Stochastic model for indirect estimation of instantaneous and cumulative loads in wind turbines: a systematic approach for off-shore wind farms

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Summary

We present our recent findings for estimating instantaneous and cumulative loads in singles wind turbines. Our framework is based on a stochastic method that we described in Energies 7(12), 8279-8293 (2014) and consists of deriving a stochastic differential equation that describes the evolution of local loads at single wind turbines, driven by wind speed measurements. Through a standard fatigue analysis of data collected at RAVE, we show that our framework is able to accurately estimate fatigue loads in any wind turbine within the wind farm. Finally, since the framework is straightforwardly applied to any load series, we discuss how it can be used to mitigate the financial efforts usually necessary for placing measurement devices of different loads in all wind turbines within one wind farm.

1. Introduction

Important challenges in wind energy research still remain to be solved, particularly in what concerns the large wind fluctuations occuring with a non-negligible probability[1] and the optimization of power production as well as the high costs implied in the construction and operation of wind turbines together with the proper devices for controlling and monitoring them[2]. Alternative methods to indirectly estimate the necessary quantities for control and monitoring wind power production could help to mitigate these costs. Here, we propose a framework for reconstructing the statistical features of loads fluctuations which enables one to accurately estimate instantaneous and cumulative loads in wind turbines within one wind farm.

2. Data and methods

The data analyzed was taken at Senvion's Alpha Ventus wind turbines, namely at AV4 and AV5, from 2012 to 2014, and is part of the project "Probabilistic loads description, monitoring, and reduction for the next generation offshore wind turbines (OWEA Loads)", funded by the German Federal Ministry for Economic Affairs and Energy. We analyze available loads at AV4 for deriving our model: the torque, the bending moments and acceleration measured at the blades and at the tower, taken at sample frequency of 50 Hz.

Using the data of loads and wind velocity at one wind turbine we were able to derive a quantitative model, recently proposed[3], that assumes a full description of the time evolution of the load defined from two separated contributions: one contribution accounting for the deterministic trend and another contribution that accounts for the stochastic fluctuations. Thus, having a set of load measurements $L(t)$ together with a set of wind velocity measurements $v(t)$, taken e.g. a cup anemometer, we derive a model for reconstructing the series of loads sketched as

$$
\begin{aligned}
L(t+\Delta t) &= L(t) + \\
&\quad (\text{"Trend-function"})\Delta t + \\
&\quad (\text{"Fluctuation"})\Delta t. \qquad (1)
\end{aligned}
$$

It is possible to show that the "trend-function" is the time derivative of the the first conditional moment of the loads[3]:

$$("\text{Trend-function}") \equiv D_1(l,v)$$

$$= \lim_{\tau\to 0} \frac{\langle L(t+\tau) - L(t)\rangle \,|_{L(t)=l,V(t)=v}}{\tau}. \quad (2)$$

The fluctuations have a stochastic influence that is modelled through a Gaussian δ-correlated white noise Γ_t, i.e. $\langle\Gamma(t)\rangle = 0$ and $\langle\Gamma(t)\Gamma(t')\rangle = 2\delta_{ij}\delta(t-t')$, but is modulated by a function $D_2(l,v)$ yielding the derivate of the *second* conditional moment. Altogether the stochastic fluctuations in Eq. (1) are given by

$$("\text{Fluctuation"}) \equiv \bar{\Gamma}_t \sqrt{D_2(l,v)} \quad (3)$$

where $D_2(l,v)$ is the derivative of the second condition moment, namely $D_2(l,v) = \lim_{\tau\to 0}\tau^{-1}\left\langle (L(t+\tau)-L(t))^2\right\rangle|_{L(t)=l,V(t)=v}$, and where it can be shown that $\bar{\Gamma}_t = \Gamma_t/\sqrt{\Delta t}$.

The model in Eq. (1) is able to reproduce the series of load load measurements, namely torque series[3] and fatigue loads[4] in wind turbines, and therefore reproduces all its statistical features. See Fig. 1 below. Here we add additional results for tower beding moments.

