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Farm-wide dynamic event classification as load input for wind turbine drivetrain lifetime prognosis

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Abstract

One of the advantages of the current industrial digitalization trend, the so-called Industry 4.0, is that machines are becoming increasingly sensorized and connected to the internet. This is similar in the wind industry. Detailed measurements from hundreds of sensors embedded in the wind turbine are being sent continuously to cloud computing data-centers. Condition monitoring techniques can leverage these huge volumes of available data to increase detection potential and insights in system behavior by long-term trending. In addition to condition monitoring, these embedded sensors offer information for failure prognosis and lifetime insights. In this paper, a framework to automatically obtain the load history of different turbines within a farm is presented using high frequency SCADA. Special attention is paid to the effects of wake. The fact that data of similar machines of a fleet is collected in a central cloud environment allows for exploiting system similarity in a monitoring and root cause analysis context.

1 Introduction

In Europe, there has been a rapid growth in the capacity of offshore wind energy. In 2019, an additional capacity of 3.6 GW was installed, bringing the total to 22.1 GW [1]. For these farms, the operating and maintenance (O&M) costs are typically higher than their onshore equivalent, among other due to logistics costs [2]. In order to minimize the O&M costs, two aspects are essential. First, it is needed to be able to predict machine failure and degradation ahead of time. In this way, scheduled maintenance can be performed, which not only allows to minimize the downtime of the machines, but also to reduce logistics costs. The latter is especially relevant for offshore farms, since jack up vessels are required to replace certain machine components such as gearboxes, which can present a significant cost in case of unexpected failures [3]. Second, it is essential to be able to pinpoint the root cause of the failure modes. In this way, these can be mitigated in future design iterations.

Within the context of Industry 4.0, wind turbines are being instrumented more extensively with sensors that allow to monitor their performance and health. This high frequency SCADA data ($\geq$ 1Hz) can be used to continuously assess parameters such as torque load, rpm, wind speed and wind direction. In this way, it becomes possible to accurately represent wake effects throughout the farm and to obtain representative loading conditions for each turbine in different operating regimes. In this paper, there is focused on developing a framework to assess the loading history at the level of the gearbox. For wind turbines, the gearbox is the component that causes the largest downtime per failure [4]. A difficulty with the prognosis of this component

is that its loading conditions can strongly vary. These will be a function of time due to seasonal effects in the wind, and of the analyzed turbine due to wake effects. Several options are available for performing prognosis depending on the failure mode of interest. For fatigue calculations at the level of the different components, it is often needed to reflect the measured loading (e.g. shaft bending, torque) to the level of specific components, either making use of analytical models or of multibody models [5]. At this stage, it is essential to work with representative loading conditions in order to predict the portion of used life [6]. For failures unrelated to fatigue, parameters such as vibration signals, currents and temperatures can be used to detect anomalous machine behavior [7]. The remaining useful life can then be assessed by calculating a probability of failure based on previous failure records. For wind turbines, a difficulty however lies in the fact that the amount of similar failures is often small. Nonetheless, the evolution of some features indicative to the failure can be tracked over different loading conditions, which will allow to gain insight in the loading conditions triggering the propagation of the failure. In [8], a framework for prognosis of bearing axial cracking is presented. This approach was demonstrated using experimental data where a relatively large amount of similar failures took place within the same wind farm. In [9], a methodology to calculate the remaining useful lifetime using current signatures is presented using test rig measurements of a gearbox.

Besides assessing the turbine loading during steady state operation, the influence of dynamics on the machine lifetime is also of interest. These can not only lead to increased fatigue, but are also hypothesized to play a role in triggering failure modes such as White Etching Cracking due to causing unfavorable tribological conditions at the level of the bearings [10].

