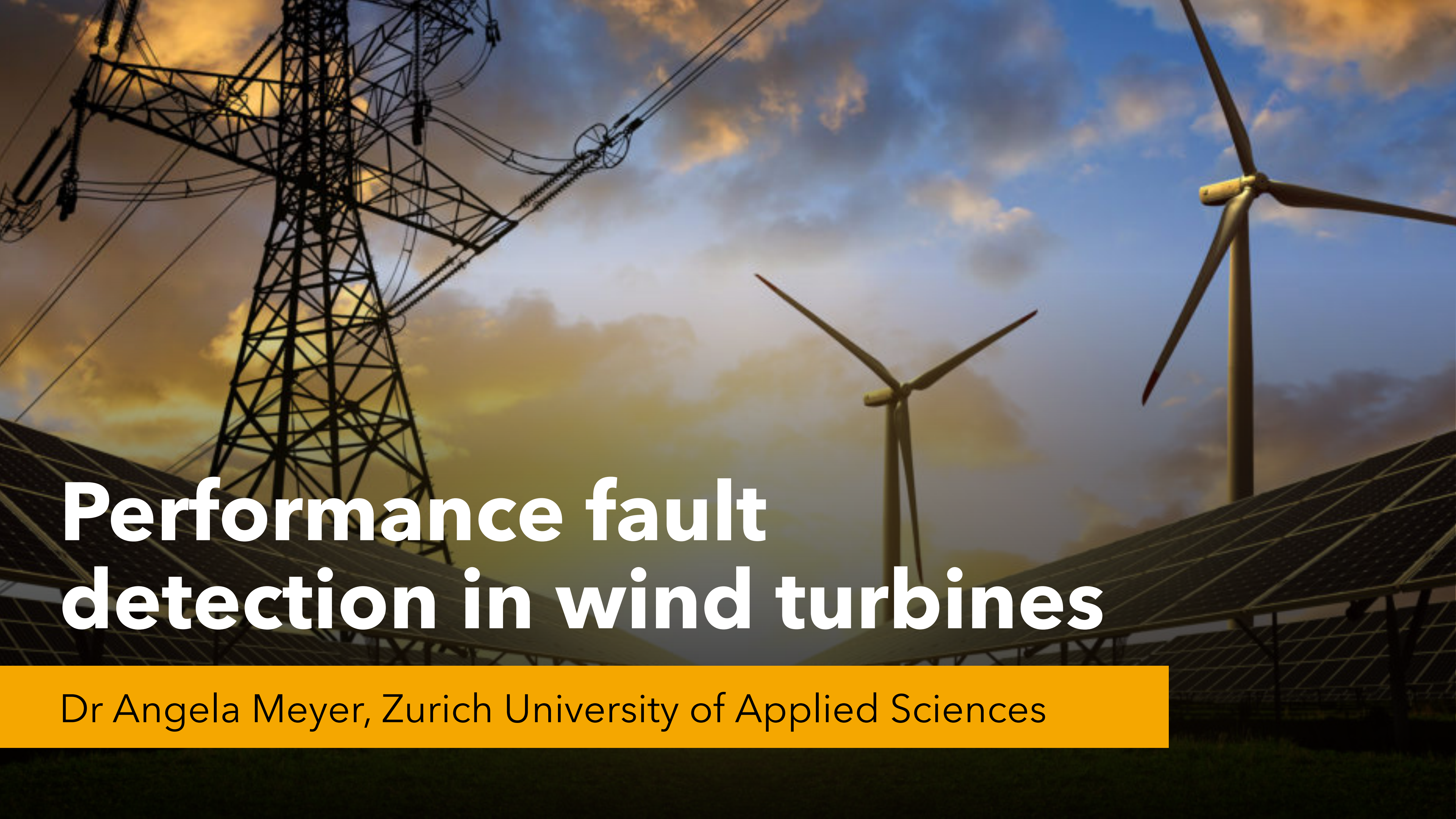
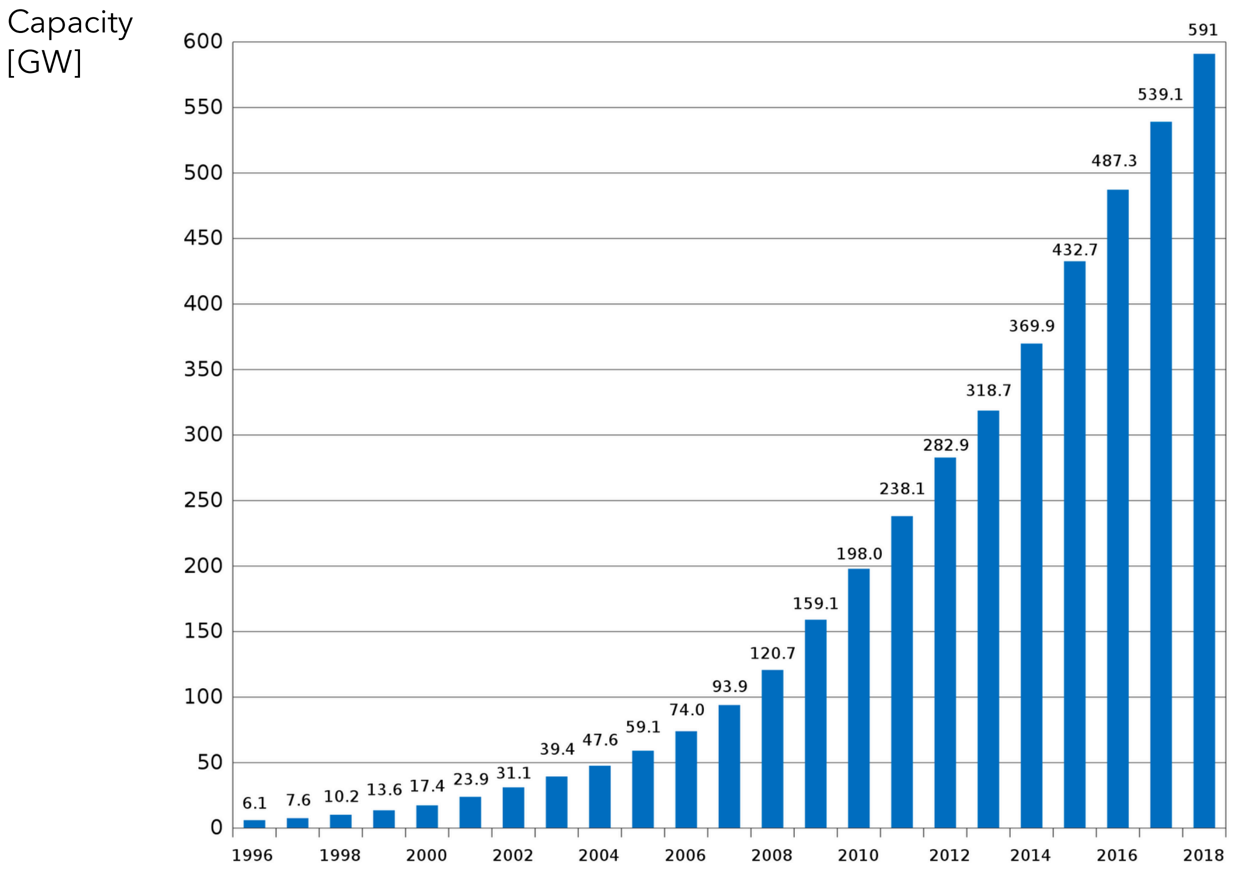