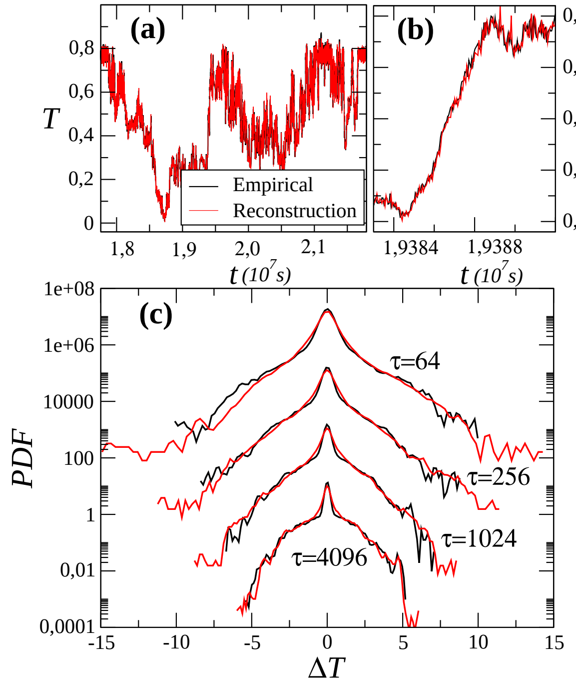

Figure 1: Reconstruction of the torque (in red) of torque measurements (black): **(a)** The explicit time-series of the torque including **(b)** the magnification of the large fluctuation, and **(c)** the probability density function of the increments (fluctuations) of the torque within different time-lags. Time is in seconds, and the Torque increments is in units of corresponding standard deviations (σ_τ).

3. Results

Having extracted the functional dependence of both coefficients $D^{(1)}$ and $D^{(2)}$ we are now able to describe the evolution of the torque by keeping track of the wind velocity, simply through an Euler-like discrete version of the conditioned Langevin equation. We take the first measurement of both wind speed and torque as initial conditions for the stochastic equation and integrate it with respect to t using at each integration step the observed wind velocity.

The reconstructed series are plotted in Fig. 1(a-b) together with the empirical series of torque measurements. Clearly, the reconstructed series are close to the real measurements. Moreover, the statistical distribution of the increments $\Delta L_\tau(t) = L(t+\tau) - L(t)$ are also well reproduced for time scales from seconds up to hours (Fig. 1(c)). All in all, from Fig. 1, one can clearly conclude the ability for the conditioned Langevin model to properly describe the evolution of the torque in one WEC.

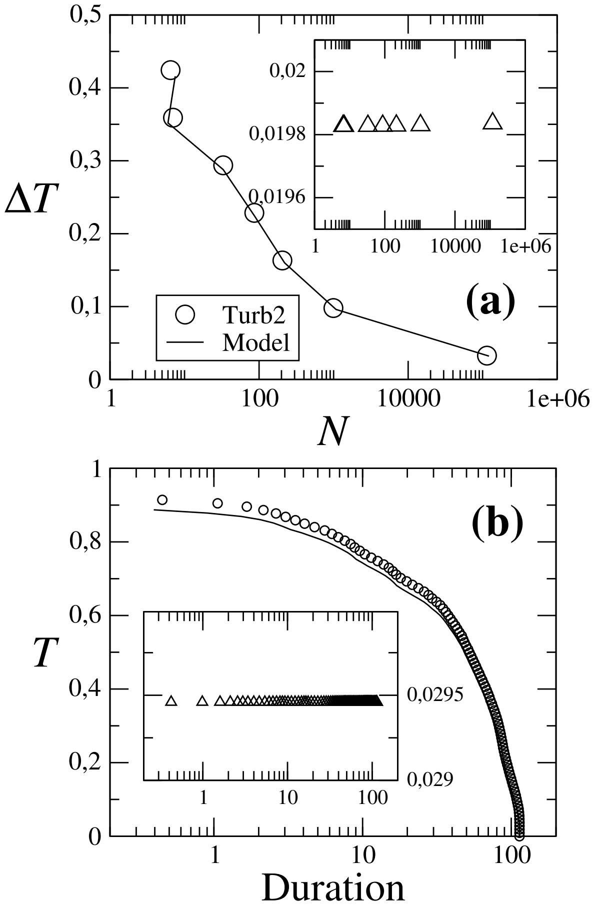

Figure 2: **(a)** Rainflow counting (RFC) of the reconstructed load series at Turbine 2, comparing it with the real series. **(b)** The load duration distribution (LDD) for the same real and reconstructed series.

