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Statistical Evaluation of SCADA data for Wind Turbine Condition Monitoring and Farm Assessment

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Abstract. Operational data from wind farms is crucial for wind turbine condition monitoring and performance assessment. In this paper, we analyse three wind farms with the aim to monitor environmental and operational conditions that might result in underperformance or failures. The assessment includes a simple wind speed characterisation and wake analysis. The evolution of statistical parameters is used to identify anomalous turbine behaviour. In total, 88 turbines and 12 failures are analysed, covering different component failures. Notwithstanding the short period of data available, several operational parameters are found to deviate from the farm trend in some turbines affected by failures. As a result, some parameters show better monitoring capabilities than others, for the detection of certain failures. However, the limitations of SCADA statistics are also shown as not all failures showed anomalies in the observed parameters.

1. Introduction

Condition-based maintenance can facilitate the shift from corrective maintenance towards more predictive approaches, by optimising the timing of maintenance and therefore avoiding premature breakdown of the system [1]. The use of data from the Supervisory Control And Data Acquisition (SCADA) system for wind turbine (WT) monitoring purposes has gained more attention due to the availability of such data at no additional cost [2]. However, since WTs operate in a stochastic environment, their performance and health state strongly depend on the environmental and operating conditions [3, 4, 5]. Understanding these could help in achieving more reliable WT condition monitoring solutions.

In contrast to other data-driven and model-based approaches using SCADA data [6, 7], the Physics of Failure approach tries to estimate WT damage accumulation. Operational statistics were used in [8] to identify WTs experiencing gearbox problems within a large wind farm. Statistical moments of high order were used in [9] as metrics to assess WT behaviour, using a bivariate skewness-kurtosis reference for the entire farm. Both approaches identified turbines with abnormal condition at a given moment, but were not necessarily applicable for a more dynamic evolution of the condition, e.g. with multiple replacements in a short observation period. In this line, this paper investigates the monitoring capabilities of several statistical parameters, covering both environmental and operating conditions throughout the asset's operating life-time. The research presented here examines the system's behaviour given the operating environment with a focus on damage and underperformance driving parameters using data from three wind farms. The objective is to assess this behaviour at both farm and turbine levels, and to identify critical operating conditions. The ultimate aim is to identify damage and underperformance indicators. Unlike previous research, the selected case studies cover several different component failures, including those identified as the most critical [10].

2. Case study data

In this paper, data from three onshore wind farms located in Spain were analysed, covering one year of operation. This duration should already limit seasonality effects, although an even longer observation period would have been beneficial. All farms are equipped with three-bladed, geared-drive and pitch-controlled turbines with capacities in the 1.5 to 2.5 MW class. The number of WTs in each wind farm is presented in Table 1.

The available SCADA data were comprised of ten-minute (10-min) average, minimum, maximum and standard deviation of active power (P), reactive power (Q), pitch angle (β), rotational speed (ω), wind speed (u) and ambient temperature (T). Additionally, operational meteorological (met) masts were available at each wind farm, all following a similar configuration. Each met mast was equipped with a wind vane and three cup anemometers, two of them installed at the top measurement height which corresponds to the WT hub height. As a result, met mast data were available for each farm consisting of 10-min aggregated data of wind speed at two different heights and wind direction (ϕ) at one height.

Failure data information was also available for the observed year of operation. Only major failures, that implied either a component repair or replacement, were considered for further analysis due to their critical effect on operation and maintenance costs and production losses. Table 1 gives a summary of the major failures registered during the period of the record.

Table 1: Major replacements in the case study data.