Performance fault detection in wind turbines

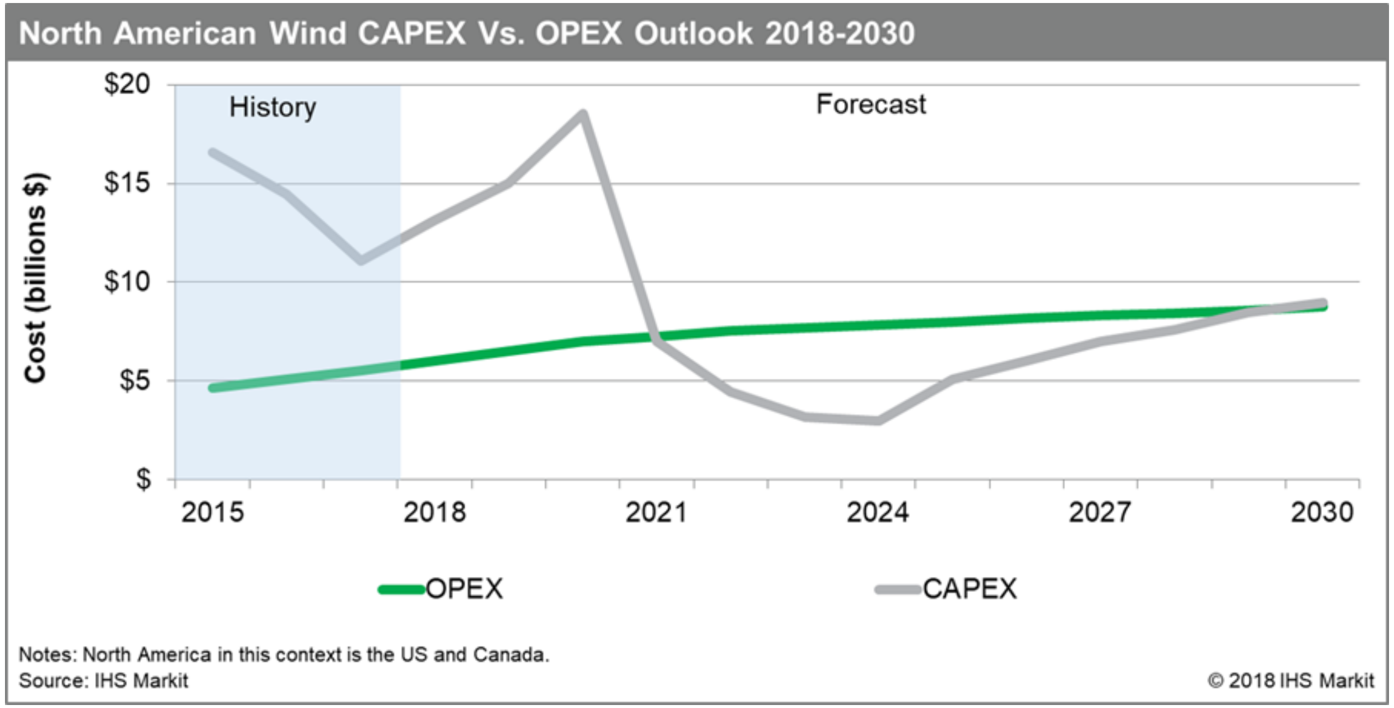
Dr Angela Meyer, Zurich University of Applied Sciences

