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Automatic Detection and Intensity Classification of Pitch Misalignment of Wind Turbine Blades: a Learning-based Approach

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Abstract. In recent years, monitoring wind turbine operations, especially in offshore and remote installations, has become crucial. System failures, challenging assessments, and costly maintenance operations are notable concerns. Blade pitch misalignment poses one of the most significant threats, being a leading cause of downtime and energy production reduction. Traditional assessments through frequent inspections are resource-intensive and time-consuming; still they are frequently required as turbines lack routine implementation of effective automatic detection systems.
To address this, our study introduces a novel machine learning-based method for autonomous pitch misalignment recognition, which relies on signals measured by a limited set of sensors, already integrated into modern wind turbines. From those signals, frequency domain features derived by harmonic analysis are extracted, ensuring robust detection also in *turbulent* wind conditions.
This innovative method lays the groundwork for early and precise wind turbine diagnostics, promoting the shift from time-based to condition-based inspections. This transition aims to reduce maintenance costs and unexpected downtime, ultimately enhancing energy production.

1. Introduction

Wind turbines operate in challenging environmental conditions, exposed to turbulent winds and severe weather. These factors, coupled with the continuous vibration generated during operation, contribute to the gradual mechanical degradation of critical components like gearboxes, sensors, motors and blades. This poses a significant risk of system failure, leading to downtime or reduced energy production. To mitigate these issues, periodic inspections are necessary to assess and maintain these components.

However, conducting maintenance interventions on these systems can be both expensive and logistically challenging, especially for installations located offshore or in remote areas. The adoption of automatic diagnostic algorithms becomes pivotal in shifting from time-based to condition-based maintenance. Indeed, these algorithms remotely provide real-time insights into the turbine's actual status by remotely describing in real-time the actual status of critical components. Thus, automatic diagnostic algorithms would not only reduce unnecessary costs, but also promote early detection of emerging faults, enhancing prognostic capabilities and allowing for timely interventions to prevent system damages.

Within this operational context, a significant concern arises in the form of pitch misalignment, a condition wherein the blades of the wind turbine become twisted, resulting in a notable decrease in energy efficiency. What sets pitch misalignment apart from other faults is its capacity to persist over an extended period without triggering immediate downtime, rendering it a complex issue with substantial long-term implications for critical power loss. The subtle nature of this problem makes it particularly challenging to detect and address promptly, emphasizing the need for proactive monitoring and diagnostic measures to prevent prolonged inefficiencies and ensure optimal turbine performance.

Modern wind turbines are equipped with Supervisory Control and Data Acquisition (SCADA) systems and with a list of sensors that are typically installed for controlling and monitoring purposes. These systems, comprising both hardware and software elements, work collaboratively to monitor and control the turbine's status in real-time. All the information provided by measurement equipment allows operators to oversee and manage turbine operations by logging data from embedded sensors monitoring accelerations, loads, angular velocities, and wind conditions. While these systems provide valuable data, there is a current lack of algorithms to effectively process and report on the turbine's status. Presently, this task relies heavily on human inspection of collected signals. However, the untapped potential of these data is substantial. Leveraging appropriate sensors, it becomes possible to early detect rotor imbalances resulting from pitch misalignment, thereby preventing damage, minimizing downtime, and avoiding power loss.

1.1. Related Works

In light of the significant impact that pitch misalignment can have on power production, various approaches have been introduced in the literature to remotely detect this issue using signals obtained from turbines. However, developing a reliable and accurate algorithm to achieve this goal poses a substantial challenge. Indeed, such approaches must deal with the turbulent wind regimes that impact actual turbines while relying on sensors that are both economical and dependable, such as those usually found in modern wind turbines. Furthermore, it must strike a balance by minimizing false positives and ensuring compatibility with a broad spectrum of rotors, reducing the design time required for application to new turbine models. Crucially, the algorithm decision logic must be interpretable, providing users with a clear and understandable explanation of the process leading to the identification of misalignment. From the conducted literature analysis, emerges that two primary approaches have been explored: the *model-based* approach and the *machine-learning-based* approach.

