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Development and validation of real time load estimator on Goldwind 6 MW wind turbine

Martin Evans[1], Han Tao[1] and Zhao Shuchun[2]

[1] DNV GL, One Linear Park, Avon St, Bristol, UK
[2] Goldwind Science & Technology Co., Ltd., No. 8 Bo Xing 1st Road, Beijing, China

Abstract. Modern wind turbines have access to highly reliable measurements of important control input signals, such as generator speed and nacelle acceleration. They also have high fidelity numerical models such as in Bladed, which can be used to estimate structural loads under simulated normal and extreme operating conditions. However, if we want to know the structural loads that occurred in a time period on the real turbine, presently this requires instrumentation with strain gauges. These sensors can be unreliable and expensive to install, calibrate and maintain. The price of reliable sensors is unlikely to drop to an affordable level for onshore wind in the near future. This paper describes a method of fusing the control input signals with the turbine numerical model to estimate structural loads online in real time. The estimator is validated in Bladed simulations of a Goldwind 6 MW turbine.

1. Introduction

In today's wind industry, companies are looking intensively at innovations that will drive turbine performance and operational efficiency, while effectively managing operational risk and safety. A challenge in the industry is how to join the dots of numerical models of the wind turbine and real operational data to offer original equipment manufacturers (OEMs) and asset owner/operators (OOs) insights that help to drive down levelised cost of energy (LCoE).

DNV GL has addressed this challenge by introducing the digital twin solution for wind asset management, where numerical models of the wind turbine are combined with real data to offer smart monitoring of the asset performance in terms of energy and loading. The framework allows the OOs to gain confidence in the whole asset lifecycle, and schedule maintenance efficiently. Key information for OEMs is extracted to improve the design and the manufacturing process.

Load estimation is one component in the DNV GL digital twin framework. The load estimator maintains a numerical model of the turbine's structural states, and fuses this information with measurements from reliable sensors that are already in use within the turbine controller. This provides more detailed insights into the turbine behaviour without the need for additional sensors. The estimated load signal can be used directly for estimation of turbine fatigue accumulation. Furthermore, it can be fed back to the controller to design a load based controller to allow the wind turbine to better react to the change of external conditions. A fleet leader approach will be used to validate the load estimates, saving the installation of load sensors on the others turbines.

This paper explains the development and validation of a structural load estimation algorithm for a Goldwind 6.x MW turbine. A numerical model of the turbine is created in the aeroelastic simulation software Bladed. The relationship between the control input signals and the structural loads is parameterised using machine learning offline, exploiting the realism of the Bladed model. The parameters are embedded into the turbine controller for online real time load estimation. The initial

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version of the load estimator presented here requires generator speed and torque, pitch angle and nacelle acceleration signals, and estimates structural loading at the stationary hub and the tower base. The algorithm can be easily extended and customised.

The load estimator is a linear parameter varying model of the turbine structure and aerodynamics. Each linearisation is valid in its own wind speed range, with several linearisations covering the operating range for the turbine. As the wind speed shifts, due to low frequency energy in the turbulence, the linear parameters adapt via interpolation between neighbouring models at run time. Figure 1 gives a process overview of the load estimator.

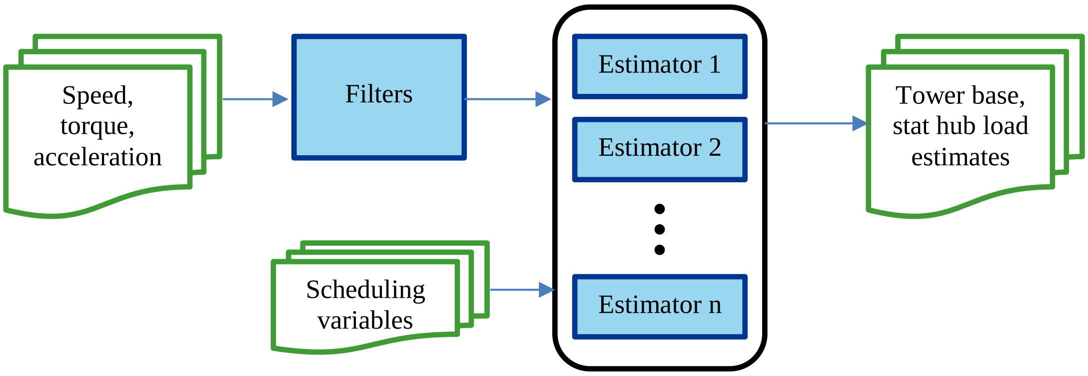

Figure 1: Schematic diagram of the load estimator at run time

This paper is organised as follows. Section 2 describes the technique to estimate loads assuming a locally linear model of the turbine. Section 3 describes how multiple linear models are combined to facilitate the operation of the load estimator across a wide range of wind speeds. Section 4 shows the results of one numerical simulation for illustration. Section 5 is a sensitivity study, giving firm quantification of the performance of the load estimator when applied to fatigue estimation. Finally, Section 6 makes some concluding remarks and suggests useful future work.