Wind farm	WTs	Nb. of failures	Faulty components
A	33	2	Generator, Blades
B	25	3	Blades, Gearbox, Generator
C	30	11	Blades, Gearbox, Generator, Bearings (x4), Hydraulic Group, Low Speed Shaft, Transformer, Other

3. Methodology

The objective of assessing the performance and operation of the wind farm as well as the turbines is addressed at two levels. First, the global farm's behaviour is studied through the general environmental conditions during operation; then, a high-level wake assessment is performed, to identify the more risky turbine locations and hence more likely to suffer from fatigue driven failures; finally, the global averaged performance of the farm is evaluated. At the turbine level, each WT is monitored evaluating its deviation from the farm average using selected operational parameters, in order to identify damage driving operating conditions or faulty behaviour.

3.1. Wake assessment

Wakes developing downstream of operating wind turbines do not only result in wind speed deficits, but also in additional turbulence and, hence, additional loads. This can therefore increase the accumulated damage on other WTs located downstream [11]. To avoid these effects, the current industry practice is to maintain a minimum distance of five rotor diameters (D) in the predominant wind direction during the design of the layout of a farm. Nevertheless, some operating assets exhibit shorter distances between turbines, increasing the risk of higher exerted loads.

In this study, a simple assessment of wake affected operation was conducted by identifying categories of near and far wake based on the distances to the nearest turbines in the current wind direction. Based on common rules from wind speed deficit typical values in single wakes depending on the distance downstream [12] but also in multiple wakes [13], a simplified wake number was derived with the following weights:

$$w_{wake} = \begin{cases} 6 & \text{if } d < 4D \wedge n > 1 \text{ (near multiple wake)} \\ 4 & \text{if } (d_1 < 4D \wedge n_1 = 1) \wedge (4D < d_2 < 8D \wedge n_2 = 1) \\ & \quad \text{(near single wake and far single wake)} \\ 3 & \text{if } d < 4D \wedge n = 1 \text{ (near single wake)} \\ 2 & \text{if } 4D < d < 8D \wedge n > 1 \text{ (far multiple wake)} \\ 1 & \text{if } 4D < d < 8D \wedge n = 1 \text{ (far single wake)} \\ 0 & \text{if } d > 8D \text{ (no wake)} \end{cases} \tag{1}$$

with the distance to the upstream turbine d and n as the count of upwind turbines at a given wind direction in this category. Here, we used a sector of $\pm 15°$ for the wind direction to consider a turbine as upstream. The final wake number is calculated as an average of the weights w_{wake} according to the occurrence of the corresponding wind directions. The obtained wake number is understood here as the level of risk of operating under wake affected conditions as well as the magnitude or severity of the wake at each turbine location. A more accurate wake model is out of the scope of this paper and would not necessarily improve the findings as no turbine-specific wind direction measurements were available for these farms.

3.2. Quantifying underperformance

Assessing the performance of WTs is not trivial due the stochastic nature of the wind speed, the non-linear characteristic of the power curve and site-specific variation. In this study, a performance ratio f_P was derived for every WT, defined as the quotient between the actual and the theoretical power production. Three different approaches were used to estimate the theoretical performance, that is the WT performance during normal operating conditions. These three approaches feature state-of-the-art techniques for WT specific power curve modelling, i.e. the industry practice based on the method of bins [14], the Random Forest [15], and the Gaussian Process algorithms [16].

The common industry standard, the method of bins (MOB), consists of averaging P for each $0.5\,\mathrm{m\,s^{-1}}$ wide bin of u [14]. Linear interpolation can be used to predict a time series of P based on the derived look-up table. In this case, density correction was applied to nacelle wind speed data to account for the linear dependency of WT power to air density. For every WT, density at hub height was estimated based on the model described in [17] and temperature data from the SCADA system.

Random Forests (RF) is a very popular non-parametric machine learning algorithm for both classification and regression. In the case of WT power curve modelling, they can give an accurate approximation of the conditional mean of the response variable, based on multivariate inputs [15]. In this case, u and T were used as inputs, while P was set as the output.

Finally, Gaussian Processes (GP) are non-parametric kernel-based probabilistic models that provide predictions together with confidence levels based on an underlying function between input and output, and noise learned from the data. An example for WT power curve modelling can be found in [16]. In this case, a univariate GP with variable noise was used to produce a power curve.