In this paper, the focus will be on analyzing the differences in loading that can take place on a fleet-wide level, focusing both on steady-state conditions and on transient events. As such, the first step will be to present a framework capable of automatically detecting all starts and stops from the different machines in the farm and to classify the conditions of this stop. This can afterwards be combined with high frequency acceleration or strain measurements in order to assess the severity of different events. This can be done based on several metrics, e.g. by analyzing their torque signature and the spectral content of the acceleration signals. The more dynamic the event, the higher the chance that it could damage the driveline and the higher the corresponding fatigue. For the spectral content, focus is on the first modes of the machine, which are important for turbine reliability. The more consistent the loading conditions during events, the more straightforward their impact on the lifetime can be assessed, and included in the prognosis framework. An overview of the presented methodology can be seen in Figure 1. It can be noted that starting from the SCADA data, the first step is to automatically separate transient events and steady state operation. Afterwards, these two categories are further characterized based on the environmental conditions (e.g. wind speed and wind direction). In this way, a condensed overview can be obtained of the operating history of each turbine in the farm. By classifying the data streams of all turbines in the farm, the relative differences between the loading conditions in the farm can be obtained, which for example allows to experimentally observe the effects of wake on turbine performance within the farm.
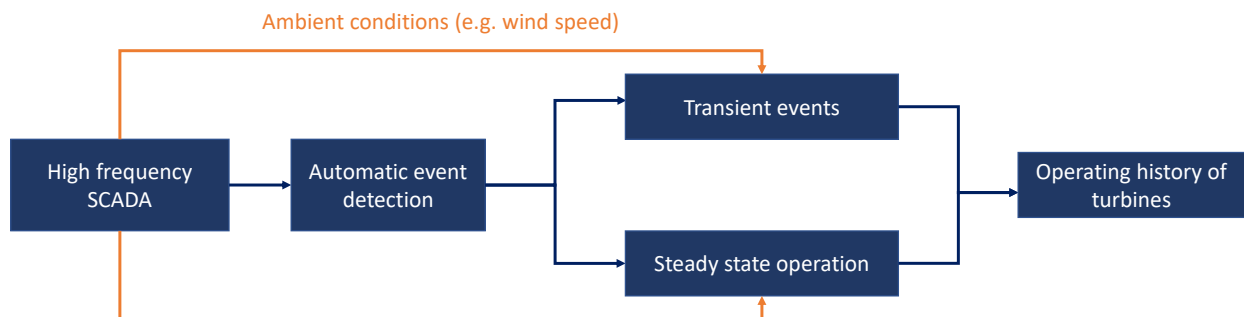
Figure 1: Overview of the methodology used in this paper.

2 Automatic event detection

2.1 Methodology

In this paper, a framework to automatically detect events critical for turbine health is developed. Since these are controlled events, their time signature in the SCADA data is expected to be similar. Therefore, a machine learning approach based on signature mining and matching is proposed. These algorithms have as objective to efficiently discover recurring signatures in a given dataset.

The first step in the process of automatically detecting the events is to manually label these in a set of training data. The less variable an event is, the smaller the number of events that need to be manually labeled. This training data is then binned and the recurring signatures are extracted. Based on these, similar shapes are identified in the time series by means of a pattern matching approach. To save computational cost, this process is only done when an event could potentially take place. This can for example be implemented by observing bin changes within the data over a certain time horizon. If there is indeed a change in bins, the time series is extracted and is tried to be matched with the ones obtained from the training step. This matching can be done by calculating the distance between the two time series. A threshold needs to be imposed by the user in order to define how variable the events can be relative to one another [12]. In order for the performance of the algorithm to not be strongly dependent on the chosen reference event, the training stage is done in an iterative way, allowing the methodology to become more capable in identifying the different events after each iteration. In this way, it is not needed to manually label a large number of events. This allows to make the methodology more robust in the identification of events, even when a significant variability is present in their shape.

For the analysis performed in this paper, this procedure is set up in order to detect both the starts and stops automatically. Since the breaking program of the turbine will be dependent on the type of stop (e.g. stop due to the wind speed dropping below the cut-in versus an emergency stop due to the controller raising an error), it is desired to be able to keep track of the conditions in which the stop has taken place. As shown in Figure 1, the detection of events takes place on the SCADA data (sampled at a frequency of least 1 Hz). More specifically, the rotor speed and the pitch angles of the blades are used, since these produce the most consistent signatures in the time series. By filtering all the transient behavior, the periods of steady state operation can readily be obtained. These are then further divided into different operating regimes based on the SCADA. A similar procedure is done for the different starts and stops. Whenever possible, the stops are allocated with their corresponding status code, allowing to attribute the precise reason of the stop.