Installed Wind Capacity growing strongly



Source: GWEC

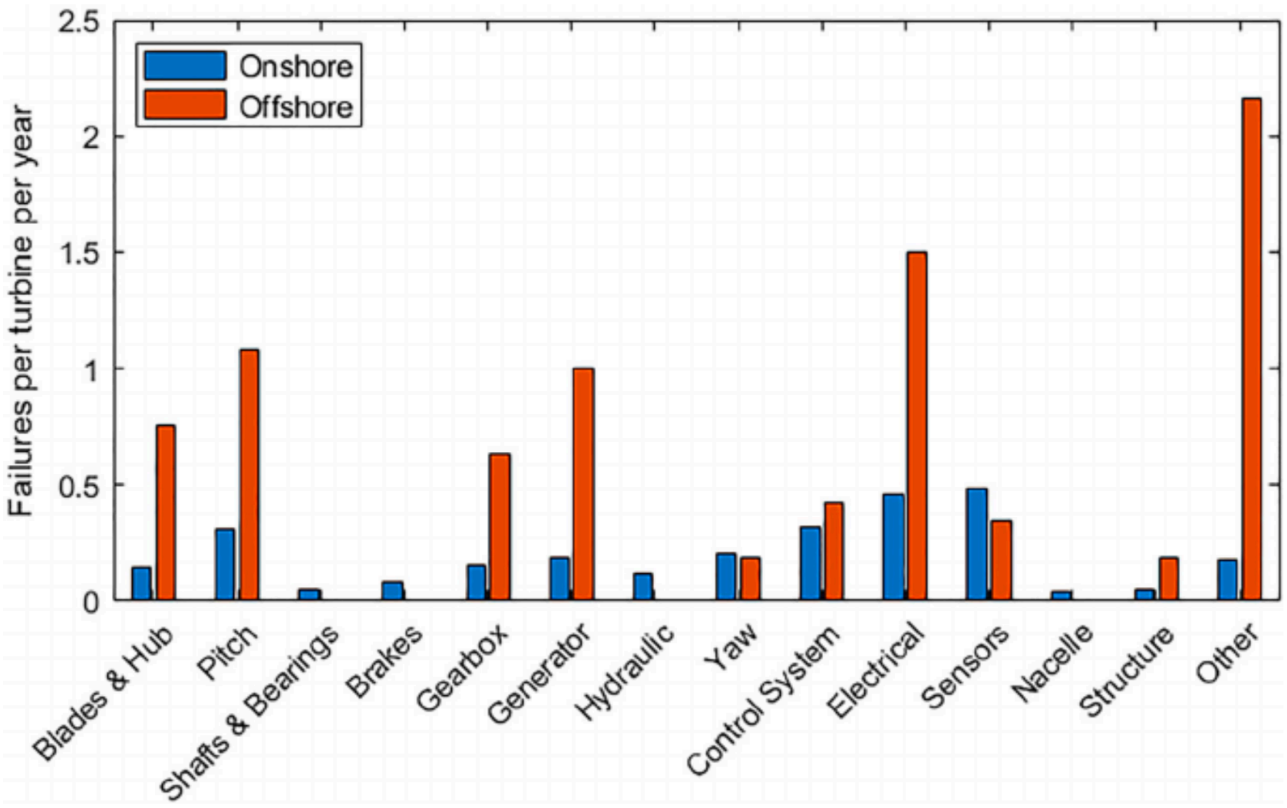
O&M costs on the rise



Rising demands for reliable and cost effective operation

Source: IHS Markit

Reliability-critical Subassemblies in Wind Turbines



Source: Dao et al. 2019

Highest Annual Failure Rates

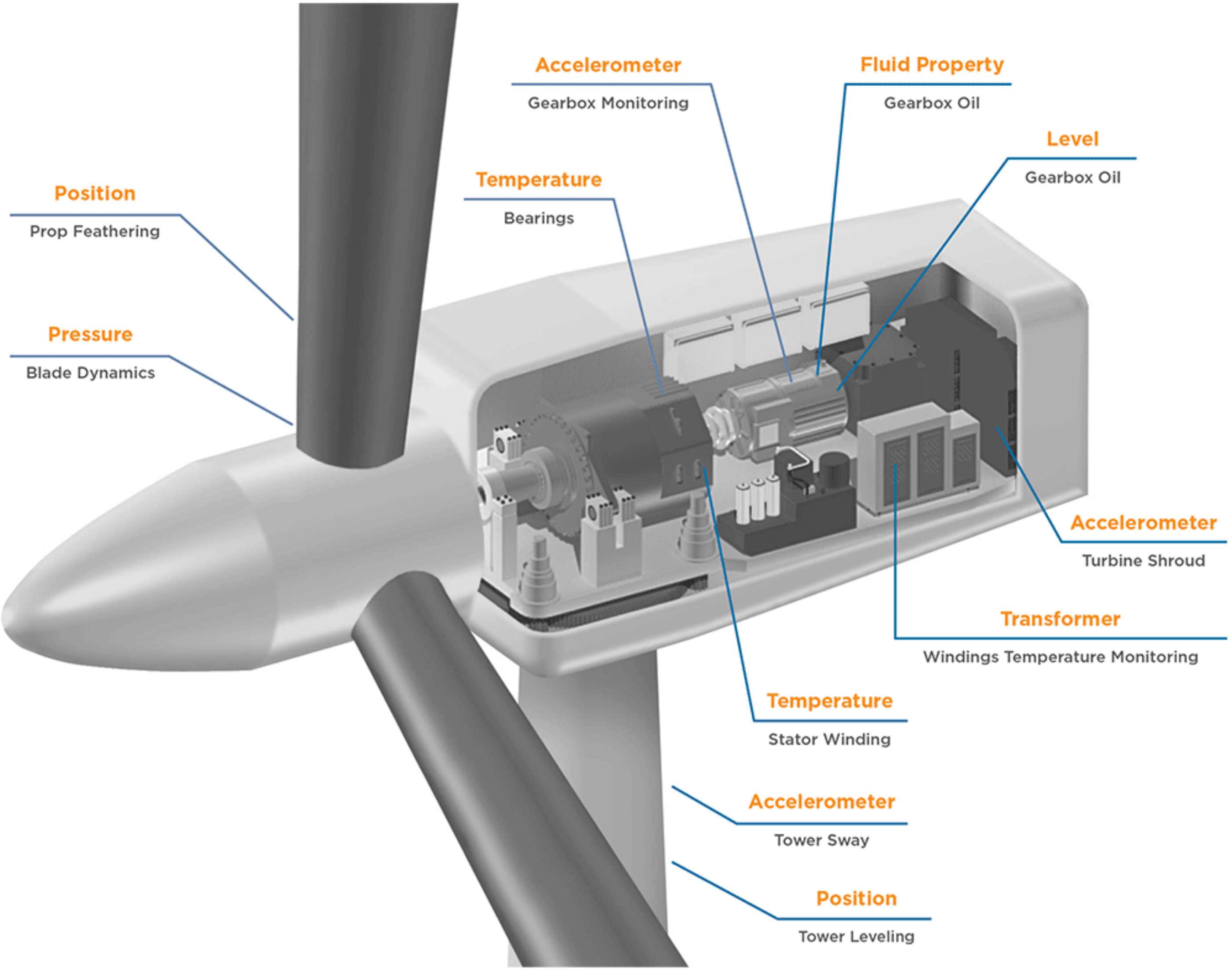
- Electrical system ~ 0.5/a
- Sensors ~ 0.5/a
- Pitch system ~ 0.3/a
- Control system ~ 0.3/a
- Yaw system ~ 0.2/a

