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Early-Life Failure Characteristics of Wind Turbines Based on Commissioning and Operational Data

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Abstract:

Early-life failures significantly affect wind turbine availability and lifecycle costs. This study analyzes commissioning and operational fault records from 1,180 wind turbines to identify dominant early failure patterns. Weibull modeling and survival analysis were applied to failures occurring within the first 12 months of operation. Results indicate that approximately 35% of early failures are associated with installation and commissioning-related deficiencies, particularly in electrical interfaces and drivetrain assemblies. The findings highlight the importance of enhanced quality assurance mechanisms during the installation and early operation phases.

Keywords

early-life failure; Weibull analysis; commissioning quality; reliability modeling; wind turbines

INTRODUCTION

Early-life failures remain a persistent challenge to wind farm availability because they occur during the initial phase of turbine operation, when stable power production is expected but corrective actions often involve high logistical costs, warranty disputes, and delayed revenue recovery. Unlike failures that appear during mid-life operation, early failures are more closely associated with installation quality, commissioning completeness, acceptance inspection, and early maintenance decisions [1]. Recent work on inspection-driven quality assurance has also shown that structured first-article inspection during wind turbine installation and early operation can improve defect identification, reduce repeated quality deviations, and support reliability improvement across subsequent turbines in the same project [2]. In practice, early failures may trigger repeated shutdowns and restarts, which can introduce secondary damage, increase component stress, and extend total downtime beyond the direct repair period. These characteristics indicate that early-life reliability should not be evaluated only through simple failure counts. Instead, quantitative models are needed to describe time-to-failure behavior and to link early operational disruptions with upstream quality factors introduced during installation and commissioning [3,4].

Substantial progress has also been made in data-driven condition monitoring and early fault detection for wind turbines. SCADA-based anomaly detection, virtual sensing, and multivariate time-series analysis have been widely used to identify early signs of component degradation and reduce false alarms under variable operating conditions. These methods have improved the sensitivity of fault warning systems and provided practical support for operation and maintenance decisions [5,6]. At the same time, the availability of public datasets and open benchmarks has gradually improved, allowing researchers to compare detection models under more consistent data conditions [7]. However, standardized fault descriptions, commissioning records, acceptance check results, and detailed maintenance logs are still difficult to obtain, which limits reproducibility and weakens the connection between monitoring results and installation-stage quality control [8,9]. At the component level, Weibull-based models, failure intensity formulations, and Bayesian reliability methods have been applied to bearings, converters, drivetrain subsystems, and other repairable components [10,11]. These studies demonstrate the value of operational data for reliability assessment, but they also show that reliability estimates may be incomplete if upstream installation and commissioning factors are not considered [12]. A key limitation in the current literature is that the mechanism behind the clustering of failures during the first year of operation remains insufficiently quantified [13,14]. Many existing studies rely on relatively small turbine samples or short observation periods, making it difficult to separate true early-life failure behavior from reporting bias, project-specific maintenance practices, or local environmental effects [15,16]. A large portion of condition-monitoring research focuses on detection accuracy, false alarm reduction, or warning lead time, but provides limited linkage to commissioning records that document installation defects, acceptance inspection results, and early corrective actions [17]. Early-life failures also involve diverse failure modes, particularly in electrical interfaces, sensors, connectors, control units, and drivetrain assemblies. When these events are treated as homogeneous failures or grouped into broad categories, failure mechanisms that are important for quality improvement may be obscured [18,19]. In addition, Weibull modeling is commonly used to describe early failure behavior, but Weibull summaries alone may not fully capture covariate effects, censoring structures, and project-level heterogeneity unless they are combined with survival analysis methods suitable for field reliability data [20,21]. These limitations are particularly important for wind farm quality management because early-life failures are not only technical events after grid connection. They often reflect the combined effect of manufacturing variation, transport damage, installation deviation, incomplete commissioning, and insufficient early maintenance response. For large wind farms, defects repeated across multiple turbines can lead to clustered failures, repeated crane mobilization, spare-part shortages, and prolonged availability loss. Therefore, early-life reliability assessment should move beyond component-level fault prediction and provide field-scale evidence that can help operators identify which commissioning deficiencies are most strongly associated with early failures. Such evidence is necessary for improving acceptance inspection, prioritizing early monitoring resources, and reducing repeated defects during the transition from construction to stable operation. Against this background, the present study examines commissioning and operational fault records from 1,180 wind turbines, with a specific focus on failures occurring within the first 12 months of operation. Weibull modeling is used to describe early-life failure behavior at the population level, while survival analysis is applied to evaluate time-to-failure patterns under censored observations. Beyond estimating overall early-life failure rates, this study links failure occurrence with commissioning-related deficiencies and identifies dominant early failure patterns. Particular attention is given to electrical interfaces and drivetrain assemblies because these systems frequently appear in early operational disruptions and are closely related to installation quality, connection reliability, and early maintenance response. The purpose of this study is to provide field-scale quantitative evidence for improving quality assurance during installation and commissioning. Its practical significance lies in supporting more targeted acceptance inspection,

earlier identification of repeated defects, and more effective monitoring strategies during the early operational phase.

