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Optimal operational planning of wind turbine fatigue progression under stochastic wind uncertainty

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Fatigue damage is one of the major design drivers for structural components of wind turbines. These machines are required to operate continuously over a lifetime of more than 20 years, during which the fatigue damage progression is influenced by control-induced loads and site-specific environmental conditions. Loads can be influenced in various ways through the wind turbine controller, e.g., by derating the power or by operating in partial overload. Since fatigue progresses slowly over the lifetime, each component or even failure mode has an individual fatigue budget that can be utilized optimally. To obtain the maximum long-term benefit from each individual fatigue budget, the trade-off between energy production and load-induced damage needs to be balanced over the complete life cycle.

For each failure mode, we can compute an optimal long-term operational planning that allows for optimal distribution of the damage contribution over the entire or remaining lifetime. This is conducted using deterministic assumptions about wind conditions. Now, we use uncertainties of annual wind distribution parameters as the basis for a probabilistic assessment of the lifetime of each component. This allows for combination using a reliability model, which yields the lifetime of the entire wind turbine system.

The impact of individual component optimizations on overall system reliability is evaluated. Results show that all approaches yield a potential for extended lifetime, however the margin and the secondary impact differ greatly. Simultaneously, the span of probabilistic lifetimes emphasizes that uncertainty has a significant impact on the selection of an optimal strategy.

Our findings provide a step towards a probabilistic and reliability-based long-term operational planning for an entire wind turbine system that is composed of multiple components.

Keywords: Wind energy, operational optimization, fatigue reliability, wind uncertainty, lifetime planning.

1. Introduction

Wind turbines are designed to operate continuously over a lifetime of at least 20 years. During this time, they are prone to high loads under various site-specific environmental conditions. All large structural components like e.g., the tower and the rotor blades are thus designed to withstand the loads over their entire lifetime under consideration of the environmental conditions. One of the main design drivers for such components, like the blades and the tower, is fatigue damage, which leads to growth of cracks, and ultimately to failure (Liao et al., 2022). Crack growth, i.e. the progression of fatigue damage, is induced by cyclic forces and bending moments at various locations across a turbine and is influenced not only by the environmental conditions, but also by the operation of a turbine. Thus, intelligent planning and adaption of the operational strategies can be used to influence the fatigue progression and make best use of the available load bearing capacity. Energy production and load-induced damage need to be balanced over the complete life cycle to obtain the maximum long-term benefit from each individual turbine. To influence the loads, a wind turbine real-time controller can implement various methods, e.g., derating or partial overload. The selection of the control method can be changed by a supervisory operational management by providing setpoints to the real-time controller. This way, the power output of a turbine can be increased, at the cost of reduced lifetime, or the lifetime can be extended at the cost of reduced power production. Optimal operational planning then provides long-term operational strategies for the selection of these control setpoints in order to pursue individual long-term objectives.

National and international standards currently focus on traditional deterministic or (semi-) probabilistic design methods to safeguard that a turbine does not break down before the desired lifetime. To make the best use of its given load budget by operational planning, it must be estimated how long the wind turbine will last and what its probability of survival over time is.

Since changes in operation usually affect different structural components and their failure modes simultaneously but differently, the desired reliability and lifetime for the overall wind turbine system is decisive. Therefore, probabilistic approaches in combination with reliability analysis are suitable for the estimation of survival probability. Applying these methods to the design of wind turbines has gained increasing attention, to the point that a separate standard is currently being developed (IEC, 2023). Sørensen and Toft (2010) gives a general overview on probabilistic wind turbine design with a special focus on structural components and their corresponding failure modes. In Liao et al. (2022), recent developments on fatigue reliability of wind turbines are summarized. The paper emphasizes the importance of this topic. The "transformation from local components to global system (fatigue) reliability" is explicitly identified as a major research topic for the future.

Surrogate models are used for a probabilistic evaluation of the remaining lifetime (Hübler, 2019), for reliability based design optimization (Hu et al., 2016), as well as for the evaluation and optimization of operating strategies (Kölle et al., 2022). Such surrogate models are created or trained on the basis of detailed load simulations and their evaluation, sometimes in combination with measured values. They are suitable for evaluating the fatigue damage of structural components of wind turbines over long periods under various influences (Dimitrov et al., 2018). Especially in the field of operation and control, the focus often lies on relative comparisons of the fatigue damage introduced to individual components using deterministic methods. Do and Söffker (2021) gives an overview of how adaptive control strategies can be combined with prognosis of structural health. It also mentions the challenges due to the multi-objective nature of the problem, when control influences loads and damages differently under various conditions.