Model-based approaches offer interpretable but model-dependent explanations, as a physical model of the system is necessary, limiting the method's generality. Among the model-based approaches, [2] and [1] employ some techniques that aim at detecting anomalies related to pitch and load misalignment. However, these methods typically necessitate tailoring to the specific application, compromising the generality of the approach. Nevertheless, these methodologies often require customization to suit a particular application, introducing a trade-off that compromises the overall generality of the approach. Furthermore, the proposed methods involve the analysis of signals from a set of data that are not usually integrated into modern turbines, presenting an additional challenge in terms of installation due to their expense and susceptibility to the harsh environmental conditions experienced by turbines. These methods concentrate on analyzing biases and faults in the sensors describing anomalies related to blade misalignment. In addition, these strategies seem to claim efficiency in constant wind regime conditions, a scenario that is not realistic.

On the other hand, machine-learning approaches [3] provide generality, demanding minimal design time while achieving high detection performance, even when relying only on a limited set of signals. However, a notable drawback emerges in terms of interpretability, especially when relying on advanced deep learning techniques, *i.e.,* neural networks.

Hence, there arises a pressing need for an approach that combines the interpretability of a model-based approach with the broad applicability of a machine-learning approach. In this context, the concept of explainable artificial intelligence emerges as a potential solution. In domains beyond wind turbines, where such a hybrid approach has yet to be fully realized, explainable models have already demonstrated their ability to deliver high performance [9]. Previous applications have shown that interpretable models facilitate the investigation of detected damages, aid in identifying false alarms, and contribute to a deeper understanding of the monitored process [10]. Interpretability in machine learning is typically achieved by understanding the impact of each feature on the predictive process of the classifier. Consequently, in the design and development of interpretable data-based models, a critical aspect is the feature extraction phase [11]. This process usually involves extracting indicators closely related to the physics of the system, ensuring that the information most relevant for detecting misalignment is intelligible to the user. By linking these quantities to the physical functioning of the turbine, an interpretable machine-learning model becomes a viable solution for pitch misalignment detection, leveraging features that hold a direct physical connection to the system's operation. Furthermore, studies such as [14] demonstrate the significance that also the choice of the employed machine-learning approach has in enhancing the interpretability of the decision-making process. In more detail, in their work, they introduce the architecture of a monitoring and diagnostics framework tailored for anomaly detection in wind turbines, underlying the importance of leveraging a tree-based classification approach. Indeed, they prove that such approaches enable the reconstruction of the decision-making process of the classifier by exploring the trees' structure, from the root to the leaves.

1.2. Novel Contributions

In response to the urgent need for a precise algorithm capable of detecting pitch misalignment exclusively through a limited set of standard sensors, even in challenging turbulent wind conditions, our study introduces an accurate and effective machine-learning framework. This framework has been meticulously designed to offer a precise detection and quantification of misalignment in rotor blades, regardless of the wind condition.

The novel contribution of our approach lies in its commitment to ensuring interpretability, despite consisting of a machine-learning framework. This goal has been achieved by only relying on physics-based features. Specifically, our framework includes an initial phase of signal processing applied to a carefully selected subset of signals. Then, a second phase occurs which extracts from the cleaned signals few effective features in the frequency domain, specifically designed to enhance frequency patterns and components directly related to the rotor's functioning. The subsequent step involves training a machine-learning classifier, with a particular emphasis on leveraging the Random Forest algorithm—a transparent and tree-based method known for its explainability. These design choices empower users by allowing the monitoring of critical physical variables for anomaly detection, facilitating in-depth analysis of the underlying causes of anomalies.

