# Hybrid signal processing and data-driven approaches for vibration-based condition monitoring of a fleet of wind turbine drivetrains

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**Résumé –** La surveillance de l'état des chaînes cinématiques des éoliennes est une tâche difficile en raison de la présence de nombreux sous-composants rotatifs dans leurs boîtes d'engrenages. Ces sous-composants génèrent de nombreuses excitations harmoniques, qui créent des signaux de vibration dominants pouvant masquer les signatures de défauts potentiels des engrenages et des roulements. En outre, les éoliennes fonctionnent dans des environnements non stationnaires, ce qui entraîne des vibrations différentes en fonction du régime opérationnel. Pour faire face à cette complexité, une approche hybride combinant le traitement du signal et les méthodes basées sur les données est utilisée. Le traitement du signal est utilisé dans un premier temps pour simplifier les données sur la base de connaissances physiques, tandis que les méthodes basées sur les données sont utilisées pour analyser les données de manière plus approfondie. Cet article présente les détails d'une telle approche de surveillance hybride appliquée aux données expérimentales d'une éolienne.

**Abstract –** The task of condition monitoring for wind turbine drivetrains is difficult due to the presence of numerous rotating subcomponents in their gearboxes. These subcomponents generate many harmonic excitations, which create dominant vibration signals that can obscure the signatures of potential gear and bearing faults. Furthermore, wind turbines operate in non-stationary environments, leading to different vibrations depending on the operational regime. To address this complexity, a hybrid approach that combines signal processing and data-driven methods is used. Signal processing is used initially to simplify the data based on physical insights, while data-driven methods are used to further analyze the data. This paper presents the details of such a hybrid monitoring approach applied to experimental wind turbine data.

## 1 Introduction

Over the past decade, wind energy capacity in Europe has experienced consistent growth, with an additional 3 GW of offshore capacity installed in 2020, bringing the total to 25 GW [1]. The growth rate of wind energy has increased in recent years, thanks in part to significant reductions in the levelized cost of energy (LCOE) for both onshore and offshore wind, which have made them more competitive with traditional energy sources [1]. Wind turbine manufacturers are now focusing on optimizing designs to reduce operational costs, with a particular emphasis on identifying the machine components that contribute most to downtime [2]. Of these, gearboxes have the longest downtime per failure, making them the key area of investigation in this paper. Figure 1 shows the relative failure rates of different gearbox components, with bearings being the most susceptible to failure, followed by gears, and HSS bearings having the highest failure rate. To reduce operational costs, it is crucial to anticipate these failures in advance to allow for preventive maintenance. At the same time, it is necessary to identify the root causes of failures to prevent them from happening in future designs.

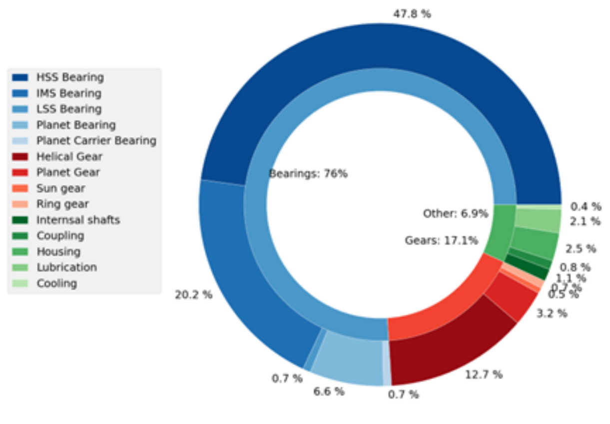


Figure 1 – Relative failure rate of the different drivetrain components [3].

Detecting problems quickly and accurately through condition monitoring is a crucial component of a typical predictive maintenance strategy. This is because optimizing spare parts and repair equipment logistics, such as crane vessels for wind turbines, is essential to avoid extended downtime. Early detection of faults is necessary for timely alarming, but merely providing a general diagnostic alarm is insufficient. Advanced signal processing techniques are utilized to predict failures using vibration data. By doing so, it is possible to conduct predictive maintenance instead of reactive or periodic maintenance. When monitoring the components of rotating machinery, vibration analysis is the most widely used approach. This is mainly because it not only enables analysis of highfrequency events typically associated with gears and bearings, but it is also relatively easy to install, has a proven track record of effectiveness, and usually allows for diagnosis of the fault type and location to some degree.