To be able to derive a system reliability depending on the operational strategy, we want to combine probabilistic methods, which are already partially used in the field of design optimization, with surrogate models for the evaluation of controller adaptations. To do this, we apply these methods to a practical application example. In Requate et al. (2022), we developed the method VIOLA, which creates an optimal long-term operational planning by optimally distributing the damage contribution over the entire or remaining lifetime. The planning makes use of the nonlinear relationship between external conditions, load reducing control and induced fatigue damage. Currently, this optimization is based on deterministic assumptions where an individual target damage needs to be specified for each component. However, there are multiple uncertainties regarding component and environmental conditions. Uncertainties in strength and conditions of an individual component cannot be influenced or altered during operation. We will focus on the effect of unknown environmental conditions, because they can be measured and compensated for by operational planning. Now, we use uncertainties of annual wind distribution parameters as the basis for a probabilistic assessment of time to failure for each component and the entire system.

The outline of the remaining paper is structured as follows. In Sect. 2, we define the objectives of the work before the methodology of the approach is explained in Sect. 3. The utilized models and use cases for the application example are briefly explained in Sect. 4. The results are presented in Sect. 5 and discussed in Sect. 6. Sect. 7 concludes the findings.

2. Objectives

Intelligent adaptive control strategies can be used to maximize the long-term value of wind farms. Besides methods for maximizing performance or adjusting operation to the electricity price, improved material utilization and lowered uncertainty of time to failure are suitable goals. To achieve this, we need to be able to compare different operational management strategies with regard to the reliability of the entire system. We are optimizing an operational strategy on a timescale of 10 minutes, to maximize the long-term value. The strategy depends on key characteristic influences. These can be environmental conditions such as wind speed and wind turbulence, but also electricity price or grid specifications. If economic evaluations are excluded for the time being, an optimal balance between damage induced and energy generated needs to be found. For example, additional yield can be achieved by saving lifetime in situations with a high ratio of damage per kWh of generated energy. However, when computing time to failure for fatigue-driven failure modes, commonly used deterministic methods yield a deterministic lifetime per failure mode. These can only be aggregated by assuming that a system without redundancy, such as a wind turbine structure, fails with the first component failure. A deterministic selection of the minimum lifetime out of various failure modes neither allows to provide a target reliability level (or probability of failure) nor is it suitable for mathematical optimization. Instead, we propose a probabilistic approach to determine the system reliability of a wind energy system, which also is a suitable evaluation method for finding optimal operational strategies. By applying the methods to a practical application example, we provide a first step towards a probabilistic and reliability-based planning of wind turbine long-term operation.

3. Methodology

The definition of a long-term operational strategy and its optimization is taken from Requate et al. (2022). We define a set of input conditions $\bar{x} := \{x_j\}_{j=1}^{B^x}$, where the dimension of x_j is given by the number of environmental input conditions. For this work, we use wind speed v and the turbulence intensity TI, i.e. $x_j = [v_j, TI_j]$. B^x denotes the total number of bins for the environmental conditions and is defined as a fullfactorial multiplication of the number of bins defined for each condition. We use 20 bins wind bins from 4.5 to 23.5 m/s and 25 TI bins from 5 to 29 %. For each combination of input conditions, an operational strategy, i.e., a set of setpoints of the wind turbine controller, $\bar{u} := \{u(x_j)\}_{j=1}^{B^x}$ is defined. Here, setpoints for reducing the available power of the wind turbine (derating) δ^P are used: $u_j(x_j) = [\delta_j^P(x_j)]$. Given an operational strategy $\bar{u}$, a set of input conditions $\bar{x}$ and a frequency distribution of these conditions over time τ, defined as $h_\tau(x; p_h)$, the total fatigue damage for a failure mode $fm \in \mathcal{F}$ after time τ is given by

$$\begin{aligned} &D_{fm}\left(\tau; \bar{u}, h_\tau(x; p_h), z_{fm}\right) \\ &= \sum_{j=1}^{B^x} d_{fm}\left(x_j, u_j(x_j), z_{fm}\right) h_\tau\left(x_j; p_h\right). \end{aligned} \tag{1}$$