Using this methodology, a complete operating history of the different turbines within a farm is obtained. This allows to easily evaluate the relative differences between the different machines, which can be useful for several goals. As already mentioned, it allows to assess typical machine behavior in different ambient conditions, which are essential inputs for simulation models in order to reflect the measured loading (e.g. shaft torque and bending) to component levels (e.g. bearings). Second, the effects of wake on the performance on the farm can be obtained. Examples of this are shown in Sections 3.2 and 4.1. Last, this history is essential for root cause analysis of failures. For example, when different turbines within the farm show similar failures, the loading and event history of these machines can be compared with the rest of the farm. In this way, similarities within the group of failed turbines can be found, and distinguishing factors between these machines and the rest of the farm can be retrieved. In this paper, over six months of continuous high-frequency data of an offshore wind farm was analyzed in order to illustrate the difference in loading history, both during steady-state operation and during transient events.

3 Analysis of steady-state operation

3.1 Assessment of dynamic behavior

3.1.1 Methodology

This section has as main idea to analyze the dynamic response of the machine in steady-state operation. For this assessment, Operational Modal Analysis (OMA) is used. The big difference compared to Experimental Modal Analysis (EMA) is the fact that no artificial excitation forces are applied. The response of the structure due to natural excitation sources is rather analyzed. A limitation of OMA within the context of rotating machinery is the fact that the harmonics can be falsely identified as structural modes [13]. In literature, multiple methods have been proposed to make OMA compatible with the presence of harmonic content, which are either based on preprocessing the data to remove the deterministic components, or make them compatible with stationary harmonics. In this work, the accelerometer signals are preprocessed with a low-pass cepstral lifter in order to reduce the influence of the harmonics [14]. Afterwards, the cross power spectra are estimated by means of a periodogram approach [15]. Finally, a poly-reference least-square complex frequency-domain (p-LSCF) estimator is used to perform the modal parameter estimation. The theoretical background behind this algorithm can be found in [16].

For the turbine under investigation, two accelerometers, measuring in orthogonal directions, are available. These do not allow to perform a detailed analysis of the mode shapes due to the limited observability, but they do allow to assess the global machine dynamics. As there is focused on the reliability aspect, especially the first global modes of the machine (i.e. drivetrain), are of interest. Furthermore, a high frequency encoder signal is available. In steady-state conditions, the dynamics of the machine will introduce speed variations. The spectral content of these fluctuations will be analyzed and compared with the poles retrieved from the modal analysis of the accelerometers. In the discussion that follows, all axes are normalized for confidentiality purposes.

3.1.2 Results

On the left of Figure 2, the speed of the turbine can be seen during full-power operation. As can be noted here, speed oscillations of up to 10% are present due to the introduced dynamics. Using OMA, the global poles of the system are estimated for the two accelerometer measurements. These can then be compared with the peaks in spectrum of the speed oscillations. This can be seen on the right of Figure 2. A close correspondence can indeed be seen between these poles and the peaks in the spectrum of the speed oscillation. The knowledge of the resonance frequencies of the system are important since these can introduce in increased fatigue loading [17]. Moreover, these can be excited during events such as starts and stops of the turbine. In [18], it was for example observed that the first mode of the drivetrain resulted in torque reversals during a grid loss event of the turbine. An analysis of the occurrence of dynamic events is therefore performed in Section 4.
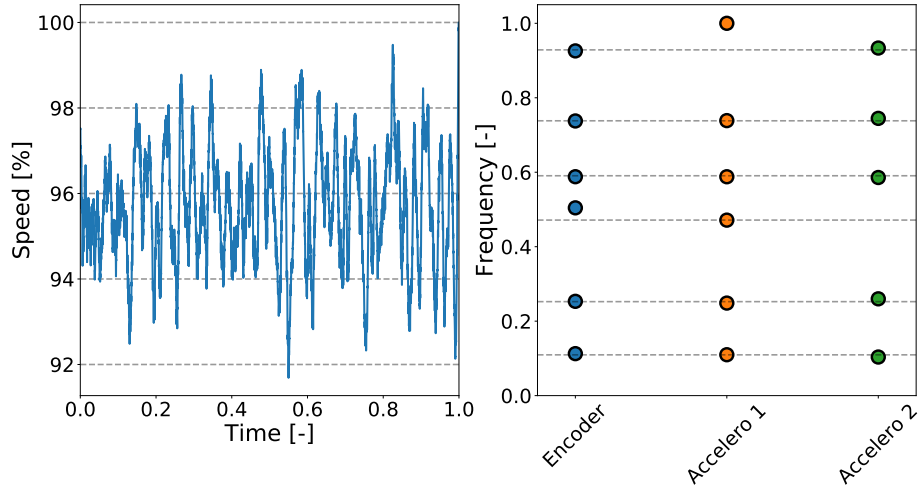
Figure 2: Zoom of the speed profile during full-power operation of the turbine (Left). Comparison between the resonance frequencies estimated with the p-LSCF estimator and the peaks in the spectrum in the speed signal (Right).

