Efficient load and power monitoring by stochastic methods

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1 Introduction

Wind energy systems operate under harsh and strongly changing conditions. Reliably monitoring the power performance of wind farms under such conditions is of great importance to all wind farm operators. Due to the strong fluctuations and site specific situations, currently such monitoring is dependant on long term data.

Stochastic methods have proven to be efficient tools in this field. Here we present latest results which confirm and considerably extend the fields of application for stochastic methods in wind energy. Namely for load modeling, performance monitoring under inhomogeneous inflow conditions, and wind farm performance monitoring new results are presented.

2 Approach

A conditional Langevin approach was shown to be successful for systems with strong and instationary variability [1], among others for the dynamic power characteristics of WEC, the so-called Langevin Power Curve [2, 3].

The conditional Langevin equation models an observed time series (such as power, force, torque) in terms of a first-order stochastic differential equation

$$\dot{X}(t) = D^{(1)}(X, y) + \sqrt{D^{(2)}(X, y)} \cdot \Gamma(t) \ . \qquad (1)$$

Here, X is the observable (e.g., power, force, or torque), y represents an external operating condition (typically the wind speed), and $\Gamma(t)$ denotes an uncorrelated, Gaussian noise. Thus, for each value of y we obtain a stochastic differential equation defined by the functions $D^{(1,2)}(X, y)$. These functions are estimated directly from measurement data in a mathematically rigorous way, cf. [1–3].

3 Results

3.1 Load monitoring in wind farms

A stochastic model following Eq. (1) has been set up for the torque on the main shaft of a multi-MW offshore wind turbine. The model was shown to accurately estimate the load time series from a

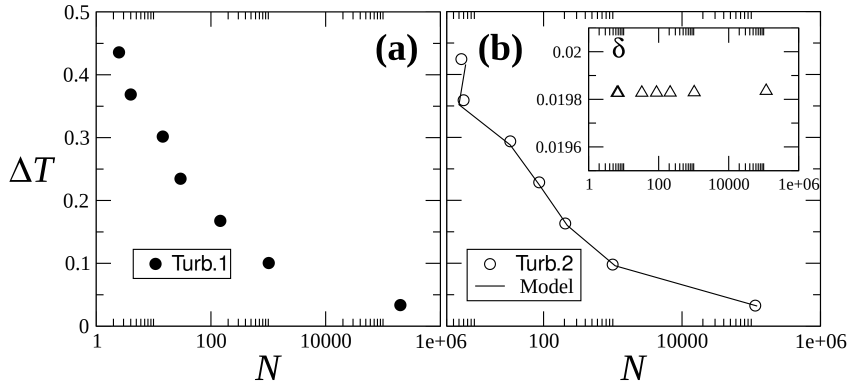

Figure 1: Torque statistics (rainflow counts) at the main shaft of two neighboring multi-MW turbines in the same offshore wind farm. (a) measured torque statistics at turbine 1, (b) torque statistics at turbine 2, both measured (symbols) and reconstructed (solid line) by the stochastic model (1). From turbine 2 only the wind speed time series of the nacelle anemometer was used.

given, respective wind speed signal. In a next step the model was generalized in order to reproduce the load time series measured at another turbine of the same type within the same wind farm. While the stochastic model had been estimated at turbine 1, for the reproduction of the loads at turbine 2 only the wind speed time series of its nacelle anemometer was used. The load statistics as presented in Fig. 1 show very good correspondence [4].

The method thus allows to monitor loads in wind farms without any additional measurement equipment. Once the stochastic model has been derived for a certain turbine type, loads are obtained using only available nacelle anemometry. Especially for offshore and remote wind farms the benefits are straightforward.

3.2 Performance monitoring independent of site conditions

From the stochastic model (1) the dynamic power characteristics of a wind turbine, the Langevin Power curve (LPC), is derived as the fixed points of its dynamics [2, 3]. A recent measurement campaign using a scanning nacelle-based wind lidar [5] demonstrated that the LPC is indeed turbine-specific and not sensitive to site characteristics, such as different turbulence levels. In Fig. 2 two LPC measurements at the same turbine are compared, where only wake or free stream inflow conditions have been used, respectively.

Traditional power curve measurement following IEC 61400-12 is known to depend on site chracteristics such as shear and turbulence conditions, which leads to a necessity of elaborate data filtering and long measurement times. Given a high quality wind inflow measurement, the Langevin Power curve provides turbine-specific performance characteristics independent of site-specific influence or, in this case, possible wake situations.