Here, $d_{fm}(x_j, u_j, z_{fm})$ is the hourly damage increment described by a surrogate model. It additionally depends on the ultimate design parameter z_{fm}. D_{fm} is a function of the input time (τ), written in front of the semicolon, depending on fixed parameters $\bar{u}$, h_τ and z_{fm} for a specific function definition (behind the semicolon). The parameters used for the combined frequency distribution of all input conditions, e.g., the parameters of a Weibull-function for the annual wind distribution, are denoted as p_h. Assuming linearity, a total lifetime for a failure mode

$$\begin{aligned} &\tau_{fm}^{life}\left(\bar{u}, h_{\Delta\tau}(x; p_h), z_{fm}\right) \\ &= \frac{\Delta\tau}{D_{fm}\left(\Delta\tau; \bar{u}, h_{\Delta\tau}(x; p_h), z_{fm}\right)} \end{aligned} \tag{2}$$

can be derived from the total damage over a reference time $\Delta\tau$. The total deterministic lifetime is determined by the weakest failure mode by

$$\tau_{det}^{life} = \min\{\tau_{fm}^{life}\}_{fm \in \mathcal{F}}. \tag{3}$$

For the probabilistic approach, uncertainties for computing D_{fm} and τ_{fm}^{life} can be added on different levels. Within this work, we only consider site-specific uncertainties in the frequency distribution of the wind by introducing the uncertainty X_{p_h} resulting in a distribution of the lifetime

$$X_{\tau_{fm}^{life}}(\bar{u}) = \tau_{fm}^{life}\left(\bar{u}, h_{\Delta\tau}(x; X_{p_h}), z_{fm}\right). \tag{4}$$

Under these assumptions, a distribution of lifetimes can be created for each operational strategy, assumption on wind conditions and ultimate design load z_{fm}. Those can subsequently be modelled by a lognormal-distribution and the corresponding cdf $F_{fm}\left(t;\bar{u},X_{p_h}\right)$ so that a reliability function

$$R_{fm}\left(t;\bar{u},X_{p_h}\right)=1-F_{fm}\left(t;\bar{u},X_{p_h}\right) \quad (5)$$

for each failure mode can be obtained. Supposing further, that each of the failure modes independently leads to failure of the entire system, the total reliability function is given by the product at each point in time:

$$R\left(t;\bar{u},X_{p_h}\right)=\prod_{fm}R_{fm}\left(t;\bar{u},X_{p_h}\right) \quad (6)$$

The total probabilistic lifetime τ_{prob}^{life} of the wind turbine is then given by solving

$$R\left(\tau_{prob}^{life};\bar{u},X_{p_h}\right)=R^{target} \quad (7)$$

where R^{target} is the target probability of survival. Eq.-7 is solved numerically for deriving τ_{prob}^{life}.

4. Application example

For the application example, the same generic 7.5 MW turbine model as well as the associated surrogate model for the damage increments $d(v,TI,\delta^P)$ as in Requate et al. (2022) are used. The considered failure modes for fatigue are the blade root bending moments in flapwise and edgewise direction (flapwise and edgewise bm) as well as the combined bending moments at the tower base (tower bm)[a]. The failure modes in flapwise and edgewise direction of the blades apply to each of the three blades. They are modelled by the same surrogate so that the individual lifetimes are always the same. For system reliability, the product of all three blades is considered, resulting in 7 combined failure modes (2 times 3 blades and the tower). Those failure modes only define a small subset of structural fatigue failure modes, but they represent major components which are influenced differently by the operating strategies for different use cases.

In each use case, we consider a reference design lifetime of $\Delta\tau=25$ years. The ultimate design parameter z_{fm} is derived from a reference wind distribution $h_{\Delta\tau}^{ref}$ with parameters p_h^{ref}. It is scaled such that

$$R(\Delta\tau_{prob};\bar{u}^{nom},X_{p_h^{ref}})=R^{target}, \quad (8)$$

with the nominal control strategy $\bar{u}^{nom}$ and the target reliability $R^{target}=0.95$. For the reference wind distribution, we define three different use cases. In each case, the parameters p_h consist of the parameters of the Weibull-wind distribution and the definition of a wind dependent distribution of the turbulence intensity (TI) in accordance with IEC-61400-1 (IEC, 2019). Those result in three different ultimate design parameters for these design-assumptions:

i) The conservative TI-design:
   - Wind distribution: Weibull IEC-class 1
   - TI-distribution: IEC class B with 90% quantile at each wind condition

ii) The less conservative TI-design:
   - Wind distribution: Weibull IEC-class 1
   - TI-distribution: IEC class B Weibull distribution for each wind condition

iii) The site-specific wind-design:
   - Wind distribution: Fitted on site-specific data
   - TI-distribution: IEC class B Weibull distribution for each wind condition