3.2 Effect of wake in steady state operating conditions

The modeling of wake and its effect on wind turbine loading and performance is a popular field of research [19, 20]. Typically, the effects of wake are attempted to be minimized by optimizing the lay out of the wind farm based on the expected wind conditions at that site [21]. Due to wake, the loading conditions of the different turbines in the farm will not be identical, which can be seen in Figure 3. Here, the normalized torque loading at the level of the main shaft is shown in case the wind is coming from the North-East. It can be noted that the turbines in the back of the farm experience around 30% less torque loading. For this analysis, only wind conditions below rated wind speed are taken into account, as the effects of wake on shaft torque (and thus power output) are not visible when the turbine is in pitch control. In this mode, the pitch angles of the turbines will nevertheless be different within the wake, which can affect other turbine loading components (e.g. thrust).
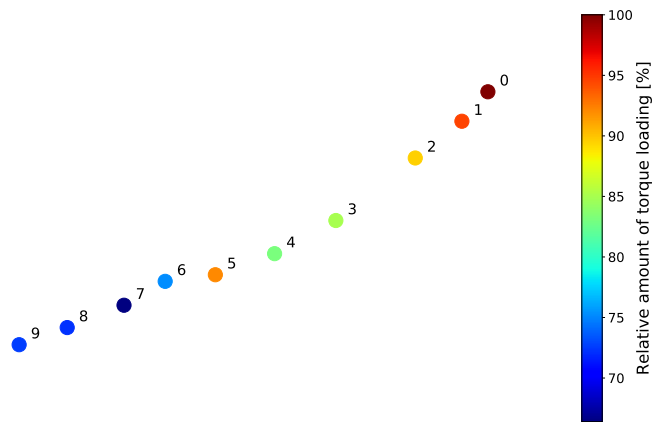

Figure 3: Average torque loading of an offshore wind farm obtained with the framework in case the wind is coming from the North-East. Under these conditions, turbine 0 is experiencing free-flow.

4   Analysis of start-stop behavior

4.1   Effect of wake on start-stop behavior

The effect of wake is also visible when looking at the number of dynamic events a turbine is experiencing. This can be seen in Figure 4. Only the stops are shown where the wind speeds are around the cut-in and where no status code is returned by the turbine in order to ensure that only the stops are registered where the turbine was shutting down due to having inadequate wind. It can be noted that the machines in the back of the farm experience up to twice the amount of events compared to the ones in free-flow. The trend in the amount of stops closely corresponds to the one of the turbulence intensity. This can for example be seen by the decrease in stops between machines 2 and 3. As there is a greater distance between these turbines, the flow will be able to recuperate more, resulting in a decrease of the turbulence intensity, and the number the stops. In Figure 5, an in-depth comparison between the stop behavior of turbines 0 and 9 in this farm is given. For both machines, the most stops are seen in the wind direction with the largest turbulence intensity. Given lay-out and the wind conditions of the farm, some turbines will thus be exposed to more dynamic events compared to others.
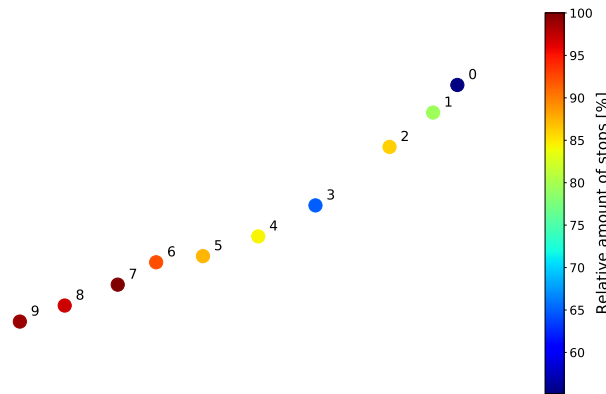