The process of analyzing vibrations to gather information about the condition of a turbine is a complex issue that has been approached by researchers and industry in various ways. Current practice in industrial condition monitoring systems typically involves tracking time-domain statistical indicators and more component-specific frequency-domain indicators [4, 5, 6]. Using simple scalar time-domain indicators has the advantage of not requiring any a-priori knowledge about the characteristic fault frequencies, which simplifies the analysis procedure considerably. However, this approach does not enable the identification of the specific component exhibiting anomalous behavior. While not having knowledge about the exact location of a fault is a drawback, it is often more straightforward and efficient to obtain a broad overview of which measurement sensor is detecting faulty behavior during an early analysis stage, without the immediate need for information about the exact component and location of failure. Later on, a more detailed frequency-based analysis can be performed to determine the missing failure information. Most monitoring frameworks typically do not process vibration data using more advanced analysis techniques beyond tracking statistical indicators and spectral amplitudes. To address this lack of advanced and in-depth analysis, this study proposes a multi-step processing approach that starts with raw vibration data and results in automated alarm indicators.

# 2 Methodology

A combination of vibration-based condition monitoring and SCADA data is typically used to identify mechanical deterioration of drivetrain components in wind turbines. This study proposes an extensive and thorough vibration analysis method that tracks the health of the drivetrain bearings and gears, while also taking advantage of detailed SCADA data and information on the working regime. The approach involves multiple processing pipelines that explore various properties of the vibration data, such as statistical, spectral, and cyclostationary properties, and employ pre-processing techniques like blind filtering, deconvolution, and discrete-random separation [2, 7, 8]. An overview of the different steps in the hybrid SCADA-vibration analysis pipeline is provided in Figure 2. The next sections describe the various processing categories involved in this pipeline.

## 2.1 Data quality assessment

Before proceeding with automated industrial monitoring based on vibrations, it is essential to determine if a new measurement is suitable for analysis. The ideal scenario is to have quasi-stationary measurements with respect to operating parameters like instantaneous rotating speed and load. Measurements during transient events, such as run-downs or control actions like curtailment, should ideally be excluded as they can complicate both the analysis and the interpretation of results [9]. To ensure a guaranteed level of data quality, an automated quality analysis is performed on both the SCADA and vibration data. The analysis examines the transient and

