Estimation of rotor and main bearing loads using artificial neural networks

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Abstract. Wind energy is one of the most important technologies for a climate-neutral energy supply. However, the premature failure of wind turbines due to unknown loads leads to a reduction in competitiveness compared to other energy sources. Here, load monitoring systems can make a significant contribution to the prevention of such failures. Most load monitoring systems for wind turbines focus on strain signals of structural components as the tower, main shaft or the rotor blade root. Based on these signals, axial forces, torsion or bending moments, which are acting on these components, are calculated. But this provides only partial information about the complete load situation, as transverse forces are not considered. Other methods use simulation or measurement data to train artificial neural networks (ANN) to estimate damage-equivalent loads acting on a wind turbine. However, this approach is accompanied by a loss of information, because the individual load components are condensed to a equivalent. In this work a method is presented that enables a measurement of rotor and main bearing loads considering all their individual load components. For this purpose, an ANN is trained with elastic multibody simulation (eMBS) data. Based on displacement signals, acting rotor and main bearing loads are estimated. The results show that even with consideration of nonlinearities, including nonlinear stiffness curves and bearing clearances, an appropriate accuracy can be achieved using the method presented.

1. Introduction and Objective
Over the last decades the size of wind turbines continuously increased [1]. The rising rotor diameter results in higher non-torque loads, which are acting on the rotor suspension system. Monitoring these loads provides many possibilities, especially to reduce the operating costs. By considering non-torque loads within the control strategy for example, the remaining useful lifetime of wind turbines can be extended significantly [2]. Based on the load history, maintenance intervals can be adapted and, if necessary, an early replacement of components can be initiated. Unfortunately, current load monitoring systems do not contain a detailed measurement of non-torque loads. Most load monitoring systems focus on strain signals of structural components as the tower, main shaft or the rotor blade root. Based on these signals, axial forces, torsion or bending moments, which are acting on these components, are calculated [3, 4]. But this provides only partial information about the complete load situation, as transverse forces are typically not measured using this technology and in the case of blade roots these methods are also subject to uncertainties due to thermal effects and nonlinear material properties [5, 6]. Additionally, classic strain gauges suffer from signal drift [7, 8] and have a limited lifetime of typically 1 to 3 years.
[8], which makes this technology inappropriate for a long-term application. Other methods use simulation or measurement data to train artificial neural networks (ANN) to estimate damage-equivalent loads acting on a wind turbine [9, 10]. However, the conversion to damage-equivalent loads means that the individual load components, such as bending moments and transverse forces, can no longer be differentiated, which complicates the application within a turbine control system or a later understanding of harmful load situations.

In this work a method for a measurement of rotor and main bearing loads is presented, which enables an adequate consideration of the individual load components. An ANN is trained with elastic multibody simulation (eMBS) data for this purpose. In contrast to other methodologies, load estimation is based only on displacement signals of the drivetrain. These kinds of signals are generally simple to access, as the corresponding sensors can be mounted quickly and easily, even when the wind turbine is in operation. In addition, in the case of non-contact sensors, a wear- and maintenance-free long-term operation of the sensor system is possible. It is analyzed what accuracy can be achieved with this methodology, even if measurement noise is considered. Further the necessary capability of ANNs for rotor and main bearing load estimation are evaluated, including the representation of nonlinearities and dynamic system behavior.

2. Methods

The target functionality of the method is to estimate rotor and main bearing loads only using displacement signals. Unfortunately, displacement signals can be subject to nonlinearities, which complicates a direct conversion of the signals into acting loads. Physical models which describe the correlation between loads and displacements often cannot be solved directly. Instead, these types of models require an iterative solving process, which computational cost can prevent a real-time application. Additionally, physical models show a less robust behaviour to measurement errors and deviation of system parameters as bearing clearances. To overcome these problems a data-driven modelling approach is chosen (Figure 1).

Based on training data, regression models are developed, which enable a direct calculation of rotor and main bearing loads and with that a real-time application. Furthermore, this type of modelling offers the possibility to increase the robustness against measurement errors by considering a distortion of the input signals within the training process. However, the performance of a regression model depends heavily on the quality of the training data. The training data has to be representative for the system response as only included correlations can be approximated reliably. A cost-effective way to generate such data is simulation. In order to do this, it is necessary to represent the system with a sufficient model depth considering the physical effects, which have a significant influence on the system response.