2. Linear estimation

The real-time load estimator in this paper is focussed on structural loads. Drivetrain, pitch actuator and other loads will be considered as part of future work. Numerical models of large wind turbines can have highly complex structural representations, with many structural modes. However, typically only a small number of these modes are required to capture the majority of the energy present in the full model during normal operation.

The inputs to the estimator (generator speed, generator torque and nacelle acceleration) were chosen because they are affected by the dominant structural modes, and thereby observe vibrations in those modes. This observation is crucial to the operation of the load estimator and is why estimators are also known as observers. An overview of the application of observers to wind turbine dynamic state estimation can be found in [1]. In this light, the present work can be seen as a simplification of an EKF, but with substantially lower costs to implement.

This section describes how the estimator processes its inputs, with the initial assumption that the structure can be described by a linear, observable system. The next section will extend the capability of the estimator to cope with nonlinearities.

The challenge with the linear estimator is to find a dynamic system to map from the inputs to the outputs, where by outputs we mean the loads to be estimated. The process of finding this system, or at least the parameterisation of the system, is called training. This training stage requires time series of inputs and true outputs, and initially these are created in simulation. Future work will repeat the training stage with measured data from the real turbine. The goal of the training stage is to minimise the sum of square errors between the estimator outputs and the true outputs.

The simplest possible linear dynamic system that could be used to map inputs to outputs for this purpose would be a matrix multiplication. A weight is given to each input-output pair, and the weighted inputs are summed. Optimal weights for such a system can be found by regression. Typically, the outputs will be better represented by an affine map than a linear map, so an extra input is introduced, which is simply a constant value of one. The weight matrix thereby has an extra column to allow the offset to be modelled. Stating the above system mathematically,

$$\hat{\boldsymbol{y}} = \Psi \boldsymbol{x} \tag{1}$$

where $\hat{\boldsymbol{y}}$ is a vector of estimated outputs at a given time step, $\boldsymbol{x}$ is a vector of the inputs at the same time step, and Ψ is the weight matrix to be found. Let us define the true loads to be estimated as $\boldsymbol{y}$, for one time step, congruent to $\hat{\boldsymbol{y}}$. For training, the same model is to be used for all time steps, so this equation can be made more general by stacking subsequent inputs and outputs transposed into tall matrices, where each row is one time step. Let $\hat{Y}$ be the estimated outputs $\hat{\boldsymbol{y}}^{\boldsymbol{T}}$ stacked, and similarly for X and Y so that $\hat{Y} = X\Psi^T$. Note the entire first column of X is unity. We now wish to find the value of Ψ that minimises the cost, which is the sum of squares of $\hat{Y} - Y$. This can be written as follows:

$$\Psi = \underset{\Psi}{\operatorname{argmin}} \big(\hat{Y} - Y\big)^T (\hat{Y} - Y). \tag{2}$$

Expanding, differentiating and rearranging, we find the ordinary least squares result that

$$\Psi^{\mathrm{T}} = (X^T X)^{-1} X^T Y. \tag{3}$$

We can now discuss how well the dynamic model suits the purpose of estimating loads. If an input-output pair are in phase, the weight will be positive. If they are 180° out of phase, the weight will be negative. But in general, the inputs and outputs will be related by some arbitrary phase and gain. Since phase lead is not possible at run time, phase lag is required. The amount of lag required is not known in the training, so several candidate lags are added to the input matrix by concatenating new columns in X. If these columns can be removed without significantly increasing the cost in the optimisation above, they are permanently removed.

The lagged columns of X are created by filtering relevant existing columns of X. This keeps the overall system linear, adds only a small number of new weights to optimise, is trivial to run online, and provides some signal noise rejection. The filters are chosen from a set of available filter types in the control algorithm, tuned using engineering judgement but in principle could be optimised numerically. Additional filters can increase the accuracy of the load estimation, but accuracy cannot be made arbitrarily high, because some structural modes may not be observable with the limited set of measurements used in the estimator.

3. Real time interpolation

Variable speed pitch regulated wind turbines have a wide range of dynamics depending on mean wind speed. Turbine control algorithm designers deal with this by configuring a suite of nonlinear compensators that operate above their respective linear feedback laws. For example, between rated generator speed and rated wind speed, the generator speed is often regulated with a PI controller on torque. The PI gains are chosen to optimise performance for a linear system, linearised from the full aeroelastic model under the conditions that the torque-speed controller is operating. Other linearisations are required for the pitch-speed loop. These linearisations combined form a linear parameter varying system, or LPV [2].