Figure 4: Total number of stops for a subset of turbines of an offshore wind farm in case the wind is coming from the North-East. Under these conditions, turbine 0 is experiencing free-flow.
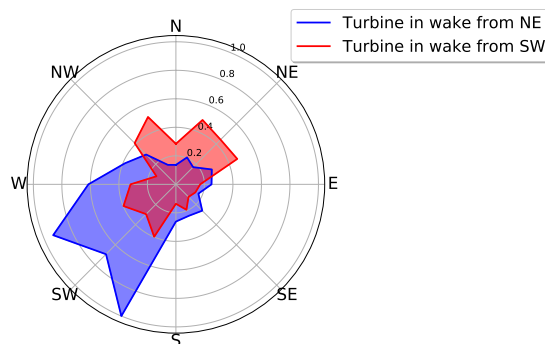

Figure 5: Decomposition of the stops of two different machines in the farm in terms of wind direction. The blue graph corresponds to Machine 0, whereas the red one corresponds to Machine 9 in Figure 4.

4.2 Variability of start stop events

An important parameter of stop events is the duration of the used breaking program. The experimental distribution of this duration is shown in Figure 6. The majority of the stops clearly takes place in the interval between 60 and 70% of the maximum observed duration. Two other clusters of stops are also present, one between 10 and 20%, and the other one around 30%. The shortest duration stops are typically the ones at wind speeds above cut-in where the turbine initiated a stop due to the controller raising an error (e.g. yaw misalignment, temperature alarm). The second category is typically linked to a stop when the turbine tries to start up around its cut-in, but where the wind speed drops to below the cut-in during start-up. In this case, the turbine will not connect to the grid. The last, most common and most variable category are the stops taking place around the cut-in speed of the turbine. The severity of the event will clearly be linked to its duration. The shorter the duration of the stop, the faster the pitching actions must take place to bring the turbine to standstill. To assess the differences between the turbine response during events, a spectral analysis is performed on the accelerometer data.
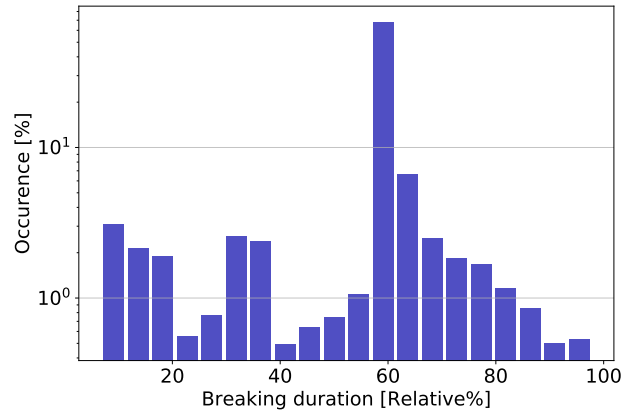

Figure 6: Distribution of the duration of the stops seen across the farm. The y-axis is in a logarithmic scale in order to be able to better appreciate the different categories.

