Estimation of Internal Gearbox Loads for Condition Monitoring in Wind Turbines Based on Physical Modeling

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Abstract. The share of wind energy in the public electricity supply in Europe is constantly growing, so that reliability and availability of wind turbines are becoming increasingly important. High availability is ensured by continuous condition monitoring, because it allows long downtimes to be avoided by reacting immediately to (imminent) failures. This paper presents a portable and real-time capable simulation model for determining internal loads on components in the mechanical drivetrain. The loads are apt for being utilized for a subsequent generation of a system reliability index in the scope of a decision support tool for demand- and degradation-oriented adjustments of the operational management. Thus, the work contributes to ensuring reliability. By determining the state of degradation of similarly loaded plants, under- or overloading of individual turbines can be proactively prevented. The analysis of the influence of individual model parameters is of particular importance here and provides evidence that even with a restricted parameter set the outputs of the load calculation model are accurate enough as inputs for a reliability calculation.

1. Introduction and motivation
In Europe and especially in Germany, wind turbines (WTs) overtook fossil technologies for electricity production and have become one of the prevailing sources of electrical energy. In 2016, wind energy overtook coal and is now the 2nd largest form of power production capacity behind natural gas [1]. In the first half of 2019 in Germany, wind energy has contributed the major share of public electricity supply [2] with a total 67.2 GWh. Due to the resulting dependency on wind energy, availability and reliability have become increasingly important. Furthermore, these contribute to low levelized cost of energy (LCOE) and ensure the affordability and competitiveness of wind energy.

Classical condition monitoring (CM) that is focused on the analysis of vibration data is practically installed in every modern WT. It is a means for detecting irregularities in the system performance and a major supporter of early failure detection. The methods used for acquiring knowledge on the health of the WT range from time-frequency analysis of vibration data [3] over statistical modeling [4] to sophisticated machine learning techniques [5]. By finding symptoms of irregular performance as early as possible, expensive downtimes can be avoided or minimized by triggering maintenance activities proactively. This supports availability, the ability of a WT “to be in a state to perform as and when required, under given conditions, assuming that the necessary external resources are provided” [6].

Reliability, however, is the ability of a WT “to perform a required function under given conditions for a given time interval” [6], which means that it is resistant against failure in general. High reliability can be achieved if the WT is operated closely at the conditions assumed in the design phase. These
operating conditions are mainly determined by the reaction of the operational management on current external conditions – namely wind and grid parameters. For example, not all turbines in a wind farm are subjected to the same load, even though they are close to each other and are exposed to the same external conditions in a first approximation. If power curtailment is required by the grid operator, the WT operator has to decide which WT to curtail or switch off. Currently, there is no tool known that would support decision making on the base of the degradation state of individual machines: Power curtailment would be meaningful for the WT with the highest state of degradation. By doing so, the degradation state of the fleet would be equalized, and overloading of individual WTs would be avoided which should increase the fleet-wide reliability.

The project in the context of which this paper is written is dedicated to providing a real-time monitoring device for WT operators to support said decision making. It takes a different approach for monitoring the condition of WTs and aims at continuously determining the degradation state of individual machine elements in WT drivetrains by application of a reliability calculation algorithm. The degradation state is a function of the loads acting on the element under consideration and cannot be measured directly. This requires the loads on the individual machine elements to be known. This paper seeks to show that these loads can be deduced from data from the supervisory control and data acquisition (SCADA) system by means of a simplified and parametric simulation model. Typical SCADA datasets contain distributions (or mean values) of technical quantities in intervals of 10 minutes. Accordingly, the load calculation model yields load distributions resp. mean values for every 10 minute interval. Dynamic effects are neglected.

Calculation guidelines for the reliability of WT gearboxes are given in VDMA 23904 [7]. This standard uses state-of-the-art models for all failure mechanisms which can be described mathematically. Based on that principle, the method is expandable to the whole drivetrain.

The load calculation requires the use of different simulation tools, as they are also used in the design phase of a WT. Complex finite element (FE) and multi body (MB) simulation models, however, usually require detailed information on the WT (comprehensive macro- and microscopic dimensions, material constants), which is not available to the plant operators. In addition, complex simulation models are very computationally intensive and are therefore not suitable for use as a monitoring tool during plant operation. In the study presented here, a significantly reduced parameter set is used, which can be derived from assembly drawings and data sheets – information that plant operators usually have available. This makes it possible to set up a tool chain as shown in Figure 1, which provides real-time information on the system reliability index during plant operation. The model presented forms the bridge between operating conditions (SCADA) and system reliability index (degradation state) by calculating the component loads.

