Hübler, C., Weijtjens, W., Gebhardt, C. G., Raimund, R., & Devriendt, C. (2019). Validation of Improved Sampling Concepts for Offshore Wind Turbine Fatigue Design. *Energies, 12*(4), 603.

Hübler, C., Wout, W., Raimund, R., & Christof, D. (2018). Reliability analysis of fatigue damage extrapolations of wind turbines using offshore strain measurements. *Journal of Physics: Conference Series, 1037*(3), 032035.

IEC 61400-1. (2019). *Wind energy generation systems - Part 1: Design requirements.* Geneva, Switzerland: IEC.

Iliopoulos, A. N., Weijtjens, W., Hemelrijck, D. V., & Devriendt, C. (2015). "Prediction of dynamic strains on a monopile offshore wind turbine using virtual sensors. *Journal of Physics: Conference Series, 628*(1), 012108.

Karlina-Barber, S., Mechler, S. & Nitschke, M. (2016). The effect of wakes on the fatigue damage of wind turbine components over their entire lifetime using short-term load measurements. Journal of Physics: Conference Series, 753(7), 072022.

Leanwind. (2017). *Driving Cost Reductions in Offshore Wind.*

Lifewind. (2019). *Demonstration of Requirements for Life Extension of Wind Turbines beyond their Design Life.* DTU wind energy.

Loraux, C., & Brühwiler, E. (2016). The use of long term monitoring data for the extension of the. *Journal of Physics: Conference Series, 753*(7), 072023.

Luengo, M., & Kolios, A. (2015). Failure mode identification and end of life scenarios of offshore wind turbines: a review. *Energies, 8*(8), 8339-8354.

Megavind. (2016). *Strategy for Extending the Useful Lifetime of a Wind Turbine.*

Murphy, J. T., Mandayam, S. T., & Sharma, P. (2012). *U.S. Patent No. 13/021,056.*

Nielsen, J. J., & Sørensen, J. D. (2011). On risk-based operation and maintenance of offshore wind turbine. *Reliability Engineering and System Safety, 96*, 218-229.

Picciotto, M. R. (n.d.). *POWER AND RENEWABLES*. Retrieved from DNV GL: https://www.dnvgl.com/services/wind-turbine-inspections-3845#

Raišutis, R., Jasiūnienė, E., Šliteris, R., & Vladišauskas, A. (2008). The review of non-destructive testing techniques suitable for inspection of the wind turbine blades. *Ultragarsas, 63*(2), 26-30.

Rezamand, M., Carriveau, R., Ting, D., Davison, M., & Davis, J. (2019). Aggregate reliability analysis of wind turbine generators. *IET Renewable Power Generation, 13*(11), 1902-1910.

Rolfes, R., Achmus, M., Albiker, J., Dubois, J., Eichstädt, R., & Häfele, J. (2018). Verbundvorhaben Lebensdauer-Forschung an den OWEA-Tragstrukturen im Offshore-Testfeld alpha ventus-GIGAWIND life: Teilvorhaben: Validierte Methoden und Strukturmodelle für ein integrales und wirtschaftliches Design von OWEA-Tragstrukturen: Schlussbericht. Leibniz Universität Hannover, Institut für Statik und Dynamik.

Rubert, T., Niewczas, P., & McMillan, D. (2016). Life extension for wind turbine structures and foundations. *International Conference on Offshore Renewable Energy 2016.*

Shen, J., Francis, R., Miller, L., Carriveau, R., Ting, D. S., Rodgers, M., & Davis, J. J. (2019). Geographic information systems visualization of wind farm operational data to inform maintenance and planning discussions. *Wind Engineering*. Retrieved from https://doi.org/10.1177/0309524X19862757

Shihavuddin, A., Arefin, M., Ambia, M., Haque, S., & Ahammad, T. (2010). Development of real time Face detection system using Haar like features and Adaboost algorithm. *International Journal of Computer Science and Network Security, 10*, 171-178.

Shihavuddin, A., Chen, X., Fedorov, V., Nymark, C. A., Andre, B. R., Branner, K., . . . Reinhold, P. R. (2019). Wind Turbine Surface Damage Detection by Deep Learning Aided Drone Inspection Analysis. *Energies, 12*, 676.

Slot, R. M., Sørensen, J. D., Sudret, B., Svenningsen, L., & Thøgersen, M. L. (2019). Surrogate model uncertainty in wind turbine reliability assessment. *Renewable Energy*.

Sørensen, J. D. (2009). Framework for risk-based planning of operation and maintenance for offshore wind. *Wind Energy, 12*, 493-506.

Tchakoua, P., Wamkeue, R., Ouhrouche, M., Slaoui-Hasnaoui, F., Tameghe, T. A., & Ekemb, G. (2014). Wind turbine condition monitoring: State-of-the-art review, new trends, and future challenges. *Energies, 7*(4), 2595-2630.

UL. (2013). *Outline of investigation for wind turbine generator life time extension (LTE).*

Wang, L., & Zhang, Z. (2017). Automatic detection of wind turbine blade surface cracks based on uav-taken images. *IEEE Transactions on Industrial Electronics, 64*(9), 7293-7303.

Williams, S. I. (2010). *US Patent No. 12/606,737.*

Ziegler, L., & Muskulus, M. (2016). Fatigue reassessment for lifetime extension of offshore wind. *Journal of Physics: Conference Series, 753*(9), 092010.

Ziegler, L., Lange, J., Smolka, U., & Muskulus, M. (2016). The decision on the time to switch from lifetime extension to repowering. *Proceedings of Wind Europe Summit.* Hamburg, Germany.

Zieglera, L., Gonzalezc, E., Rubert, T., Smolka, U., & Melero, J. J. (2018). Lifetime extension of onshore wind turbines: A review covering Germany, Spain, Denmark, and the UK. *Renewable and Sustainable Energy Reviews, 82*, 1261-1271.