Modelling the failure behaviour of wind turbines

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Abstract. Modelling the failure behaviour of wind turbines is an essential part of offshore wind farm simulation software as it leads to optimized decision making when specifying the necessary resources for the operation and maintenance of wind farms. In order to optimize O&M strategies, a thorough understanding of a wind turbine's failure behaviour is vital and is therefore being developed at Fraunhofer IWES. Within this article, first the failure models of existing offshore O&M tools are presented to show the state of the art and strengths and weaknesses of the respective models are briefly discussed. Then a conceptual framework for modelling different failure mechanisms of wind turbines is being presented. This framework takes into account the different wind turbine subsystems and structures as well as the failure modes of a component by applying several influencing factors representing wear and break failure mechanisms. A failure function is being set up for the rotor blade as exemplary component and simulation results have been compared to a constant failure rate and to empirical wind turbine fleet data as a reference. The comparison and the breakdown of specific failure categories demonstrate the overall plausibility of the model.

1. Introduction

Operation and Maintenance (O&M) for wind turbines has evolved as a sector with important levers to increase availability, energy yield and thereby increasing financial profits of wind farm projects. At the same time O&M costs are to be lowered constantly, mainly by shifting towards a more preventive approach on turbine O&M.

Especially in the offshore sector a wide range of O&M simulation and modelling tools are available on the market to support decisions on O&M strategy and resources like ships and personnel to be allocated in order to achieve the most efficient operational setup. The development of these tools is being supported by public research projects and industry partnerships.

While these tools strive hard to model the full range of the complexity of offshore O&M processes including weather and wave conditions and restrictions for vessel operations on the wind turbine service side there remains a large uncertainty on the demand side which is the characteristics of failure behaviour of wind turbines.

2. Existing failure models in offshore O&M tools

Existing offshore O&M tools have been compared in their capabilities and results by [1]. In the reference case for the comparative study the failure behaviour was modelled by applying a constant failure rate for five different failure categories. This simplified approach is the basic starting point for modelling the failure behaviour, which enables comparing different tools.

ECN O&M Cost Estimator

The ECN O&M Cost Estimator uses the mean time to failure (MTTF) on a component level to represent the failure characteristics of wind turbines. Failure modes are grouped by components and main systems based on the RDS-PP structure [2]. Maintenance actions are categorized into different categories and fault type classes with individual resource use and costs associated. The overall number of failures is taken is required as input from the user and may be taken from internal experience or published literature. These input parameters may be determined or updated by using the O&M data analyser, a complementary tool, which analyses the operational data structured in an event list and provides information on the frequency of failure events per components [3]. Additionally it shows confidence intervals for the failure rates that have been derived from empirical data [4].

Far Offshore Wind Interactive Tool - University of Strathclyde

The Far Offshore Wind Interactive Tool (FOWIT) developed by the University of Strathclyde references a study by Raademakers and Braam [5] for failure rates of offshore turbines. The failure model allows choosing between a subsystem or a five repair categories approach with different durations for repair actions and logistic efforts. Statistical distributions such as power law and Poisson processes in order to model the bathtub curve with early failures, intrinsic failures and deterioration may be applied [6].

NOWIcob / SINTEF

The NOWIcob model by SINTEF assigns maintenance strategies to maintenance tasks and includes corrective and time-based maintenance. It considers the main systems of wind turbines with a set of maintenance tasks each. Poisson processes are used to distribute the failure rate over time [7].

MAINTSYS™ / Shoreline

The Offshore Wind Simulation Model by the University of Stavanger, which has been taken forward as the commercial software MAINTSYS™ also use a homogenous Poisson function to model the dynamic behaviour of the failure rate. The wind turbine is subdivided into 19 components according to the RDS-PP structure and occurring failures are categorized by using the failure type classification [8].