All these three power curve models were trained using data from the first month of data in each farm. Furthermore, data was preprocessed to discard all the events unlikely to be

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representative of normal operating conditions. A detailed description of the robust filtering methodology applied here can be found in [15].

3.3. Windowed turbine statistics

In the physics of failure studied by Gray and Watson [8] several parameters describing the operational behaviour were defined based on a cumulation of all available data. This was possible due to the fact that the observed failures happened towards the end of the observation period. In this study with a short observation period and multiple failures at various dates of the year, a more flexible approach was required with statistics in windows with a defined length. The aggregation of all operational data might reveal key differences in a farm, but some effects will only be recognised in shorter aggregation periods. The raw 10-min statistics, however, are more affected by external dynamics and aggregation in windows of at least one hour are more suitable to avoid transitional events and ensure that internal factors drive the dynamics of the system [3]. In an iterative process, a window length of one day was derived.

Several basic statistical parameters were defined as listed in Table 2 by also using the reference wind and rotational speeds for rated power condition (index 'rat'). It has to be noted that the derived turbulence intensity is not a true representation of the turbulence observed by the WT, but rather describing the turbulence after the rotor. However, it can give an indication of the incoming turbulence.

Table 2: Statistical parameters.

Direct averages	Derived parameters
Wind speed (u)	Maximum of mean wind speed MWS = $max(u)$
Reactive power (Q)	Power dynamic PD = P_{std}/P
Ambient temperature (T)	Turbulence intensity TI = u_{std}/u
Met mast wind shear (α)	Turbulence intensity at standstill TIS = TI | $P < 100\,\mathrm{kW}$
	Ratio of high wind speed HWS = $mean(1, \text{if } u > u_{rat}, 0 \text{ else})$
	Ratio of full load FL = $mean(1, \text{if } P > P_{rat}, 0 \text{ else})$
	Ratio of high rotor speed HRS = $mean(1, \text{if } \omega > \omega_{rat}, 0 \text{ else})$

3.4. Signal dissimilarity

An alternative approach to identify anomalous behaviour of a WT was developed based on the dissimilarity of signals as described by the multidimensional Euclidean distance. For each WT, each SCADA signal was compared with the corresponding signal in all other WTs in the farm in a pairwise matter. Subsequently, the median of the distance was used to describe the similarity compared with the farm behaviour. This procedure was conducted with the data split in daily sets to allow an assessment of trends over time. A high dissimilarity will indicate abnormal behaviour as the given WT is not behaving similarly to other turbines in the same farm. On the contrary, a low dissimilarity value will mean a WT behaviour aligned with the rest of the turbines in the farm. In comparison with the statistical parameter defined in the previous section, the signal similarity might be able to better detect shorter deviation in operational behaviour that might be unnoticed using an average.

4. Results and discussion

The results of the study are presented in two sections focusing on the identified features at the farm and turbine level, respectively.

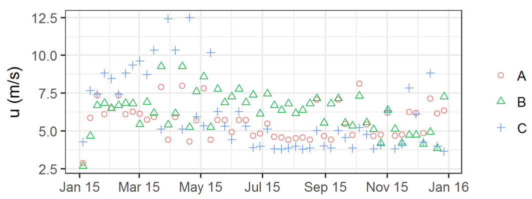


Figure 1: Weekly averaged wind speed.