Fig. 1 shows the site-specific wind distribution in comparison to the IEC class 1 distribution. The site-specific Weibull-distribution is fitted to 30 year hourly ERA5-data in the north sea. In addition, a distribution is also fitted for each year separately. From the annual variation, we derive a normal distribution for the two parameters of the

[a]bending moments are abbreviated with bm from this point onwards

Weibull-distribution λ and k which define the uncertainty X_{p_h}. Fig. 2 shows the combined relative frequency of wind and TI combinations with the site-specific wind distribution without uncertainty. The different operational strategies are optimized based on the distribution shown in Fig. 2.

Three different operational strategies named

- A (edge)
- B (flap)
- C (tower)

are optimized. Each of them adapts operation such that maximum energy is produced until the turbine fails in one specific failure mode, i.e. in edgewise bm (edge), flapwise bm (flap) or tower bm (tower):

$$\max_{\bar{u}} E\left(\Delta\tau; \bar{u}, h_{\Delta\tau}(x; p_h)\right) \tau_{fm}^{life}\left(\bar{u}, h_{\Delta\tau}(x; p_h)\right) \tag{9}$$

Here, energy E is calculated in the same way as damage using Eq. 1, but replacing the damage increment by an energy increment. The strategies define a percentag power value δ^P for each combination of wind speed and TI, which are shown in Fig. 3. In the nominal strategy, the power value is set to 100% for all conditions. This strategy is not explicitly shown. In this case, the whole field would be coloured in yellow. Each of the strategies reflects the individual deterministic relationship between wind speed, TI and control inputs on the damage increments. The strategy A favours a moderate reduction in power mainly at lower wind speeds (cf. Fig. 3A). The other two strategies reduce power to their maximum value

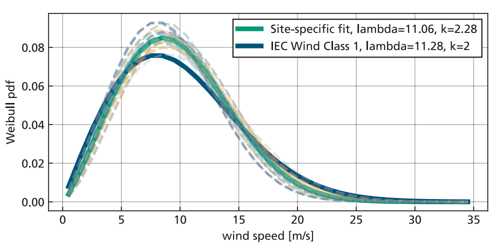


Fig. 1. Site-specific wind distribution (solid green) in comparison to the IEC class 1 distribution (solid blue). The dash-doted lines show the distribution fitted on year of data each

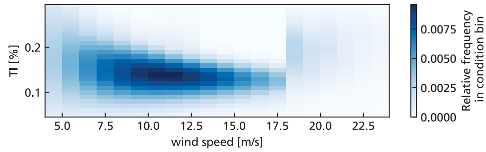
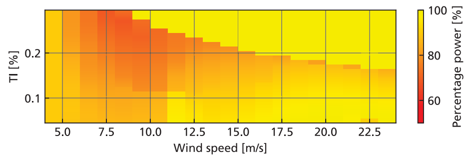
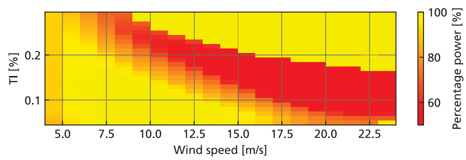


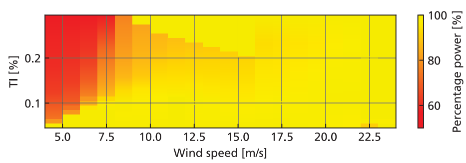
Fig. 2. Frequency of wind and TI combinations for site-specific wind distribution



A (Edge)



B (Flap)



C (tower)

Fig. 3. Three different operational strategies with focus on damage reduction for each failure mode separately.

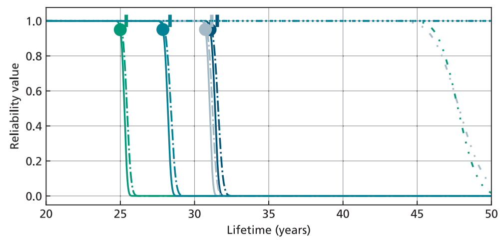
of 50% in certain regions either at combinations of high wind speed and high TI (cf. B, Fig. 3B) or at low wind speeds (cf. C, Fig. 3C). The change of the operational strategies by reducing power under some combinations always affects the damage increment of all three components in different ways. In order to assess the net benefit for the entire system, we evaluate how the three optimized operational strategies affect the deterministic and probabilistic lifetimes compared to the nominal strategy.

