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Application of the Power Law Process in the Reliability Analysis of a Wind Farm: A Case Study Approach

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ABSTRACT

Wind energy is becoming increasingly popular as a clean and environmentally friendly form of renewable energy. As a result, wind turbines are being used more as a primary power source. With this, failure analysis on wind turbines is becoming necessary for large-scale wind turbines. In this study, the reliability of wind turbines is analyzed using SCADA data. To diagnose any faults in the wind turbines, the alarm data of each turbine was assessed. This allowed for a reliability analysis to determine which wind turbine is the most and least reliable, and the state of reliability of the wind farm. The results showed that the overall reliability of the wind turbines was deteriorating, with a high probability of failure observed in a relatively short time. These highlight the importance of regular maintenance and monitoring of wind turbines to ensure their continued operation and to minimize the risk of failures. This study demonstrates the value of using SCADA data and reliability analysis techniques to assess and predict the performance of wind turbines. With the increasing use of renewable energy sources such as wind power, it is important to continue researching and developing methods to improve the reliability and efficiency of these systems.

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INTRODUCTION

Background of the Study

Energy from the wind has been used for ages, according to Chang (2021). Various benefits that can be derived from harnessing the power of the wind come from the fact that it is renewable. In addition, it is environmentally friendly, reduces fossil fuel usage, and, more importantly, does not cause pollution. In other words, it doesn't release airborne toxins or hazardous compounds that can harm humans and the environment.

Wind turbine use is encouraged to capture wind energy. According to Ibrahim et.al. (2023) and Seddiek et.al. (2021), a wind-electric turbine's blades collect the wind's kinetic energy. Wind energy generates electricity by transferring energy from one medium to another. Wind turbines function simply: they use the wind to generate electricity instead of utilizing power to create wind, like a fan.

Related Literature

Supervisory control and data acquisition (SCADA) systems are typical equipment on wind turbines and offer a wealth of operational data for nearly all subcomponents. Numerous studies employing SCADA data for condition monitoring and fault detection were created as a possible low-cost and wide-coverage solution were discussed in Liu et.al. (2021, 2022, 2023) and Maldonado-Correa et.al (2020). Most of these studies use SCADA data in predictive modeling for wind turbines and condition monitoring systems. In this paper, an exploration of the existing wind turbine SCADA data failure for the development of reliability analysis was conducted. The failure data came from the latest data from a failure diagnosis study conducted by the same authors within the same scope.

Ali et.al. (2023) showed a reliability analysis of a wind turbine considering the imperfect repairs that the said turbine underwent. The study made use of fault tree analysis and was able to analyze the reliability of the turbine. The importance of reliability analysis is emphasized in this study, which relates the turbine's physical condition to its reliability level. This further shows that the maintenance of wind turbines is crucial and plays a massive role in their performance.

Other studies in reliability analysis involve studies relating to specific components of wind turbines. Zhao et.al. (2023) and Jiang et.al. (2022) show reliability analysis focused on the main shaft bearings. These studies were able to evaluate the effects of the condition of the specific component on the overall reliability of the wind turbine. It is further suggested that more information about the overall reliability of the wind turbines can be obtained from individual components.

Several studies on reliability analysis also focus on the different types of wind turbines. A study by Zhang et.al. (2023) shows the reliability analysis of an offshore wind turbine, and another study by Moan et.al. (2020) shows the reliability analysis of a floating wind turbine. These studies showed that the environment affected by the type of turbine indicates the reliability level of wind turbines. These factors significantly affect how wind turbines perform, particularly their reliability.

A study by Ayoub (2020) also presented a reliability study analysis where the algorithm could detect weak subsystems that could affect the reliability of the wind turbine. The results show that the SCADA data could help improve the reliability of wind turbines by applying it to a failure detection process.

Reliability analysis also involves using several methods, particularly mathematical modeling approaches. One study by Zhao et.al. (2020) used a non-Gaussian wind load impact competition failure model. In contrast, a study by Magomedov (2019) used failure mode, maintenance analysis, failure modes, effects, and criticality analysis and applied them to wind turbines. The challenge faced by these studies was the availability of data vital for applying these models and analysis procedures. Figure 1 shows a flowchart generally used for alarm analysis, indicating the need for such a database.