SIMLOX / SYSTECON

The commercial software Simlox from the Swedish company Systecon also applies a Poisson process to model the failure characteristics. The wind turbine is subdivided into subsystems with failure modes and related failure mode frequencies for condition based and preventive maintenance. Calendar time and operational time are the underlying factors. Maintenance actions such as inspection, repair or replacement for each failure modes are defined and may consist of several sub processes. For preventive maintenance measures anticipation and deferment times are set [9].

Discussion

Although these approaches succeed in varying the failure rate over time they neglect a number of known characteristics of failure behaviour. They rely on time-based distribution only. Thus they do not take into account the physical mechanisms in the modelled failure modes and do not reflect the characteristics visible from empirical operation and event data.

Results of FMEA studies have been published by [10], [11], [12] and show the most critical failure modes and components. Among these are converter, pitch and yaw systems and the rotor blades with their respective failure modes.

Empirical data from the University of Strathclyde [13], Reliawind [14] and the WInD-pool [15] also provide data on the affected components. Moreover, the German scientific measurement and evaluation programme (WMEP) also shows statistics of failure causes giving shares of component failures and external causes like storm, lightning or icing. There is a seasonal pattern for the occurrence of failure due to these causes and it is also a known correlation that the failure probability increases at higher wind speeds [16], [17], [18].

These effects are relevant for offshore O&M modelling as they affect the accessibility of turbines at the time the failure occurs. Therefore are more detailed approach is proposed in this abstract. Recent research papers have already indicated that further parameters on the underlying physical failure mechanisms are to be included in the failure modelling:

Holmstrøm has shown a validation of the rate of occurrence of failures used in the non-homogenous Poisson process models with real farm data on a yearly basis over a 20-year lifespan and found a time dependent rate to match better [19]. A detailed approach including covariates, unobserved heterogeneity and seasonality has been outlined by [20] based on data analysis of the WMEP.

Building the link to the physical failure mechanisms Asgarpour and Sørensen suggest applying deterioration curves for structural components, discrete degradation functions for mechanical components and bathtub curves for electrical components [21]. Jürgensen has developed a model adding condition monitoring data to calculate individual failure rates for components [22].

3. Modelling different failure mechanisms of wind turbines

The proposed approach builds on a reliability block diagram of the wind turbines sub-assemblies and components. Additionally an extra layer is inserted into the block diagram to represent the failure categories for different failure mechanisms. The overall framework is illustrated in the following figure.

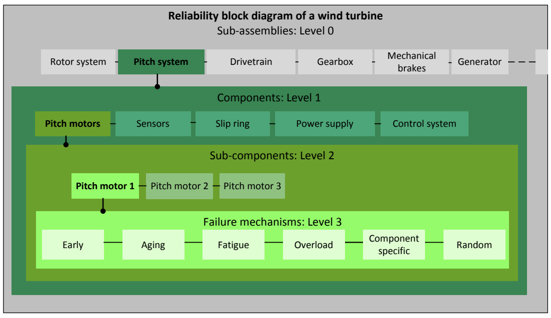


Figure 1: Framework for modelling different failure mechanisms of wind turbines

3.1. Turbine structure

A wind turbine is a system of over one thousand components which can be divided into component groups. Therefore, the system of the wind turbine is described as a combination of individual components and for the simulation of a wind turbine, a commonly used method for network analysis is applied. Reliability block diagrams (RBD) are used in several studies for modelling the failure behaviour and the reliability of wind turbines (for example [23]). The structure of a RBD defines the logical interaction of failures within a system. Each block is to represent both components and subsystems. In various literature the series connection of components or groups of components is chosen for modelling a wind turbine. Since part failures usually lead to a stop of the entire WT, this principle is also used in the described approach. However, redundancy of components means that a failure of one of these components does not lead to failure of the entire system as a functionally identical component ensures continued operation and a parallel connection is used in the case of redundant components. In a further breakdown, each component group is regarded as a series connection of individual components at the next level.