4.3 Spectral analysis of dynamic events

After having classified the different events based on several parameters (e.g. breaking duration, wind conditions), it is important to be able to assess their influence on the machine. Ideally, detailed load and accelerometer data are available for this evaluation. Within the context of this paper, only the two aforementioned accelerometers are available, which do not allow to fully assess the impact of the events on the levels of the different subcomponents. Nonetheless, it still allows to to gain insight in which events result in a globally increased dynamic response. To this end, a spectral analysis is performed around the time windows where an event has taken place. Multiple events with different durations of the breaking program are selected to be analyzed. An example of an acceleration signal during a wind gust, which causes yaw misalignment, can be seen on the top of Figure 7. The two dotted lines indicate the timestamps during which the turbine was in standstill. From this graph, there can be noted that there is an increase in the amplitude of the vibration signal at the moment the rotor is no longer properly aligned with the wind. The turbine therefore decides to shut down in order to be able to properly realign itself with the wind. On the bottom graph, the spectrogram of this signal can be seen. It can be noted that after the misalignment takes place, the amplitude of the resonance around $f_{norm} = 0.1$ increases. During standstill, the response remains dominated by this resonance. For the stops caused by low wind conditions, no strong increase in the amplitude can be seen, even at the moment that the resonance frequencies and the rotor harmonics coincide with one another. Since the accelerometers however only capture the global machine behavior, no definitive conclusions can be made on the the influence of these events on machine subcomponents (e.g. bearings).
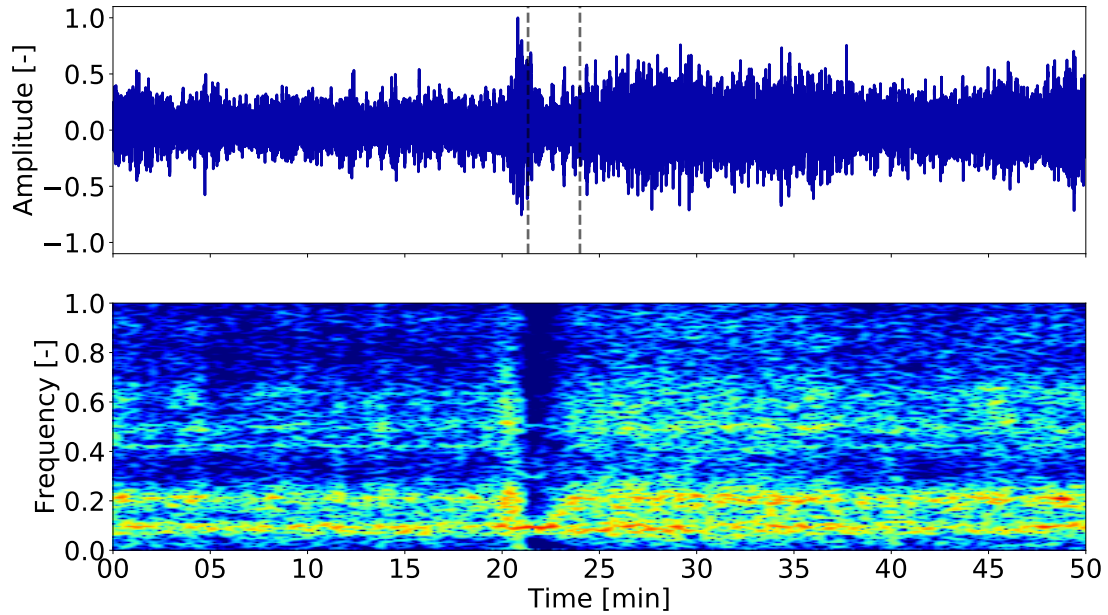
Figure 7: Example of the turbine response during a yaw misalignment.

5   Conclusions

This paper has investigated a methodology to automatically detect start-stop events in time series data. Based on this detection, a separation between transient and steady-state behavior was done. These two categories were then further classified based on the SCADA of the turbine. In this way, a history of the environmental and loading conditions the machine was exposed to, is obtained.

For the steady-state data, a modal parameter estimation was performed on two accelerometers and a high resolution encoder in order to obtain the eigenmodes of the system. This was done since the excitation of these modes can result in unfavorable loading conditions during dynamic events. Second, the effect of wake on the turbine loading was illustrated.

For the transient events, there was first illustrated that wake effects can trigger an increased amount of stops. Furthermore, the duration of the extracted stops was discussed. Based on this, the occurrence of the different breaking programs could be derived. Finally, an analysis of the spectral behavior around these events was performed. Increased dynamic excitation was seen around the events which cause an emergency stop. For the slow stops around the cut-in, no increased dynamic excitation was seen when analyzing the available accelerometers.

Acknowledgements

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