As a prove of principle study, a nonlinear and dynamic simulation model of a wind turbine is developed, which provides a very detailed model depth. Operational rotor and main bearing loads are
estimated by using resulting displacement signals of the wind turbine model. In this way, the accuracy is determined that is basically achievable with the presented approach. Furthermore, the requirements regarding the representation of nonlinearities and dynamics are evaluated.

2.1. Simulation model
The analysis of this study refers to a 2.3 MW low wind speed turbine (rotor diameter: 141m; nominal wind speed: 9 m/s) that has been developed in the context of the project “MaxCap” [11]. The rotor suspension system is designed as a four-point suspensions, as it is shown in Figure 2.

![Figure 2. Principle sketch of considered four-point suspension](image)

A cylindrical roller bearing (CRB) as a floating bearing and a double row tapered roller bearing (TRB) as a locating bearing are used as main bearings. The CRB has a radial clearance, whereas an axial clearance is specified for the TRB. Both clearances are dependent on temperature, manufacturing and mounting and therefore are subject to scatter. Bearing clearances have a significant influence on the resulting displacements, since they lead to a discontinuity of the bearing stiffness curve. A simulation model that is intended to represent the relationship between displacements and loads must take this relationship into account.

The gearbox is connected to the machine carrier by a hydraulic suspension. This type of torque supports is characterized by a high torsional stiffness, whereas a translational movement of the gearbox in relation to the machine carrier is only met with a low resistance [12]. Thereby, the rotor input torque is supported only by this component, leaving non-torque loads being supported mostly by the main bearings. Since its functionality is realized by fluid-filled elastomer chambers, this component has a strongly nonlinear stiffness behaviour, which must be considered by an appropriate modelling.

As required by the current guidelines for load calculation, the rotor and tower dynamics must be represented in the model. A simulation model must therefore include an aero elastic load calculation and take into account the flexibility of structural components. Otherwise, the simulation results in wrong structural dynamics and loads.

To meet these requirements a detailed eMBS-model of wind turbine has been developed using the multi body simulation software SIMPACK (Figure 3).
Figure 3. Elastic multibody simulation model of considered wind turbine

Inside this model, relevant structural components are represented as flexible bodies so that structural-dynamic effects are taken into account, when calculating the system response. This includes following components: rotor blades, hub, tower, main shaft, main bearing housing, machine carrier, gearbox housing, and planet carriers. The elastic properties of the bearings in the drivetrain are taken into account by lumped-parameter roller bearing models in their software implementation. In this implementation, the bearing reaction forces are calculated using algebraic equations [13, 14] on basis of bearing ring kinematics and a lamina roller model [14]. Using lamina roller models, the roller is discretised into multiple slices along the roller axis. The contact stiffness is then calculated for every slice of the roller, which enables the consideration of a roller profile and bearing clearance. Especially the consideration of the bearing clearance is necessary to calculate the correct bearing ring displacements, as these variables are directly influenced by this parameter. Within the wind turbine model, this approach was used to model the main bearings and planet carrier bearings. Thereby, parameter values have been determined using the manufacturers’ specifications. The stiffness and damping characteristics of the torque supports were determined by experiments on a component test bench and implemented as nonlinear spring-damper elements. Loads acting on the rotor blades are calculated in respect to local wind speed and wind direction given by turbulent wind fields generated with TurbSim [15]. This is done using the blade element theory in its implementation in the AeroDyn code [16]. Table 1 shows the specification of the simulations performed.

|                     | Wind speed (incrementation) | Radial clearance deviation at floating bearing (incrementation) | Axial clearance deviation at locating bearing (incrementation) |
|---------------------|-----------------------------|---------------------------------------------------------------|---------------------------------------------------------------|
| Training Data       | 3 m/s to 24 m/s (1 m/s)     | 0 µm (-)                                                     | 0 µm (-)                                                     |
| Testing Data        | 6 m/s to 12 m/s (3 m/s)     | 0 µm (-)                                                     | 0 µm (-)                                                     |
| Sensitivity Analysis| 6 m/s to 12 m/s (3 m/s)     | -100 µm to 100 µm (50 µm)                                    | -150 µm to 150 µm (25 µm)                                    |

For training data, the wind speed is varied from 3 m/s (cut-in speed) to 24 m/s (cut-out speed), while clearances of the main bearings are kept constant in accordance with their nominal values. Thereby a
wide load range of the wind turbine is covered by the training data. Constant clearances and three wind speeds, covering different operation modes (partial, nominal and full load), are considered for testing. In contrast to that, a clearance deviation based on the estimated scatter of these parameters is considered within the data for sensitivity analysis. Here, one clearance is varied while the other is kept constant at its nominal value. In this study, clearance deviation is considered only for the main bearings as most of the displacement signals used for load estimation are given locally at these components. Thereby the estimation is assumed to be most sensitive to these parameters.