For the breakdown the wind turbine is to be divided into different areas of functional relationships and an unambiguous assignment of the components is needed. With the Reference Designation System for Power Plants, short RDS-PP® [24], a standard was introduced to designate parts of the system.

The structuring of a wind turbine according to RDS-PP® is classified according to functions and functional units.

3.2. Failure Categories

To simulate the failure behaviour of a component a categorization of failures based on the phases of a bathtub curve and the various types of damage has been performed.

The development of failure intensity with time for non-repairable systems is well known and is often described by the bathtub curve, which divides the lifetime of a technical system into three phases. The first phase is marked by falling failure intensity due to ‘early failures or teething problems’. This is followed by a longer second phase, when failure intensity is constant due to ‘intrinsic or random failures’, which can be called failure rate. This is followed by a period of rising failure intensity as damage accumulates with operational age due to ‘wear out’.

In addition, there are several factors that influence the WT failure rate, such as wind speed, turbine concept and climatic conditions, which should be part of any appropriate reliability analysis.

The failure categories are derived from the bathtub curve and a general classification of failures of technical systems in wear and break mechanisms. Early failures are used to represent the infant mortality of turbines as a decreasing failure rate over the first years. Wear effects include aging and fatigue failures whereas overload refers to break mechanisms which may be due to heavy gusts of wind. Component specific mechanisms allow to model individual risks to a component that may be related to the specific time or place of the site e.g. lightning damages to the blades. Finally, there remains a random block with a constant failure rate that cannot be tied to other mechanisms.

- **Early failures**: failures that occur at the beginning of the start-up phase, for example, due to installation or manufacturing errors of individual components.
- **Random failures**: failures, which is a constant risk based
- **Aging failures**: failures of a component that occur due to aging effects, e.g. corrosion.
- **Fatigue failures**: failures that occur because of fatigue or wear.
- **Overload failures**: failures of a component due to an overload of a component.
- **Component specific failures**: this category allows modelling additional effects. This could also comprise natural events such as lightning strikes, earthquakes and damage due to bird strike

3.3. Parameter estimation

In the following section the procedure of modelling the failure behaviour is described stepwise.

3.3.1. Determine the total number of failures for the simulation period. In the first step of modelling the value of the average failure rate of the modelled subsystem or component needs to be selected from a suitable study. This value determines how often the component fails in a selected period.

3.3.2. Weighting of failure modes. In the next step the total number of component failures with respect to the weighting of the different failure categories must be allocated. Depending on the component selected the number of failures per category can vary greatly.

After having all failure modes divided according to the presented categories, the next step is to describe a corresponding function for the failure behaviour of the different categories.

3.3.3. Functions of time-dependent failures. Time-dependent failures are modelled by using Weibull distributions. The function of the failure rate is

$$\boldsymbol{\lambda(t) = \frac{\beta}{\eta - t_0}\left(\frac{t - t_0}{\eta - t_0}\right)^{\beta - 1} \quad for \quad t \geq 0} \qquad (1)$$

where ß is the corresponding form factor, η the characteristic lifetime and t_0 the failure-free period. These parameters need to be adjusted to fit with the weighted empirical failure rates for the different components.

Random failures are characterized by constant failure rates over time. In this case the form factor has the value 1 and the Weibull distribution turns into an exponential distribution.

For modelling the early failures a form factor of 0.4 << 0.9 is used, so that the lifetime distribution is described with a decreasing failure rate. For design-related or installation failures it is assumed that the probability of a component failure due to these causes is high at the beginning and after a component specific period decreases to nearly zero and the probability of failure is only very low. Therefore an additional limitation of the lifetime distribution period, e.g. failures occurring only in the first 2 years, is necessary.

In the case of aging failures the failure rate increases over the age of the component. The shape parameter is assumed to be <1. Additionally, the beginning of the aging phase and therefore the failure-free period, which is strongly dependent on the component, needs to be estimated. Since wind turbines are usually designed by the manufacturer with a minimum service life of 20 years, for most components the beginning of the aging phase will occur after at least 10 years.