For deriving the model in Eq. (1) we use the load measurements and wind velocities taken at Turbine 1 (AV4) and after that we reconstruct the load measurements at Turbine 2 (AV5) using only the wind velocities measured at its cup anemometer. In Fig. 2a we plot for both real and reconstructed series the rainflow counting (RFC) for Turbine 2, showing that the model retrieves a correct estimation of the rainflow spectra. In the inset one sees the relative error $\eta = \frac{A_r - A_e}{A_r}$, where A_r and A_e are the amplitudes observed for the real and estimated values. The relative errors of the rainflow counting for the estimates is less than 2 %.

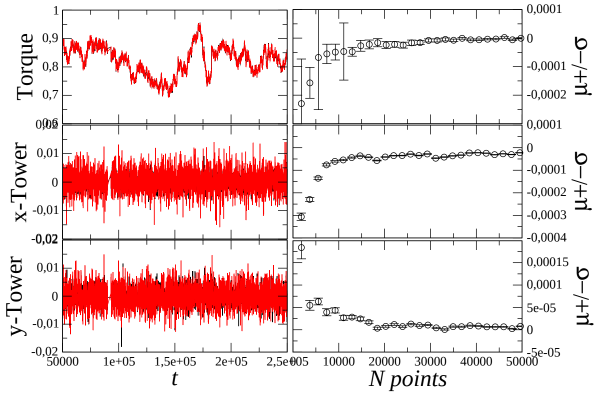

Figure 3: On the left we show the reconstruction of torque and the components of the tower bending moments. On the right the corresponding average cummulative square deviations between real measurements and reconstructed series is shown as a function of the number of points.

In Fig. 2b we also show the load duration distribution (LDD), given the amount of time a load with a given amplitude is observed: similarly to what is observed for the RFC, the LDD is also properly reproduced for sufficiently sampled loads (largest values).

Finally, we show in Fig. 3 that our approach not only is able to reconstruct instantaneous and fatigue loads on the drive train but also of other types of loads, e.g. tower bending moments.

4. Discussion

In this paper we applied a framework to one single turbine of Alpha Ventus wind farm for reproducing the loads observed in other similar wind turbines of the same wind farm. The framework consists of the derivation of a stochastic evolution equation for the loads constrained to the wind speed observed at each wind turbine. Using rainflow counting methods and load duration distributions to empirical and modeled data we show that our framework is able to accurately estimate fatigue loads.

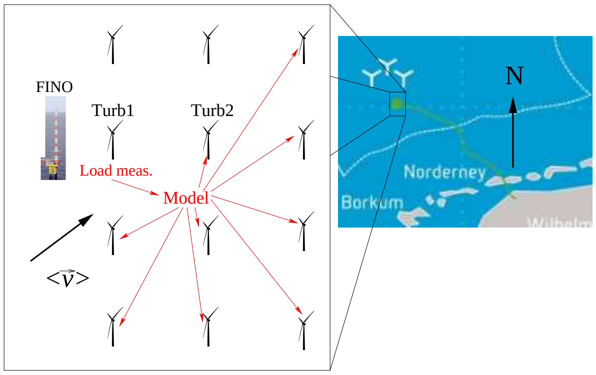

Figure 4: Sketch of the Alpha Ventus wind farm, located in the North Sea, near the north-eastern coast of Germany. The study here described is based on measurements taken at the two wind turbines, "Turb1" and "Turb2" (named after AV4 and AV5 respectively).

In a more general context, this procedure can be applied to other properties one wants to access for monitoring and controlling wind turbines. All in all, as sketched in Fig. 4, such a framework could be used to mitigate the financial efforts usually necessary for placing measurement devices in all wind turbines within one wind farm.

References

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