Output variables of the simulations are the six rotor loads (Fx, Fy, Fz, Mx, My and Mz) acting at the main shaft’s rotor flange. Their location and orientation are given by the load reference point and the corresponding coordinate system shown in Figure 2. Additionally, the main bearing loads are calculated including two radial forces of the floating bearing (Fy,fB and Fz,fB) and one axial and two radial loads of the locating bearing (Fx,l,B, Fy,l,B and Fz,l,B). Displacements are calculated for the three translational displacements and two tilting displacements (relative motion of inner ring to outer ring) for each main bearing. Additionally to these 10 variables, the three translational displacements at each gearbox torque arm at the torque supports are used, resulting in a total of 16 displacement signals. In a post-processing procedure, according to estimated sensor uncertainties, the calculated displacement signals are superimposed with an artificial normal distributed measurement noise. Here, the measurement noise is modelled as a normally distributed error, which is added to the actual simulation result. The distortion of the signals is necessary, because otherwise the chosen method would achieve an unrealistic estimation accuracy that could not be achieved under real measurement conditions. In order to evaluate the method in terms of its applicability, the measurement error must therefore also be simulated.

2.2. Regression models
On the basis of the noisy displacement signals and the corresponding rotor and main bearing loads, different regression models are trained. As the simplest regression model, a linear regression (LinReg) of input and output values is performed. This model type thereby approximates the considered system with a static and linear behaviour. Even if it is known in advance, that the system has nonlinear and dynamic characteristics, this rather unsuitable regression model provides a benchmark for other regression models.

To model even strongly nonlinear correlations between displacements and loads, ANNs are chosen as further regression models. In a first approach, feedforward neural networks (FNN) are trained to estimate rotor and main bearing loads. FNNs enable the consideration of nonlineairities but still only approximate a static behaviour of the system. Additionally to FNNs and to overcome this abstraction loss, long short-term memory (LSTM) layers are used to expand an ANN topology. LSTM layers give the ANN the functionality to store information from previous time steps of sequence data and enable the consideration of time-dependent effects. Therefore a nonlinear and dynamic representation of the system is achieved with LSTM networks.

In this study, linear regression models, FNNs and LSTM networks are compared with each other. For all ANNs, the training data is split into two data sets. Thereby 180,000 data samples are used for actual training and 84,000 data samples for validation. For both, FNNs and LSTM networks, training is ended when no further improvement in accuracy is achieved for the validation data set. In parallel, linear regression is performed on the same training data used to train the ANNs.

Different parameters are calculated to evaluate the individual regression models. A first parameter is the Root Mean Square Error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2}$$  (1)
where \(y_i\) describes the calculated load, \(\hat{y}_i\) the estimated load and \(N\) the number of samples in the testing data. This parameter evaluates the absolute estimation error of the individual load component. Based on this parameter the relative RMSE is calculated.

\[
Relative \ RMSE = \frac{RMSE}{Load \ Range}
\]

(2)

This parameter sets the RMSE in context to the load range of the testing data. Thereby it can be evaluated, if the estimation error is sufficient for the planned application. Additionally, to quantify the quality of the regression itself, the coefficient of determination is calculated.

\[
R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \bar{y})^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2}
\]

(3)

where \(\bar{y}\) is the mean of the load within the testing data.

3. Results

Training of the linear regression model, FNN and LSTM network has been performed with simulation data without any variation of main bearing clearances according to the specification of Table 1. The load range of the calculated rotor and main bearing loads covered by the training data is used to calculate the relative RMSE. The RMSE is determined based on the difference between calculated and estimated loads. The trained models are used to estimate the loads of the testing data (Table 1) where bearing clearances are kept the same as for training and no deviation occurs. In Table 2 the evaluation parameters are shown for the estimation of calculated rotor loads using the displacement signals of the simulation model. Similarly, Table 3 shows the results for the estimation of the calculated main bearing loads.

