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# A comprehensive review of vibration-based analysis for wind turbine condition monitoring

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This article contributes to:

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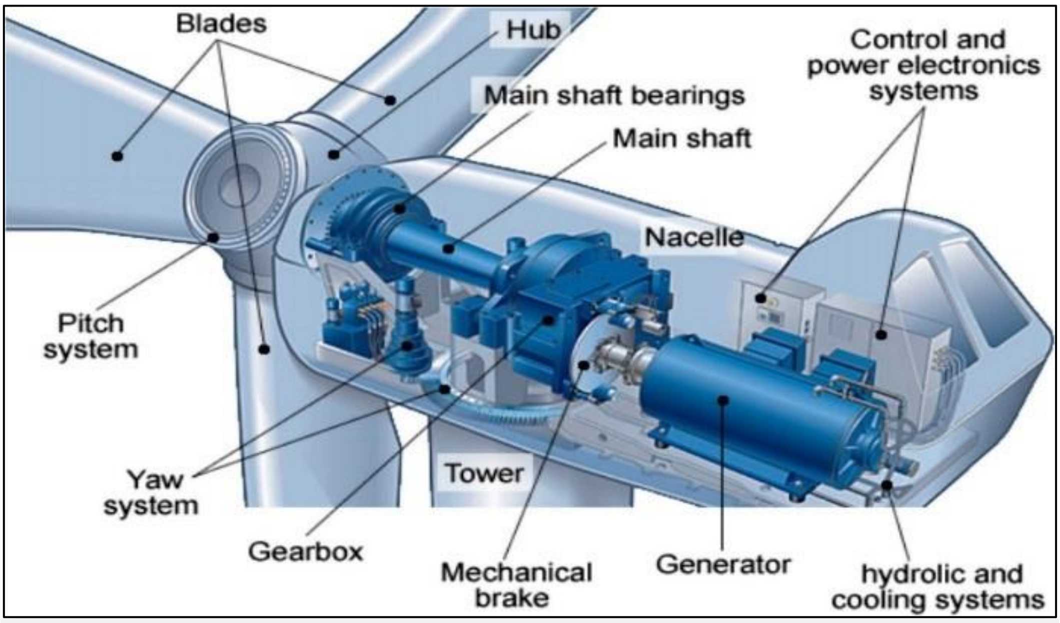


**Highlights:**

- Importance of Wind Turbine Efficiency in wind energy production.
- Routine Monitoring and Maintenance to ensure optimal operation, reduce costs, minimize downtime, and enhance lifespan.
- Vibration-Based Analysis as a key technique for monitoring wind turbine conditions, facilitating early detection of mechanical faults and abnormal behaviours.
- Vibration-based condition monitoring is effective and essential for maintaining the efficiency of wind energy systems.
- A comprehensive review of various vibration-based condition monitoring techniques, their advancements, and associated challenges and trends.

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## Abstract

Wind energy production relies heavily on the efficiency of wind turbine systems. The routine condition monitoring and maintenance of these systems are necessary to maintain healthy operation, reduce maintenance costs, minimize downtime, and extend the lifespan. Vibration based analysis is an essential technique for wind turbine condition monitoring that enables early detection of mechanical faults, abnormal behavior and degradation mechanisms, and lessens the risk of unexpected failures. This review paper explores an intensive review of various vibration based techniques of condition monitoring, their advancements, challenges, and trends. This review paper reveals that this technique of condition monitoring is effective and essential to ensure the efficiency of wind energy systems. The review paper identifies future research prospects and potential technological advancements to ensure wind energy systems' reliability, safety, and optimal performance.

**Keywords:** Condition monitoring; Maintenance; Wind energy; Wind turbine; Vibration

# 1. Introduction

Wind energy has experienced remarkable growth globally from 2010 to 2024. The global wind capacity increased from approximately 200 MW in 2010 to over 1 GW in 2023, as shown in **Figure 1**. Regional differences in wind energy implementation are notable from the developed countries to East and South Asian countries that are leading in wind capacity. Due to challenges from financial constraints and low natural gas prices around 2010, the wind industry demonstrated resilience and sustained cumulative capacity growth. Technological advancements and economies of scale have driven down costs, rendering wind energy increasingly competitive and forecasting continued cost reductions for onshore and offshore installations. These developments highlight wind energy as an important contributor to global electricity generation. The use of vibration monitoring since 2015 boosted turbine efficiency by 15%, that was leading to more installations. By 2020, real-time condition monitoring cut unexpected failures by 20%, and further supported industry growth.