3.3.4. Function of fatigue failures. The modelling of the fatigue failure is not described as a function of the "calendar" age because wind turbines are exposed to the effects of fatigue only in operation and a different lifetime characterizing variable needs to be introduced. For many components, the operating time or the hours of full load are more meaningful values for indicating the development and the state of fatigue. Therefore, fatigue can be modelled by tracking the turbine’s working hours and capacity factor. However, the overall failure function as well as the choice of influencing parameters is strongly component specific. A different approach to implement the effects of fatigue would be to model the function depending on the strain gradient or the number of load cycles of a component.

Similar to the aging failures, the failure behaviour described by the corresponding lifetime characteristic is expressed by a Weibull distribution. For the failure-free period it can be assumed that fatigue effects act on the component from the start-up. With the additional assumption of an increasing failure rate, a value of the shape factor must be estimated. Here fore it is necessary to translate the results coming from failure statistics to the changed lifetime variable (for example, energy generated since commissioning of the component).

3.3.5. Function of overload failures. For the modelling of failures due to overload another lifetime characterizing variable needs to be introduced. In general, strong mechanical forces, temperatures or high electrical voltages to components are possible causes of overload failures.

In the case of a wind turbine, it is obvious that the most dominant factor for overload failures for the majority of the components can be seen in the wind, which introduces forces to the wind turbine. The dependence of reliability on wind speed is analysed in general in [17]. The relation between failure rate and wind energy index is shown for a population of Danish WTs in [16], with failure rate increasing at higher wind speeds and electrical subassembly failure rates showing the strongest dependency.

A reasonable assumption is that an increase in the risk is proportional to the wind speed. At too low wind speeds no overload failures will occur. At high wind speeds the wind turbine is shut down and it is believed that the risk of failure for most of the components due to overload is then negligibly small. Therefore, the corresponding function for overload failure can be based on the current wind speed with a progressive function beginning at cut-in wind speed ending just after the cut-out speed.

The overload of components due to much stronger storms (for example hurricanes) will not be displayed in this function and the resulting risk of failure can be found in the category of random failures or in the group of natural disasters such as earthquakes and lightning strikes.

3.3.6. Component specific failures. Even though the majority of reported failures are attributable to defective or loose components in many cases the faults were caused by external influences such as storms, lightning, ice accretion or network outages. These failure causes are represented in the model as “component specific”, as shown in Figure 1). While as a cause of breakdowns network outages are not dependent on season or location, the other external conditions show both a clear seasonal and geographic dependency. For example, most damage and interruptions to operations caused by direct or indirect lightning damage – i.e. voltage surge damage following lightning strikes into the electricity network – are reported during the summer (in Germany). As most operational problems caused by ice accretion arise between December and March (a period with normally good wind conditions), a significant loss of yield can sometimes be expected in the case of such breakdowns. Therefore it is essential to include those effects in a suitable reliability model.

3.3.7. Combined failure function. The failure categories are weighted system or component specific and then summed up to build an overall failure function. This requires modelling the different failure categories independently from one another. The combined function looks like

$$\lambda(t, X_1, X_2, X_3) = \lambda_{konstant} + \lambda(t) + \lambda_{fatigue}(X_1) + \lambda_{overload}(X_2) + \lambda_{specific}(X_3) \quad (2)$$

with

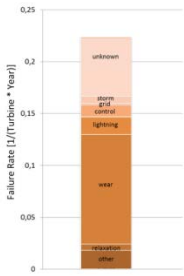
$$\lambda(t) = \lambda_{Aging}(t) + \lambda_{Early}(t) \quad (3)$$

4. Simulation of the reliability behaviour

With the described framework for modelling the reliability behaviour it is possible to set up a reliability module which can be implemented in an overall software tool. Fraunhofer IWES has developed an in-house O&M modelling tool with a multi-agent approach throughout the project MAS-ZIH [26]. The tool serves as the development environment for the analysis and simulation results presented in this paper. It is based on a time-step Monte Carlo simulation and includes individual failure transitions for specific components and failure impact factors.