When tested on an extensive simulated dataset, the presented approach proves its accuracy and robustness, encompassing various wind speeds and turbulent scenarios. Specifically, the results demonstrate its capabilities in assessing misalignment severity within a range from

Simulations info	
Features	**Value**
Air density	$\rho = 1.225\ kg/m^3$
Turbulence Type	NTM
Turbulence Class	A
Wind Speed Range	$v = 1 : 39 m/s$
Mean Yaw Misalignment	$0\ deg$

Table 1: Simulation Parameters

0.3 degrees to 2.0 degrees. Furthermore, it provides valuable insights into the key physical features instrumental in the predictive process. This combination of accuracy, interpretability, and robustness to turbulent wind conditions make our model an effective solution for pitch misalignment estimation in real-world operational environments. Furthermore, its reliance solely on sensors, which are already standard in modern turbines, ensures a practical applicability that allows for straightforward applicability in current farms.
The structure of the article is as follows: in Section 2 the simulation environment and the exploited dataset for the analysis are outlined. Section 3 compares the expected physical behaviour of a wind turbine affected by pitch misalignment on a single blade to the experimental evidence obtained from extensive virtual experimental data encompassing both nominal and anomalous conditions. Additionally, it details the adopted techniques to extract significant and effective features in the frequency domain. In Section 4, the machine learning methods designed for this study are described. Then, the achieved results are presented and discussed in Section 5. At last, Section 6 highlights the principal accomplishments of the proposed work and suggests potential avenues for future developments.

2. Simulation Environment and Dataset

This Section provides some insights into the simulation environment and the exploited dataset. The virtual data generator consists of a reference 5 MW wind turbine [4] implemented in the software `Cp-Lambda` (a Code for Performance, Loads, Aeroelasticity by Multi-Body Dynamics Analysis) a state-of-the-art general-purpose multibody simulator[15]. The model features flexible tower, blades, and shaft, whereas the blade element momentum theory is used for modeling rotor aerodynamics, including hub- and tip-losses and tower shadow. The turbine model is also equipped with several virtual sensors. Several 600-second simulations were conducted in different inflow and pitch misalignment conditions. The turbulent inflow was defined according to IEC Normal Turbulence Model. The pitch offset was individually imposed on the three blades. Multiple simultaneous offsets are not part of this work. In particular, the full list of DLC1.1 simulations (from cut-in to cut-out speed), was repeated 50 times, for different pitch misalignments, changing every time the turbulence seed. Specifically, the simulations are conducted with an air density set at $\rho = 1.225\ kg/m^3$ and, in order to add realism to the simulation data, with different turbulence levels, corresponding to class A or B. Furthermore, the examined wind speeds span a range from $v = 1\ m/s$ to $v = 27\ m/s$, with the wind direction aligned with respect to the rotor (zero mean yaw misalignment). In Table 1, the key characteristics for the conducted simulations are summarized. The table includes information on air density, turbulence level, and wind speed, providing an overview of the varied conditions explored in the study. Specifically, 24 sets were dedicated to misalignment in blade 1, 10 sets for both blade 2 and 3, and 6 sets for the balanced scenario, *i.e.,* without misalignment. The maximum severity of the considered pitch offset is 2.0 deg, whereas the minimum one is equal to 0.3 deg.

3. Preliminary Analysis and Features Engineering

This Section delves into the comparison between the theoretical and experimental performance of a wind turbine operating under both healthy and faulty conditions. Our aim is to provide the reader with a comprehensive understanding of the rationale behind selecting the extracted features. We endeavor to demonstrate the direct connection of each feature to meaningful patterns that hold a physical relevance to a misalignment condition, wherein the rotor becomes unbalanced.

3.1. Signals Processing and Exploratory Analysis

In the initial phase of our proposed framework, our objective is to identify the essential signals of interest from the extensive array of data typically captured by usual turbine sensors, encompassing accelerations, loads, mechanical moments both on the fixed reference frame of the wind turbine system and on the rotating frame of the blades. In addition, wind speeds, and supplementary details regarding the rotor, such as the azimuthal rotation.

Moreover, we also intend to opportunely transform these signals to facilitate the subsequent extraction of physics-related features, thus laying the foundation for the design of an interpretable machine-learning framework. To achieve this, we exploit our in-depth domain knowledge of the turbine system, ensuring a targeted and informed selection and transformation of the signals.