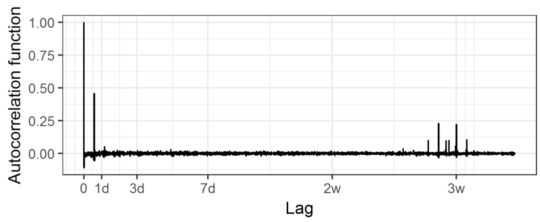
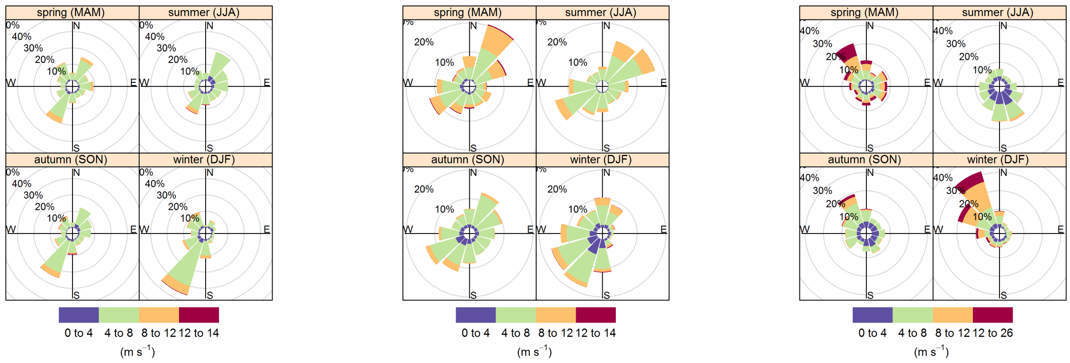


Figure 2: Periodicity in wind speed.



(A) (B) (C)

Figure 3: Seasonal wind roses for the three farms.

4.1. Farm assessment

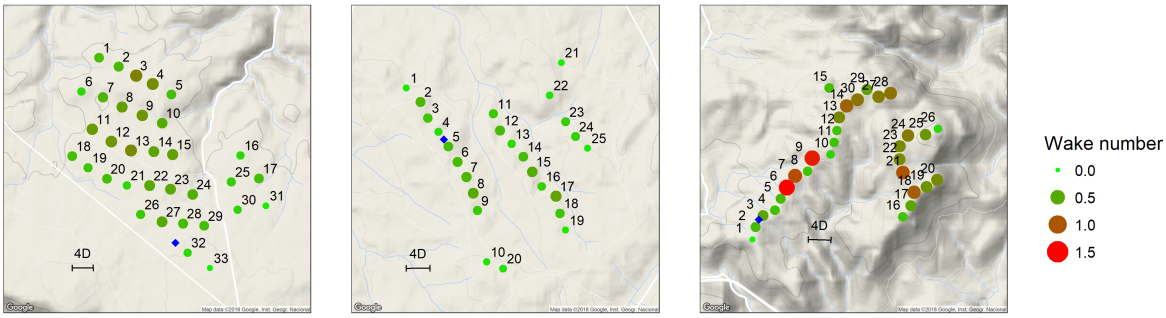
The measured wind speed was analysed to identify general trends and differences between the farms. Figure 1 shows the general wind speed trends observed by the met masts of the three farms. In general, farms A and B saw a more constant wind speed throughout the year, while farm C was affected by very high wind speeds in spring and winter, but lower wind speeds in summer. An autocorrelation analysis of the wind speeds in all met masts and turbines revealed a strong cyclic feature with the period of approx. 14 h and a weaker periodicity in 20-21 days, as exemplary shown in Figure 2 for met mast data from farm A. The seasonal wind roses in Figure 3 show that while farm A and C had a predominant wind direction (that was reversed in summer for farm C), farm B saw more evenly distributed wind directions throughout the year.

The vertical wind shear at each time step was estimated using the power law, based on the wind speed measurements at the two available heights for each met mast. The shear measurement at the met mast may not be fully representative for each turbine in the farm. However, the met mast statistics given in Table 3 indicate that the farms might have seen different levels of shear. The accuracy of the absolute shear value can be questioned as the shear did not vary significantly with the wind direction or season. However, the relative shear variation might be still correct and indicated a high fluctuation of shear, which might result in challenging loading on the rotor and drive train.