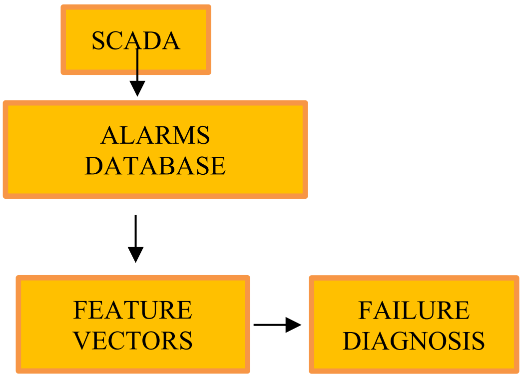

Fig. 1. Alarm Analysis Flowchart

Due to the lack of readily available data, many reliability models and maintenance decision-making tools rely on assumed failure rates. Recent research suggests employing Supervisory Control and Data Acquisition (SCADA) warnings to supplement already available failure records. These studies use the SCADA data available in a particular wind farm and the power law process in the reliability analysis. A summary table of the highlights of previous reliability analysis studies and the method presented in this study is shown in Table 1 below.

Table 1: Summary Table of Reliability Analysis Studies

Previous Reliability Analysis Study	Method Used	Highlights of the Research
Radovanović et al., (2023)	Fault Tree Analysis (FTA)	Applied FTA to identify critical failure paths in wind turbine subsystems, which improved prioritization for maintenance.
Al-Duais et al., (2023)	Markov Chain Monte Carlo (MCMC)	Used MCMC to dynamically estimate failure probabilities of wind turbine components under variable conditions.
Li et al., (2022)	Weibull Distribution	Modeled component failure rates using the Weibull distribution, capturing variability in failure times and supporting life-cycle assessment.

This Study	Power Law Process (PLP)	Integrating the power law process in the analysis to effectively model the failure behavior of wind turbines over time, offering more profound insights into their operational reliability and potential areas for improvement.

These studies illustrate diverse approaches to wind farm reliability analysis, each with unique strengths and limitations. Radovanović et al. used Fault Tree Analysis (FTA) to identify critical failure paths, providing a clear structural view of risk areas in wind turbine subsystems; however, FTA's static nature limits its ability to account for evolving failure rates. Al-Duais et al. applied a dynamic Markov Chain Monte Carlo (MCMC) method, which is more adaptive to changing conditions but requires substantial, high-quality data inputs and lacks environmental factor integration, such as wind or weather effects on reliability. Li et al. employed the Weibull distribution to model time-to-failure for offshore wind turbines, accurately capturing failure variability but assuming component independence, which may oversimplify the interdependencies within turbine systems. While each method provides valuable insights, gaps in addressing time-dependent failure, environmental impacts, and component dependencies highlight opportunities for more comprehensive modeling presented in this reliability study.

The research gaps in the previous literature focused on the lack of available data that could affect the input for the method or algorithm used. Furthermore, the dependencies of the different components of the wind turbines are not emphasized. This study used raw SCADA data that were then preprocessed to ensure that the input for the model is a concrete representation of the turbines. It also incorporates failure data across various systems, showing dependencies between them.

Novelty of the Method

This study improves existing methods by leveraging SCADA data to perform a comprehensive reliability analysis using the power law process. Unlike traditional approaches that often rely on assumed failure rates or incomplete data, our method utilizes real-time SCADA data, providing a more accurate and detailed assessment of wind turbine reliability. This approach allows for the early detection of faults and better predictive maintenance planning.

Additionally, by integrating the power law process, the analysis can more effectively model the failure behavior of wind turbines over time, offering more profound insights into their operational reliability and potential areas for improvement. This innovative application of SCADA data and the power law process represents a significant advancement in wind turbine reliability analysis, with practical implications for optimizing maintenance strategies and enhancing wind energy systems' overall efficiency and sustainability.