The situation is similar for load estimation, in that the optimal weight matrix found from training data at mean wind speed v_1 will generate load estimates when operating at mean wind speed v_2 that diminish in accuracy as $|v_1 - v_2|$ increases. The solution given in the present work is to train a 'bank' of weight matrices, each trained at a distinct mean wind speed, and interpolate the weight matrices when running the estimator online. Since the estimator states are determined by the filters, which are stable, the estimator states are stable. Since the estimated loads are weighted sums of the estimator states, these are also stable, regardless of interpolation.

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As with gain scheduling in the pitch-speed loop, e.g. [3], the anemometer signal is not reliable for scheduling. Above rated wind speed, the pitch angle is a more reliable proxy for the wind conditions, and below rated, the generator torque is appropriate. We actually want one scheduling variable, not two, so a weighted sum of pitch angle and generator torque is used in this work, since this is monotonically increasing in steady state. From the training data at mean wind speed v_i, the optimal weight matrix Ψ_i is calculated, and the operating point λ_i is found by weighted sum of the mean pitch angle and mean torque.

Now in run time, for each time step, t, the weight matrix $\Psi(t)$ is calculated by linear interpolation as follows:

$$\Psi(\mathrm{t}) = \big(1 - \alpha(t)\big)\Psi_i + \alpha(t)\Psi_{i+1} \tag{4}$$

where

$$\alpha(t) = \frac{\lambda(t) - \lambda_i}{\lambda_{i+1} - \lambda_i} \tag{5}$$

and where $\lambda_i < \lambda(t) \le \lambda_{i+1}$. Special conditions are put on $\alpha(t)$ for cases where $\lambda(t)$ is outside bounds of the bank of weight matrices.

4. Numerical examples

The following numerical examples were performed on the Goldwind 6MW Bladed model. Values have been omitted from the axes to protect proprietary information on the turbine design. Figure 2 gives an overview of the numerical model, showing inputs and outputs of the load estimator.

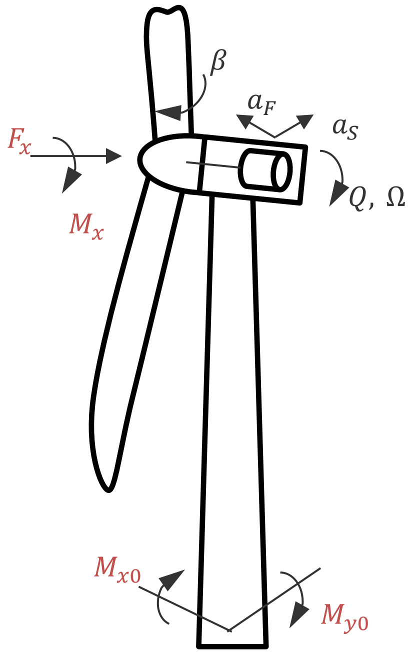

Figure 2: An overview of the wind turbine model used in this work. Inputs to the load estimator, known at run time, are β pitch angle, a_F, a_S fore-aft and side-side nacelle acceleration, and Q, Ω generator torque and speed. Outputs, to be estimated at run time, are F_x, M_x stationary hub thrust and in-plane moment, and M_{x0}, M_{y0} tower base fore-aft and side-side bending moments.

The time series data used in this validation exercise consists of Bladed output data from 60 power production simulations, each of duration 600 seconds. The wind fields applied in these simulations are six random turbulence seeds at each of ten mean wind speeds from 4 m/s to 22 m/s. For each mean wind speed, one simulation is used for training the local linear estimator and finding the operating point. The other five are used for testing the performance of the nonlinear estimator. The test procedure will be described later in this paper. The ten training simulations give the operating points shown in Figure 3 and the ten weight matrices Ψ_1 to Ψ_{10}.

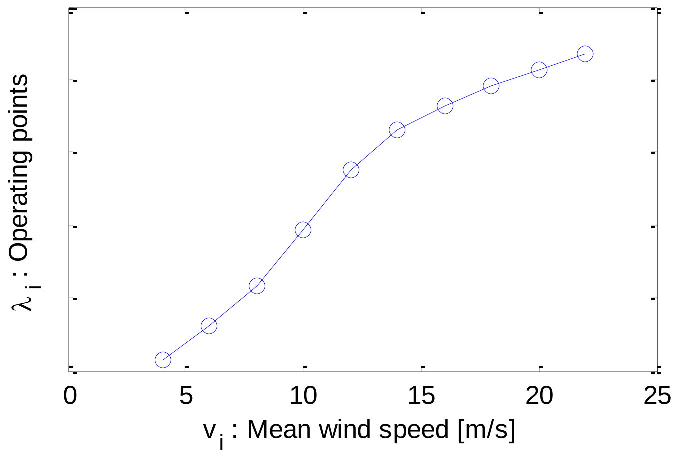

Figure 3: Operating points λ_1 to λ_{10} corresponding to each mean wind speed in the training data. Online, this table is used for interpolation.