Figure 4 shows the results of the wake assessment overlaid on the wind farm layouts of the three farms. As can be seen, the layout of wind farm A and C imply the appearance of some risky locations. Significant wake numbers are indeed observed at WT3, WT4, WT12 or WT13 in farm A, and even worse for WT6, WT7 or WT9 in farm C. As a result, these turbines should be exposed to higher risk of suffering from fatigue-driven failures and lower expected lifetime. In general, the layout of farm C shows the most negative effects among the three farms, with very high wake numbers at several turbine locations. This, together with a higher terrain complexity,

Table 3: Shear statistics from met masts.

		Farm A	Farm B	Farm C
General	Mean	0.34	0.13	0.02
	Standard deviation	0.18	0.18	0.10
	Strongest periodicity	14 h	14 h	14 h
Directional	0° to 90° mean	0.30	0.14	0.03
	90° to 180° mean	0.35	0.12	0.02
	180° to 270° mean	0.35	0.14	0.02
	270° to 360° mean	0.39	0.12	0.01
Seasonal	Spring mean	0.34	0.12	0.02
	Summer mean	0.32	0.12	0.01
	Autumn mean	0.33	0.14	0.05
	Winter mean	0.38	0.16	-0.01



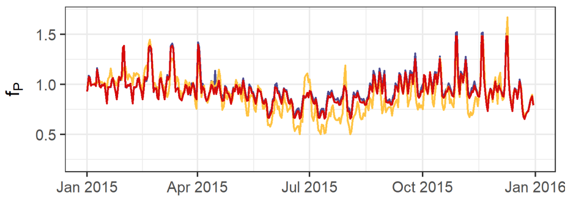
(A) (B) (C)

Figure 4: Wind farm layout with wake number per turbine (met mast shown with diamond).

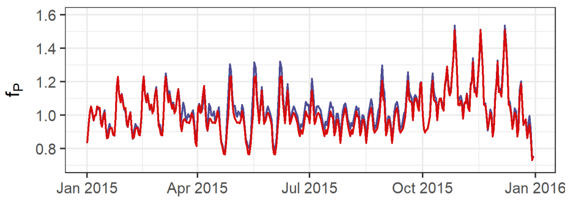
aligns with the higher number of observed failures of mechanical components (see Table 1). As illustrated here, wind farms not respecting the industry practice of a minimum distance of five rotor diameters will exhibit higher wake numbers. Consequently, these wind turbines will operate in more severe wakes, with a greater risk of higher loads and increased damage [11].

Figure 5 shows the average performance ratio of the three trained power curve models from all turbines in each farm. It can be seen, that farm A generally performed worse during summer although both the MOB and the RF should account for seasonal changes due to the applied density correction. Possible causes lie in the selection of one winter month for training and strong differences of the other unaccounted environmental parameters such as turbulence, shear, wind direction or atmospheric stability. However, the performance in farms B and C was more constant throughout the year. While the three power curve models showed similar mean trends in farm A and B, there is a stronger disagreement of the models in farm C where the RF claims a higher performance than the MOB and GP. Indeed, as only 10-min data were available, a low number of observations was finally retained for training purposes. RF can incur into prediction inconsistencies when the whole gamut of possible observations is not included in the training. Therefore, the two other methods were considered to give more consistent results in this case.

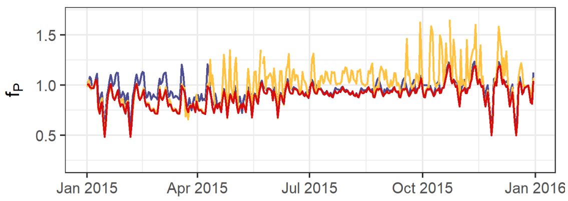
Figure 6 shows the performance ratios for one WT in each farm where a clear underperformance was observed: WT33 in farm A, WT3 in farm B and WT5 in farm C. The underperformance of the three turbines cannot be explained by the wake as described in the wake number. In contrast, WT 33 in farm A was experiencing exceptionally high wind speeds, but failed to show a corresponding increase in power output according to the models. As a result, this simple assessment allowed us to identify underperforming wind turbines in the context of farm operation.