The rapid increase in wind energy generation emphasized the importance of reliable wind turbine operation [1]–[3]. This relies heavily on technological advancements to optimize performance and reduce downtime. To maintain efficiency and ensure sustainable growth in wind energy, it is important to enhance the condition monitoring methods tailored to the unique operational demands of wind turbines. Among these, vibration based techniques for wind turbine condition monitoring have become vital for diagnosing faults and preventing failures.

Although previous reviews and studies have extensively discussed vibration based condition monitoring for wind turbines, there remains a significant gap in exploring how recent innovations have transformed these techniques. Existing literature regularly provides a general overview or focuses on some conventional methods without delving deeply into the latest advancements and their potential for addressing specific challenges unique to wind turbines. This review paper uniquely contributes to this field by offering a comprehensive examination of recent innovations in vibration based condition monitoring. Most specifically, the review addresses methods developed in the past fifteen years.

This review emphasizes the application of emerging technologies, such as big data analytics, artificial intelligence, and machine learning. They are offering a fresh perspective on how these advancements can enhance the accuracy, efficiency, and adaptability of condition monitoring in wind energy systems. This review provides also novel insights into future directions for research and development in the field by systematically analyzing these advancements. This aims to bridge the current knowledge gaps and underscore practical implications for enhancing operational reliability in wind turbine systems.

The review paper is constructed as follows: Section 2 discusses the wind turbine systems and their vibration based techniques of condition monitoring. Section 3 elaborates on the faults and signals in wind turbine systems. Section 4 briefs about the existing techniques in vibration based techniques of condition monitoring, while section 5 focuses on the progressions in the vibration based techniques of condition monitoring. Section 6 highlights the challenges in vibration based techniques of condition monitoring, while section 7 discusses the trends in vibration based techniques of condition monitoring, and. Finally, section 8 presents the conclusion and recommendations.

Harnessing wind energy has been a practice since ancient times. Its significance has grown in contemporary energy strategies [4]. The wind turbine industry has grown substantially with the increasing awareness of the environmental impacts and the depletion of fossil fuels. According to the Global Wind Report 2023, the global installations of wind turbines have experienced significant growth. Because of market crises and economic slowdown due to COVID-19, there was a 17.1% reduction in wind turbine installation from 2021 to 2022 [5]. Advances in wind turbine technology have enabled the development of wind turbine systems. They are not only more powerful but also capable of operating under more severe mechanical loads and extreme weather conditions [6]–[8]. However, these modern turbine systems face significant operational challenges.

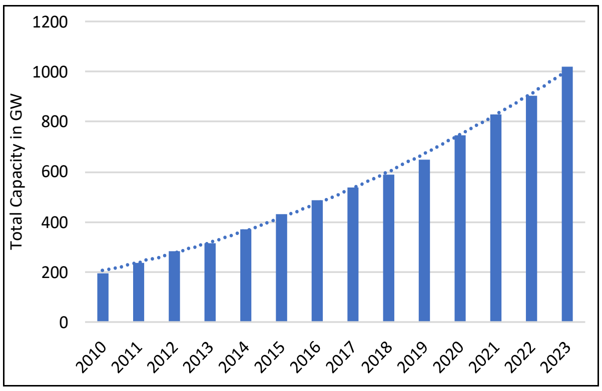


**Figure 1.** Installation growth of wind turbine capacity from 2010 to 2023

This leads to a required sophisticated condition monitoring and maintenance practices to ensure their efficiency and longevity [9].