To briefly illustrate of the performance of the load estimator, the results from a simulation at mean wind speed of 12 m/s are shown. This mean wind speed was selected to demonstrate the ability of the load estimator to cope with rapidly changing dynamics as the wind conditions vary between above rated and below rated.

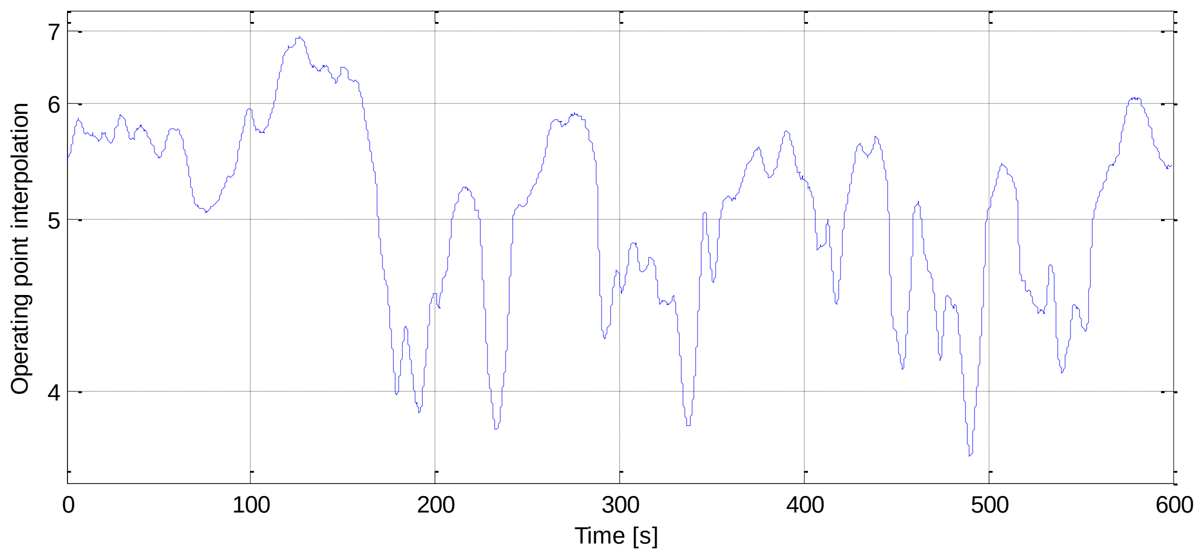

Figure 4: Operating point index as it varies over a 600 second simulation at mean wind speed 12 m/s.

Figure 4 shows which weight matrices are used during the run. For example, at time step 300, the weight matrix in use is a linear combination of Ψ_4 and Ψ_5. The graph shows how much the load estimator uses the multiple linearisations to handle turbulence. Operating point values on the vertical axis are replaced with the respective operating point indices.

Figures 5-8 show the accuracy of the load estimator in the same simulation. Note, the load estimator only has access to the input signals of the controller as it would be on a real turbine. The measured signals are taken from the Bladed results file for comparison and evaluation only.

