Remaining Useful Life Determination for Wind Turbines

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Abstract. Since wind turbines have become one of the prevailing sources of electrical energy, their reliability and availability are of enormous importance. Predictive maintenance is a strategy for keeping both factors high and thus heavily under research. Maintenance based on the actual condition of a turbine would be the ideal way in the field of tension between benefit and effort. However, determining the condition of machine parts and elements traditionally requires the expensive application of measurement techniques and inspections. In many cases load-based maintenance – powered by few simple sensors and a model-based derivation of the condition from the history of loads – would be a good compromise. This paper presents a novel method for modeling wind turbines with minimal data requirements for the purpose of calculating inner loads and deriving the condition of machine elements. The applicability is demonstrated in the form of a remaining useful lifetime estimation of gearbox bearings.

1. Motivation

Wind turbines (WTs) have become one of the prevailing sources of electrical energy. In Europe, wind energy overtook coal in 2016 and is now the 2nd largest form of power generation capacity behind natural gas [1]. Due to the resulting dependency on wind energy, availability and reliability have become very important and must be ensured to guarantee a stable energy supply.

Predictive maintenance as defined in DIN EN 13306 [2] is a maintenance strategy based on the condition of elements in the respective machine system. It requires a forecast of the degradation of the item in focus and aims at preventing failures and downtime by taking maintenance measures just at the right time. Therefore, predictive maintenance can make a valuable contribution to keeping availability and reliability high: Maintenance activities become plannable with respect to minimal downtime and maximum material utilization.

The central challenge is that the current machine condition and its change over time must be known in order to determine the remaining service life resp. the failure time. Condition monitoring (CM) in the classical sense aims at detecting irregular symptoms during operation [3] and is therefore an important enabler for predictive maintenance. Approaches known from literature range from time-frequency analyses of vibration data [4] over data mining and statistical models [5] to machine learning techniques [6]. Those techniques do not actually measure the condition of a machine, but rather the symptoms caused by the current condition. Symptoms that are different from what is considered to be the normal condition may be used for predicting the failure time.

The ideal and most accurate prerequisite for predictive maintenance would be to measure the condition of important elements in a WT directly. Practically this is not achievable, as it requires...
expensive regular inspections or even tests of material samples. Boog [7] and Brinkschulte [8] categorize and rate strategies for predictive maintenance as depicted in Figure 1. The “investment” axis refers to the necessary expenses for implementing the respective strategy. The horizontal axis relates to the potential of reducing the levelized cost of energy (LCOE). The LCOE relates the lifetime costs of an asset to the total amount of energy it produces and is the predominant criterion for comparing the costs of energy from different sources [9].

![Figure 1. Maintenance strategies according to Boog and Brinkschulte](image)

According to Figure 1, load-based maintenance is a good compromise between investment and the potential of reducing costs, as it does not require the condition to be measured directly. In the load-based maintenance approach, the condition of a WT is determined from the collective of occurred loads. Compared to the condition, the loads can be measured more easily. This paper goes one step further and presents a method for the calculation of loads from available operational data records by a physically motivated simulation model. With that model, the complete load history of WTs becomes accessible and can be used for monitoring the continuously increasing lifetime consumption. The suitability of the model for predicting the remaining useful life of bearings in the mechanical drive train is demonstrated. For brevity, this paper focuses on WT gearbox bearings. The model could be used for continuously monitoring e.g. mechanical loads on shafts or gears in the gearbox or thermal loads on generator components equally well.

Related studies have also been carried out in other industries – cf. Olabarrieta’s approach to monitoring the lifetime consumption of bearings in machine tools [10].

Section 2 gives an overall description of the simulation model for load calculation. The focus here is on the mechanical components of the drivetrain, as this part of the WT is subject of the use case remaining useful life (RUL) estimation. In section 3, the model validation is shown using the second stage of a WT gearbox as an example. Section 4 explains how the simulation results – component loads – are further used for calculating the RUL of gearbox bearings. Section 5 summarizes the results and gives an outlook on future work and the applicability of the model described.