2.Materials and Methods

2.1 Sample and Study Area Description

This study uses commissioning and operational data from 1,180 utility-scale onshore wind turbines installed at several wind farms located in regions with similar wind conditions and grid access. The turbines were commissioned between 2018 and 2022 and had rated capacities ranging from 1.8 to 3.3 MW. All turbines operated under manufacturer-defined control settings during the early operational stage. Only turbines with complete commissioning records and fault documentation covering the first 12 months of operation were included. Turbines that underwent major component replacement or structural modification before grid connection were excluded so that the observed failures reflect early operational behavior rather than post-commissioning interventions.

2.2 Study Design and Group Definition

A retrospective cohort approach was used to examine early-life failure behavior and its relation to commissioning quality. Turbines were classified according to whether a failure occurred within the first 12 months after grid connection. For further analysis, failures were categorized as commissioning-related or non-commissioning-related based on maintenance descriptions and service records. Commissioning-related failures included events linked to installation errors, incorrect adjustment, or incomplete acceptance procedures. The comparison group consisted of failures associated with external events or normal operational degradation. This classification follows standard industry practice and enables evaluation of the contribution of commissioning deficiencies to early failure occurrence.

2.3 Failure Identification and Quality Control

Failure events were identified using maintenance logs, fault codes, and service reports recorded in the wind farm management system. Each event was reviewed to confirm the affected subsystem, repair action, and time of occurrence. Electrical interfaces, sensors, converters, and drivetrain assemblies were treated as separate failure categories. Quality control steps included cross-checking fault codes against written reports, removing duplicate records, and excluding non-failure activities such as scheduled inspections or software updates. Only events requiring corrective maintenance were retained to maintain consistency across turbine models and sites.

2.4 Data Processing and Reliability Modeling

Failure time was defined as the interval between the grid connection date and the first recorded failure within the 12-month observation window. Early-life failure behavior was first described using a two-parameter Weibull distribution,

$$F(t)=1-\exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right],$$

where $F(t)$ denotes cumulative failure probability, β is the shape parameter, and η is the scale parameter. To account for censored data and to compare failure risk across categories, a survival model was applied,

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

where $h(t)$is the hazard function, $h_0(t)$ represents the baseline hazard, and X includes commissioning-related indicators. Model parameters were estimated using maximum likelihood, and proportional hazard assumptions were checked using residual diagnostics.

2.5 Observation Window and Endpoint Definition

For each turbine, the observation period began at grid connection and ended at the first recorded failure or after 12 months of operation, whichever occurred first. Turbines without recorded failures during this period were treated as right-censored observations. An early-life failure was defined as any unscheduled event requiring corrective maintenance within the observation window. This endpoint definition is consistent with common reliability analysis practice and supports comparison of early failure behavior across large turbine populations.

3.Results and Discussion

3.1 Fleet-wide characteristics of early-life failures

Analysis of the 1,180 turbines shows that early-life failures were unevenly distributed among subsystems. Electrical interfaces and control-related components accounted for the largest number of recorded events, while drivetrain-related failures occurred less frequently but were associated with longer repair times and greater operational impact. This contrast reflects a common fleet-level pattern in which electrical faults are frequent but short in duration, whereas drivetrain faults are less frequent but more disruptive. Similar subsystem-level distributions have been reported in recent fleet reliability studies, where drivetrain and gearbox failures contribute a disproportionate share of downtime despite lower occurrence rates [22,23]. Fig. 1 provides a reference example of this imbalance between failure frequency and downtime contribution, which helps place the present first-year observations in a broader operational context.

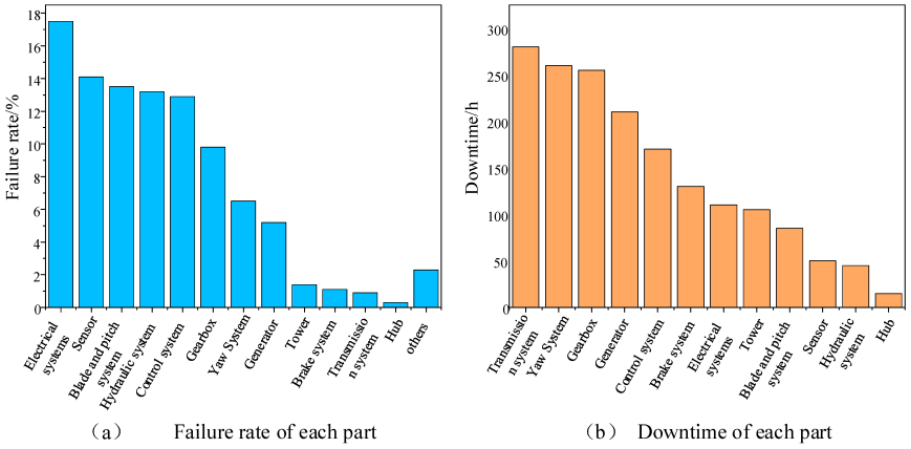


Fig.1.**Distribution of failure frequency and associated downtime among major wind turbine subsystems in the early operational stage.**

3.2 Weibull and survival analysis of early-life failure behavior

Weibull modeling of failures occurring within the first 12 months indicates a clear early-life failure phase rather than a constant random-failure regime. The estimated shape behavior corresponds to a higher hazard level shortly after commissioning, followed by a gradual reduction as operation stabilizes. Survival analysis further distinguishes turbines with commissioning-related issues from those without such records. The resulting survival curves do not converge rapidly, indicating that part of the early failure risk is established at handover rather than generated solely by later operating conditions. These results support a reliability interpretation in which early-life failures arise from latent weaknesses introduced during installation and commissioning and then revealed under normal loading, thermal cycling, and start–stop operation [24,25].

