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Quantitative Assessment of Drivetrain Alignment Deviations and Their Impact on Wind Turbine Reliability

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Abstract:

Drivetrain alignment accuracy is widely recognized as a critical factor in wind turbine reliability, yet quantitative field evidence remains limited. This study investigates the relationship between measured alignment deviations and subsequent failure behavior using field data from 104 utility-scale wind turbines. Laser alignment records collected during commissioning were correlated with gearbox bearing temperatures, vibration spectra, and failure logs over a 30-month period. Regression and survival analyses indicate that axial misalignment exceeding 0.12–0.15 mm increases drivetrain-related failure rates by approximately 17–21%. These findings provide quantitative support for stricter alignment control during installation and commissioning activities.

Keywords

drivetrain alignment; gearbox reliability; commissioning quality; survival analysis; wind energ

INTRODUCTION

The reliability of modern wind turbines is strongly influenced by the operational condition of the drivetrain, as gearbox- and bearing-related failures continue to account for a substantial proportion of unplanned downtime and maintenance costs in both onshore and offshore wind farms [1,2]. For large wind projects, drivetrain reliability is not only an operation and maintenance issue, but also an installation-quality concern, because early geometric deviations and assembly inconsistencies can affect load transmission after turbines enter service. Recent quality-assurance research has emphasized that inspection-driven acceptance procedures should be more closely connected with operation and maintenance feedback, particularly through structured mechanisms that link installation verification with later reliability outcomes [3]. This view is especially relevant for drivetrain systems, where installation-stage alignment conditions may not immediately trigger commissioning alarms but can gradually influence bearing temperature, vibration behavior, gear contact stability, and failure risk during operation.

Recent research has placed considerable emphasis on drivetrain condition monitoring. SCADA-based models, vibration analysis, and high-frequency operational signals have been widely used to improve fault detection performance, reduce false alarms, and support maintenance decisions [4,5]. Complementary studies have examined gearbox and bearing damage mechanisms through surface inspection, thermal behavior analysis, lubrication assessment, and vibration feature interpretation, providing useful evidence on failure evolution under variable loading conditions [6]. These studies have improved the ability to identify abnormal drivetrain behavior during operation. However, most of them focus on detecting degradation after abnormal signals have appeared, while the linkage between observed operational degradation and upstream installation-related factors remains insufficiently quantified. Drivetrain alignment is widely recognized as a critical installation-quality factor because alignment deviations can increase bearing loads, alter gear contact patterns, and introduce additional vibration components that accelerate fatigue damage under variable wind and control conditions [7]. Misalignment may also increase local heat generation and change the distribution of dynamic loads across drivetrain components, making its effect difficult to isolate through single-variable monitoring. Recent studies have expanded misalignment research beyond single-sensor diagnosis toward multi-signal fusion and data-driven classification methods, showing that combined temperature, vibration, electrical, and operational measurements can improve the robustness of misalignment detection [8,9]. Reliability-oriented modeling has further indicated that manufacturing and installation uncertainties, including assembly tolerances and alignment deviations, can significantly affect vibration responses and system-level reliability indicators [10,11]. These findings suggest that alignment quality should be treated as a reliability-relevant parameter rather than only a procedural installation check. However, important limitations remain in the existing literature. A large proportion of alignment-related studies rely on laboratory experiments or numerical simulations in which misalignment conditions are predefined rather than measured during actual turbine commissioning. Although these studies are useful for mechanism interpretation, they do not fully reflect the uncertainty of field installation, site-specific assembly conditions, and long-term operational exposure [12,13]. Field studies often lack standardized and traceable alignment records, making it difficult to establish a direct connection between initial geometric conditions and subsequent drivetrain behavior [14]. In addition, many investigations emphasize diagnostic accuracy or fault classification performance, while less attention is given to time-dependent failure behavior and fleet-level risk accumulation [15,16]. Because drivetrain failures are censored and exposure-dependent, simple event counts or alarm statistics may not adequately represent their reliability impact. Another practical challenge is that condition monitoring indicators, such as bearing temperature trends, vibration spectra, and power-related deviations, are often analyzed without reference to verified alignment baselines established during installation. This separation complicates causal interpretation, because wind variability, control strategies, operating load, curtailment, and seasonal conditions may obscure the contribution of pre-existing alignment deviations [17,18]. Survival analysis and hazard-based modeling are suitable for evaluating time-to-failure behavior in turbine populations, but their use in alignment-related reliability assessment remains limited [19,20]. As a result, commissioning and acceptance practices still lack field-supported alignment tolerance thresholds expressed in terms of quantified failure risk. In this context, this study provides a field-based quantitative assessment of drivetrain alignment deviations and their impact on wind turbine reliability. Laser alignment measurements collected during commissioning are linked with subsequent gearbox bearing temperatures, vibration spectra, and failure records over an extended observation period. By combining regression analysis with survival modeling, this study evaluates how measured axial misalignment influences drivetrain-related failure risk while accounting for censoring, heterogeneous operating durations, and fleet-level variability. The aim is not only to detect drivetrain abnormalities during operation, but also to determine whether commissioning-stage alignment quality has measurable reliability consequences after turbines enter service. This design allows installation-quality evidence to be