THEORETICAL CONCEPTS

Bathtub Curve

The Weibull distribution is widely used in reliability and life data analysis due to its versatility. The Weibull distribution may be used to represent a variety of real-world behaviors, depending on the parameters' values. The form of the probability density function curve, dependability, and failure rate are three features of the Weibull distribution that are significantly influenced by the values of the shape parameter β.

The Bathtub Curve is a visual model, a garnered form of the Weibull Distribution, to illustrate the three key periods of product failure. It is not calibrated to depict a graph of the expected behavior for a particular product family. It represents the three periods of a specific system depending on the value of β, as shown in Figure 2.

Weibull distributions with $\beta<1$, also known as infantile or early-life failures, have a failure rate that reduces over time, as seen by the plot. The failure rate of Weibull distributions with β near or equal to 1 is stable, indicating either random failures or usable life. Weibull distributions with $\beta > 1$ have wear-out shortcomings, which are Weibull distributions with an increasing failure rate over time. These make up the three parts of the traditional bathtub curve.

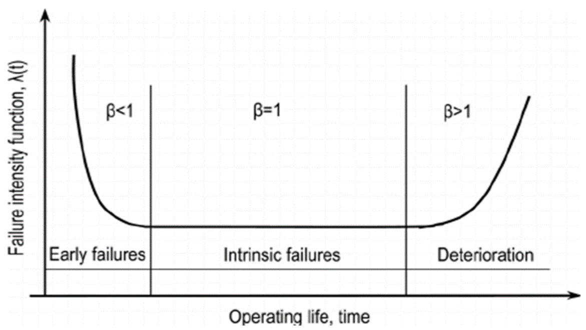

Fig. 2. The Bathtub Curve

Power Law Process

The Power Law Process (PLP) model is a popular infinite Non-Homogeneous Poisson process (NHPP) model used to describe the reliability of repairable systems based on the analysis of observed failure data, and this model was derived from the hardware reliability area. There is much literature on the PLP model from a classical statistics view, as shown by Al-Turk (2014).

The distribution function of the PLP, as a typical nonhomogeneous Poisson process, agrees well with the "bathtub curve" of the failure rate of mechanical equipment in three phases. As a result, it is commonly used to assess the dependability of repairable mechanical equipment.

Zheng et al. (2020) provided steps to establish an analysis using PLP, which are summarized below for better understanding.

1. Problem Analysis – m is the number of wind turbines, T is the time truncation of the shutdown failures, the fault statistics interval for the j^{th} wind turbine is [0, T], $t_{j,i}$ is the time of occurrence of i^{th} failures, n_j is the number in a total of failures.

2. Hypothesis – H_0: $\beta = 1$, HPP distribution, opposite H_1: $\beta \neq 1$, NHPP distribution.

3. The Failure Process model – The various indices of wind turbines of a failure process model include the intensity function $\sigma(t)$, instantaneous mean time between failures (MTBF) $u(t)$, cumulative MTBF $w(t)$, and the cumulative intensity function g(t), which are expressed in the equations below.

$$\sigma(t) = \lambda\beta(\mathrm{t})^{\beta-1} \quad [1]$$

$$u(t) = \frac{1}{\lambda}\beta(\mathrm{t})^{\beta-1} \quad [2]$$

$$w(t) = \frac{1}{\lambda}(\mathrm{t})^{\beta-1} \quad [3]$$

$$g(t) = \lambda t^{B} \quad [4]$$

where λ is the scale parameter, β is the shape parameter, and t is the running time.

4. The MLE or method of maximum likelihood is used to calculate the parameters $\hat{\lambda}$ and $\hat{\beta}$, respectively.

$$\hat{\lambda} = \frac{\sum_{j=1}^{m} n_j}{T^{\hat{\beta}}} \quad [5]$$

$$\hat{\beta} = \frac{\sum_{j=1}^{m} n_j}{\sum_{j=1}^{m}\sum_{i=1}^{n}(T/t_{j,i})} \quad [6]$$

5. The analysis of model results, in terms of $\hat{\beta}$; When the value is more than one, the fault strength of the wind turbine grows with operation time, and the dependability falls, indicating that the wind turbine is deteriorating. When =1, the fault strength of the wind turbine remains constant as the working duration increases, and the reliability remains constant, indicating that the wind turbine is in a stable condition. When <1, the wind turbine's fault strength reduces with increasing running time, and dependability rises, indicating an improved state.