Condition Monitoring in Wind Turbines

> 100 data points every 10 minutes

Commercial on-shore turbine in Western Europe

All data has been anonymised



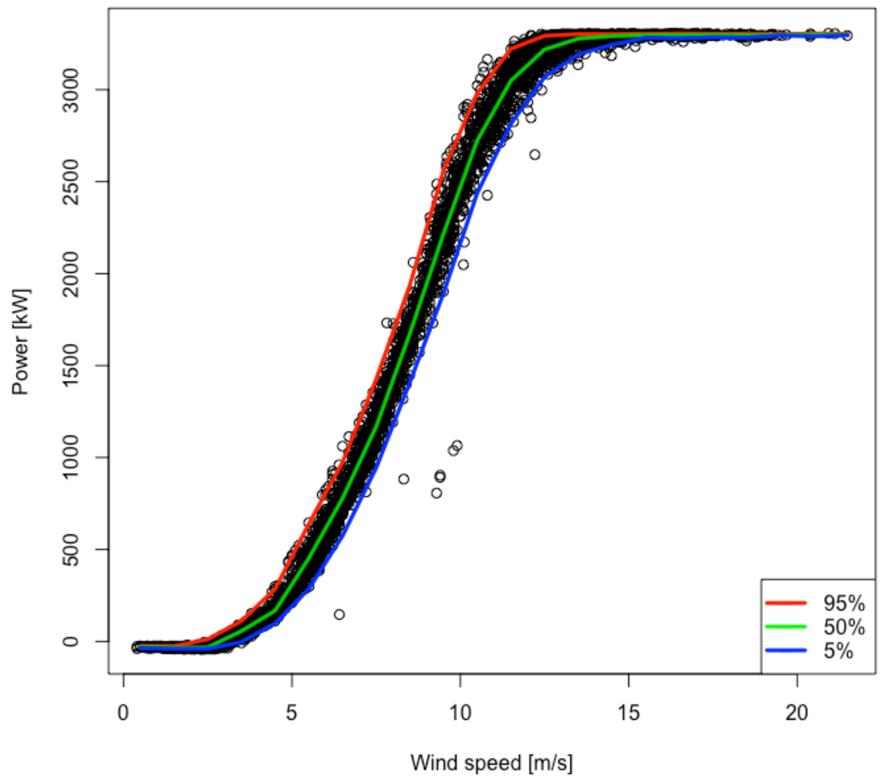
Source: TE Connectivity

Power reference model

$$P \sim v_{\text{wind}} \tag{1}$$

$$P \sim v_{\text{wind}} + \alpha_{\text{wind}} \tag{2}$$

$$P \sim v_{\text{wind}} + \alpha_{\text{wind}} + T_{\text{air}} \tag{3}$$

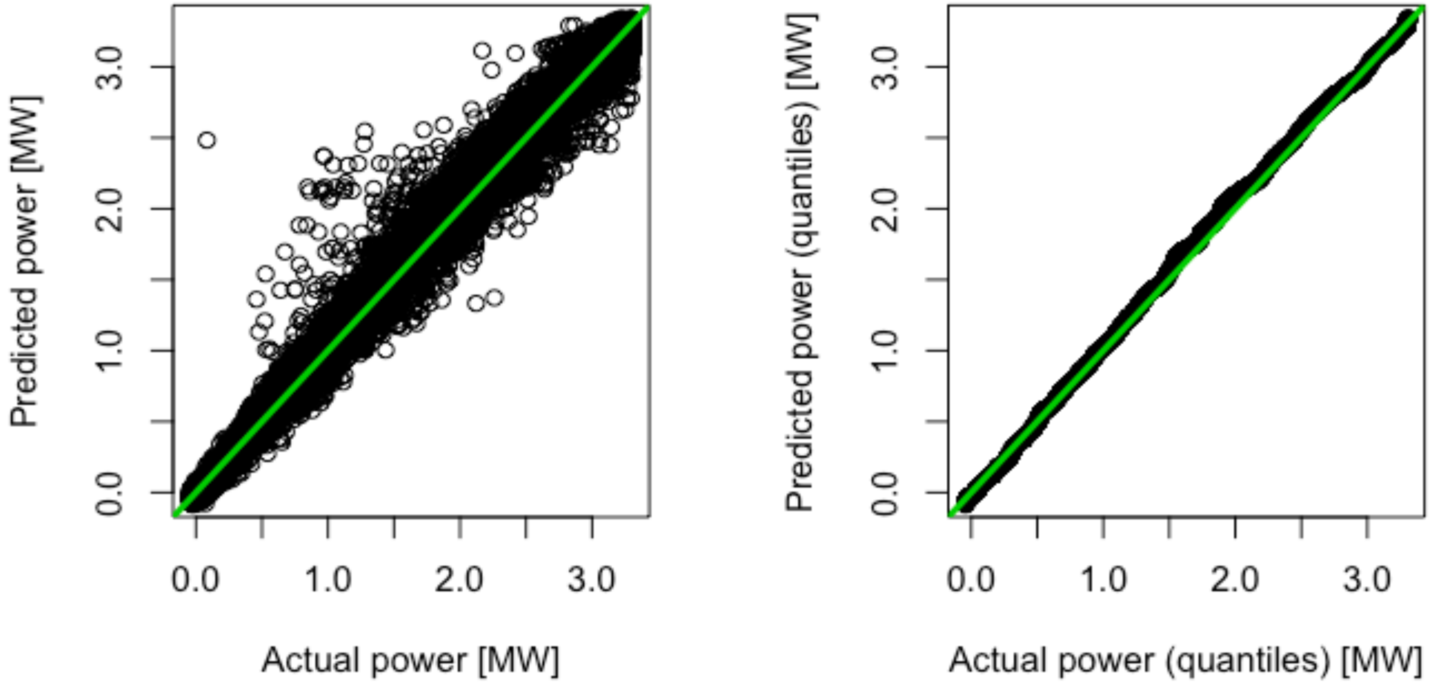