![Figure 1: Calculation of component loads as prerequisite for system reliability estimation](image)

Apart from decision making in the operational management, the calculated degradation state can also be utilized as a decision support for strategic maintenance planning (spare parts stockkeeping, appropriate maintenance strategies for old WTs) and for wind farm life extension.

According to various sources [8, 9], gearbox bearings cause the major amount of WT downtime. Therefore, it seems a valid approach to focus on the bearings of two spur gear stages in a three-stage gearbox of a 2.75 MW research WT for demonstrating the principle in brief.
Section 2 describes the real-time capable and parametric model used for load calculation. Section 3 gives information on the validation of that model and examines the influence of individual parameters on the accuracy of the load calculation to determine the minimum required parameter set. The loads acting on a gearbox bearing are used for demonstrating the method. In section 4, the results and their further usability are discussed.

2. Load calculation in the mechanical drivetrain

The load calculation model presented in this paper is generic and focuses on the WT’s electro-mechanical drivetrain. It consists of several analytical sub-models corresponding with the components of WTs – one of them being the mechanical transmission system depicted in Figure 2. In the initialization phase, all model parameters are read from a dedicated database; thus, it can easily be configured to reproduce the behavior of different WTs. After that, the model is connected to the supervisory control and data acquisition (SCADA) data record of the respective WT. 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 (ranging from basic load calculations to power loss determination) are identified automatically. Output quantities are written to a database which contains the state of the model at each calculation time step.

The model is implemented in MATLAB and allows for a calculation of inner loads of various types (forces, moments, temperatures) from typical SCADA datasets. These do normally contain the rotor torque resp. the generator torque (calculated from voltage and current), but not forces and bending moments acting on the rotor. These loads are generated by a rotor sub-model (not depicted in Figure 2) based on the current wind parameters and the WT’s operating state. From the rotor loads the model calculates inner loads acting on components of the gearbox (gears, bearings). Static mechanic equations and basic analytic models, as they are also used in the preliminary design phase, govern the load calculation. While iterating over the gearbox shafts and stages, the gear forces are calculated first. Next, the bearing forces are determined. These are used for calculating the stage efficiency, which reduces the power and therewith the torque passed on to the subsequent stage. As it is based on rather small equation systems, the model has considerable performance advantages as compared to more complex models.

3. Model validation

The validation of the drivetrain model consists of three steps. In the first step, the general ability to determine meaningful values for a reliability calculation is proven (sec. 3.1). The next steps aim at
deriving a description model for the uncertainty of the model output in dependence of the parameter uncertainties. One approach is a linear model that considers all the main effects and interactions between the parameters. Analogous to a description model for the system [10] it is described by the following equation:

\[ \Delta y = c_0 + \sum_{i=1}^{n} c_i \Delta x_i + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} c_{ij} \Delta x_i \Delta x_j \]

\( \Delta y \) is the uncertainty of the original model, \( \Delta x_i \) are the uncertainties of the \( n \) model parameters (to be provided by the user), \( c_i \) and \( c_{ij} \) are the coefficients for main effects resp. interactions to be determined by a series of test simulations. If the explanatory power of the simple linear description model is not sufficient, higher order models can also be applied. In order to generate the uncertainty model, a univariate sensitivity analysis (sec. 3.2; variation of only one model parameter at a time) is conducted at first to identify parameters that do not have to be considered in the multi-factorial sensitivity analysis, sec. 3.3. As the multi-factorial analysis requires much more computational effort, this two-step approach has been chosen.

3.1. Quantification of the model quality by comparison with a complex MBS-model

The Center for Wind Power Drives (CWD) has operated a 2.75 MW research WT on its system test bench [11] in several projects. The data acquired in the various measurement campaigns have been used to validate a complex system model of this WT [12], which serves as a reference for assessing the accuracy of the analytical model presented in this work. The complex model comprises all main mechanical subsystems of the WT in form of an MBS model with elastic elements, the electric and power-electronic components as well as the control system.

For the validation step, time series with a duration of 10 minutes and a resolution of 1 second have been used (however, the time resolution does not influence the results, as the model does not reflect dynamic effects). Figure 3 shows time series of the radial bearing forces acting on a bearing at the intermediate speed shaft, calculated by the complex MBS model (blue) and the simplified analytical model (orange). The overall performance of the analytical model is good with a deviation of 0.7 % in the median and 0.5 % in the corrected standard deviation from the complex MBS model. The RMS error of the deviation is 2.6 %.