(A)

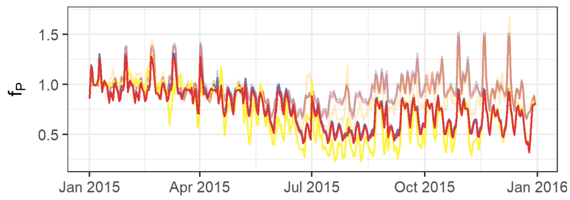


(B)

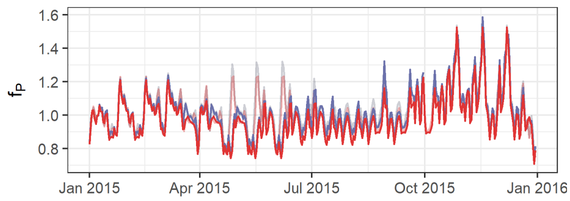


(C)

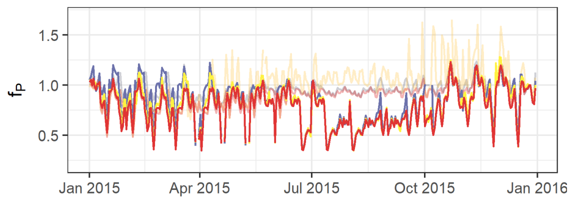
Figure 5: Mean performance ratio of each farm based on MOB (blue), RF (yellow) and GP model (red).



(A) WT33



(B) WT3



(C) WT5

Figure 6: Performance factor for selected underperforming turbines based on MOB (blue), RF (yellow, not used in farm B due to missing data) and GP model (red). Farm average performance in transparent colours.

4.2. Turbine assessment

The parameters listed in Table 2 were monitored and examined per WT in each wind farm, together with the failure data, containing information about the failure date and the faulty component. As a result, some anomalies could be identified due to their deviation from the average farm behaviour. This work focuses on qualitative results to identify indicators or drivers of failures. However, if a monitoring tool shall be developed in the next step, a definition of specific thresholds will be required.

In general, WTs experiencing failures of mechanical components (Gearbox, Blades, Bearings) were found to be more likely to exhibit underperformance prior to the failure occurrence, as exemplified in Figure 7. Also, some failure of mechanical components occurred after periods of higher maximum wind speeds and higher cumulated hours of full mode operation. Indeed, excessive loads can instigate a failure in an already damaged component. Moreover, failure of electrical components, especially generators, were found to be related to higher reactive power and hence lower power factor, and also exhibited higher levels of TIS. Low power factor can