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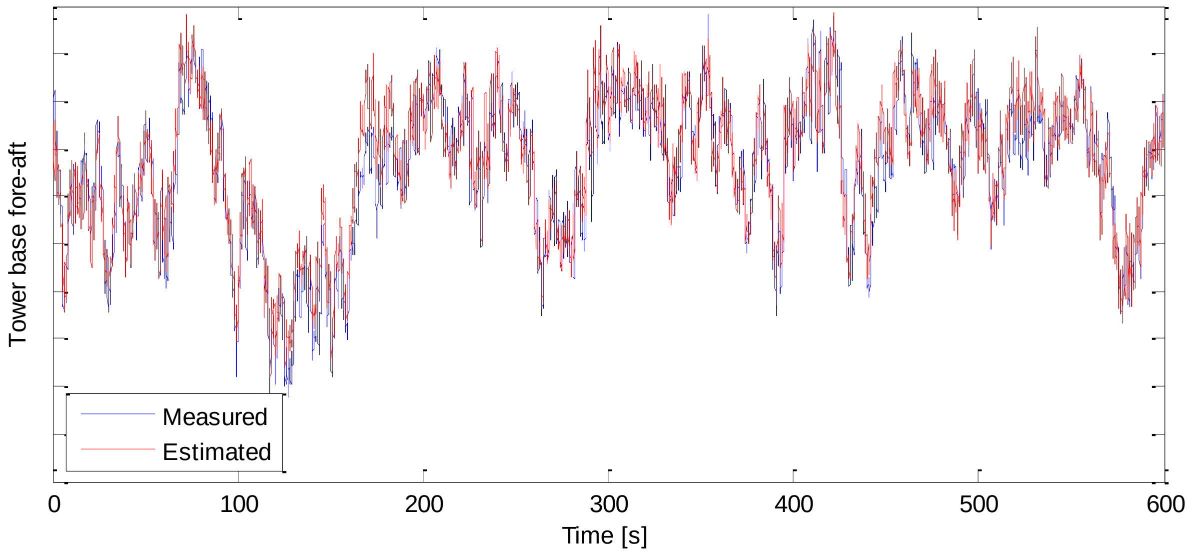

Figure 5: Measured and estimated tower base fore-aft bending moment for the example simulation.

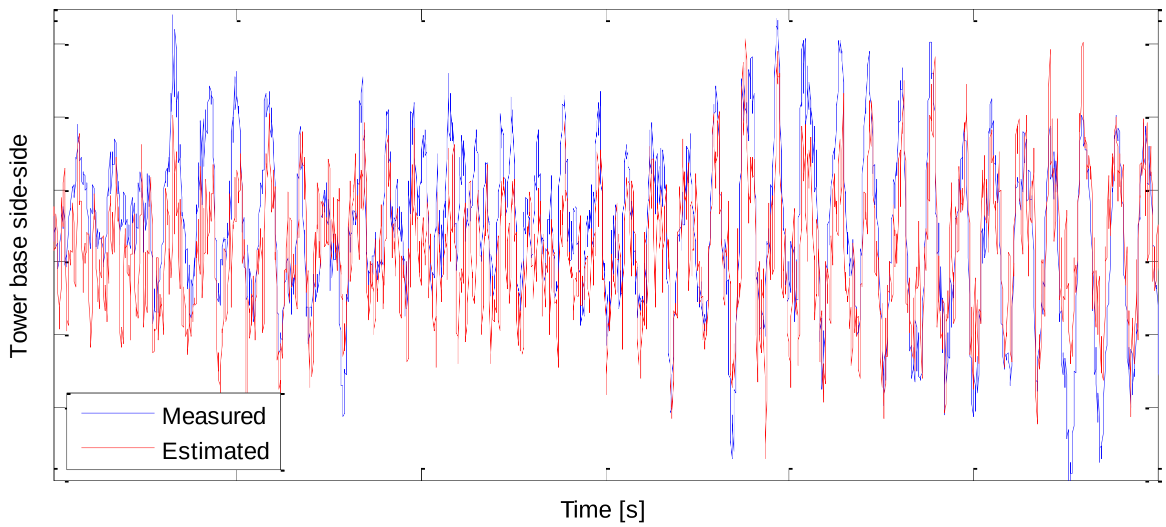

Figure 6: Measured and estimated tower base side-side bending moment for the example simulation. The results are zoomed in time to show detail and the time axis labels removed to protect design details because this load component is dominated by rotor speed.