Power reference model

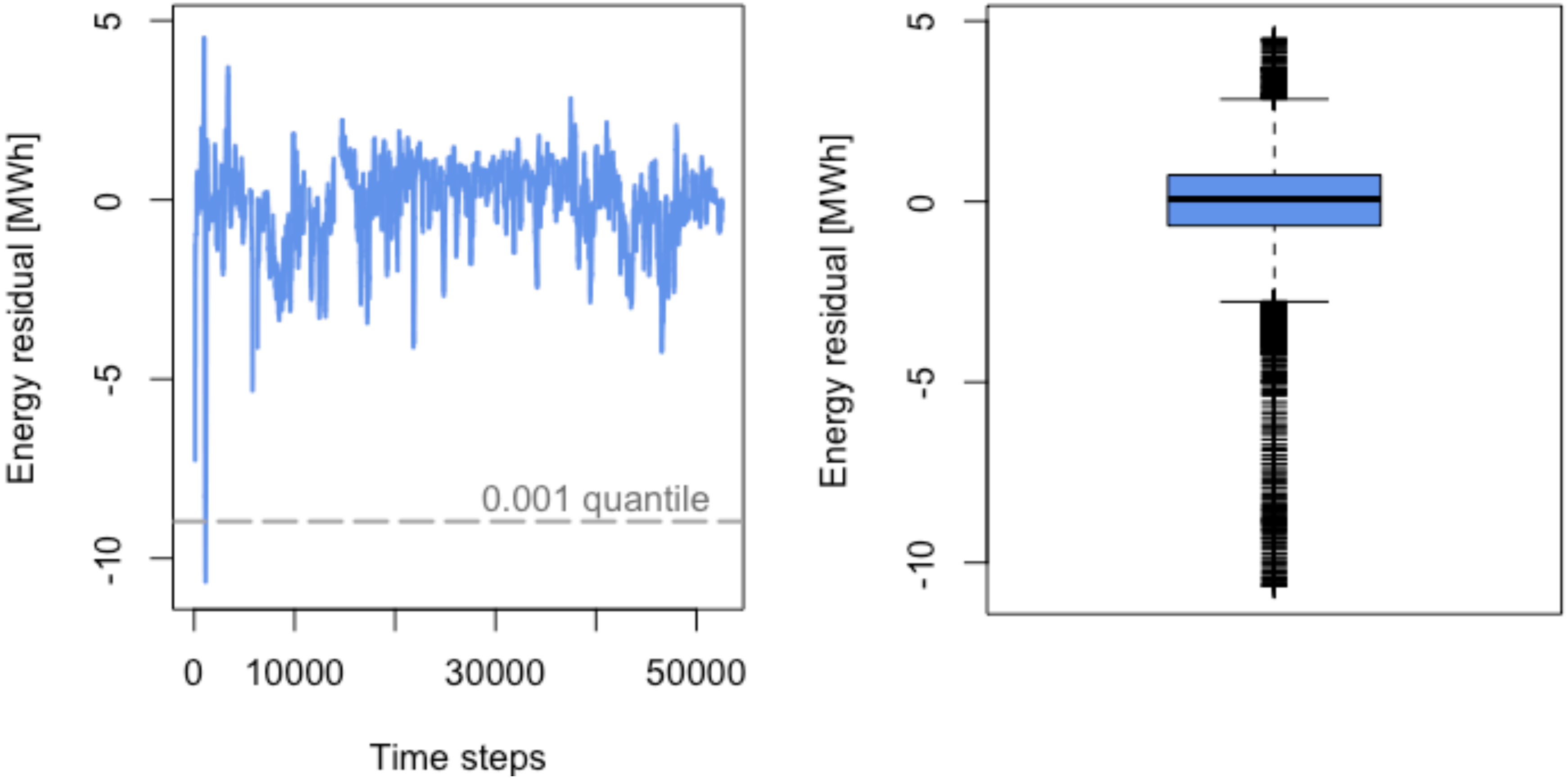
ESTIMATION ACCURACIES FOR $P \sim V_{WIND} + \alpha_{WIND} + T_{AIR}$

Algorithm	RMSE in kW	R^2
Random Forest	67.1	0.997
Gradient Boosting	68.1	0.997
BRNN	72.8	0.996
SVM	75.5	0.996
kNN	185.5	0.977
GAM	360.4	0.913
GAM LOESS	136.8	0.987

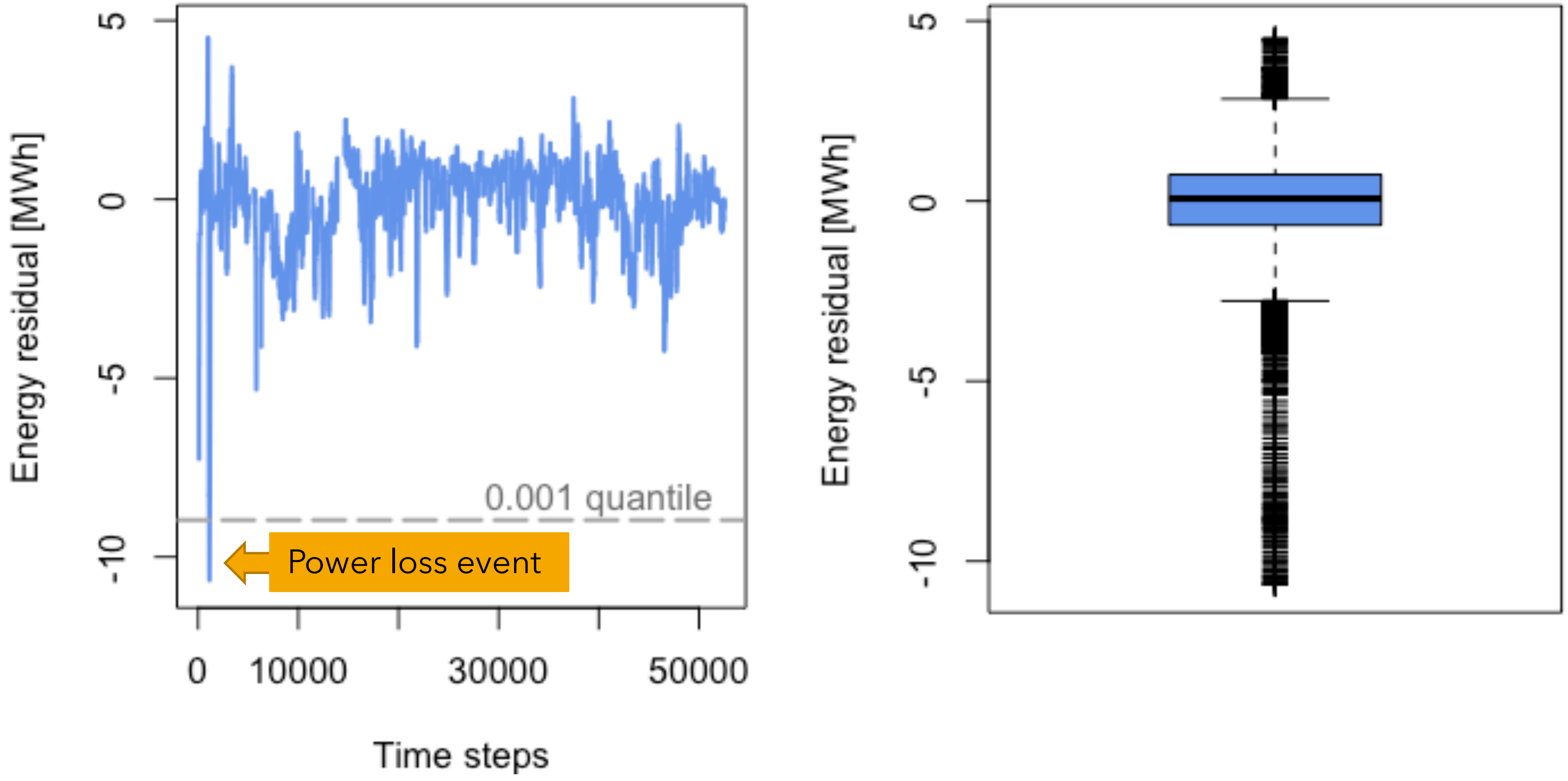
Power reference model $P \sim v_{\text{wind}} + \alpha_{\text{wind}} + T_{\text{air}}$