5. Results

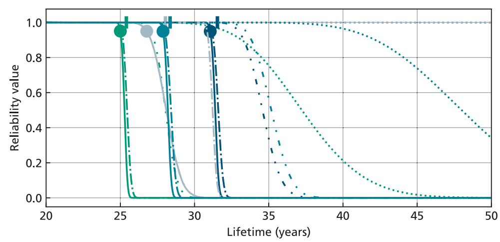
As a comparison, we evaluate the results of deterministic and probabilistic approaches for all three design-assumption cases with each of the four operational strategies. Fig. 4 shows the combined reliability value for each of the strategies together with the reliability values for the single failure modes (non-solid curves). The deterministic lifetime cannot be related to a reliability value. Therefore, it is plotted as a small line around the reliability value of 1 as a comparison. In most cases, the total reliability value is dominated by the edgewise bm for both the probabilistic and the deterministic case. This is due to the properties of the edgewise bending moment, which mainly depends on the rotational speed of the turbine and much less on the TI than the other two bending moments. In the conservative TI-design (i), the lifetimes for both failure modes, the tower bm and the flapwise bm are already significantly higher than the edgewise bm with the nominal operating strategy $\bar{u}^{nom}$ (cf. Fig. 4i)). The failure modes of the flapwise bm have a probabilistic and deterministic lifetime of about 70 years and thus go beyond the limit of the axis. All three optimized strategies achieve a lifetime extension. Due to the low variance of the reliability function and the dominance of the edgewise failure mode, the probabilistic lifetime is only slightly lower than the deterministic lifetime for all three strategies A, B and C.

In the less conservative TI-design (Fig. 4ii)), the combined reliability values are very similar for the nominal strategy as well as for strategies A and C, compared to the more conservative design (Fig. 4i)). In this case, the difference between the reliability functions of the separate failure modes is not as high as before, but the edgewise bm still dominates. The combined reliability for strategy B shows a different behaviour: For both, the deterministic and the probabilistic case, the tower bm failure mode dominates, because lifetime for both failure modes of the blades (egde and flap) are increased significantly by the operating strategy.

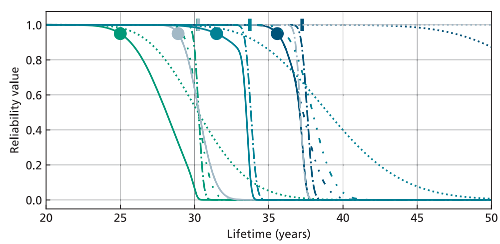
This behaviour is also reflected in the use case with site-specific wind-design, Fig. 4iii). For strategy B, the failure mode for the tower dominates. In particular for the nominal strategy and for strategy C, overall reliability is significantly lower than



i) Less conservative TI-design



ii) Less conservative TI-design



iii) Site-specific wind design

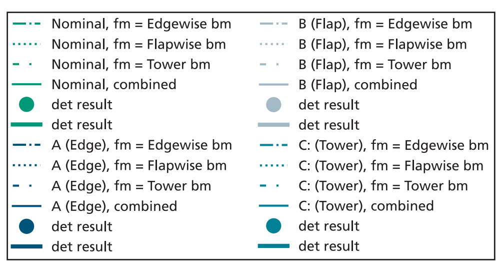
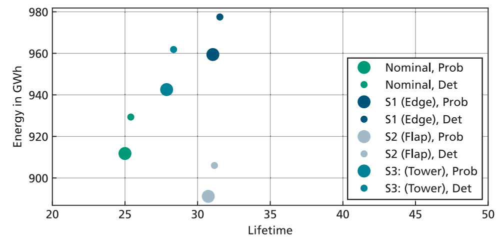


Fig. 4. Combined reliability value for each of the three use cases and reliability functions of single failure modes. The solid dot denotes the lifetime at 0.95 reliability. The deterministic lifetime is represented by a line around 1

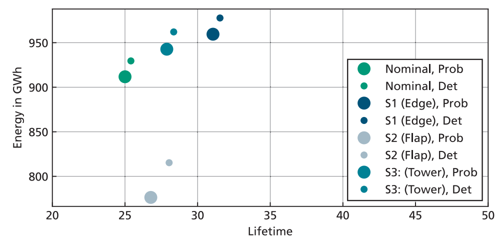
the reliability of each single failure mode. In the deterministic case, for strategies A and C, again the edgewise failure mode lifetime is the shortest. For strategy B, it is the lifetime of the tower failure mode.