Condition monitoring is needed to maintain the performance and reliability of turbine systems. Given the hard operating conditions and the critical nature of wind turbine components, early detection of damage and accurate estimation of its severity are important [10]. Effective condition monitoring systems reduce the costs associated with maintenance, repairs, and component replacements. **Figure 2** shows the maintenance and operation costs for a wind turbine system. Furthermore, they minimize these losses of revenue by reducing the downtime required for such activities [11]. Implementing a healthy monitoring system within the wind turbine infrastructure allows for optimized maintenance schedules, enhancing operational availability and extending the lifespan of the wind turbines [8], [12]–[14]. Vibration analysis reduced maintenance costs by 25% between 2016 and 2020. Predictive maintenance using vibration data also cut operational costs by 30% compared to traditional methods.

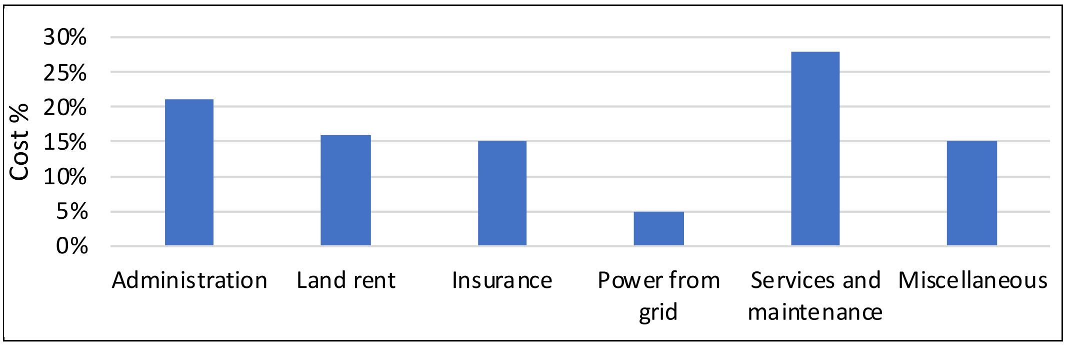


**Figure 2.** Operation and maintenance costs for a wind farm

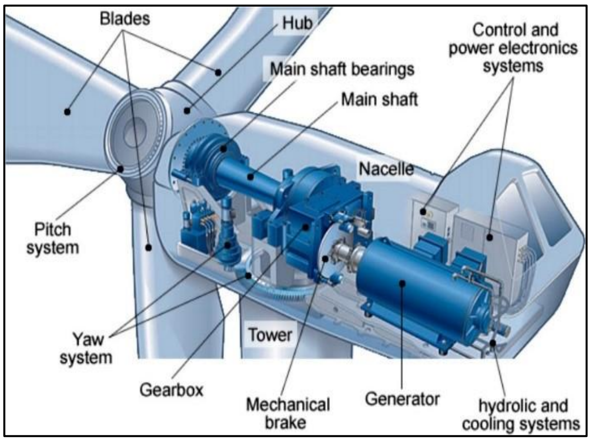


**Figure 3.** Main components of a wind turbine [8]

Effective condition monitoring processes are important for the efficient operation of wind turbines [15]. These systems help in early fault detection and accurate damage assessment, to ensure the turbine's operation reliable and efficient [16]–[19]. By repeatedly monitoring the status of wind turbine components, condition monitoring processes provide timely alerts, allowing for proactive maintenance, reducing the likelihood of catastrophic failures [20]. **Figure 3** shows the main components of a wind turbine.

The wind turbine components are related to the trend in the number of available reviews on condition monitoring of wind turbines from 2010 to 2024. This can be examined by looking at how advances in monitoring technologies and the growing importance of maintenance have driven research interest in specific turbine components [21]. There is an increased focus on reliability and maintenance of the rotor blades, gearbox and generator. That is, condition monitoring systems for rotor blades have become more advanced, with new sensors to detect structural integrity [22]. Techniques like blade vibration analysis and ultrasonic testing are the common topics. The gearbox is a critical component predisposed to failure [23]. This has driven extensive research into the vibration analysis, oil debris monitoring, and acoustic emission techniques. Monitoring the generator's performance through thermal imaging, vibration analysis, and electrical signal monitoring has been a significant focus that has been reflected in the published literature. The development of advanced sensors and the integration of the Internet of Things (IoT) for real-time monitoring have encouraged more research. Reviews often cover the application of these technologies across multiple components, including blades, the gearbox, and the generator.