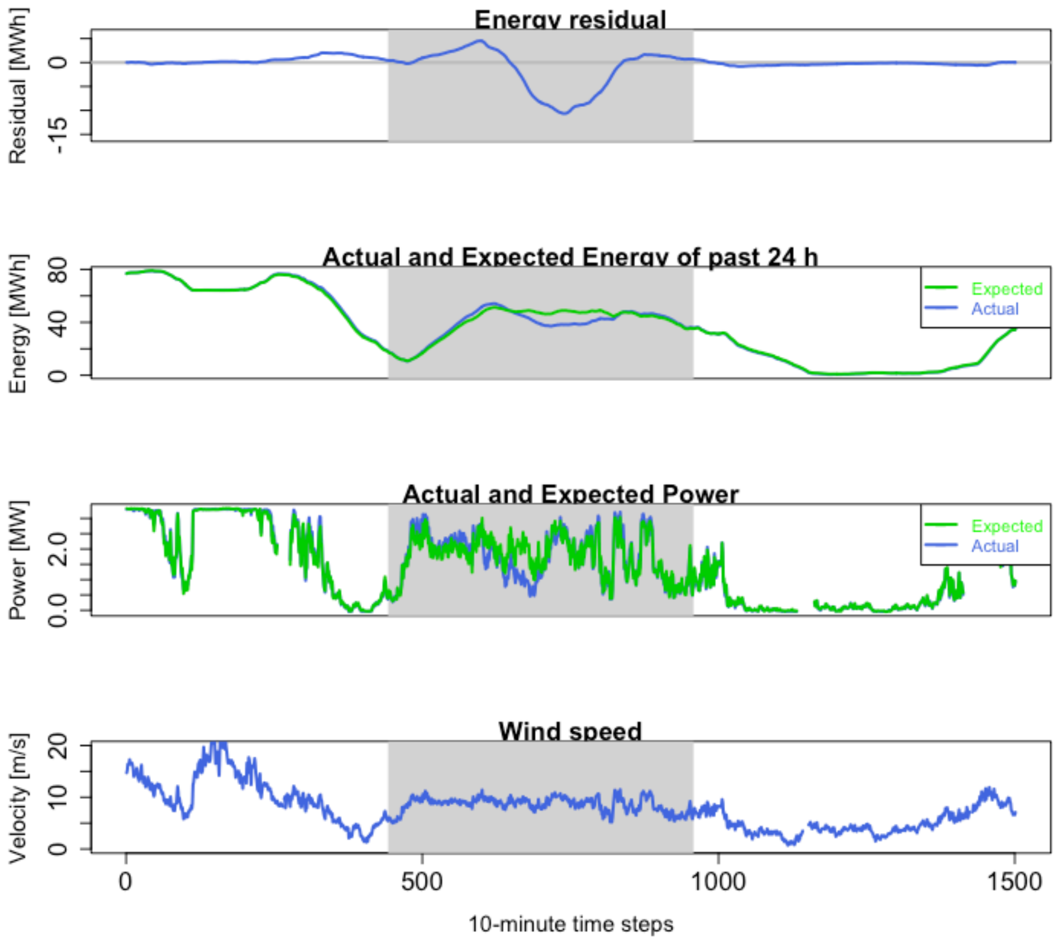
Energy Residuals



Energy Residuals

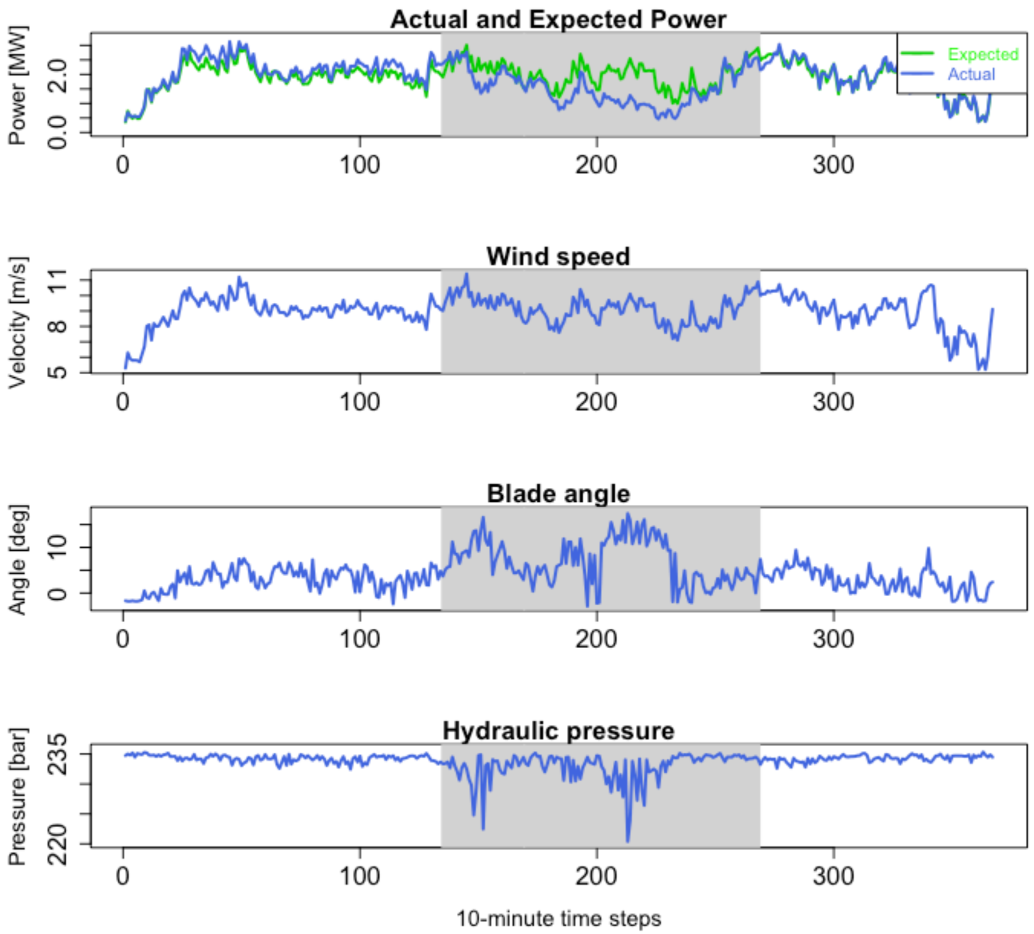


Power Loss event



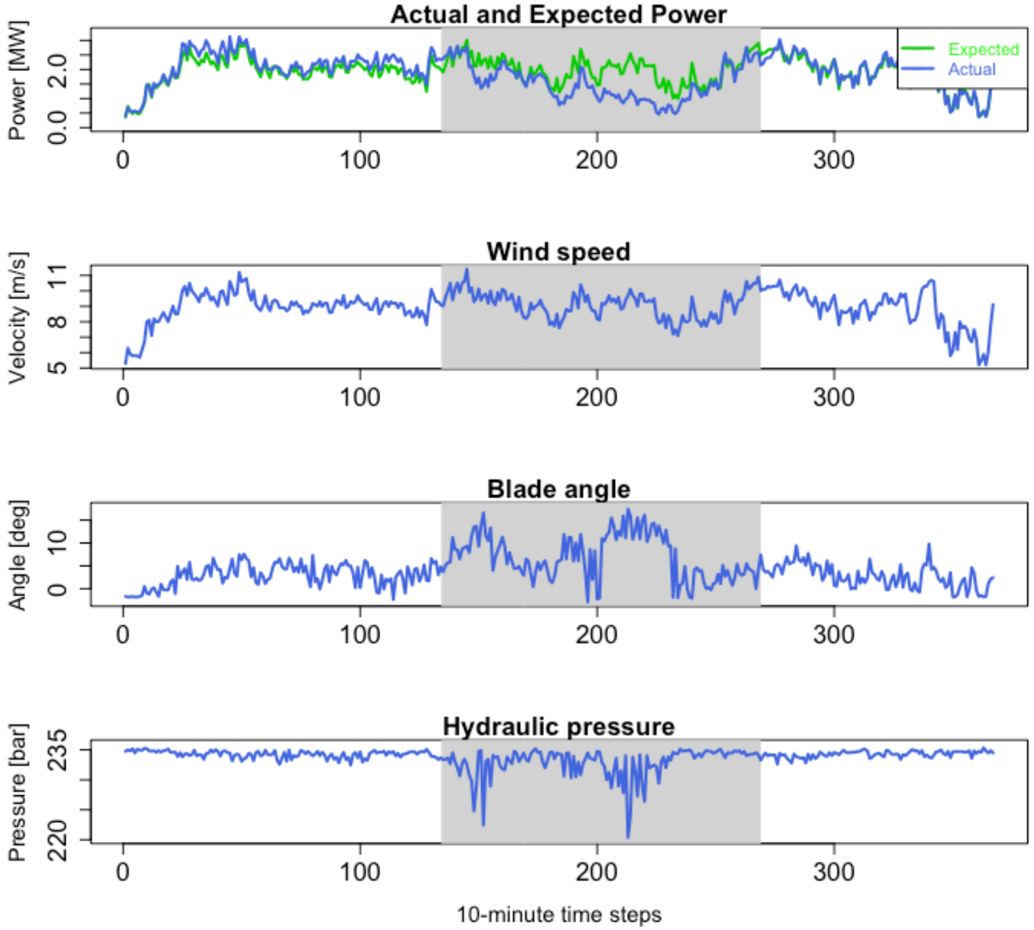
- One week shown
- 10.3 MWh lost within 24 hours
- Decline in power generation despite constant wind speed
- Underperformance lasted for about 15 hours