In balanced rotors, loads are transmitted to the fixed frame at harmonics multiple of the number N_B of blades only (in the case under study, $N_B = 3$). Conversely, unbalanced rotors transmit loads at all harmonics, with the $1 \times Rev$ frequency being the most energetic and deceptive one. The primary indicators highlighting the existence of the 1 × Rev harmonic contribution in a misaligned scenario are the Hub Nodding M_y and Yawing Moment M_z. These represent the rotor moments along the lateral and vertical axes, respectively, within the fixed reference frame. Therefore, in our framework, we concentrate exclusively on these two signals from the comprehensive set of logged signals. Furthermore, as demonstrated in previous works ([5],[6],[2],[7]), under stationary conditions, the loads exerted on the blades of a balanced three-bladed rotor exhibit periodicity and a $120-degree$ phase shift, with the period corresponding to the rotor frequency, Ω. In the fixed frame, these loads exhibit harmonics at frequencies of $nB\Omega$, where n is an integer and B is the number of blades. For a balanced three-bladed rotor, this results in harmonics at 3Ω, 6Ω, and 9Ω characterizing the fixed frame loads. The impact of pitch misalignment on a blade is observed through changes in the amplitude of the 1× Rev harmonic conveyed to the fixed reference frame, providing insights into the severity of the misalignment through its amplitude. In turbulent wind conditions, the blade moments deviate from exact periodicity. However, with a sufficiently long time window analysis, turbulence effects tend to compensate and balance, revealing only minor 1× Rev harmonic contributions in a healthy balanced rotor. Therefore, detecting the presence of the 1× Rev harmonic in the response of these signals unequivocally indicates misalignment while the amplitude of the peak is linearly dependent on the severity of the anomaly.

When considering different wind speeds, the peak position is shifted along the spectra frequencies. To remove this dependency, the Fourier Transformations applied on blade moments are performed with respect to the Azimuth signal. In such a way, the harmonic response depends on the rotor frequency revolutions only remaining at the 1 × Rev harmonics, regardless of wind speed. In Figure 1, the Nodding Moment M_y, is analyzed in the frequency domain considering different wind speeds ($V = 7m/s$, $V = 15m/s$). As depicted in the figure, the Power Spectrum, computed from the time-based Fourier Transform, reveals a shifting position of the expected peak at the rotor frequency $f = 0.2Hz$, depending on the considered wind velocity. In contrast,

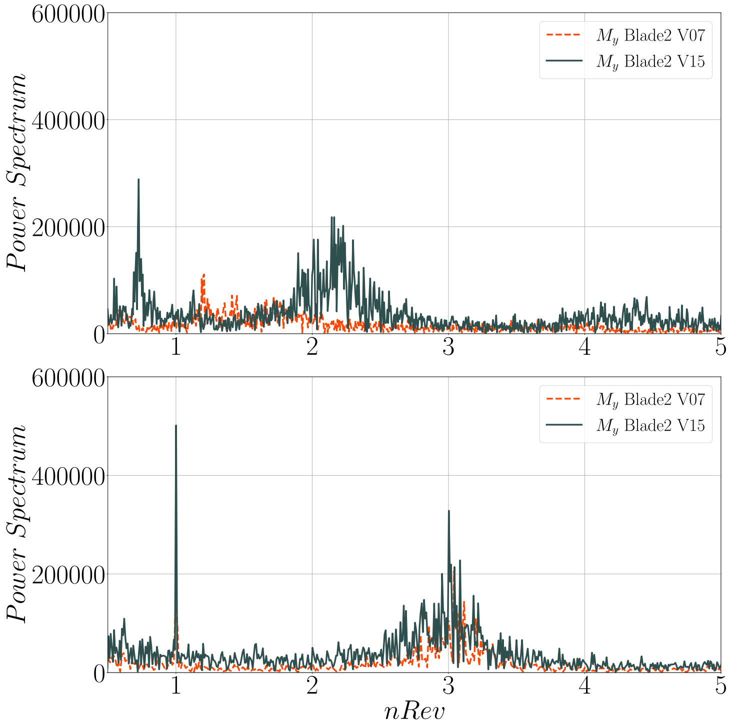

Figure 1: In this figure the Nodding Moment is analyzed in the frequency domain. The expected peak at $0.2Hz$ is changing position when considering two different wind speeds in the upper figure. It remains consistently centered around the $1 \times$ Rev when performing the spectrum analysis with respect to the Azimuth Signal, as reported in the lower figure