In the following the reliability module is described. It contains the information about the reliability behaviour of the different wt components. As described before it can be seen as a serial connection of the different components. This allows the flexibility needed since the natural characteristics of the components can be taken into account to the extent needed for the simulation processes. The flexibility also comprises the level of detail chosen for the different components. Since the input for estimating the parameters describing the failure function comes from failure statistics, it is necessary to have some default values for those components for which the failure characteristic is not well known. The parameter estimation follows the steps described before and a model with estimated parameters for the rotor blades is shown as an example within this subchapter.

The failure behaviour of the rotor blades of wind turbines with a capacity in MW range is subject in several statistics, such as the ReliaWind study [14] and the WMEP [25]. These statistics provide some indispensable information about the most common causes of failure of rotor blades. The possible failure causes shown in Figure 2 were assigned to the various event categories. Since no direct information about certain categories is available, the assignment needs to be conducted using some additional weighting.



Average Rotor Blade Failure Rate:
λ = 0.225 /(Turbine * Year)

Failure Mechanism	Share of total Failure Amount [%]
Early	5
Random	15
Aging	15
Fatigue	55
Overload	10

Figure 2: Failure statistic for failure categories of rotor blades

The rate of random failures makes a total of about 15% of the total failure rate of the rotor blade, about 5% of the total losses correspond to the early failures and with the assumption that about 20% of failures "wear" and about 10% of failures due to "relaxation" are counted in the category aging, a share of 15% of total losses results for the aging failures.

With these shares the function parameters need to be estimated using some further assumptions. It is believed that early failures on rotor blades occur only in the first two and a half years and that the expected value of the probability density function lays between a half and one year. With the assumption of a declining failure rate, a form-factor is β = 0.5 estimated. For describing the function for the aging failures the assumptions are made that an increasing failure rate exists, that aging failures occur only after 10 years after installation but at the latest after 40 years and that the expected value of the distribution density function is at approximately 20 years. This leads to

$$\boldsymbol{f(t) = 0,25 * \left(\frac{t}{2}\right)^{-0,5} e^{-\left(\frac{t}{2}\right)^{0,5}}} \tag{4}$$

for the early failures and for the aging failures to

$$\boldsymbol{f(t) = 0,09 * \left(\frac{t-10}{17}\right)^{0,3} e^{-\left(\frac{t-10}{17}\right)^{1,3}}} \tag{5}$$

The dominant failure group for the rotor blades can be seen in the fatigue failures. For the calculation of f(x) for the distribution density function a run-time variable needs to be chosen and being translated out of the existing statistics. The energy generated or the cumulated number of full load hours is taken as life-describing parameter for components that are constantly running during time of energy production.

Because components are subject to fatigue failure over the entire operating period, the average failure rate of fatigue failures can be expressed with 0.55 times the average failure rate of the rotor blade. This in turn would mean a mean time to failure due to fatigue of about 8 years. With an average wind speed of 8.5 m/s, a 4MW plant produces about 1,84MW, so that the energy produced in 8 years corresponds on average to approximately 129GWh. It is believed that the expected value of the failure due to fatigue is at that time at which a wind turbine has produced this energy. The value of the energy delivered, approximately 129GWh, corresponds to the expected value of the associated probability density function. With an increasing failure rate for fatigue failures, the form factor is selected with 2.2 so that the failure rate slowly rises at the beginning and in the course faster. The value of the characteristic lifetime of a rotor blade can be calculated from this data and is approximately 160GWh. With the assumption that the fatigue effects are applied on the rotor blades from the beginning and occur at any later time with probability greater zero, the distribution function is valid for all times t>0. With these assumptions, the distribution density function of fatigue failures can be described completely.