connected with operational and maintenance outcomes in a traceable way. The significance of this study lies in its shift from post-fault diagnosis to reliability-oriented acceptance support. By quantifying the relationship between measured alignment deviations and later drivetrain failure risk, the proposed approach provides statistical evidence for stricter alignment control during installation and commissioning. It also offers a practical basis for improving acceptance criteria, prioritizing early inspections, and identifying turbines that require closer monitoring after handover. Overall, this work complements existing condition monitoring research by linking drivetrain operational degradation with verified installation-quality metrics, thereby supporting a more evidence-based framework for wind turbine reliability management.

2.Materials and Methods

2.1 Sample and Study Description

Field data were collected from 104 utility-scale horizontal-axis wind turbines operating in multiple onshore wind farms located in regions with similar wind conditions and terrain features. All turbines were equipped with three-stage gearboxes and had rated capacities ranging from 2.0 to 2.5 MW. The turbines were commissioned between 2019 and 2021 and operated under standard manufacturer-defined control settings throughout the study period. Only units with complete drivetrain alignment records at commissioning and continuous operational monitoring data for no less than 24 months were selected. Turbines that experienced drivetrain replacement or major structural modification were excluded to preserve consistency of initial installation conditions. The final dataset represents a relatively uniform turbine population suitable for reliability analysis.

2.2 Experimental Design and Control Group Definition

A field-based comparative design was used to examine the effect of drivetrain alignment deviation on subsequent reliability performance. Turbines were divided into two groups according to axial alignment values measured during commissioning. The control group consisted of turbines whose axial deviation remained within the manufacturer-specified tolerance range. The experimental group included turbines with axial deviation exceeding this limit. This grouping approach follows practical commissioning acceptance criteria and avoids artificial manipulation of operating conditions. Turbine type, rated capacity, and site-level exposure were comparable between groups, which helps limit the influence of non-alignment-related factors on reliability outcomes.

2.3 Measurement Procedures and Quality Control

Drivetrain alignment measurements were conducted during commissioning using calibrated laser alignment instruments in accordance with standardized installation procedures. Axial misalignment was defined as the measured offset between the gearbox output shaft and the generator input shaft. Gearbox bearing temperatures and vibration signals were collected continuously through the turbine condition monitoring system at fixed sampling intervals. Failure information was obtained from maintenance records and verified using supervisory control system logs. Quality control procedures included sensor consistency checks, removal of records affected by known sensor malfunctions, and cross-validation of alignment values with commissioning documentation. Only data satisfying predefined completeness and accuracy requirements were retained.

2.4 Data Processing and Modeling Formulation

Operational measurements were aggregated to monthly representative values to reduce short-term fluctuation while retaining long-term trends. Alignment deviation was treated as a continuous variable in regression analysis and as a categorical variable in reliability modeling. The association between axial misalignment and drivetrain-related failure rate was first examined using a linear regression model expressed as

$$\lambda=\beta_0+\beta_1\Delta_a+\varepsilon,$$

whereλ denotes the estimated failure rate and Δ_a represents axial alignment deviation. Time-dependent failure behavior was then evaluated using a Cox proportional hazards model,

$$h(t)=h_0(t)\exp(\gamma\Delta_a),$$

where h(t) is the hazard function, $h_0(t)$ is the baseline hazard, and γ reflects the effect of alignment deviation on failure risk. Model validity was assessed using standard residual-based diagnostics.