The power law process (PLP) is frequently utilized in reliability analysis to model systems where failure rates are not constant over time but follow an increasing or decreasing trend. This behavior is especially relevant in wind farms, where mechanical and electrical components experience wear and degradation due to continuous operation and exposure to environmental conditions, as stated by Bošnjaković et al (2024) in their article. The PLP, as a non-homogeneous Poisson process (NHPP), enables modeling such time-dependent failure rates by incorporating a time-varying intensity function. In particular, the intensity function of the PLP is defined by a scale parameter λ and a shape parameter β, where $\beta > 1$ indicates an increasing failure rate—a common scenario in aging wind farm components.

For wind farm reliability analysis, the PLP is a tool to predict and evaluate failure occurrences over time, thus assisting in maintenance scheduling and decision-making according to Zhu & Li (2018). Wind turbine components, such as gearboxes, generators, and blades, often exhibit an increasing failure rate as they age, making them ideal candidates for PLP modeling. By applying the PLP, analysts can estimate the time intervals where failures are likely to become more frequent, enabling proactive maintenance strategies and reducing unexpected downtimes. This predictive approach is critical for wind farms, where operational continuity is paramount to economic viability and energy production goals as appended by Merizalde et.al (2019) and Zhou et.al. (2023).

In addition to maintenance planning, the PLP helps quantify the reliability of the entire wind farm system over its operational lifespan. By fitting a PLP model to historical failure data, researchers can assess whether the overall system reliability declines consistently or stabilizes after specific interventions, such as component replacements or upgrades. This is especially valuable for optimizing component design and lifecycle management and improving resource allocation for high-risk components. Thus, the PLP provides a flexible, data-driven framework to address the dynamic reliability challenges inherent in wind energy systems.

The power law process aids in creating more accurate reliability benchmarks across different wind farm sites by normalizing the failure trends for age and usage intensity differences as discussed by Sohoni et.al (2016). This standardization allows for better comparisons across sites and supports the continuous improvement of wind turbine designs. Consequently, the PLP supports individual wind farm maintenance and contributes to the broader field of renewable energy reliability engineering by offering insights that can drive more resilient wind power infrastructure.

METHODOLOGY

Data Collection and Preprocessing

The data used for the study comes from a wind farm consisting of 14 wind turbines in 2020. The available data from the SCADA of each wind turbine were gathered in 10-minute sample resolution and used for the reliability analysis using the power process law. These data are directly downloaded from the SCADA feature of the wind turbines.

Data preprocessing is vital in ensuring that the data set included as input for the method is healthy, as shown by Qiao et.al. (2021) in their article. Table 2 shows the data filter used in this study and the corresponding notation.

Table 2: Data Filter and Notation

Data Filter	Notation
Missing Data Filter	delete x_t if $\{x_t \| x_{ti} = not\ available\}$
General Boundary Filter	delete x_t if $\{(x_t \| x_{ti} > upper\ bound)$ or $(x_t \| x_{ti} < lower\ bound)\}$
Efficiency Filter	delete x_t if $\{(x_t \| x_{ti} > upper\ limit)$ or $(x_t \| x_{ti} < lower\ limit)\}$

Failure Data

The previous studies by Qiu et.al (2020) and Gonzalez et.al (2016), which focused on understanding the failures of wind turbines through alarm analysis of SCADA data, provide us with valuable knowledge about the different ways these turbines can malfunction. By carefully examining the alarms triggered by unusual events or issues, the study was able to categorize and create a comprehensive list of failure modes. This information is incredibly valuable for a new study, which aims to analyze the reliability of wind turbines in a more compassionate and caring manner. Table 3 shows the list of all available alarms for each component of the wind turbine and the total frequency for the entire year or duration used in the study.