3.3 Contribution of commissioning and installation deficiencies

Approximately 35% of early-life failures were linked to installation and commissioning deficiencies. Electrical interfaces and drivetrain assemblies appeared most often in this group. For electrical systems, common mechanisms include connector seating quality, grounding practice, cabinet workmanship, and strain relief for sensor wiring. These issues may pass basic functional checks but fail under vibration and temperature variation. For drivetrain assemblies, the records are consistent with sensitivity to assembly quality, including fastening practice, tolerance control, lubrication handling, and alignment-related stress. Such conditions can accelerate wear or trigger protective shutdowns early in operation. Previous studies have noted similar challenges in quantifying early-life mechanisms because commissioning data and maintenance records are often incomplete or inconsistent [26,27]. By directly linking commissioning records with first-year failure timing, the present analysis provides clearer fleet-scale evidence of these mechanisms.

3.4 Comparison with existing studies and implications for quality assurance

Much of the recent literature on wind turbine reliability emphasizes fault detection and classification using SCADA and condition-monitoring data. These approaches improve detection speed but address failures after underlying weaknesses are already present. In contrast, the results presented here highlight the preventive value of commissioning-stage quality control. Fig. 2 illustrates a typical data-driven fault detection workflow used in current practice, which operates downstream of installation activities. The comparison suggests that improved commissioning quality assurance can reduce the number of early alarms, service interventions, and availability losses before advanced monitoring methods are required. From an operational standpoint, the findings support stricter acceptance checks for high-risk electrical interfaces and drivetrain-related work, as well as improved digital traceability linking commissioning actions to early operational outcomes [28,29]. Such measures can help convert early-life reliability from a reactive maintenance issue into a controllable installation-quality target.

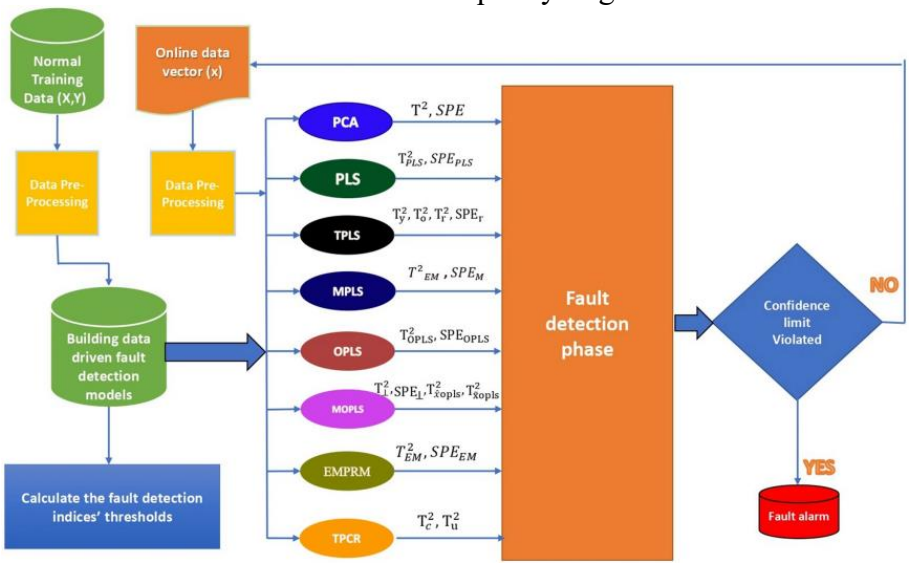


Fig.2.**Standard data-driven process used for fault detection based on wind turbine operational signals.**

4.Conclusion

This work reports a field-based analysis of early-life failures in wind turbines and shows that a significant portion of first-year reliability risk is linked to installation and commissioning quality. Using fault records from 1,180 turbines, Weibull modeling and survival analysis were applied to characterize early failure behavior. The results indicate that early-life failures are not random but are associated with latent conditions introduced during installation, especially in electrical interfaces and drivetrain assemblies. The main contribution of this study is the use of time-to-failure methods to quantify early-life reliability and to connect failure occurrence directly with commissioning-related deficiencies, extending previous studies that have mainly emphasized operational fault detection. From an engineering perspective, the findings suggest that improved quality assurance, clearer acceptance checks, and better documentation during installation and commissioning can reduce early downtime and maintenance cost more effectively than relying on monitoring systems alone. The study is limited by the length of the observation period and by variation in the detail of fault descriptions across sites. Further research should include longer follow-up, more detailed commissioning records, and operational load information to support refinement of reliability-oriented commissioning practices.

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