The literature trend shows a steady increase in the number of published reviews. **Figure 4** illustrates a graphical representation of the trend in the number of these published reviews on condition monitoring of wind turbine from 2010 to 2024. The data reveals an increase in research activity over this period of time. This reflects growing interest and advancements in the field and

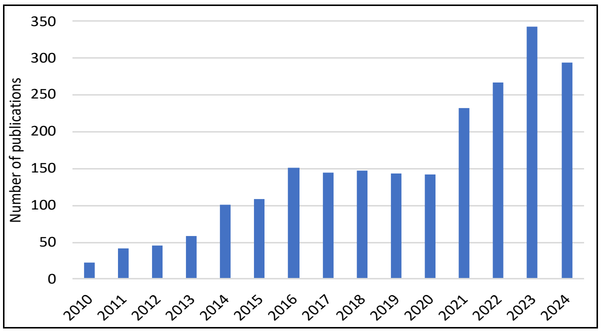


**Figure 4.** Number of published reviews on condition monitoring of wind turbines from 2010 to 2024

heights awareness of the importance of renewable energy monitoring techniques. **Table 1** summarizes a brief description of some published review papers during this period. From 2015 to 2023, reviews with experimental data increased by 40%. The share of field data studies grew from 20% in 2012 to 50% in 2023, highlighting a shift towards evidence-based research.

**Table 1.** Critical analysis of published reviews in condition monitoring of wind turbines from 2010 to 2024

| Ref. | Year | Brief Description/Topics | Critical Analysis | Gaps Identified |
|---|---|---|---|---|
| [24] | 2010 | Focus on electrical signature analysis for fault detection in generators. | Early studies highlighted electrical techniques but were limited by a lack of integration with mechanical data. | A gap in cross-method integration with mechanical monitoring. |
| [25] | 2011 | Overview of drivetrain condition monitoring, with emphasis on gearbox maintenance. | Highlights gearbox as a costly subsystem, but lacks predictive capabilities using newer data methods. | Need for predictive monitoring integrating SCADA and big data for gearbox faults. |
| [26] | 2012 | Emphasizes the complexity of fault types and the need for cost-effective prognostic techniques. | Broad view on multiple fault modes but does not suggest specific data-driven solutions. | Insufficient focus on machine learning for handling complex faults. |
| [27] | 2013 | Overview of current practices and technologies for wind turbine condition monitoring. | Lacks a critical view of emerging techniques like AI; predominantly descriptive. | Requires exploration of data-driven advancements in fault diagnostics. |
| [28] | 2013 | Focus on reducing operational costs and improving availability. | Valuable for cost-efficiency but limited discussion on advanced sensing technologies. | Needs coverage of IoT and AI advancements for cost reduction. |
| [29] | 2013 | Performance improvement through condition monitoring. | Overviews basic methods without delving into predictive techniques. | Lacks discussion on predictive maintenance using big data. |
| [11] | 2014 | State-of-the-art overview, future challenges. | Identifies future challenges but lacks AI and machine learning implications. | Emerging AI and data analytics are left unexplored. |
| [30] | 2014 | Commercial and technical challenges in condition monitoring. | Addresses industry concerns but doesn't consider emerging AI techniques for real-time monitoring. | Needs integration of real-time data handling techniques. |
| [31] | 2014 | Focus on gearboxes and blades, critical components. | Key insights on component-specific monitoring but does not explore multi-component data fusion. | A gap in the fusion of data for holistic turbine condition insights. |
| [10] | 2015 | Surveys state-of-the-art fault diagnostic technologies. | Comprehensive survey, yet lacks a critical comparison of methodologies. | Insufficient focus on comparing machine learning vs. traditional methods. |
| [32] | 2016 | Non-invasive techniques for O&M cost reduction. | Demonstrates cost benefits but overlooks data-driven improvements. | Need for detailed data-driven cost analysis. |
| [33] | 2017 | Neural network-based monitoring via SCADA data. | Highlights neural network potential but is limited to single-method use. | Lack of hybrid approach combining different AI methods. |
| [34] | 2017 | Uses SCADA for optimized maintenance strategies. | Promising use of SCADA, but limited multi-source data integration. | Gaps in SCADA-data fusion with other real-time monitoring sources. |
| [35] | 2018 | Advanced monitoring and early fault diagnosis. | Valuable for early detection but lacks diverse data-source incorporation. | Gap in multi-source data for fault prognosis. |
| [36] | 2019 | Supervised ML classification using SCADA data only. | Effective use of SCADA but limited without combining real-time data. | Needs multi-sensor data for better prediction accuracy. |
| [37] | 2020 | SCADA and AI for condition monitoring. | Integrates AI but lacks exploration of deep learning potentials. | Opportunity to integrate deep learning for enhanced diagnostics. |
| [38] | 2021 | Advances in intelligent, signal-based, and data-driven monitoring. | Comprehensive approach but lacks hybrid model discussion. | Limited insight into hybrid model performance evaluation. |
| [39] | 2022 | Signal-based and model-based monitoring for diagnosis and prognosis. | Good overview of prognosis techniques but lacks emphasis on ML. | Missing use cases for machine learning in fault prognosis. |
| [40] | 2023 | Data-driven predictive techniques for condition monitoring. | Advances predictive maintenance but overlooks fault complexity in wind systems. | Lacks in-depth analysis of fault interactions. |
| [41] | 2024 | Data processing and fusion algorithm strategy using ML and DL. | Provides advanced data fusion; however, lacks real-world test results. | Research is needed on real-world applications of fusion techniques. |
| [42] | 2024 | A model integrating multiple real-world parameters for offshore turbine structure. | Promises practical utility; limited to offshore structures without broader application analysis. | Broader generalization for onshore and various environmental conditions is needed. |