Table 3: Alarms List per Component

Subsystem	Failure Diagnoses
Rotor and Blade	Acceleration sensor fault Cable twist sensor fault Encoder blades 1, 2, & 3 faults. Pitch drive blade 1, 2, &3 fault. Rotor cabinet temperature fault Rotor locking pin sensor fault. Rotor speed sensor fault SBP loader blades 1, 2, & 3 faults. **Total Frequency: 767**
Nacelle and Control	CAN heartbeat fail Ethernet switch fault Nacelle cabinet temperature fault Nacelle PLC CM202 card 17 CAN kernel fault Nacelle temperature signal fault Outside temperature signal fault **Total Frequency: 478**
Drivetrain & Electrical	Bearing 1 & 2 temperature fault Generator air temperature 1 & 2 fault. Generator stator temperature 1, 2, 3, 4, 5, & 6 fault. Ground isolator feedback fails. GUSP ARU negative half-power fail MCB open fail MCB Operation Fail **Total Frequency: 222**
Cooling & Environmental	Cooling water internal fan failure Cooling water pump1&2 failure Wind meter fault Wind vane 2 fault **Total Frequency: 42**

Reliability analysis plays a vital role in ensuring wind turbines' smooth operation and longevity. It helps predict and manage potential failures, assess the turbines' availability for operation, and make informed decisions regarding maintenance and repairs. The data from the previous study calculates critical factors like failure rates for each identified failure mode.

Power Law Process

Reliability analysis is a recommended form of data analysis in terms of mechanical information assessment of the failure rate of the machine's systems, whether repairable or non-repairable. Figure 3 shows the framework for the reliability analysis used in the study.

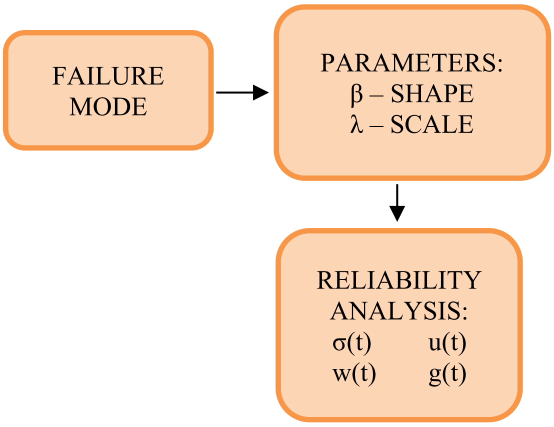

Fig. 3. Reliability Analysis Framework

The chance that a product will fulfill its intended function under certain conditions over a specific amount of time is defined as reliability. Reliability engineers and researchers use field data, tests, and analytical approaches to assess the failure rates of items over time under specified settings. Then, they collaborate with design engineers to make products more durable.

However, the most recurrent challenge by several studies that concerns reliability analysis is that there is/are no uniform way of data gathering for Failure modes. This is why the analysis of the alarm from the previous study is used as a data analysis to obtain the failure data of each wind turbine for the reliability analysis study.

RESULTS AND DISCUSSION

Beta Parameters

In the Weibull Distribution, several parameters should be calculated for a reliability analysis assessment of a given system. The parameters to be estimated are only the β and λ parameters. The β parameter is the shape parameter, which, in the researcher's observation, is the key and most important parameter to calculate. It describes the shape of the failure graphs of the Wind Turbine Reliability. To reinstate, the graph is decreasing if β<1. If β=1, the graph is seen to be steady. Lastly, the graph is seen to be increasing if β>1. Now, the importance of calculating the β is that this parameter also describes the period of the lifetime that a Wind Turbine is at. Figure 4 shows the visual figure of the beta parameters of the wind farm used in the study.

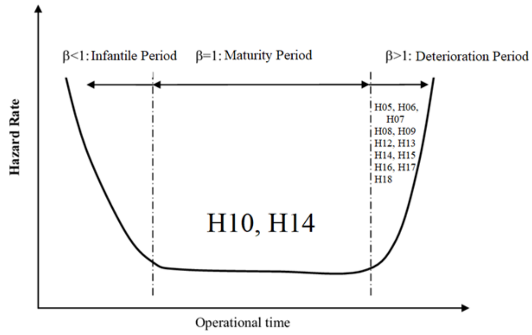

Fig. 4. Beta Parameters Visual Figure of the Wind Farm

The beta parameter in the Weibull distribution has practical applications in reliability analysis, quality control, and maintenance planning. When beta is less than 1, it indicates a decreasing failure rate, often associated with early-life failures or "infant mortality" in products. A beta equal to 1 signifies a constant failure rate commonly used in modeling random shortcomings, such as those due to external shocks. A beta greater than 1 suggests an increasing failure rate, typical of aging systems or wear-out failures. Using the results of the beta parameter, industries can optimize preventive maintenance schedules, predict product lifespan, and design reliability tests to enhance system performance and reduce downtime.