In Figure 4, the performance comparison is extended to the whole operating range of the WT. The boxplots show minimum and maximum values as well as the quartiles of the respective time series generated by the complex MBS model (blue) and the simplified analytical model (orange). Good congruence is given throughout the whole operating range. Only at very low wind speeds, the simplified analytical model over-estimates the resultant bearing load. However, these low loads do not determine the degradation state.
Figure 3: Time series of radial bearing forces calculated by the complex MBS model (blue) and the analytical model (orange) at a wind speed of 16 m/s

Figure 4: Performance comparison of the complex MBS model and the simplified analytical model. The box plots show statistical parameters of time series similar to the one depicted in Figure 3.

3.2. Univariate determination of the model sensitivity

Aim of that step is to identify the sensitivity of outputs of the simplified analytical model towards errors or uncertainties in individual model parameters. In a series of simulation runs, a one-factor-at-a-time (OFAT) method has been applied to generate main effects diagrams for each model parameter. For the two gearbox stages highlighted in Figure 3, \( n = 24 \) model parameters have been varied in two steps (0.9 \( x_i \), \( x_i \), 1.1 \( x_i \) with \( x_i \) being the nominal value of each parameter). Table 1 lists the categories of varied parameters and their effect on the resulting bearing load. “High sensitivity” means that the error in the respective parameter is amplified (\(|\Delta y/\Delta x_i| \geq 1\)); “low sensitivity” designates under-proportionate error propagation (\(|\Delta y/\Delta x_i| < 1\)). “Negligible” parameters affect the result by less than 1% (\(|\Delta y/\Delta x_i| < 0.01\)).
Table 1: Categories of varied parameters and their effect on the load calculation

| Categories of model parameters | Model sensitivity                  |
|--------------------------------|------------------------------------|
| Positions of shafts (lateral)  | High sensitivity                   |
| Positions of bearings on the shafts (axial) | High sensitivity       |
| Positions of gears on the shafts (axial) | High sensitivity        |
| Masses of rotating parts       | Negligible                         |
| Gear properties                | Modulus: High sensitivity          |
|                                | Helix angle: Low sensitivity        |
|                                | Gear width: Negligible             |

This investigation does not require much computing effort. For generating the results listed in Table 1, \(2n + 1 = 49\) simulation runs have been conducted. The influence of all masses of rotating parts and the gear widths, which do hardly influence the bearing loads, can be neglected. That reduces the number of model parameters to be considered in the multi-factorial sensitivity analysis from 24 to 16 and therewith the complexity significantly.

3.3. Multi-factorial determination of the model sensitivity

A full-factorial sensitivity analysis for calculating all constants of the uncertainty model would require \(3^n = 3^{16}\) simulation runs (3 steps, 16 parameters) – still by far too much, especially if we take into consideration that the model of the whole turbine would consist of significantly more parameters. In order to nonetheless quantify the uncertainty, we use the methods of design of experiments [10, 13]. In concrete terms, so-called Latin Hypercubes are used for defining the parameter combinations for the simulation runs. The parameter combinations are adjusted in such a way that, on the one hand, the entire validity range is scanned in a fine resolution for each parameter in the totality of the simulations and, on the other hand, the variation of the parameters between the individual simulation runs is uncorrelated [14]. By doing so, the number of required simulations no longer depends on the number of parameters, but rather on the targeted complexity of the description model. Practical application shows that a first-order model (as noted in the above equation) achieves already a coefficient of determination beyond 95% in most cases.

If the simulation results are normalized before fitting the description model, the relative importance of the parameters can be read directly from the coefficients \(c_i\). In the present study, the gear modulus has been identified as the most crucial parameter for the accuracy of radial bearing forces, whereas the helix angle of the gears is taking the most significant influence on axial bearing forces.

4. Conclusion and outlook

The present paper describes an approach for modeling WTs for the purpose of calculating inner loads from SCADA records in quasi real time with minimal parameter requirements. Therefore it is applicable by WT operators. Results from the model validation show that the quality of the output quantities is high enough to use them for a continuous reliability index calculation, which provides continuous decision support throughout the WT’s service life. As compared to more sophisticated FE and MB modeling strategies, the presented approach is quasi real-time capable.

Based on statistical considerations, a method for deducing a linear description model for the accuracy of the output quantities as a function of the given parameter set has been presented. With that, the uncertainty of each output quantities can be assessed individually. Furthermore, the results of a sensitivity analysis quantify the contributions of individual parameters to the quality of the model outputs.

The complete tool chain for the continuous calculation of the reliability index has not yet been completed. Its feasibility has been demonstrated on individual elements – global and local load
calculation, uncertainty assessment, application of methods of reliability estimation. Further publications will present a full prototype which can be used by plant operators for testing purposes and thus prove its practical applicability.

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