Fig 5 show the total energy yield over the determined lifetime for each strategy with deterministic evaluation and the probabilistic evaluation. Strategies A and C lead to significantly increased energy production compared to the nominal strategy. Strategy B, on the other hand, mainly reduces the damage increments of the flapwise failure mode and yields lower total energy production. In all cases three cases, the other two failure modes, i.e. either the edgewise bm or the tower bm, are still dominant. This way, increasing the reliability of the flapwise bm only has a low influence so that the overall relationship between induced damage and energy becomes worse.

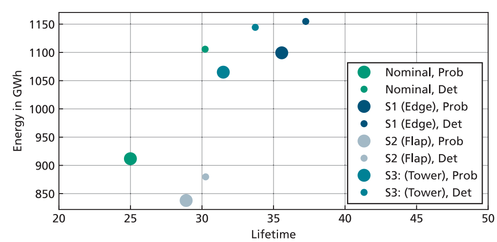
In the first two cases, the relative increase (or loss) in energy production is similar for both, the deterministic and the probabilistic evaluation. For the site-specific case, the increase in energy production for strategies A and C is significantly higher for the probabilistic case. Here, the lifetime extension compared to the nominal strategy is higher, because the dominant failure mode changes for either of the three optimized strategies A, B and C is used,



i) Less conservative TI-design



ii) Less conservative TI-design



iii) Site-specific wind design

Fig. 5. Energy production at probabilistic (prob) and deterministic (det) lifetime for each of the three use cases

6. Discussion

The results of the application example give an insight how different operational strategies can influence the deterministic and the probabilistic lifetime of major wind turbine failure modes. However, focus of this work was on the combination of failure modes, not on the selection of failure modes themselves, their fatigue model and the wind turbine reliability model. Therefore, the results should be used as an illustration of the different influences and the possibility of summarizing failure modes. We assume, that deviations in numeric values will be present when using more detailed models for real-world application. All results only consider relative differences due to environmental conditions and operational strategy. With an existing design, these environmental and operating quantities are the most important ones. Environmental conditions will always differ from the original design assumptions and the operational strategies can be adapted to those conditions. Nevertheless, the application neglects some major other uncertainties, e.g., from the load-stress relationship, the surrogate modelling or material parameters. It needs to be investigated what influence they have on the evaluation of the planning strategies when those are taken into account. Overall, results will become more accurate, with more considered uncertainties and quantities. For finding an optimal strategy, a trade-off between accuracy and computational effort must be found. It is also possible to use a rough estimation of total reliability to be used for optimization and afterwards, some selected optimized strategies can be re-evaluated with a higher level of detail.

The results also clearly show how the design-assumptions influence the assessment of operational strategies for the probabilistic and the deterministic case. In the presented example, one of the failure modes, the edgewise bm, clearly dominates. This leads to comparatively small differences between the deterministic and probabilistic approaches. However, the effect of the operational strategy is limited by the influence of the selected setpoint of the real-time controller. So far, only one degree of freedom, the percentage reduction in power, is considered. This reduces load on each of the failure modes to different degrees under different conditions, but still all of them at the same time. With additional degrees of freedom here, balancing the influence of all the different failure modes with a system target reliability becomes more important and increased the options for even better planning.

7. Conclusion and Outlook

Within this work, we have shown that probabilistic analysis can be used to determine a system fatigue reliability of a wind turbine depending on different operational strategies. This provides a basis for optimizing those to meet the desired target reliability. The example clearly shows the different influences of design and operating strategies. Based on the example, the applied method must be extended by integrating more realistic assumptions for additional uncertainties. This also allows the target values for reliability to be adjusted accordingly so that they are consistent with other sources and standards. Also, a calculation of the reliability index with first-order reliability methods (FORM) or second-order reliability methods (SORM) can be applied to finally use the probabilistic approaches within a mathematical optimization of the operational strategy. In addition, an efficient evaluation of the reliability as an objective function or constraint is necessary to deal with a high number of optimization variables, unlike it is often the case in probabilistic design optimization. Finally, the optimization for long-term value of a wind energy system also requires taking into account economic factors in combination with the reliability value.

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