The wind turbines that are in their maturity period (β=1) are transitioning to the deterioration phase (β>1), whereas the maturity period must be the most reliable. The maturity period is the period of the Wind Turbine where failures are normalized, and the Wind Turbine is learning from its experience. Therefore, the most reliable wind turbines are H10 and H14.

The unreliable Wind Turbines have their β calculated as more than 1. In this stage, they are old, and wear-out failures are most likely to occur. Since there are no wind turbines with their β<1, and the only two most reliable Wind Turbine is discussed in the preceding paragraph, it follows that the group of old Wind Turbines – not trustworthy, in consequence – are the remaining Wind Turbines not mentioned which are H05, H06, H07, H08, H09, H11, H12, H13, H15, H16, H17, & H18.

Lambda Parameters

Another parameter to calculate in the reliability analysis is the λ parameter. This parameter is called the scale parameter. The scale parameter determines how vast or tiny the failure graph is since it is the scale of the failure. It stretches or compresses the reliability graphs. This parameter doesn't necessarily have a significant consequence on the system reliability; however, it is considered a parameter that indicates time-to-failure. It represents the expected occurrence of failure in each unit of time. The higher the scale, the higher the time before failure or more reliable, and may state otherwise. Figure 5 shows the different wind turbine reliability assessment scales. In H05, for example, it is found that λ=4.21e-5 is tiny, and the unit of time used in this paper is an hour. It can then be concluded that H05 has such low reliability.

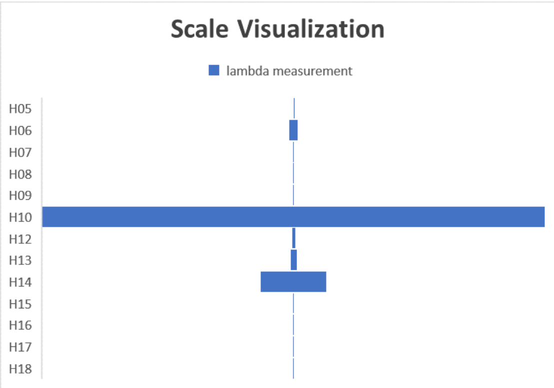

Fig. 5. Lambda Scale Visualization

The lambda parameter in the Weibull distribution is critical for quantifying the time scale at which failures occur. It represents the characteristic life, where approximately 63.2% of the population will have failed if beta is held constant. Practical applications of lambda include determining warranty periods, optimizing inventory for spare parts, and assessing system reliability. This is critical for wind turbine heads, as shown in this case, which have very low lambda measurements.

Failure of Intensity

An article by Cevasco et.al. (2021) defines failure intensity as when a system/item fails in a specified period. It measures the rate of wind turbine failures in their reliability assessment. It is an important metric to measure in reliability analysis as it can be used to predict a system's future failures. With the information on future failures in hand, the prevention of such failures can then be planned to increase the reliability of the Wind Turbine.