### Table 2. Results for rotor loads and constant bearing clearances

| Absolute RMSE | Load Range | Fx | Fy | Fz | Mx   | My   | Mz   |
|---------------|------------|----|----|----|------|------|------|
| LinReg        | 550 kN     | 35 kN | 9 kN | 12 kN | 31 kNm | 51 kNm | 49 kNm |
| FNN           | 220 kN     | 24 kN | 7 kN | 11 kN | 13 kNm | 42 kNm | 32 kNm |
| LSTM          | 22 kN      | 22 kN | 8 kN | 11 kN | 9 kNm   | 45 kNm | 32 kNm |

| Relative RMSE | LinReg | 6,3% | 4,2% | 5,5% | 1,0% | 0,5% | 0,5% |
|---------------|--------|------|------|------|------|------|------|
| FNN           | 4,3%   | 3,4% | 5,0% | 0,4% | 0,4% | 0,3% | 0,3% |
| LSTM          | 4,1%   | 3,6% | 5,2% | 0,3% | 0,4% | 0,3% | 0,3% |

| R²            | LinReg | 84,01% | 48,39% | 52,06% | 99,69% | 99,84% | 99,76% |
|---------------|--------|--------|--------|--------|--------|--------|--------|
| FNN           | 93,99% | 58,83% | 61,49% | 99,94% | 99,85% | 99,89% |
| LSTM          | 93,97% | 59,92% | 60,65% | 99,96% | 99,87% | 99,88% |
Table 3. Results for main bearing loads and constant bearing clearances

| Load Range | $F_{y,FB}$ | $F_{z,FB}$ | $F_{x,LB}$ | $F_{y,LB}$ | $F_{z,LB}$ |
|------------|------------|------------|------------|------------|------------|
| Absolute RMSE | LinReg | 33 kN | 34 kN | 34 kN | 31 kN | 31 kN |
| | FNN | 19 kN | 27 kN | 23 kN | 18 kN | 23 kN |
| | LSTM | 19 kN | 25 kN | 21 kN | 20 kN | 22 kN |
| Relative RMSE | LinReg | 0,6% | 0,5% | 5,2% | 0,6% | 0,5% |
| | FNN | 0,3% | 0,4% | 3,5% | 0,3% | 0,4% |
| | LSTM | 0,3% | 0,4% | 3,2% | 0,4% | 0,4% |
| $R^2$ | LinReg | 99,62% | 99,79% | 86,41% | 99,70% | 99,81% |
| | FNN | 99,86% | 99,86% | 95,40% | 99,89% | 99,89% |
| | LSTM | 99,83% | 99,87% | 95,40% | 99,87% | 99,89% |

FB: Floating Bearing
LB: Locating Bearing

It can be stated, that without any deviation in main bearing clearances, ANNs show a more accurate load estimation compared to a linear regression model. Using ANNs, especially radial forces of the main bearings ($F_{y,FB}, F_{z,FB}, F_{x,LB}, F_{z,LB}$), torque ($M_x$) and bending moments ($M_y, M_z$) at the rotor flange can be estimated with a relative RMSE of less than 1%, referring to the load range to be covered. However, rotor thrust ($F_x$), transverse forces at the rotor flange ($F_y, F_z$) and axial forces of the main bearing arrangement ($F_{x,LB}$) are associated with a significantly higher relative RMSEs, but mostly less than 5%. Comparing FNNs and LSTM networks it is shown that no significant improvement can be achieved with the exception of the rotor input torque $M_x$. Here the RMSE can be reduced by 30 % by using LSTM networks instead of FNNs. A similar pattern arises for the coefficients of determination. Values of more than 99 % are achieved for torque and bending moments at the rotor flange and radial forces of the main bearings. Rotor thrust, axial main bearing forces and especially transverse forces at the rotor show a worse coefficient of determination.

To evaluate the sensitivity of the regression models to clearance deviations, the corresponding data set (Table 1) is analysed. Within this data set, the radial clearance of the floating bearing and the axial clearance of the locating bearing is varied. The resulting RMSE quantifies the error of estimating the calculated loads using regression models which do not include this variation within the training data. The estimation errors for rotor loads, depending on the clearance deviation are shown in Figure 4.
Figure 4. RMSE for rotor load estimation depending on radial clearance deviation of floating bearing (main bearing arrangement) and axial clearance deviation of locating bearing (main bearing arrangement).