2. Structure of the model

Load calculation on the level of machine parts and elements has been part of the design process for a long time. With finite-element and multi-body models, very elaborate numeric investigations are possible. These methods are not applicable for CM, as they require fully featured geometrical data and are far from being able to calculate in real time today. Furthermore, detailed design data is frequently not available to WTs’ operators.

The model presented in this paper is completely generic and focuses on the WT’s electro-mechanical drivetrain. It consists of several sub-models corresponding with the components of
WTs. Figure 2 gives an overview of the topology of the model presented in this work. In order to guarantee for easy adaption to different WTs, the parameter space is completely separated from the logic and physics of load calculation. All available model parameters are stored in a dedicated database (“Design data”). During the initialization process, the model is being configured to match a specific WT contained in the design data base and connected to its supervisory control and data acquisition (SCADA) record, which delivers the input data set. From the SCADA standard signals, especially the following are considered:

- Wind speed
- Gearbox oil temperature
- Generator power and rotational speed
- Winding temperatures
- Current and voltage levels between generator and transformer

Figure 2. Topology of the WT model

Depending on the availability of individual parameters and input data channels, the model’s scope of validity changes. Valid calculation paths through different model layers with varying depths (ranging from basic load calculations to power loss determination) are identified automatically. Model output quantities are piped into a database which contains the state of the model at each calculation time step.

All main parts of the model have been implemented in MATLAB and Simulink.

2.1. Sub-model Rotor
This sub-model is essentially a reduced model of the whole WT. The rotor loads (axial and lateral forces, bending moments) are normally not contained in available standard signals, however, they are indispensable for the consideration of the loads on e.g. the rotor bearing(s). This sub-model is the attempt of making the rotor loads accessible: By using the FAST software suite [11], a time-domain simulation is carried out for every SCADA interval. A turbulent wind field, that matches the mean wind speed from the SCADA record and considers site-specific turbulence conditions, constitutes the input. The main challenge in this sub-model is that the controller characteristics must be known, since they have a significant influence on the rotor loads.

Current results show that the approach described above allows for generating time series of the rotor loads whose statistical distribution matches the distribution of time series created with a fully featured validated model. Due to complexity, details of the sub-model composition and validation will be shown in a later publication.
2.2. Sub-model TRANSMISSION
This sub-model comprises all components of the drivetrain in the power flow between rotor and generator. With information on non-torque loads from the ROTOR sub-model and the rotor torque from the SCADA data record, forces and bending moments acting on the main components are determined. These are then used to calculate the inner loads on machine elements (gears, bearings) in the gearbox. Rigid beam models and analytical basic equations are used for the load calculation both at component level and at machine element level, as they are also used in the preliminary design. The following paragraphs describe the required steps for calculating the bearing forces in the intermediate-speed shaft of a three-stage WT gearbox.

Figure 3 shows an exemplary diagram of all forces acting on the shaft. There are two bearings (B2 is the fixed bearing) and two gears (G2 is the drive). All rotating masses are acting in the center of gravity.

![Figure 3](image.png)

Figure 3. Force diagram for an intermediate-speed shaft in a gearbox

In the current state of development of the model, the load calculation consists of three steps: In the first calculation step, the efficiency of each stage of the gearbox is being calculated by considering torque, rotational speed, and temperature of the respective operating point. The calculation is based on available models for friction losses in the gears and bearings [12].

In the second step, the gear forces are determined from the torque acting on the shaft. The third step comprises the calculation of the bearing forces. A linear system of five equations is formed by considering the equilibria of forces and moments according to the depiction in Figure 3. This system can easily be solved and yields the components of all forces of both bearings.