# 2. Faults Diagnosis in Wind Turbine Systems

Wind turbine systems are susceptible to various faults stemming from different factor like mechanical, electrical, and environmental factors. The vibration signals associated with these faults are important for effective condition monitoring and timely maintenance [21], [35]. Advanced signal analysis techniques and multi-sensory data integration perform an important function in early fault detection. This enables proactive maintenance and ensures the reliability and longevity of wind turbines. Harnessing complicated data patterns and correlations across diverse sensory inputs can add more value to analyzing methodologies and techniques. This proactive approach minimizes downtime and repair costs and, at the same time, maximizes energy production efficiency, safeguarding the sustainable operation of wind farms and bolstering the overall resilience of renewable energy infrastructure [43], [44]. The fault occurrence percentage of wind turbine components is shown in **Figure 5**.

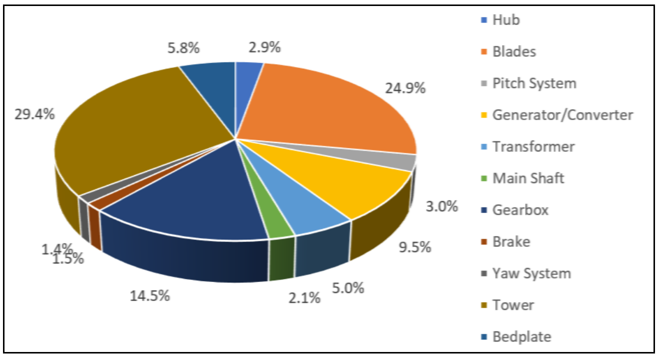


**Figure 5.** Fault occurrence percentage within wind turbine components

## 2.1. Common Faults in Wind Turbine Systems

Analyzing these fault-related signals often involves sophisticated signal processing techniques, such as Fast Fourier Transform (FFT), wavelet analysis, and time-frequency analysis [45]. Integration of these techniques aids in identifying specific fault frequencies, harmonics, and modulation sidebands, allowing for accurate fault diagnosis. Furthermore, the fusion of multiple sensor data streams, including vibration sensors, temperature sensors, oil condition sensors, and SCADA data, facilitates a comprehensive understanding of wind turbine health [44], [46]. For instance, combining vibration analysis with oil condition monitoring enables a holistic assessment of gearbox health [23], [47]. Despite advancements in fault detection methodologies, challenges persist in accurately differentiating between normal operational variations and incipient faults [48], [49]. Failures within wind turbine components can be attributed to various factors, ranging from design flaws and manufacturing defects to environmental conditions and operational issues [50]. Vibration sensors for wind turbine applications need to have strength, sensitivity, and durability to monitor turbine health effectively. They must bear various environmental conditions while providing precise data on wind turbine vibrations. Accuracy and reliability are very important to ensure optimal performance and prevent potential damage. Based on the needs of wind turbine applications, **Table 2** summarizes the vibration sensor requirements to analyze the fault-related signals. However, there are some common failures and faults within wind turbine components that can be addressed in detail. **Table 3** shows these common faults in wind turbine systems.

### 2.1.1. Gearbox Faults

Gearbox failures represent one of the most critical issues in wind turbines [23]. Faults such as gear tooth wear, pitting, and misalignment generate distinct vibration patterns. Studies have emphasized the importance of gear fault detection through vibration analysis and spectral signature recognition [12]. The two main causes of gearbox failures are lubrication issues and misalignment. Inadequate lubrication or lubricant breakdown can result in increased friction, heat, and wear within the gearbox. This can lead to a gear failure, reducing the efficiency of the entire turbine [31]. Also, improper alignment of gearbox components can cause uneven loading and increased stress, leading to premature failure [51], [52].