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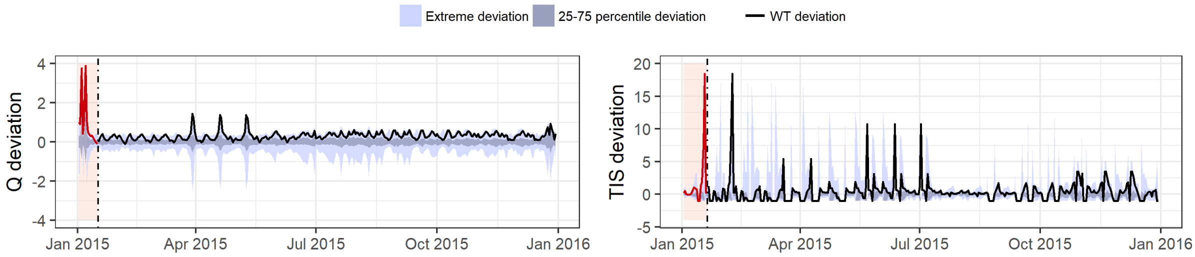
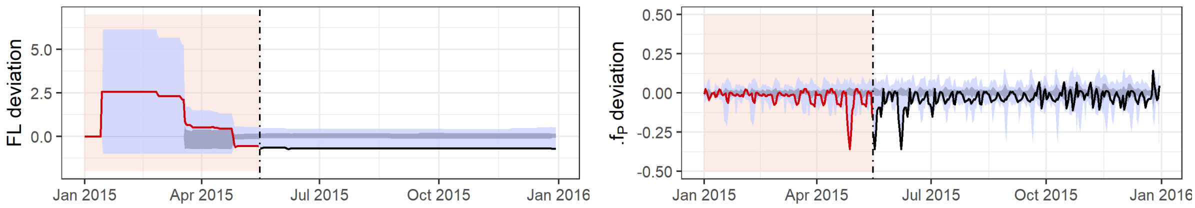
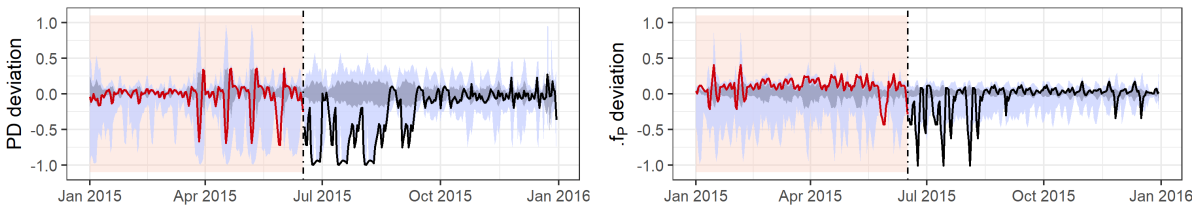


(A) Generator failure



(B) Gearbox failure



(C) Blade failure

Figure 7: Parameter evolution for three different failures in the three farms (A,B,C). A red shaded area indicates anomalous WT behaviour before the failure, which occurrence is marked with a dotted line.

actually cause excessive current and higher overall loads. This could be therefore interpreted as a sign of a faulty generator.

Examples of three failures, one per wind farm, are illustrated in Figure 7 with relevant statistical parameters (or the performance ratio) shown as deviation from the farm average trend. An example of a generator failure shows higher reactive power and turbulence at standstill than the farm average before the failure (see Figure 7 (A)). The example of the gearbox failure reveals much higher cumulated hours at full load of the failing WT than the general farm behaviour; concerning its performance, the turbine starts to deviate significantly from the farm one month prior to the failure (see Figure 7 (B)). As concerns the WT behaviour before a blade failure in farm C, a very significant change in the trend of the power dynamic is observed three months prior to the actual failure; some underperformance is also observed a month before the failure, but not as significant (see Figure 7 (C)). This might be due to the training period selected for the normal performance models definition. Indeed, blade failures generally develop in the long term, and the performance during the training period was possibly already affected by some degradation. Availability of earlier operational data would have allowed to better track WT performance degradation. Some significant deviations were also observed after the failure (farm B and C), which were possibly linked to downtime for maintenance activities.

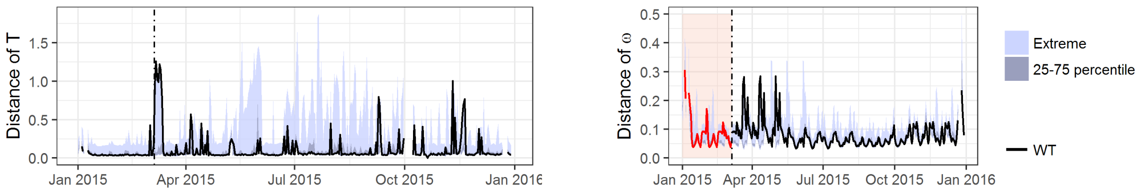


Figure 8: Signal dissimilarity for Generator failure at WF B with a high distance of T during failure and anomalous behaviour in ω before and after the failure (marked with a dotted line).

Table 4: Summary of observed features with an arrow (↑) and 'a' indicating a anomalous behaviour before a failure and after the replacement, respectively.