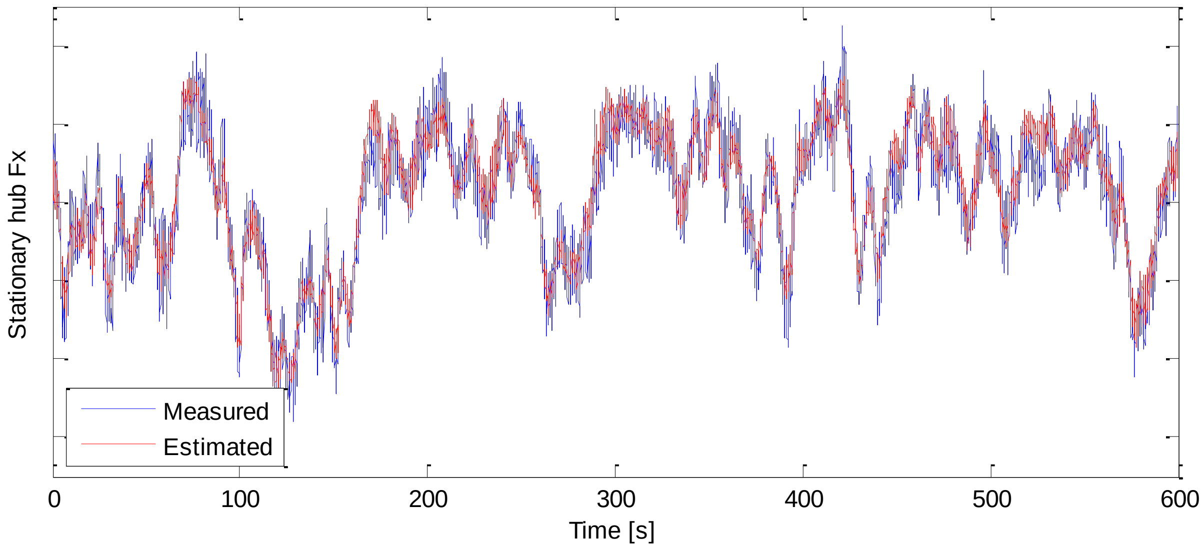

Figure 7: Measured and estimated stationary hub Fx (thrust force) for the example simulation.

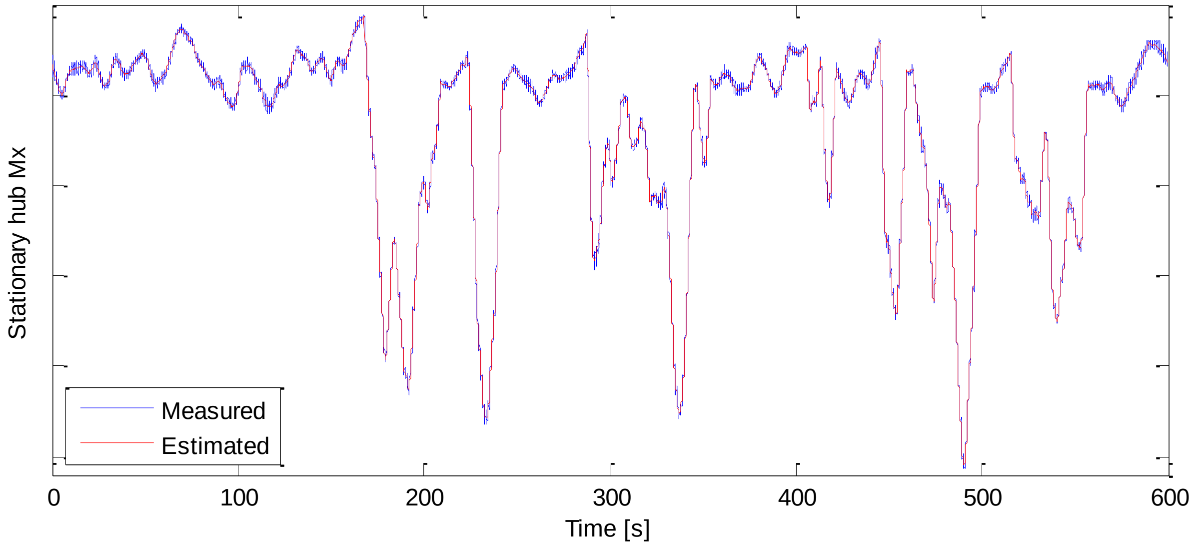

Figure 8: Measured and estimated stationary hub Mx (torque) for the example simulation. Note the accurate response of the load estimator during transients such as around 160 seconds.

The time series above are given to illustrate the performance of the load estimator. They are representative of the performance across the full operating range. Figure 9 shows the same results in the frequency domain. The next section gives a detailed analysis of the accuracy of the estimator in terms of damage equivalent loads (DELs) over the full wind speed range.

Small differences between estimated and true loads are generally due to turbine dynamics of higher orders than within the estimator such as higher structural modes. Therefore, the estimator slightly underestimates the fatigue. However, by testing the estimator in a wide range of wind conditions, as is done in the following section, it is seen that the amount each load component is underestimated by is consistent and predictable. It is therefore justified to use the validation of the load estimator to determine a correction factor to be applied to the DELs. This factor is constant once determined and is chosen so as to minimise the square error between estimated and true DELs across the full validation set of wind conditions. The correction is not part of the load estimator – rather, it is applied after rainflow counting and can be considered a basic form of damage estimator.