3.3 Wind farm performance monitoring

Also for performance monitoring of wind farms the Langevin Power Curve turns out to provide sensitive and helpful information. In an onshore wind farm of 12 turbines of the 2 MW class the cumulative electrical power output was recorded, and both ten minute averaged (denoted as IEC power curve) and LPC power characteristics of the wind farm were derived. The case of a downtime

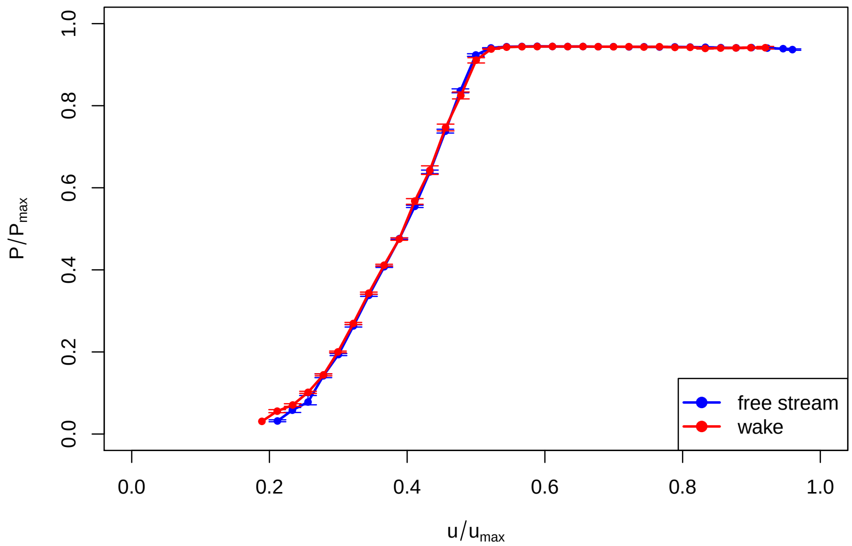

Figure 2: Langevin Power Curves (LPC) of a multi-MW offshore wind turbine. Wind speed was measured by a nacelle-based scanning lidar system [5]. Power performance is shown for free stream (blue line) and wake conditions (red line).

of one or two turbines was simulated in the power data in several variants. The LPC showed higher sensitivity to detect the downtimes in all cases [6].

Fig. 3 shows results for the case of 12 h downtime of one turbine. While the IEC power curve of the wind farm (left) is not affected at all, especially the drift coefficient $D^{(1)}$ (cf. eq. (1)) shows significant deformation (middle). Because the affected wind speed regime is narrow, in the LPC (right) only one additional fixed point is obtained for the respective wind speed. It nevertheless clearly and quantitatively points out the temporal performance reduction.

4 Conclusion

New results significantly extend the range of applications for stochastic methods with respect to wind energy systems. The Langevin Power curve turns out to provide accurate turbine-specific information from standard measurement signals without the need to install additional monitoring equipment, which is especially important for offshore locations. Using properly estimated stochastic models, power output and loads can be estimated and sensitively supervised both for single turbines and wind farms.

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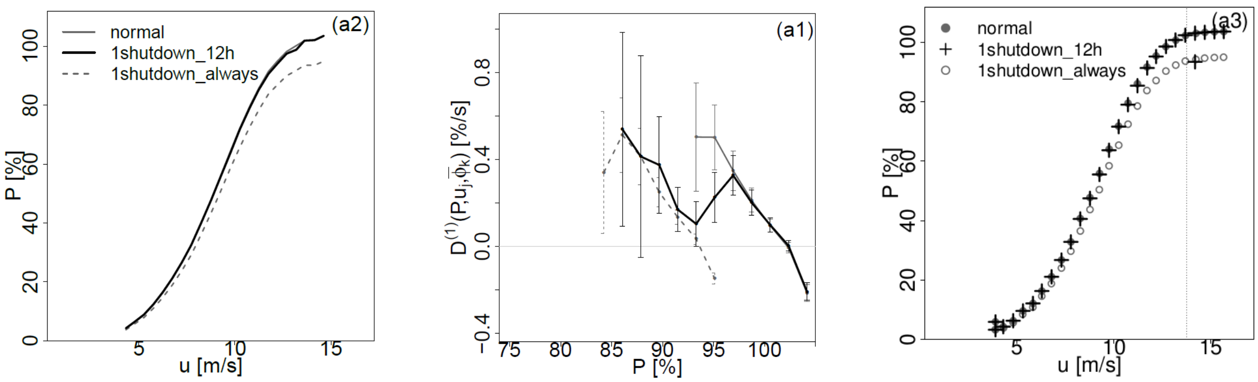

Figure 3: Wind farm performance monitoring by 10 minute averages as in IEC 61400 (left), by the drift coefficient $D^{(1)}$ of eq. (1) (middle), and using the LPC (right). Line styles of the left graphic apply to the middle one as well, here showing clearly a transition between two power performance states. The measured cumulative power output of twelve turbines was used, where the contribution of one turbine was artificially set to zero for 12 h.

Learning objectives

Application of stochastic modeling and Langevin Power Curve for

- load monitoring by stochastic modeling,
- wind turbine performance monitoring independent of wake or free stream conditions, and
- sensitive wind farm performance monitoring.

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