2.3. Sub-model GENERATOR
The GENERATOR sub-model consists of electrical, thermal, and mechanical models of various types of generators common in WTs. Just like in the TRANSMISSION model, all functions are constituted by equations as they are used in the preliminary design phase. All input quantities (torque, rotational speed, current, voltage, temperature level) are taken from the SCADA data record and used to calculate power loss and bearing loads.
3. Validation

The Center for Wind Power Drives has operated a 2.75 MW research WT on its 6 degrees of freedom system test bench [13] in several projects. In doing so, a considerable amount of measurement data has been acquired. These data have been used to validate a complex model of this WT [14], henceforth referred to as “complex model”, which serves as a reference for assessing the accuracy of the “simplified model” presented in this work.

The core of the complex model is a detailed multi-body simulation (MBS) of the entire drivetrain and structural components. Furthermore, it contains an aero-elastic rotor model, the research WT’s original control algorithm, and electromagnetic transient (EMT) models of generator, converter, and grid. However, it does not have a thermal representation of the WT and is not able to calculate efficiencies. All data used for validating the simplified model have been generated by means of the complex model.

The results shown below are related to an operating point in the nominal region of the research WT (mean windspeed 16 m/s with a turbulence intensity of 16 %). The model behaves equally well at all wind speeds in the rated area.

For a reduced complexity, this chapter describes only the validation of the sub-model TRANSMISSION. The validation of other parts of the model will be subject of further publications. Non-torque loads at the rotor flange are neglected in the simplified model, as various results from tests show that the loads on the bearings of the mid-speed shaft under consideration do not depend on external loads other than torque [15]. The efficiency of all components in the simplified model has been set to 1, because the power loss calculation cannot be determined with the complex model.

In Figures 4-6, a comparison of the simulation results between the complex and the simplified model are given using the example of the loads acting on bearings B1 and B2 according to Fig. 3.
For the residual time series, the root mean square errors (RMSE) have been determined with
\( N \) being the number of samples in the given period and \( y \) resp. \( \hat{y} \) the normalized results of the
complex resp. the simplified model.

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{N} (\hat{y}_i - y_i)^2}{N}}
\]  

(1)

For the radial load of B1, both models fit best with an RMSE of 2.9 %. The axial load on
B2 has a RMSE of 3.2 %. The error can be explained with the fact that the floating bearing B1
does not take any axial load in the simplified model by design, whereas in the complex model,
frictional effects lead to a low axial force, which is not included in the equilibrium of forces in
B2. The radial load of B2 fits least with a RMSE of 6.4 %. This is due to differences in the
model parameterization and not a systematic error.

However, the overall results are adequate with respect to the purpose of load monitoring,
especially in view of the low parameter requirements and the short computation time required
for the simplified model. Naturally, the complex model yields results such as the load distribution
over the width of teeth of the gears or effects caused by elasticities. This cannot be calculated
with the simplified model due to the different modeling strategy.

4. Use case: Remaining useful lifetime estimation

This section explains the algorithm used for estimating the RUL of bearings in the gearbox.
The present paper does not claim to develop a new wear model for improving state-of-the-art-methods for lifetime calculation. The aim is to demonstrate the feasibility of combining a
simplified model for load monitoring with a RUL algorithm. In this case, the modified life rating
\( L_{nm} \) as defined in ISO 281:2007 [16] is applied. This approach is not deterministic (the fatigue
model does not allow for predicting the exact time of a failure in an individual bearing), but
statistically valid, as long as there is no wear in the bearing. Furthermore, the results can be
used for comparing similar WTs relative to each other.

The algorithm works as follows: For each operating point, constituted by a SCADA interval
of typically 10 minutes, actual load, rotational speed, and oil sump temperature are stored.
(All gearbox bearings are supplied with oil from the sump, thus the underlying assumption
that the bearing oil temperature equals the oil sump temperature seems to be correct in first
approximation.) In the next step, the equivalent speed of rotation

\[
n_{eq} = \frac{1}{T} \sum_{i=1}^{N} n_i \cdot \Delta t_i
\]

(2)

and the equivalent bearing load

\[
P_{eq} = \sqrt{\frac{\sum_{i=1}^{N} \frac{1}{a_{ISO,i}} \cdot n_i \cdot F_{i}^{p} \cdot \Delta t_i}{\sum_{i=1}^{N} n_i \cdot \Delta t_i}}
\]

(3)

are calculated according to the procedure suggested by Schaeffler [17].