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when the Power Spectrum is conducted with respect the Azimuth signal, the peak at $0.2Hz$ no longer changes its position with different wind speeds; instead, it consistently remains centered around the $1 \times$ Rev.
The analysis of the simulated data supports these findings. Figure 2 illustrates azimuth-based power spectra at a medium wind speed of $v = 15m/s$ for the Hub Nodding moment in a healthy case and two anomalous cases (0.5 deg and 1.5 deg misalignment, respectively). As anticipated, the healthy case lacks a peak at $1 \times$ Rev, while the two anomalous cases exhibit a peak, whose amplitude is proportional to the misalignment. The same pattern is observed in the Yawing spectra regardless of the wind speed. Therefore, in this context, the crucial factor for distinguishing between the healthy and expected behaviour, characterized by a minimal peak amplitude, and the anomalous rotor instances, where an increase in peak amplitude results in a higher area value, is the area subtended the peak at the $1 \times$ Rev harmonics.

3.2. Features Extraction

As explained in Section 1, the extraction of interpretable features is pivotal for providing interpretability to the designed a machine-learning framework. In this specific application, our set of features of interest is directly derived from the outcomes of our exploratory analysis. Consequently, we have formulated physics-based features, driven by the recognition that the area beneath the peak at the $1 \times$ Rev harmonics serves as a critical indicator for distinguishing nominal rotor behavior—characterized by a negligible peak amplitude—from misaligned rotor cases, identified by higher area values. So, we compute the area subtended the peak the $1 \times$ Rev harmonics from the Nodding and Yawing moments, simulation by simulation, encompassing each

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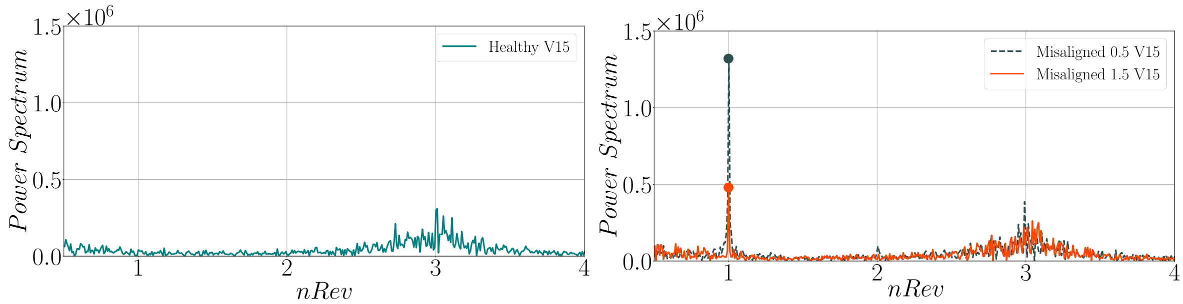

Figure 2: Hub Nodding moment spectra for a healthy (on the left) and two different misaligned cases (on the right) all at speed of 15 m/s.

anomaly case and various wind velocities.
These frequency-domain related features are extracted using a moving window approach, ensuring that the generated predictions by the classification algorithm are in real-time. The selection of the window size involves a fine-tuning process to strike a balance—avoiding an excessively large window, which may be ineffective at low wind velocities, and a too short window, which could result in nonsensical signal dynamics. Notably, the choice of a moving window based on the number of rotor revolutions, rather than a fixed time window, is an innovative contribution. This aligns with the decision to perform the Power Spectrum analysis with respect to the Azimuth signal. This approach allows for a focus on the behavior of the scenario within a specified number N of rotor revolutions, irrespective of the time required for these revolutions. Given the duration of the simulations (each lasting 600 seconds) and the range of wind velocities, a window of 40 Azimuth revolutions has been adopted. This window size ensures a robust Fourier transform and effectiveness across different wind velocities. According to this procedure, each window is transformed into a two-dimensional instance, characterized by the Hub Nodding and Yawing moments spectrum area. Overall, there are 257 instances for healthy cases, 287 for lower misalignment, 517 for medium misalignment, and 78 for higher misalignment degrees.