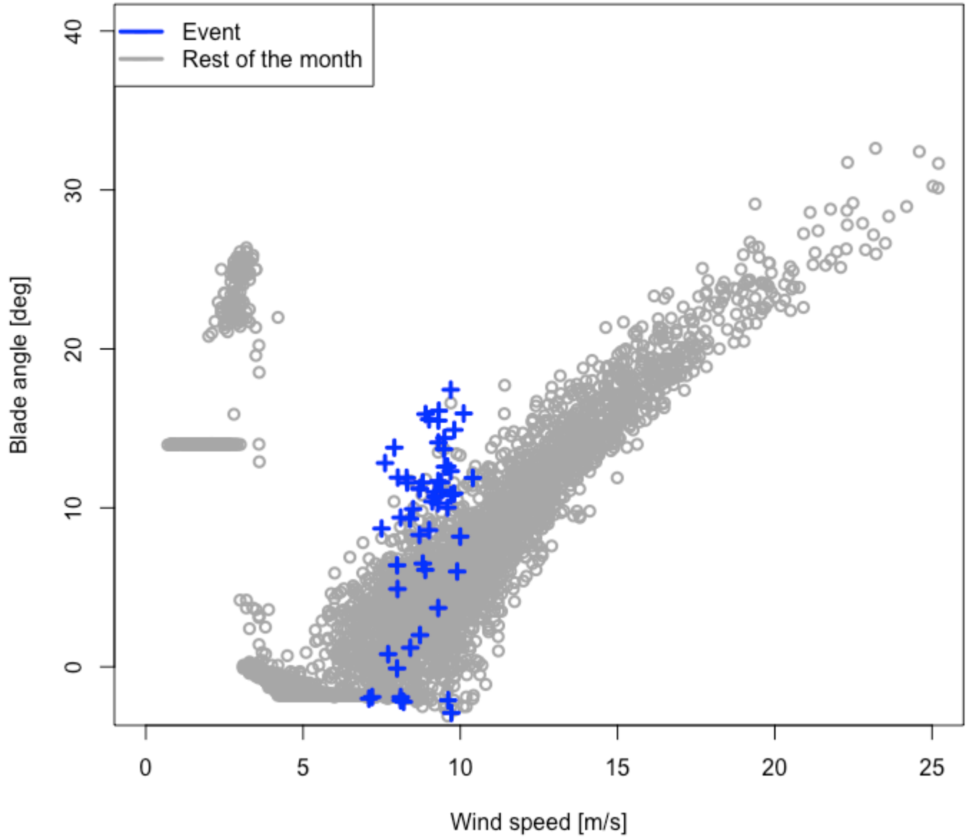
Power Loss event



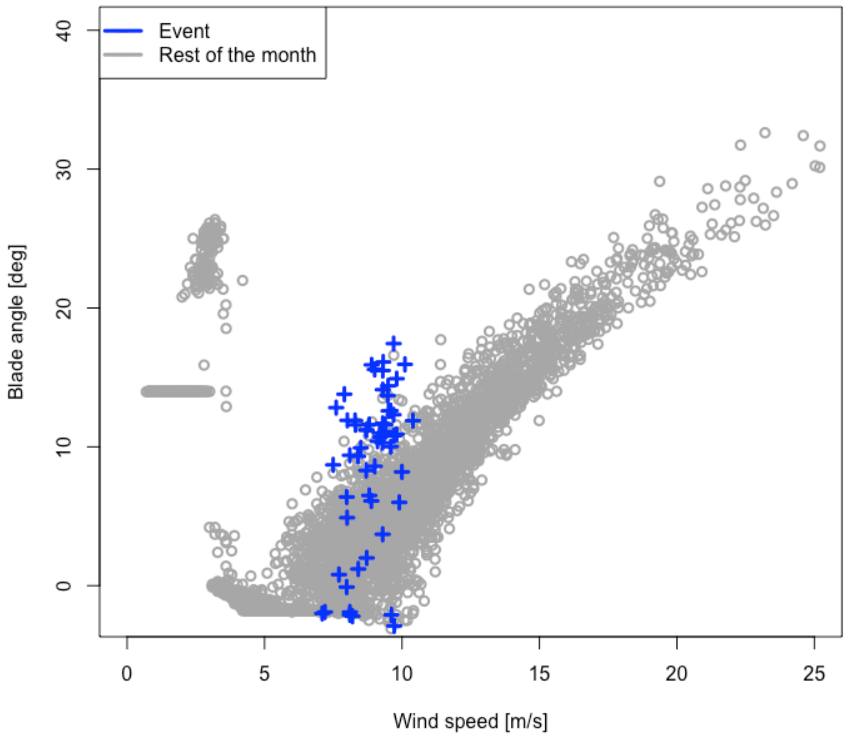
- Zoom in to 2 days
- Underperformance despite relatively constant wind speed around 9 m/s
- Coinciding with unusually large blade angles at given wind speeds
- Coinciding with sudden declines in hydraulic pressure

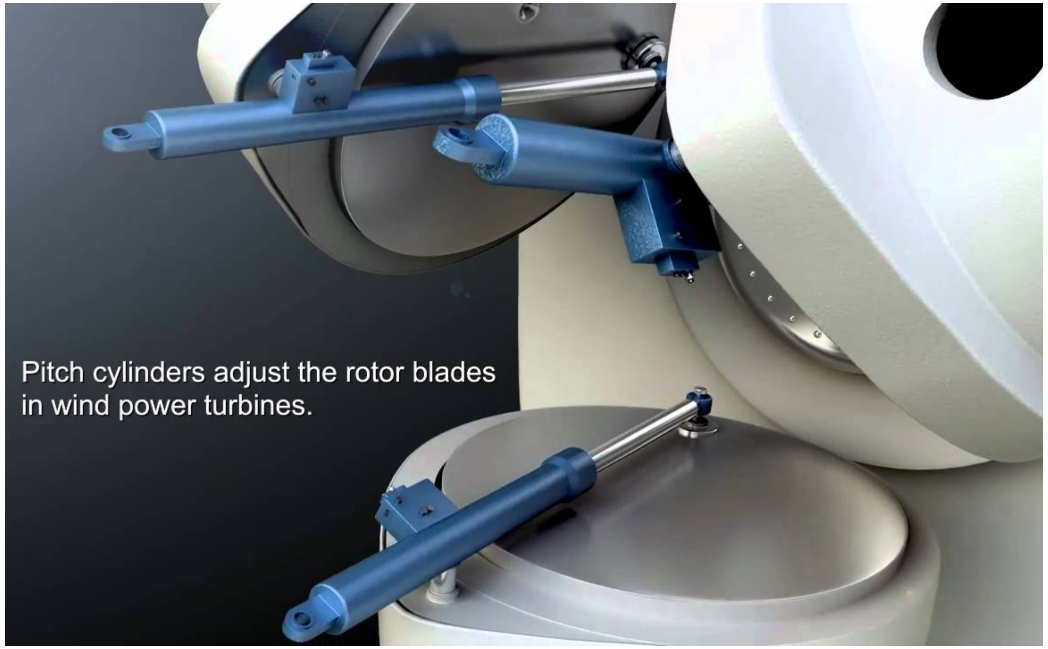
Power Loss event





Power Loss event





Source: Trelleborg AB

Performance Fault Detection in Wind Turbines by Dynamic Reference State Estimation

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***Abstract*— The operation and maintenance costs of wind parks make up a major fraction of a park's overall lifetime costs. They also include opportunity costs of lost revenue from avoidable power generation underperformance. We present a machine-learning based decision support method that minimizes these opportunity costs. By analyzing the stream of telemetry sensor data from the turbine operation, estimating highly accurate power reference relations and benchmarking, we can detect performance-related operational faults in a turbine- and site-specific manner. The most accurate power reference model is selected based on a combinations of machine learning algorithms and regressor sets. Operating personal can be alerted if a normal operating state boundary is exceeded. We demonstrate the performance fault detection method in a case study for a commercial grid-connected onshore wind turbine. Diagnosing a detected underperformance event, we find that the observed power generation deficiencies coincide with rotor blade misalignment related to low hydraulic pressure of the turbine's blade actuators.**

***Index Terms*— Fault detection and diagnosis, Gradient boosting, Performance optimization, Power modelling, Wind turbine**

I. Introduction

THE globally installed wind power capacity reached 591 GW at the end of 2018 and continued growth is expected by at least 55 GW annually until 2023 [1]. The operation and maintenance (O&M) costs of commercial wind turbines constitute a large fraction of the overall lifecycle costs. They