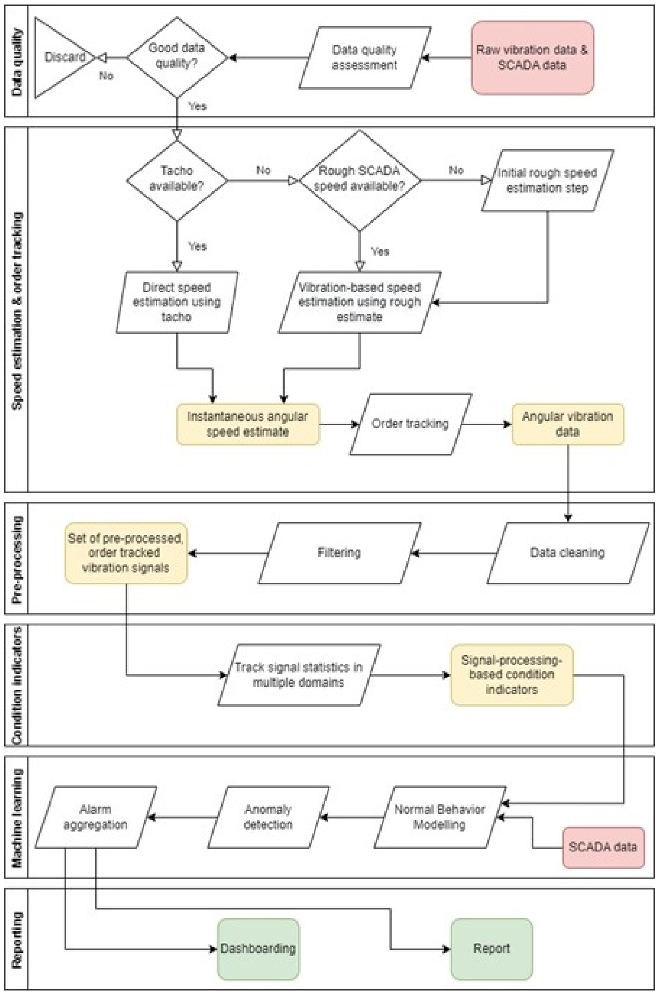


Figure 2 – Overview of hybrid SCADA-vibration monitoring pipeline for fleet-wide analytics on wind turbine drivetrain.

control events in the former data source and verifies the presence of anticipated mechanical component signatures in the time and frequency domain in the latter.

## 2.2 Speed estimation

After verifying the quality of the data, the next step typically involves obtaining an accurate estimate of the instantaneous rotating speed. If there is access to an angle encoder or tachometer, the speed can be directly deduced from the measured pulse signal. However, if such a high-resolution pulse signal is unavailable, the SCADA data may serve as an alternative source, provided that a rough speed parameter is available for one of the gear stages in the drivetrain or the generator. In this case, a vibration-based speed estimation algorithm, such as the Multi-Order Probabilistic Approach [7] or the Multi-Harmonic Demodulation [10], can refine the rough speed estimate. The former uses a time-frequency distribution of the vibration signal as a probability density map of the instantaneous angular speed, while the latter employs the phase of multiple harmonics. If the SCADA data does not contain a rough speed parameter, a preliminary rough speed estimation can be performed on the vibration data using a set of parameters that allow for wide-range speed estimation. An example of vibration-based speed estimates of the high-speed shaft is shown in Fig. 3, which originates from a diagnosis contest held at the International Conference on Condition Monitoring of Machinery in Non-Stationary Operations in 2014. After estimating the rotating speed, the vibration data is order tracked to result in stationary signals in the angle domain.

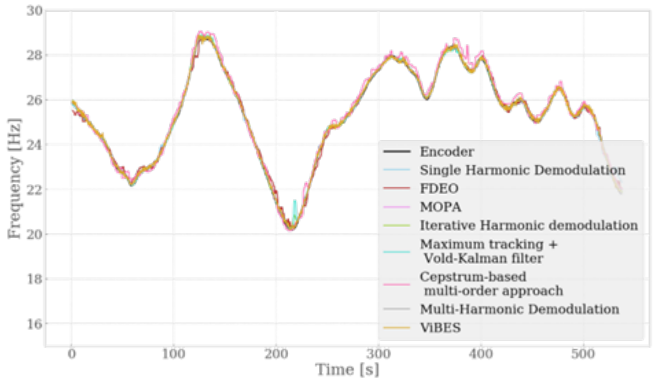


Figure 3 – Example of instantaneous angular speed estimates of the high-speed shaft obtained by 8 different vibration-based methods on vibration data of a wind turbine gearbox housing.

## 2.3 Vibration pre-processing

Further pre-processing is required for the resulting angular domain vibrations to ensure proper tracking of the drivetrain condition. Typically, a monitoring scheme aims to track both periodic events (such as gear vibrations) and random events (such as bearing impulses) simultaneously [11], which require different approaches for vibration analysis. Standard spectral analysis techniques are generally suitable for monitoring periodic events, while achieving satisfactory early detection time for random events usually requires proper data cleaning. However, the distinction between periodic and random events is not always straightforward in modern wind turbine drivetrains, as most gearboxes contain at least one planetary gearset, resulting in intermittent periodic vibrations and a complex transfer path due to the rotary motion of the planet gears and planet carrier. To effectively monitor such a gearset, special care must be taken to deal with the rotary motion of the planet gears. Advanced deterministic-stochastic signal separation techniques can be used to achieve the necessary data cleaning for stochastic event monitoring [12]. Figure 4 shows an example of a wind turbine gearbox vibration spectrum before and after this separation, where the contributions of different components in the measured vibration signal are separated to simplify the analysis. Besides the many different vibration source characteristics, many mechanical faults are also narrow-band phenomena and thus benefit from adaptive frequency-based techniques that increase the signal-to-noise ratio of the potential fault [13] .