$$f(t) = \begin{cases} 0 & \text{for } \ t < 0 \\ \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}} & \text{for } \ t \geq 0 \end{cases} \tag{6}$$

leading to

$$\boldsymbol{f(t) = 0,01375 * \left(\frac{t}{160}\right)^{1,1} e^{-\left(\frac{t}{160}\right)^{2,2}}} \tag{7}$$

For the overload failures an additional parameter describing the failure probability is needed. In most cases the average failure rate for overload failures can be assigned to the value of the mean wind speed at hub height of the wind turbine.

With the assumptions described afore the profile of the failure rate of the category of overload failures is described as a linear function with the slope

$$m = \frac{\lambda(v_{average})}{v_{average} - v_{min}} \tag{8}$$

Resulting in the function

$$\lambda_{Overload}(v_{Wind}) = \begin{cases} 0 & for\ v < v_{min} \\ m * (v - vmin) & for\ v_{min} < v < v_{max} \\ 0 & for\ v > v_{max} \end{cases} \tag{9}$$

The overall function describing the failure behaviour can be expressed combining the aforementioned single functions for the different categories.

5. Results

For the assessment of the model quality a comparison has been conducted. Three distributions have been compared. The first distribution can be seen as the starting point for the simulation of the reliability behaviour. A constant failure rate with no dependencies is simulated for a large offshore wind farm over the whole lifetime. The second distribution comes from the simulation using the developed reliability module. A clear shift towards a broader distribution with smaller peaks throughout the lifetime can be seen. For the reference case a set of event data, which has not been used for the establishment of the model, has been analysed. The distributions are illustrated in Figure 3.

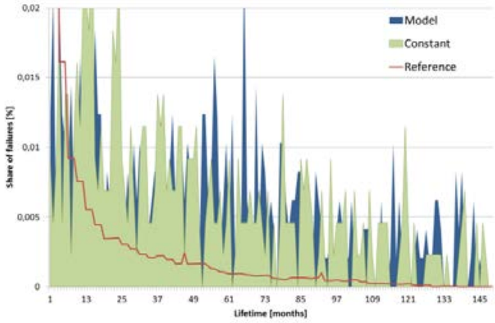


Figure 3: Empirical distributions for a) constant failure rate b) reliability model and c) reference case

Even though the curves appear to be quite similar, some differences can be seen. In order to demonstrate the better fit of the reliability model the difference to the reference scenario has been calculated. The RMSE for the constant failure rate is at 2,01 while the RMSE only slightly decreases to 2 for the developed model. The main difference can be seen for both simulations in the incredible higher amount of failures in the very beginning of the components life. This might be a statistical artefact due to the fuzziness of the failure definition. In the reference scenario the larger amount of early failures might be explained by the fact that the simulation covers only failures leading to a turbine downtime whereas the event database also comprises smaller component defects. Nevertheless, the comparison demonstrates the overall plausibility and proves that the outcome is in the same order as the initial simulation. Therefore, for showing the real value of the model a deeper investigation of the results is needed.

In a first step the breakdown according to the different failure categories is presented and the desired output is discussed. The breakdown of the failures for the different failure categories is shown in Figure 4.

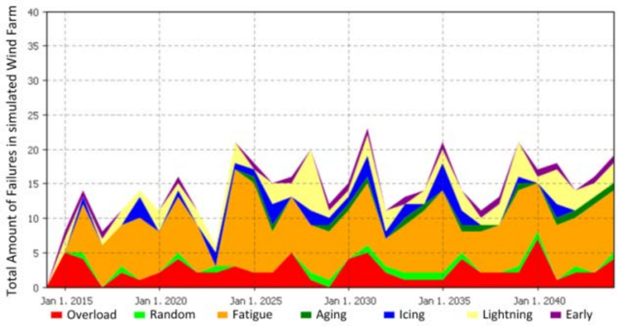


Figure 4: Breakdown of simulated failures according to the failure categories

It can be seen that the share of the different categories show the proportion of the initial assignment. The main share is at the fatigue failures and the simulation results confirm the proper behaviour of the model. Since the simulation is done by simulating a wind farm over the whole lifetime and by having component exchanges included, we can see that the early failures, which are due to the components life and not the turbine life, occur over the whole period. The aging failures however only appear to happen after a certain amount of time.