4. Severity Assessment and Method

Each window corresponds to a point in a 2D space. The coordinates of this point are determined by the area subtended the peak the $1 \times$ Rev harmonics from the Nodding and Yawing moments within that window. The entirety of instances derived from this process serves as the foundation for training and evaluating the performance of a *Random Forest Classifier*. This classifier is instrumental in discerning the presence of misalignment and quantifying its severity, thus contributing to a robust and effective assessment of the turbine's operational condition. Random Forest algorithm, chosen for its explainability and robustness, is one of the most interpretable state-of-the-art bagged tree-based classification techniques [12]. As a matter of fact, the exploited algorithm, combines the results from numerous binary tree classifications that divide data based on specific criteria, minimizing disparities in the identified clusters at each iteration. Accuracy, precision and the Gini index [8] are the primary considered criteria during the splitting process. Considering the severity assessment, a label is provided for each instance according to the misalignment entity. In more detail, the classifier is trained to recognize four classes:

- *0 deg PM* for healthy cases
- $0.3\ deg \leq p < 0.6\ deg\ PM$ for low misalignment
- $0.6\ deg \leq p < 1.5\ deg\ PM$ for medium misalignment
- $p \geq 1.5\ PM$ for large misalignment.

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Classification Report				
Label	**Precision**	**Recall**	**F1-score**	**Support**
Healthy	0.95	0.94	0.95	157
Low	0.92	0.91	0.93	187
Medium	0.93	0.95	0.94	217
High	0.93	0.87	0.90	58

Table 2: Metrics computed from the fault and quantification output

where p represents the actual value of the detected misalignment.
The data is split according to a stratified and balanced fashion into 70.0% for training and 30.0% for testing in a stratified manner; furthermore 10-fold cross-validation is applied, and the average performance isreported.

5. Results and Discussion

The comprehensive outcomes of our framework application are outlined in Tab.2, presenting average results across various evaluation metrics, including precision, recall, F1-Score, and support. These metrics have been specifically chosen for their significance in evaluating the performance of anomaly detection techniques. Precision serves as a crucial metric, quantifying the accuracy of predictions by assessing the instances correctly predicted within the total predicted instances for the given class. In contrast, recall or sensitivity measures the accuracy of predictions for a class relative to all instances belonging to that class. The F1-score integrates both recall and precision metrics, typically being regarded as the harmonic mean of the two indices. Lastly, support denotes the frequency of each label occurrence within the considered class.

By considering F1-Score as a metric, our approach proved effective at detecting the presence of misalignment and further classifying its severity class, with an average F1-Score of 93.5% regardless of the turbulence intensity and the wind speed. Delving into specifics, our framework exhibits a noteworthy F1-Score performance, achieving 95.0% accuracy in detecting the healthy class, 93.0% for the low, 94.0% for the medium, and 90.0% for the high misalignment class. These achievements stand out as remarkable, given the diverse and challenging operating conditions inherent in our experiments, including turbulent scenarios and strong winds. Notably, our approach excels in accurately identifying even minimum pitch misalignments in case of strong turbulence, showcasing a distinctive strength. Indeed, to the best of the author's knowledge, no existing approach in the literature has demonstrated the capability to recognize such reduced misalignments. This proficiency not only sets the stage for robust prognostic capabilities but also holds the promise of reducing energy loss by enabling early-stage misalignment detection. Furthermore, the adaptability of our classifier, relying on an Azimuth-based Fourier Transform, extends its applicability to simulations across varying wind speeds. Indeed, it assesses high detection performance and robustness regardless of wind speed variations, thus enhancing the versatility and practicality of our approach.
To delve more into the details of the classification outcomes, Figure 3 provides a graphical representation of these results, showing the actual and the estimated severity degree for each predicted window. In the plot, each point represents a window, and its coordinates are the normalized area under the $1 \times$ Rev harmonics for the Hub Nodding and Yawing moments. As proved in the figure, the data are accurately classified, as the predicted points consistently overlap with the actual ones, proving correspondence between the real and predicted system behavior. The effectiveness of this visual representation underscores the good interpretability