2.5 Observation Period and Reliability Endpoint Definition

For each turbine, the observation period started at the commissioning date and ended at the occurrence of the first drivetrain-related failure or at the end of the study window. The maximum observation duration was 30 months. Drivetrain-related failures were defined as events involving gearbox bearings, shafts, or lubrication systems that required corrective maintenance. Turbines without recorded drivetrain failures during the observation period were treated as right-censored cases in the survival analysis. This endpoint definition is consistent with common reliability assessment practices in wind turbine operation and supports time-to-failure comparison across the study population.

3.Results and Discussion

3.1 Commissioning misalignment distribution and fleet-level signal behavior

Commissioning measurements revealed that axial alignment deviations were concentrated within a narrow central range, while a smaller subset of turbines exhibited noticeably higher deviation values. Turbines in this high-deviation group displayed earlier increases in gearbox bearing temperature and elevated vibration feature levels compared with turbines in the low-deviation group. These differences remained visible when operational signals were summarized at a monthly level. The observation supports the view that misalignment acts as a persistent load bias rather than a transient disturbance, leading to sustained changes in thermal and vibration behavior. Similar conclusions have been reported in recent studies that emphasize the joint use of multiple operational signals to characterize drivetrain loading conditions under realistic wind variability [21,22]. Fig.1. Workflow for constructing and validating a wind turbine gearbox virtual sensor using multibody simulation and machine learning.

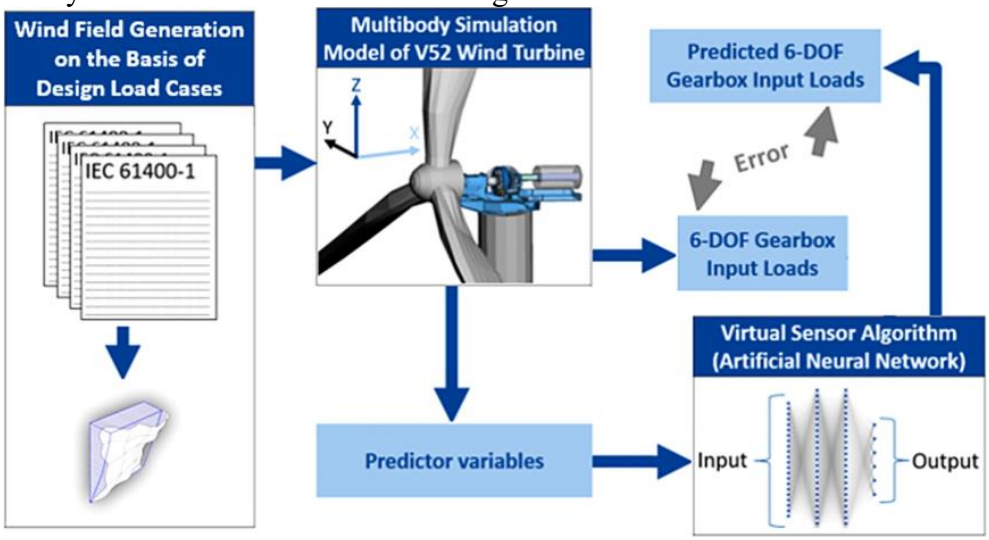


Fig.1.**Diagram showing how drivetrain alignment measured at commissioning is linked to gearbox load indicators obtained from operational data.**

3.2 Temperature and vibration response associated with increased misalignment

Statistical analysis showed a clear association between axial misalignment magnitude and key drivetrain condition indicators. Higher misalignment values corresponded to increased gearbox bearing temperatures and stronger vibration responses in frequency bands commonly linked to shaft-line and coupling effects. This relationship remained stable after basic data screening and temporal aggregation, which suggests that it is not driven by isolated operational events or sensor noise. In contrast to many recent studies that focus primarily on classifier performance or feature selection for fault diagnosis, the present results emphasize the long-term persistence of misalignment-related signal changes. This perspective aligns with field-oriented monitoring research that treats temperature and vibration trends as indicators of sustained mechanical loading rather than short-term fault signatures [23,24].

3.3 Reliability impact assessed through time-to-failure modeling

Time-to-event analysis provided a direct link between commissioning alignment quality and drivetrain reliability. Turbines with axial misalignment exceeding approximately 0.12–0.15 mm exhibited a higher probability of drivetrain-related failure within the 30-month observation period. The estimated increase in failure rate ranged from 17% to 21% across the fleet. This result is important because it converts a geometric installation parameter into a time-dependent reliability metric while accounting for censored observations. Recent maintenance-planning studies have shown that hazard-based models are well suited for wind turbine reliability assessment when operational exposure varies across assets [25]. By comparison, many misalignment studies rely on laboratory data or labeled datasets and therefore do not provide direct guidance for installation tolerance management in operating wind farms [26].