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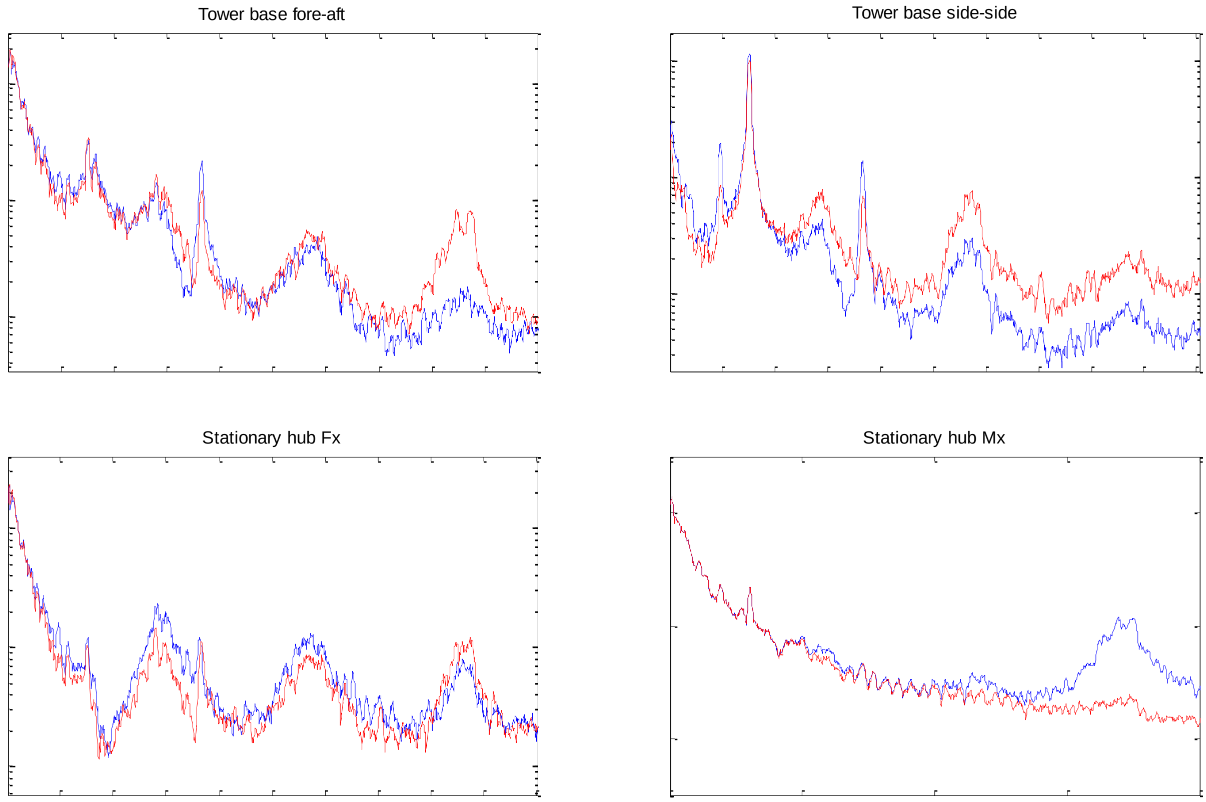

Figure 9: Measured (blue) and estimated (red) four load components, for the same simulation as illustrated in Figures 5-8, shown in the frequency domain. Axis numbers have been removed to protect intelectual property.

5. Sensitivity study

Each operating point is trained on a small set of time series and tested on a full set of IEC [4] power production simulations. This validation gives high confidence that the load estimator is accurate and not over-tuned. Since a potential use for the load estimates is for fatigue estimation, the estimated loads are rainflow counted and converted into DELs. As described in Section 4, each load component has a scaling factor for its DELs to remove predictable underestimation in DELs from higher order dynamics. Our measure of accuracy for DELs is the coefficient of determination of the estimated DELs (D_e) against the true DELs (D_t). Coefficient of determination is defined as:

$$R^2 = 1 - \frac{\mathrm{Var}(D_e - D_t)}{\mathrm{Var}(D_t)} \tag{6}$$

where Var is variance. Coefficient of determination is appropriate because it represents the proportion of true variation in the variables that is captured, or explained, by the estimates.

Figure 10 shows estimated and true DELs for tower base fore-aft moment for the normal turbulence cases. This was the set of load cases for which the scaling factor for DELs was chosen. The value of 99.31% means that the variance in fatigue estimation across normal turbulence simulations is 0.7%.