Failure	WT	Statistical parameter										Dissimilarity		
		f_P	Q	α	TIS	PD	MWS	FL	u	TI	T	Q	ω	T
Generator	A 7		↑	↑	↑							↑		
	B 14		↑		↑	↑							↑	a
	C 8				↑									
Blade	A 15						↑							
	B 10	↑				↑	↑							
	C 15	↑	a			↑					↑			
Gearbox	B 3	↑						↑						a
	C 4	↑						a	↑					
Bearings	C 4													
	C 6									↑				
	C 13							↑						
	C 14	↑	↑		↑			↑						

On the other hand, the approach based on dissimilarities showed only limited capabilities. Some anomalous behaviour in terms of the rotational speed and reactive power was observed before generator failures. Also, changed ambient temperatures were seen after some failures, presumably due to maintenance. An example of a generator failure is presented in Figure 8.

Table 4 summarises all the observed statistical features and dissimilarities linked to the failures which occurred in the three farms during the observed year of operation. While some interesting patterns were identified from both approaches prior to several failure occurrences, there were also similar anomalies after failures or in WTs without failure. Although some parameters are found to exhibit better monitoring capabilities in the detection of some specific failures, more sophisticated approaches would be needed to achieve effective failure detection, and therefore confirm these identified capabilities.

In addition, the present study is clearly limited by the short period of record. Many problems with failures of mechanical components develop in the long term. Longer periods of data are necessary to ensure that early normal operating conditions are included. Ideally, SCADA data available since the commissioning date would allow a complete overview of the WT's operation and potential degradation.

5. Conclusion

One year of data from three wind farms has been analysed to characterise the assets' operation and to identify statistical features that are linked to failures and underperformance.

At a farm level, all the wind farms were affected by challenging wind characteristics such as a strong periodic wind speed pattern and possibly alternating shear. An assessment of wake affected operating conditions has been presented. Despite its simplicity, the wake number allows to easily identify turbine locations at higher risk of being exposed to higher loads and increased fatigue. Additional research would be needed to validate it against more sophisticated wake models. For the analysed farms, the wake number obtained at every turbine location highlighted that, although the layout was presumably optimised to reduce energy losses due to wake effects, the turbines were still affected by different wake intensity. In combination with the terrain complexity, these environmental and operating conditions are very likely to negatively affect the loads exerted upon the turbines. Turbine-specific measurement of environmental conditions, including wind direction, turbulence or wind shear, would enable a better understanding of WT operation and condition variability.

Additionally, three power curve models have been trained to monitor the performance for every WT in each farm. The results showed that failures of mechanical components like blades, gearbox and bearings are apparently more likely to show underperformance prior to the failure occurrence. The cause of other identified underperformance in some other cases could not be fully explained by wake effects or any external or operational parameter.

The observation of the evolution of statistical parameters describing environment and operation as well as a signal dissimilarity analysis revealed interesting patterns before failures. In particular, an increased reactive power generation and high turbulence in standstill was observed before generator failures. Most mechanical problems seemed to show some degree of agreement with higher loading than the farm average in terms of rated power operation. However, the parameters cannot be considered as fully reliable failure indicators, as anomalous behaviour was also seen when no failure was recorded. Although the use of the identified indicators could be privileged in the development of new monitoring solutions, more sophisticated techniques should be used to confirm the suggested capabilities and to achieve effective monitoring. Further work is required to investigate whether it is possible to accurately predict failures solely based on these statistics.

The findings of this study highlight the importance of considering the full load history for any approach of predicting WT failures. The available data covered only one year of operation which was clearly too few to fully understand the development of failures or underperformance. A better understanding of the environmental conditions would also help to diagnose the variation in performance. Therefore, dedicated on-site wind measurements and early onset of data recording and monitoring would be advisable.

Author contributions
Both Elena Gonzalez and Jannis Tautz-Weinert conducted the research work and wrote the paper. Julio J Melero and Simon J Watson supervised the research work.

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