\( T \) is the considered time span consisting of \( N \) intervals with duration \( \Delta t_i \). For each interval,
speed of rotation \( n_i \) and bearing load \( F_i \) are known. The oil temperature \( \vartheta_i \) is implicitly contained
in the life modification factor \( a_{ISO,i} \). The exponent \( p \) is defined by the type of bearing.

In the next step, the equivalent load \( P_{eq} \) is used to calculate the modified life rating:

\[
L_{nm} = \left( \frac{C}{P_{eq}} \right)^{p}
\]

(4)
$L_{nm}$ yields the number of revolutions the bearing should be able to survive without failure with a probability of 90%. $a_{ISO}$ is already implicitly included in $P_{eq}$. The bearing’s actual number of revolutions $L_{act}$ is counted by multiplying the equivalent speed of rotation $n_{eq}$ with the considered time span $T$.

In the final step, the RUL, which represents the bearing’s remaining lifetime as a share of the total lifetime, is formed:

$$RUL = 1 - \frac{L_{act}}{L_{nm}}$$

The procedure calculates the modified life rating based on the loads the WT has experienced and implicitly assumes that the future load situation does not significantly change. This is only valid for a time span $T$ that is large enough. Previous research by the authors shows that the minimal time span should be in the order of one year.

As most bearings in WT drivetrains are (intentionally) highly supersized and mostly fail due to reasons other than fatigue, the use of this method for RUL monitoring makes only limited sense. However, the prevailing reasons for bearing failures are load-dependent [18]. Founded by this fact, an empirical method for RUL determination has been developed:

From available field SCADA data, the load history of bearings can be calculated by use of the model described above. Based on documented failure cases, a “failure load collective” for a specific bearing in a specific assembly situation is generated. For RUL monitoring, the load collective experienced by the bearing under consideration at a given time is being compared against the failure load collective, see Figure 7.

![Figure 7. Exemplary comparison of failure load collective and actual load collective](image)

The difference between both load collectives constitutes the determining factor of the RUL. As the monitoring is directly based on loads, the theoretical error of the RUL estimation is the same as in the load calculation and not augmented by an algorithm with a specific transfer function. The need for documented failure data can be seen as a major drawback, however, this is exactly how the proximity to realistic failure cases is ensured.

5. Conclusion and outlook

The present paper shows a novel approach for modeling WTs for the purpose of calculating inner loads from SCADA records with minimal parameter requirements. The model outputs may be utilized for different applications. A method for calculating the RUL of gearbox bearings has been shown as an example. As the configuration of the model is carried out in a completely automated way, it is easily applicable to a multitude of WTs at a time and represents a powerful tool in the field of CM.
The sub-model ROTOR may be an alternative to backward calculation methods to obtain statistical distributions of the non-torque loads. The usability of the model would even increase if the essential loads were available in all parts of the WT.

With physically based modeling, as it is also used in preliminary design, results that can be used in many ways can be achieved. Which data are required for this will be shown in further work on the topic: By carrying out a comprehensive sensitivity analysis on model parameters as well as on signals from the SCADA dataset, the most crucial modeling aspects will be identified. The accuracy of model instances with reduced parameter sets will be assessed with reference to the “complex model” described above.

Estimation and continuous monitoring of the RUL are possible, as the required load parameters become accessible in real-time. The state of the art currently offers only fatigue methods, but as soon as more complex wear models are available, the presented load calculation model can supply them with input variables.

Acknowledgments
The authors would like to thank the European Union and the German federal state of North-Rhine Westphalia (NRW) for the financial funding. They also like to thank the Leitmarktagentur.NRW for the academic and administrative project support and all industrial partners for the good teamwork.

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