The clearance deviations do affect the individual load components differently. For rotor thrust $F_x$, the accuracy of the ANNs can only be kept in a small range of clearance deviation. Outside of this range the estimation error increases drastically, whereby the linear regression model shows a more robust behaviour. A similar statement can be made for estimating the transverse force $F_z$ and bending moment $M_y$. In contrast to that, the estimation of the transverse force $F_y$, torque $M_x$ and bending moment $M_z$ using ANNs show a better accuracy than using a linear regression model over a wide range of clearance deviation. Analogously, the estimation errors for main bearing loads are shown in Figure 5.
Figure 5. RMSE for main bearing load estimation depending on radial clearance deviation of floating bearing (main bearing arrangement) and axial clearance deviation of locating bearing (main bearing arrangement)

As with the estimation of the rotor loads, the estimation of main bearing loads can component-wise be separated in two groups. Regarding radial forces $F_{z,FB}$ and $F_{z,LB}$ as well as the axial force $F_{x,LB}$, the accuracy of ANNs has its validity only for minor clearance deviations. Outside a rather small deviation range, ANNs are outperformed by simple linear regression models. In contrast to that, estimating the radial forces in y-direction ($F_{y,FB}$ and $F_{y,LB}$) using ANNs shows a superior accuracy, even though there is a wider deviation of main bearing clearances.

4. Discussion
The results show that the approach of estimating rotor and main bearing loads using regression models is reasonable and promises a good accuracy. Training and testing data have been generated using a detailed state-of-the-art eMBS model, what promises a good comparability with the real application. Even though measurement errors have been considered, relative RMSE of the individual loads of no
more than 5% are achieved. The fact that the accuracy of ANNs is better than the accuracy of linear regression models proves that the nonlinearity of the system should be taken into account by the simulation model used for training data generation. Otherwise these nonlinearities cannot be approximated by a regression model, what lowers the accuracy.

It is outstanding, that for most of the considered loads, a dynamic representation of the system does not increase the estimation accuracy significantly. In particular, the use of an LSTM network decreased the RMSE of the rotor input torque estimation. This effect is comprehensible, since the estimation of this load is mainly driven by the displacements of the torque supports. This component has relevant damping properties, which are accompanied by a corresponding hysteresis of the torque arm displacements. Therefore, it is understandable that a time series-based estimation provides a better accuracy for this load. However, for all other loads, a static representation of the system appears to be sufficient for load estimation.

The sensitivity analysis has shown partial disadvantages of ANNs due to varying bearing clearances. The estimation of certain load components using ANNs show a high sensitivity to this system parameter and are even outperformed by the use of linear regression models. This can be explained by the fact that the ANNs were trained and optimized to have the best accuracy for the system represented by the training data. In contrast, the systems represented in the data for sensitivity analysis have bearing clearances whose deviations are not included in the training data. The results show that the significant accuracy of the ANNs for the original system is not transferred to these deviating systems. Considering the less accurate but more robust properties of a linear regression, an opposing relationship between accuracy and robustness is indicated. Accordingly, a trade-off between these two attributes may has to be made. One solution strategy for this problem could be the inclusion of a clearance scatter within the training data. The ratio between accuracy and robustness could then be controlled by the width of the scatter considered in the training data. Alternatively, the regression model could be changed. For instance, nonlinearities could also be represented by polynomial regression models, where the ratio of accuracy and robustness could be adjusted by the degree of the polynomial.

5. Conclusions and Outlook

With the approach presented, it was possible to estimate rotor and main bearing loads considering the individual components of the load vector. This is done by using ANNs which are trained with displacement signals of the drivetrain. This kind of measurement signals are easy and cheap to record, which makes this method practical for commercial use. Since measurement uncertainties and nonlinearities were taken into account, it can be assumed that similar results can also be achieved for the real system of a wind turbine. Consequently, the next step must be a transfer of the methodology applied here to the real system of a wind turbine, in order to prove its usability in practice.

Nevertheless, a sensitivity of the estimation accuracy to varying system properties could be shown. The scatter of system parameter like bearing clearances can massively decrease estimation accuracy if it is not considered by the estimation model. Future research must therefore also develop solution strategies on how to achieve the necessary balance between accuracy and robustness considering scattered system parameters. It is becoming apparent that load-component-specific solutions promise better results than a general solution approach. For example, it might be more appropriate to use a linear regression model to estimate rotor thrust, while at the same time an ANN might be better suited to estimate rotor bending moments. However, in order to find a sensible trade-off, it will be necessary in the future to specify what kind of accuracy or robustness is required, which can vary strongly depending on the load monitoring application.
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