**Table 2.** Vibration sensor requirements and specifications for wind turbine components

| Component | Rotor blade | Main bearing | Gearbox low-speed | Gearbox high-speed | Generator bearing | Tower and nacelle |
|---|---|---|---|---|---|---|
| Number of Sensors | Two single-axis | Two single-axis | One single-axis | Three single-axis | Two single-axis | Two single-axis |
| Directions of Measurement | Axial and transversal | Radial and axial | Radial | Radial and axial | Radial | Axial and transversal |

**Table 3.** Common faults in wind turbine systems' components

| Component | Category | Influence/Faults |
|---|---|---|
| Gearbox | Mechanical faults | Abnormal noise, vibration, gear tooth wear, bearing condition, and gearbox alignment |
| | Lubrication system (oil analysis) | Oil pressure, gearbox lubrication, gearbox filter condition, gearbox breather, and seal integrity |
| | Operational monitoring (torque monitoring) | Electrical signals, temperature, and gearbox housing condition |
| Bearing | Surface damage | Outer race damage, inner race damage, rolling element damage, and cage damage |
| | Wear and deterioration | Brinelling, false brinelling, and corrosion |
| | Overheating | Bearing failure, gearbox damage, generator winding damage, and electrical component failure |
| Blade | Operational impact | Reduced energy production, increased maintenance costs, loss of revenue, system instability, and vibration and noise |
| | Structural concerns | Mechanical stress, safety risks, and structural integrity |
| | Environmental and efficiency | Aerodynamic performance and environmental impact |
| Generator | Connectivity faults | Short circuits and ground faults |
| | Voltage and current fluctuations | Voltage sags and surges, and harmonic distortion |
| | External factors | Lightning strikes |
| Yaw and pitch systems | Mechanical failures | Yaw drive failure, yaw brake failure and Yaw bearing wear |
| | Sensor issues and malfunctions | Yaw misalignment (sensor failure or miscalibration) and pitch sensor malfunction |
| | Actuator problems | Pitch actuator failure |
| | Control system issues | Pitch system lag |
| | Wear and tear | Yaw bearing wear and pitch bearing wear |
| Environment (external) | Atmospheric conditions | Wind speed and direction, turbulence, air density, and altitude |
| | Weather conditions | Temperature, humidity, lightning and electrical storms, ice and snow, and severe weather events |
| | Regulatory and social factors | Environmental regulations, wildlife impacts, and visual considerations |

### 2.1.2. Bearing Faults

Bearing defects, including inner race, outer race, and roller element faults, are prevalent in wind turbines. Bearings are important in supporting the rotating components of a wind turbine, such as the main shaft, generator, and gearbox [53]. They are subjected to heavy loads, varying speeds, and challenging environmental conditions, making them susceptible to wear and damage over time [54]. Vibration signals from bearings often exhibit characteristic frequencies and sidebands [19]. wind turbines are often located in remote areas, and the surrounding environment exposes bearings to dust, moisture, and other contaminants [47], [55]. These can penetrate the bearing seals, causing abrasive wear, corrosion, and reduced lubrication effectiveness. A comprehensive technique for wind turbine bearings condition monitoring may focus on fault identification through vibration analysis and signal processing methods [45].