to be monitored. A variety of condition monitoring approaches have been proposed for wind turbines, including oil analysis, vibration, acoustics and strain monitoring [4]. More recently several multivariate data mining approaches to condition monitoring have been proposed for detecting performance-related faults and quantifying underperformance in the power generation of wind parks. These approaches make use of turbine telemetry data comprising sensor-measured and control variables for estimating power curve models in a parametric or non-parametric manner [5]. Several parametric methods have been proposed, e.g. [6]–[8]. Among the parametric approaches, for instance [6] proposed a monitoring method which calculates a power curve by spline interpolation of mean power values per wind speed bin and then learns upper and lower limits to the power curve and issues an alarm if the limits are exceeded. Being based on discrete bins and parametric interpolation, this method may be prone to provide less accurate estimates than highly flexible machine learning regression models. Moreover, it issues alarms based on single 10-minute average outlier values, which may result in a large number of alarms even in case of brief transient deviations. An underperformance detection in the power generation was proposed in [7] based on power curve modelling with stepwise linear models and Weibull cumulative distribution functions. It is found that such parametric approaches can be limited in their flexibility to capture power relations and to reflect the characteristics of individual turbines and sites.

Among the non-parametric approaches, several regression,

New Article

Meyer and Brodbeck 2020

[arXiv:2005.00370](https://arxiv.org/abs/2005.00370)

Thank you!

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Thank you!

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