The Pareto chart is a valuable tool for analyzing wind turbines' failure intensity as it identifies the most significant contributors to overall failures, as shown by Santelo et.al. (2022). By ranking failure causes in descending order of frequency or impact, the chart helps prioritize critical components or failure modes that require immediate attention, such as gearboxes, blades, or electrical systems. This aligns with the Pareto principle, often revealing that a small percentage of components accounts for most failures. In the context of wind turbines, where

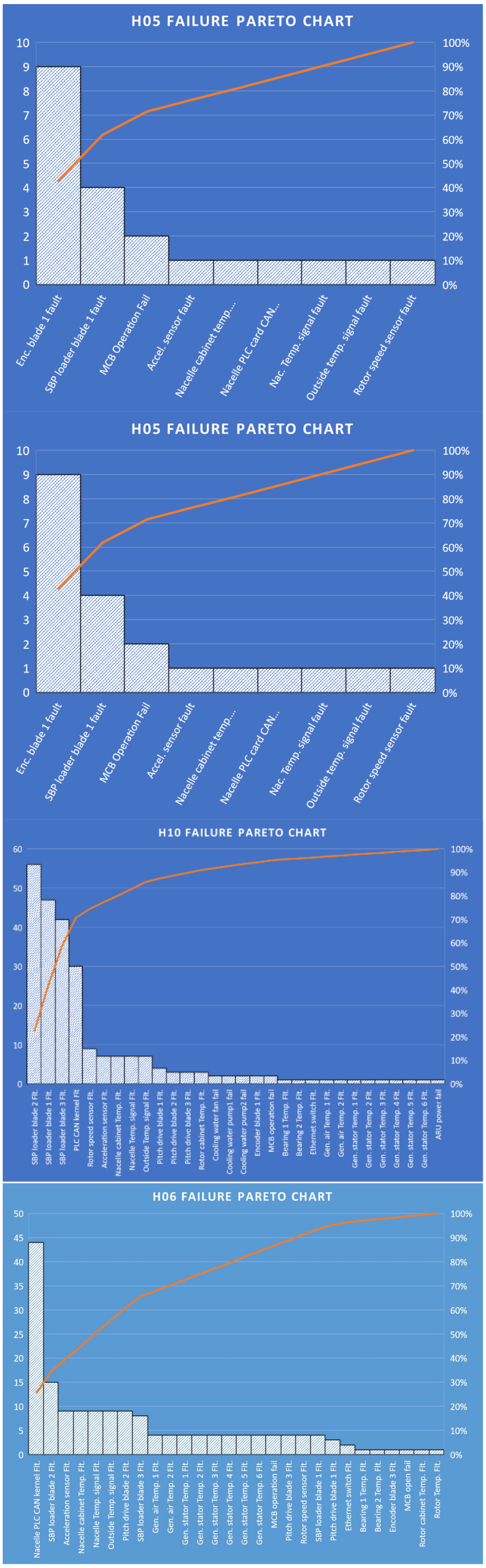

Fig. 6. Pareto Chart of Some of the Wind Turbines

operational efficiency and maintenance budgets are crucial, using a Pareto chart ensures targeted maintenance strategies, optimized resource allocation, and enhanced reliability by addressing high-impact areas first.

As discussed earlier, only two wind turbines are reliable; the rest are not, as most Wind Turbines are old. Most wind turbines have high failure intensities, suggesting that they experience failures frequently, as discussed by Peng et.al. (2023). As the time range (x-axis) is uniform across reliability graphs, it can be deduced that the y-axis, in this case, the failure intensity, is most likely not. Figure 6 shows the Pareto chart of some of the wind turbines used in the study.

In the failure intensity graphs shown previously, only H07 shows a failure intensity of 1/10, while the others show 1/100, which means that H07 has the highest frequency of failure rates. As discussed above, H07 is part of the group of unreliable wind turbines, but is the only one with a more substantial probability of failure occurrence. This means that H07 is currently the most unreliable wind turbine among them.

It is important to note that this failure rate differs across wind turbine graphs, leading to their graph orientations. Some increase first before steadying, while some show otherwise, and some increase steadily.

Mean Time Between Failure

In Chapter 12 of the book “Measurement and Instrumentation" by Bakshi (2020), the Mean Time Between Failure (MTBF) is defined as the metric that shows the average time that a failure can occur. The MTBF is usually described as the inverse of reliability; therefore, an increasing MTBF graph is a system with decreasing reliability, and a decreasing MTBF is a system with increasing reliability.

In analyzing the MTBF graphs, one turbine stands out with a consistently increasing trend in its MTBF value—H10. As discussed earlier, H10 and H14 are recognized as the most reliable wind turbines in a generally low-reliability group. However, based on the MTBF analysis, it can now be concluded that H10 demonstrates superior reliability compared to H14. This distinction is evidenced by the consistent performance improvements depicted in H10's MTBF graph, shown in Figure 7.