### 2.1.3. Blade Damage and Imbalance

Blade defects, such as cracks, erosion, or imbalance, result in unique vibration patterns [56]. The use of modal analysis and vibration monitoring may detect blade damage and imbalance in wind turbine s. Material fatigue, erosion, and corrosion are the main causes of blade failures [57], [58]. That is, constant exposure to wind and changing weather conditions can lead to material fatigue in turbine blades. The cyclic loading and unloading of the blades over time can cause structural damage and eventually lead to failure [59], [60]. Also, environmental factors such as rain, hail, and saltwater can cause erosion and corrosion of blade surfaces, compromising their structural integrity [30].

### 2.1.4. Generator and Electrical Faults

Electrical faults in generators or associated components can lead to anomalies in electrical signals [57]. The use of current and voltage signals can be explored to detect electrical faults and emphasize the significance of electrical signal analysis in condition monitoring. Electrical failures and overheating are mostly the main two causes of generator failure [54], [61]. Issues such as insulation breakdowns, short circuits, or electrical component failures can result in generator malfunctions. These failures can be caused by manufacturing defects or during operational stresses. Also, overheating of the generator can lead to insulation degradation and ultimately failure. Mostly, it is due to excessive loading or poor cooling systems.

#### 2.1.5. Yaw and Pitch Systems' Faults

Yaw and pitch systems' faults can interrupt the alignment and positioning of wind turbine components. Abnormal yaw or pitch signals indicate potential faults in the wind turbine systems. They need to necessitate precise monitoring for early fault detection [62]. Yaw device misalignment can result in the turbine not facing the wind correctly [63]. This results in increased strain on the structure and capability failures [15], [51]. Moreover, mechanical wear and tear in Yaw system components over the years can bring about reduced reliability and eventual failure [50], [64].

#### 2.1.6. Environmental Influences

The vibration analysis of wind turbines inside the context of environmental influences is needed to ensure their structural integrity, overall performance, and longevity [59]. Wind loading, temperature and weather, earthquakes, and lightning moves are some examples of environmental consequences [15], [52], [65]. Wind turbines are regularly subjected to a version of environmental factors which can set off vibrations, that impact their components and normal operational efficiency [66]. These vibrations may additionally bring about early wear and tear, that is doubtlessly main too pricey maintenance and downtime. Moreover, severe climate conditions can get worse these results, causing significant demanding situations to wind turbine overall performance.

### 2.2. Methods for Detecting Faults in Wind Turbine Systems

The fault detection and analysis in wind turbine systems are critical for making sure the reliability and overall performance of those renewable energy resources. Vibration alerts were widely employed for fault detection in wind turbines. Various methods and strategies have been developed for this cause. The integration of sign processing, system learning, and deep getting to know strategies has revealed promising effects in enhancing the accuracy and efficiency of fault detection in wind turbines. **Table 4** highlights the advantages and challenges of each method along with potential strategies for enhancing their performance in wind turbine fault detection.

**Table 4.** Strengths and limitations of methods for detecting faults in wind turbine systems [67]–[77]

| Technique | Strengths | Limitations | Potential Improvements |
|---|---|---|---|
| Vibration Signal Analysis | Provides detailed time-frequency representations (e.g., wavelet packet analysis) useful for identifying specific faults. | Sensitive to noise and environmental variability; limited integration with AI-driven methods, impacting accuracy in complex fault conditions. | Hybrid approaches integrating with machine learning for robustness. |
| Machine Learning (ML) | Support vector machines (SVM) effective in classifying faults and condition monitoring with kernel-based models. | Struggles with large datasets and complex relationships in real-time monitoring; lacks standardization in feature extraction, affecting consistency across turbines and conditions. | Combining SVM with deep learning for better scalability and interpretability. |
| Deep Learning (DL) | Convolutional and long short-term memory networks handle large-scale vibration data; effective in fault localization with attention mechanisms. | Requires extensive labeled data, high computational costs, and lengthy training, which limit real-time applicability and scalability. | Development of scalable, less data-intensive models for real-time applications. |