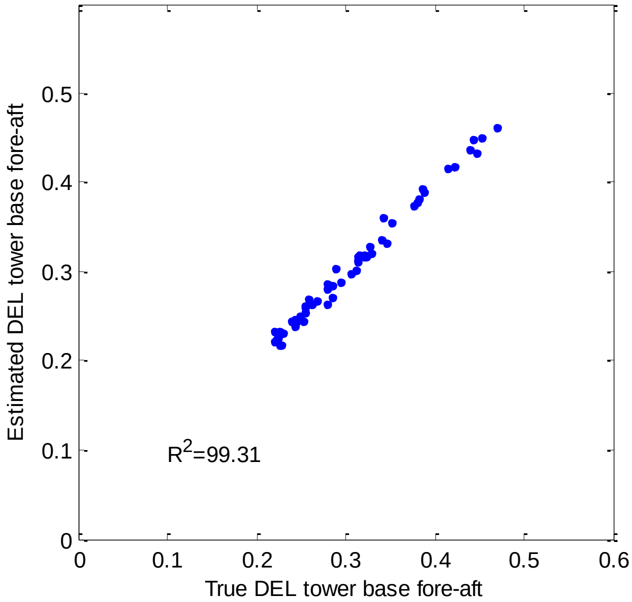

Figure 10: Tower fore-aft damage equivalent loads (normalised) from 60 simulations across ten wind speeds from 4 m/s to 22 m/s under normal turbulence conditions, from the load estimator against the true values. Coefficient of determination R^2 = 99.31%.

Table 1 gives the coefficients of determination for the all four load components for nine different wind conditions. The load estimator was not re-trained for these conditions, nor was the scaling adjusted for estimated DELs. Rather, the numbers represent the accuracy of the fatigue estimation under conditions that do not match the conditions under which the estimator was trained. They show that the estimator is insensitive to wind conditions.

Tower base side-side fatigue stands out as slightly less accurate than other load components in this study, but note that side-side moments at the tower base contribute significantly less than the fore-aft moments to overall tower base fatigue.

Table 1. Coefficients of determination for 60 simulations in each of nine wind conditions

Wind conditions	**Tower fore-aft**	**Tower side-side**	**Stationary hub Fx**	**Stationary hub Mx**
High turbulence	98.89	96.43	98.10	99.44
Normal turbulence	99.31	98.26	99.52	99.69
Low turbulence	99.11	97.89	99.36	99.74
8 degrees of flow inclination	98.99	98.44	99.46	99.71
16 degrees of flow inclination	99.06	98.56	99.37	99.71
-10 degrees of nacelle heading	99.04	98.21	99.33	99.67
+10 degrees of nacelle heading	99.02	98.04	99.34	99.70
0.07 wind shear	99.02	98.56	99.48	99.69
0.28 wind sheer	98.95	98.17	99.37	99.67

6. Conclusions

Reliable measurements that are already available to the wind turbine control system are used to estimate loads for which sensors are typically expensive or unreliable over the lifetime of the turbine. The estimation algorithm consists of a bank of linear estimators, receiving the raw measurements combined with carefully designed filtered channels. The output of the estimator is a weighted sum of the inputs, where the weights are chosen by linear interpolation over the operating range. Each estimator is trained offline, using simulation time series or measurements if available.

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A numerical example is given of the load estimator running in wind conditions where the mean wind speed moves above and below rated wind speed, due to low frequency energy in normal turbulence. Furthermore, the results of many such simulations are combined to find the optimal damage equivalent fatigue estimation parameters. Coefficients of determination give an indication of the extent to which the fatigue is correctly estimated. A sensitivity study is performed with the trained parameters fixed and the wind conditions varied, totalling 540 simulations, each of 600 seconds.

The results of the sensitivity study show that under the conditions in which the turbine is designed, most load components have estimated DELs with less than 1% error. Furthermore, even under unusual or unexpected wind conditions, the estimated DELs did not exceed 2.5% error, except in turbulence that would be too severe for the turbine to operate continuously.

Future work will perform field validation against carefully calibrated load sensors on a fleet leader turbine, representative of its type and site conditions. The history of fatigue estimates over a long period of operation for each turbine in a fleet forms a digital twin system, with potentially vast impacts on turbine remaining life estimation, effectiveness of both wind turbine and wind farm controllers, scheduled maintenance and investment insights.

7. References

[1] Ritter BA, Schild AX, Feldt MA, Konigorski UL. The design of nonlinear observers for wind turbine dynamic state and parameter estimation. In Journal of Physics: Conference Series 2016 Sep (Vol. 753, No. 5, p. 052029). IOP Publishing.

[2] Bianchi FD, Mantz RJ, Christiansen CF. Control of variable-speed wind turbines by LPV gain scheduling. Wind Energy. 2004 Jan 1;7(1):1-8.

[3] Leith DJ, Leithead WE. Appropriate realization of gain-scheduled controllers with application to wind turbine regulation. International Journal of Control. 1996 Sep 1;65(2):223-48.

[4] IEC 61400-1-3.1 Edition, WIND TURBINES - PART 1: DESIGN REQUIREMENTS, 2014, International Electrotechnical Commission (IEC) Publishing