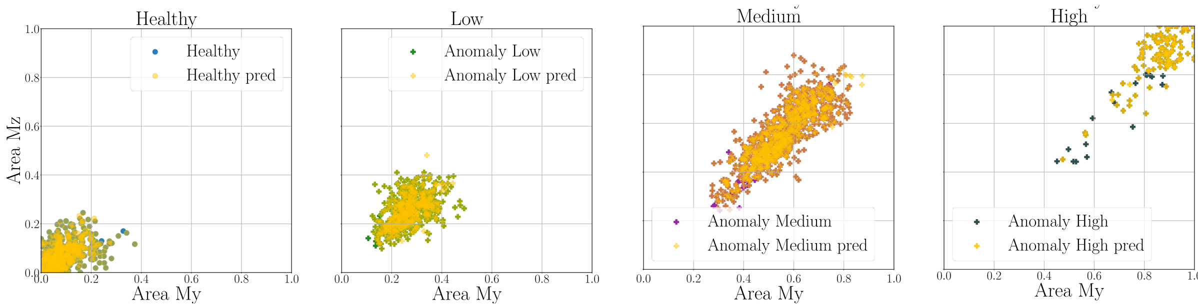

Figure 3: Misalignment Severity Assessment Results. This Figure shows a comparison of predicted misalignment severity (in yellow) with the actual one, demonstrating consistency across severity levels.

embedded in our approach. Indeed, it proves the physical understanding of the system, which allows expert users to discern that minimal areas under the Nodding and Yawing moments must be detected. The unequivocal indication of misalignment arises from the presence of the $1\times$ Rev harmonic in the spectrum of these signals. Notably, the amplitude of the peak demonstrates a linear dependence on the severity of the anomaly. As instances gravitate toward the top right zone of the plot, it signifies a higher likelihood of a misaligned blade condition. A key strength lies in our system's capacity to identify misalignment irrespective of the affected blade, thus offering a versatile and comprehensive diagnostic capability. Importantly, the explainability of our system empowers users by providing a transparent and understandable insight into the decision-making process.

6. Concluding Remarks and Outlook

In this article, we have introduced a novel machine-learning framework specifically tailored for the detection of pitch misalignment in wind turbines, utilizing signals collected from sensors typically installed in modern wind turbines as the only data source. Our approach not only exhibits robustness in turbulent wind scenarios and varying velocities but, more notably, it stands out for its inherent explainability, overcoming the lack of interpretability that usually characterizes conventional machine- and deep-learning methods. This key achievement has been provided thanks to an ad-hoc design of features explicitly tied to the physical aspects of the system. In more detail, the presented approach strategically extracts frequency domain features designed to emphasize the area subtended under the peak at the $1 \times$ Rev harmonics, which is known to be an essential indicator for distinguishing normal rotor behavior from anomalous conditions.

Extensive validation, conducted through numerous experimental simulations encompassing scenarios with turbulent wind regimes and varying velocities, serves to underscore the accurate and real-time performance of our method. Our approach consistently exhibits the ability to detect even minor misalignments, requiring intervention after 40 revolutions of the rotor and updating predictions with each subsequent revolution. This methodology yields an impressive average F1-Score of 93.50% across pitch misalignments ranging from 0.3 degrees to 2.0 degrees, regardless of the affected blade. The capability of distinguishing small misalignments even in the case of strong turbulence by only relying on a subset of the available signals, namely the Yawing and the Nodding moments, represents one of the key contributions provided by our method.

As we advance in our research, our focus will shift towards formulating a regression problem, enabling the precise reporting of specific misalignment degrees. This evolution aims to provide a more detailed and accurate assessment of this fault, facilitating both detection and isolation of faults, particularly in scenarios involving multiple simultaneously unbalanced blades. Such advancements would contribute to the transition from a time-based to a condition-based turbine maintenance scheduling approach, thereby reducing downtime and maximizing energy production.

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