## 2.4 Condition indicators

After cleaning and stabilizing the vibration data, signal processing techniques can be applied to derive various condition indicators. These indicators typically involve computing several statistics in the time domain, spectral amplitudes, and modulation features. As a result of processing the vibration

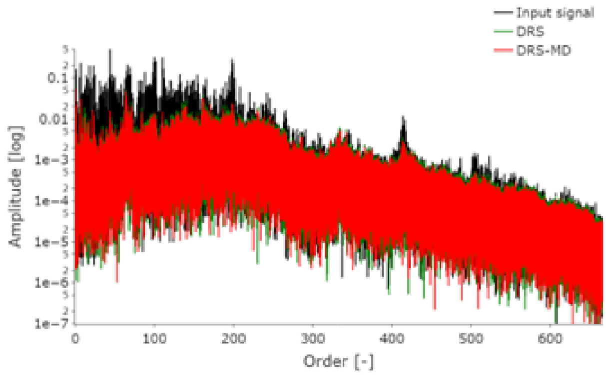


Figure 4 – Example of the residual amplitude spectra of a wind turbine gearbox vibration signal after deterministic-random separation with two different techniques, DRS and DRS-MD [14]. The reference order used for the x-axis is the HSS speed.

signals, the number of potential indicators can increase significantly, especially when tracking different frequency bands. Therefore, a rigorous pre-processing phase and a detailed indicator computation step can generate a vast set of indicators [9]. However, manually examining such a large set of indicators is impractical, and these indicators are specific to the operating conditions and do not consider any operational information except for speed compensation.

## 2.5 Machine learning

The last stage of data processing involves normalizing the condition indicators relative to the turbine's operating conditions at the time of measurement and reducing the extensive set of indicators. Ideally, each indicator should be independent of the turbine's operating regime for a one-to-one comparison. To achieve this normalization, a normal behavior model is trained on a subset of healthy data [15, 16]. First, k-means clustering is performed on the operational data to make the indicators independent of the operating conditions. Then, the data is binned per operating regime, and linear Bayesian Ridge Regression is used to map the operational parameters to a specific indicator. Properly quantifying all types of uncertainty is necessary for the anomaly detection mechanism to analyze deviations from a healthy linear trend in terms of the model's noise [17]. A typical example of an operating condition-independent anomaly trend is depicted in Fig. 5. Low-level normalized indicators are used for anomaly aggregation, leading to high-level anomaly scores for different turbine sensors, allowing for a quick assessment of the drivetrain's health.

## 2.6 Conclusions

This paper proposes an integrated framework for gaining insights into drivetrain health. Initially, SCADA data is automatically annotated to obtain wind turbine loading conditions automatically. The annotation framework also ensures that vibration measurements acquired during transient conditions are not processed. Advanced signal processing pipelines analyze the approved datasets, removing speed fluctuations and

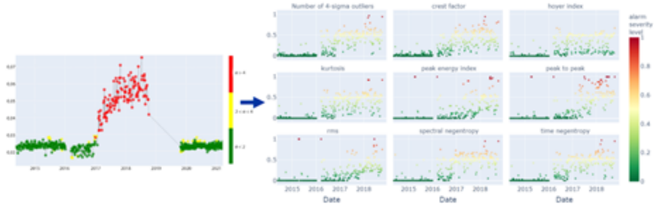

Figure 5 – Example of a typical turbine workflow where individual indicator anomaly trends are aggregated into higher-level alarm indicator trends on the sensor level.

cleaning up vibration signals to compute operating regime-independent condition indicators. Finally, these indicators are utilized for automatic anomaly detection with the aid of a normal behavior model that facilitates automatic alarming. This approach provides continuous, in-depth insights into the drivetrain condition of the turbine fleet.

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