For a clearer picture the dependencies regarding the external effects are investigated in order to validate the simulation results. Icing is being modelled using statistical information on icing events. Icing season is from November to March with a clear maximum in January. The distribution over the other months may vary.

The characteristics of lightning failures are site specific. For this analysis the events have been modelled with reference to a study on lightning climatology in the German federal state of Saxony. [27]. For lightning events a strong seasonality on yearly and daily time scale are well known from experience and statistical data.

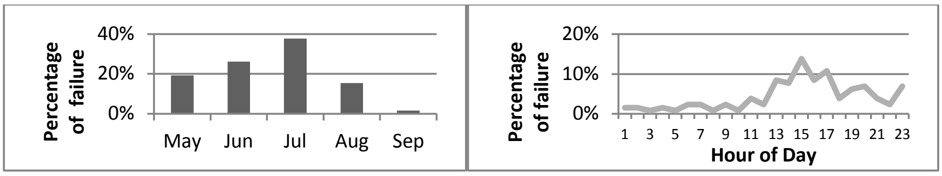


Figure 5: Failures due to lightning events per month and per hour of day in failure model output.

The wind dependent module in the failure function in the model produces a dynamic failure rate that follows the fluctuations of wind speed. As wind speed has seasonal and daily patterns as well these are also considered in the model. Figure 7 shows the difference in the general rate level between summer and winter season.

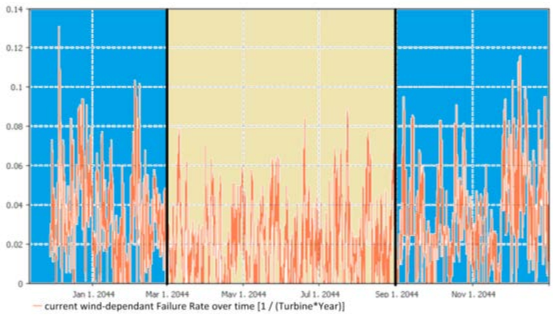


Figure 6: Wind speed dependent failure rate in failure model over one year

6. Conclusions

Modelling the failure behaviour of wind turbines is an essential part of offshore simulation software as it forms the demand side for all O&M processes and related costs incurred. State-of-the-art O&M tools use advanced models to represent the failure behaviour of wind turbines but come short when considering characteristic impact factors on specific components or failure causes. Important effects not yet modelled include increased failure rates at higher wind speed and seasonal effects on failures due to lightning or icing.

To address these issues a failure model based on a reliability-block-diagram incorporating different failure mechanisms has been proposed. It described the failure behaviour based on failure categories derived from the bathtub curve and fundamental wear and break mechanisms and has been fitted with available data to match empirical failure rates. The failure model has been implemented in Fraunhofer IWES multi-agent-system for modelling O&M processes.

The development of a detailed failure function for the rotor blade has been described and simulated. The fit to empirical data proves the general plausibility of the concept. The definition of failures in model and operational data needs further analysis to reduce existing uncertainties especially in the early stages of component life.

The proposed framework for a more detailed model of failure behaviour is essential for better including preventive maintenance strategies to wind farms and a step towards a more functional modelling of component failures. A key factor to benefit from the more detailed model is the availability of high quality O&M data from operational experience which is needed to identify the input data.