Practically, the reliability of H10 suggests that its design, maintenance strategy, or operational conditions may serve as a benchmark for enhancing the performance of less reliable turbines. Identifying and replicating the factors contributing to H10's higher MTBF can guide targeted interventions across the wind farm, improving overall reliability and reducing maintenance costs.

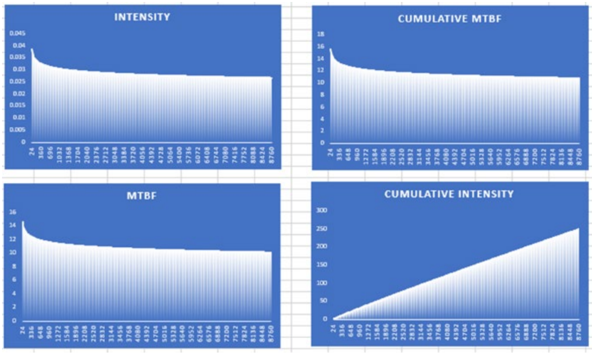

Fig. 7. Reliability Graphs of Wind Turbine H10

Cumulative Counterparts

An almost identical perspective of the MTBF and the cumulative MTBF alone can be seen in the graphs presented in Figure 7, which shows how MTBF may still look the same. However, some cumulative Intensity graphs show an opposite trend of the Failure Intensity, while some change their trend entirely, but almost always show that the cumulative Intensity is going upward. These show that in the future, the Failure Intensity of Wind Turbines may be detrimental and is predicted to be in its wear-out stage as discussed by Sakarvadia et.al (2023). This is unsurprising as all technologies may go old, and wind turbines are no stranger.

In the broader context, the data and failure graphs presented in this study indicate that most wind turbines in the wind farm are operating in their deterioration phase, with some still transitioning into it. This trend is reflected in the declining performance and increasing failure rates observed across the turbines. The findings from the reliability analysis provide valuable insights that can serve as a foundation for developing maintenance strategies tailored to the current operational stage of the turbines. Practically, this information enables the implementation of targeted, condition-based maintenance to address aging components proactively, reduce unexpected failures, and extend the operational lifespan of the turbines. Moreover, identifying turbines nearing the deterioration phase allows for more efficient allocation of resources and prioritization of maintenance activities, ultimately improving the reliability and cost-effectiveness of the wind farm.

CONCLUSION

The study provides crucial insights into the failure behavior and reliability trends of wind turbines in the wind farm, offering practical implications for operational improvement and cost reduction. The findings underscore the importance of continuous monitoring and targeted maintenance strategies to mitigate failure frequency and minimize their economic and environmental impacts. Proactive reliability studies are essential to identify evolving failure trends and inform maintenance schedules that enhance overall wind farm performance.

The analysis reveals that most wind turbines are in the wear-out stage, akin to the aging phase in humans, with only H10 and H14 remaining in the maturity phase but showing signs of transition. This suggests an urgent need to address the aging infrastructure, particularly for turbines like H07, which are identified as the least reliable. Conversely, H10 demonstrates high reliability, making it a potential reference model for operational best practices. These findings highlight the value of tailoring maintenance plans to the specific lifecycle stages of each turbine to maximize reliability and efficiency.

RECOMMENDATION

The study recommends several actionable steps to improve reliability management. First, conducting a comprehensive physical reliability assessment of the turbines will help identify aging components and critical failure points. Second, prioritizing the systematic collection and analysis of detailed maintenance reports will facilitate data-driven decision-making and trend analysis. Third, implementing advanced maintenance planning strategies, including predictive and condition-based approaches, will ensure timely interventions to prevent failures. Lastly, future research should explore statistical reliability evaluation techniques, such as the stress-strength interference theory, to incorporate external load effects and provide a more robust understanding of turbine performance under varying conditions. These steps, coupled with ongoing data collection and innovation in reliability modeling, will support wind energy systems' long-term sustainability and economic viability.

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