3.4 Comparison with existing studies and engineering implications

Compared with prior work, this study differs in that alignment deviations are measured at commissioning and then traced through operational indicators to verified failure records. This end-to-end linkage enables a reliability-based discussion of alignment tolerance rather than a purely diagnostic interpretation. Experimental and test-bench studies remain valuable for understanding signal mechanisms and for controlled algorithm evaluation, particularly when multi-sensor synchronization is required [27]. However, such settings cannot fully capture fleet-level variability in loading, maintenance practice, and operating duration. The field evidence presented here suggests that tighter alignment control during installation and commissioning can reduce downstream drivetrain failure risk. Remaining limitations include potential unrecorded maintenance actions and site-specific load differences. These factors can be addressed in future work by incorporating turbine-level load proxies, more detailed maintenance annotation, and longer follow-up periods. Fig.2. Example of a multi-sensor misalignment experiment integrating laser alignment, vibration, and electrostatic measurements.

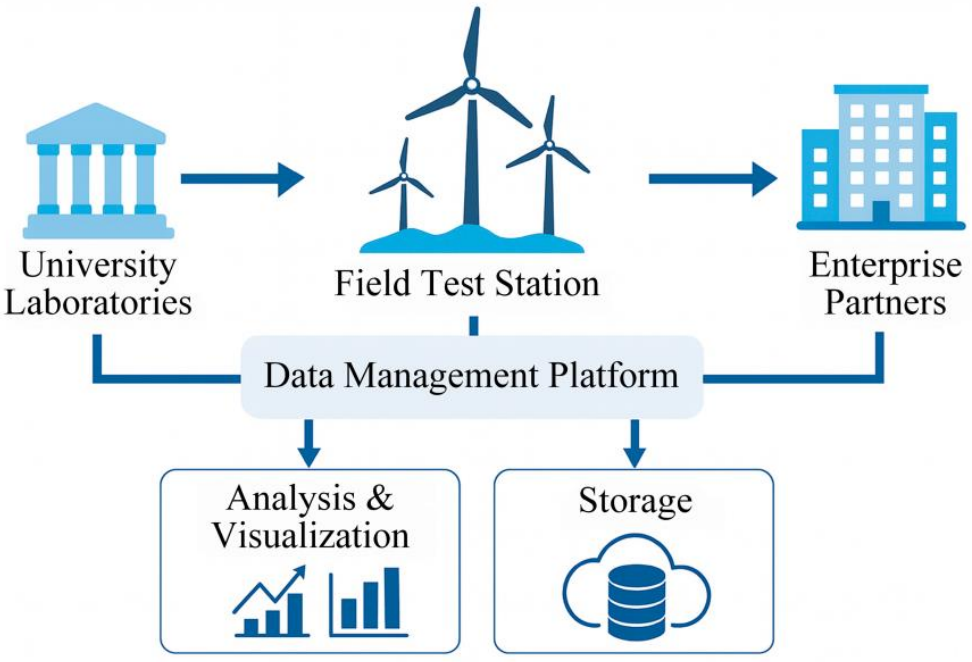


Fig.2.**Layout of a multi-sensor setup combining laser alignment, vibration, and electrostatic measurements for drivetrain condition monitoring.**

4.Conclusion

This study presents field evidence showing that drivetrain alignment at commissioning has a clear and persistent effect on wind turbine reliability. Laser-based measurements of axial alignment deviation were linked with long-term records of gearbox temperature, vibration, and failure events from a utility-scale turbine fleet. The results show that axial misalignment greater than

approximately 0.12–0.15 mm is associated with a 17–21% increase in drivetrain-related failure risk over a 30-month operating period. The key contribution of this work is the conversion of a geometric installation metric into a time-to-failure indicator through survival analysis. This approach extends existing misalignment research, which has mainly focused on fault detection, by providing reliability-oriented evidence relevant to commissioning decisions. From a practical standpoint, the findings indicate that stricter alignment control and verification during installation can reduce later maintenance demand and unplanned downtime at relatively low cost. The study is constrained by the limited observation duration and by possible maintenance activities that were not fully documented, as well as by site-specific loading effects that cannot be completely isolated. Future research should include longer monitoring periods, detailed load and control information, and combined analysis of alignment with other installation or manufacturing tolerances to further improve reliability-based commissioning guidelines.

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