References

[1] I Dinwoodie et al 2015 Reference Cases for Verification of Operation and Maintenance Simulation Models for Offshore Wind Farms *Wind Engineering* pp. 1–14

[2] H Braam, T H Obdam, R van de Pieterman and L Rademakers 2011 Properties of the O&M Cost Estimator (OMCE)

[3] M Asgarpour and R van de Pieterman 2014 O&M Cost Reduction of Offshore Wind Farms - A Novel Case Study

[4] L Rademakers 2013 How to assist operators? The development of low cost load monitoring and decision support rules

[5] L Rademakers and H Braam O&M Aspects of the 500MW Offshore Wind Farm NL7

[6] University of Strathclyde: 'The Tool. URL: http://www.esru.strath.ac.uk/EandE/Web_sites/14-15/Far_Offshore_Wind/our_work/our_work_files/pages/the_tool.html#TUT'

[7] M Hofmann and I B Sperstad 2013 A Tool for Reducing the Maintenance Costs of Offshore Wind Farms *Energy Procedia* pp. 177–186

[8] J O Endrerud, J P Liyanage and N Keseric 2014 Marine logistics decision support for operation and maintenance of offshore wind parks with a multi method simulation model *Proceedings of the 2014 Winter Simulation Conference* pp. 1712–1722

[9] J Johansson 2013 Operational Validation of SIMLOX as a Simulation Tool for Wind Energy Operations and Maintenance (O&M), Master thesis

[10] M Spring et al 2015 Top 30 Charts of wind turbine failure mechanisms *Proceedings of the EWEA Annual Event*

[11] M G Bharatbhai 2015 Failure Mode and Effect Analysis of Repower 5M Wind Turbine *International Journal of Advance Research in Engineering, Science & Technology (IJAREST)*, 2 (2015) 5

[12] H Jung et al 2014 Abschlussbericht für das Verbundprojekt „Erhöhung der Verfügbarkeit von Windkraftanlagen"

[13] J Caroll et al 2015 Offshore Wind Turbine Sub-Assembly Failure Rates Through Time *Proceedings of the EWEA Annual Event*

[14] J B Gayo 2011 ReliaWind final report. More efficient and reliable wind turbines by 2011'

[15] S Faulstich 2015 Performance and reliability benchmarking using the cross-company initiative WInD-Pool *Proceedings of the rave international conference*

[16] P J Tavner et al 2012 Study of weather and location effects on wind turbine failure rates *Wind energy*

[17] B Hahn 1997 Zeitlicher Zusammenhang von Schadenshäufigkeit und Windgeschwindigkeit'

[18] P J Tavner et al 2006 Influence of Wind Speed on Wind Turbine Reliability *Wind energy*

[19] K M Holmstrøm 2014 How can more advanced failure modelling contribute to improving life-cycle cost analyses of offshore wind farms?

[20] V Slimacek, B H Lindqvist 2016 Reliability of wind turbines modeled by a Poisson process with covariates, unobserved heterogeneity and seasonality *Wind energy*

[21] M Asgarpour, J D Sorensen 2016 O&M Modeling of Offshore Wind Farms – State of the Art and Future Developments

[22] J H Jürgensen 2016 Condition-based Failure Rate Modelling for IndividualComponents in the Power System: Licentiate Thesis

[23] I Athamna 2015 Zuverlässigkeitsberechnung von Offshore-Windparks

[24] RDS-PP – Application Guideline: 'Part 32: Wind Power Plants', 2014

[25] Fraunhofer IWES 2014 *Windenergie Report Deutschland*

[26] V Berkhout et al 2015 MAS-ZIH - Einsatz von Multi-Agenten-Systemen als Unterstützung für eine zuverlässigkeitsorientierte Instandhaltung. Abschlussbericht : Laufzeit des Vorhabens: 01.10.2011 - 31.03.2015.'

[27] A Schucknecht, J Matschullat 2014 Raum-zeitliches Blitzaufkommen im Freistaat Sachsen – Ursachen, Phänomene, Risiken (BlitzSn)