#### 2.2.1. Vibration Signal Analysis for Fault Detection

Vibration signal analysis remains a foundational method for fault detection in wind turbines. Specific techniques like wavelet packet analysis allow for detailed time-frequency representations essential for identifying component-specific faults. Studies using wavelet packet analysis highlight its strengths in identifying unique fault features though its application is often limited by sensitivity to noise in real-world conditions [78]. Research on estimating shaft rotating frequencies through phase-locked loops has expanded operational insight as well as enabling fault identification based on deviations in vibration patterns [67], [68]. However, few gaps remain in integrating this wavelet packet analysis with more advanced AI-driven techniques in order to improve accuracy in complex fault conditions. Inconsistencies also arise regarding the effectiveness of wavelet packet analysis in varying environmental conditions. This indicates a need for more robust, hybrid approaches that combine wavelet packet analysis with data-driven methods like machine learning for consistent performance in diverse conditions [70].

#### 2.2.2. Machine Learning Approaches for Fault Detection

Machine learning techniques, particularly support vector machines have demonstrated significant accuracy in classifying fault types in wind turbine systems [71], [72]. The versatility of support vector machines has been effective in condition monitoring and fault diagnosis. This includes traditional and newer kernel-based models. However, while support vector machines excel in classifying faults, they face limitations in handling large datasets and complex relationships found in real-time monitoring [73]. This is an area where deep learning techniques often outperform. This comparison underscores a research gap in combining support vector machines with deep learning methods to enhance fault detection capabilities without compromising interpretability [72]. Flaws within machine learning approaches suggest a need for standardized feature extraction methods to ensure reliability across different turbine models and operational conditions [70]. This is particularly the choice of features extracted from vibration signals.

#### 2.2.3. Deep Learning Techniques for Fault Detection

Deep learning approaches have shown promise in addressing the limitations of traditional machine learning methods by analyzing large-scale vibration data effectively [74], [75]. This includes convolutional neural networks and long short-term memory networks [76]. The multiscale convolutional neural networks developed for gearbox fault diagnosis offer improved fault localization, yet they require extensive labelled data [23]. This is not always available in wind turbine applications. Additionally, the integration of attention mechanisms with the limitations of traditional machines has enhanced temporal fault detection [69], [77]. This is though its computational complexity can be a limitation in real-time applications. Contradictory findings on the effectiveness of convolutional neural networks versus traditional signal processing methods indicate that hybrid models could address the unique challenges presented by wind turbine structures. Examples of these findings are the influence of rotational speed and environmental factors. The gap here lies in developing scalable and less data-intensive deep learning models that maintain high accuracy while reducing training time and computational requirements. This would facilitate real-time fault detection and enhance wind turbine reliability.

## 3. Vibration based Techniques of Condition Monitoring of Wind Turbines

Vibration based techniques of condition monitoring has gained prominence as a practical alternative to traditional monitoring techniques [30]. This method involves analyzing the vibration signals generated by different wind turbine components during operation. These signals provide valuable indications into the health of these components. Vibration based monitoring allows for precise fault detection and diagnosis by identifying characteristic vibration patterns associated with different types of faults. This approach is mainly useful for scheduling maintenance activities before unexpected failures occur [21]. Thereby, it prevents costly downtimes and enhances the overall reliability of the wind turbines.

Vibration based techniques of condition monitoring involve installing some accelerometers and other types of sensors at several locations of the turbine system. The collected signals and data of vibration are analyzed to identify patterns and anomalies which indicate potential issues [43], [45], [79]. This vibration based monitoring is particularly very effective for detecting faults in rotating machinery, especially bearings and gears [50]. It offers several advantages, including real-time monitoring, high sensitivity to faults, and the ability to predict failures before they occur [65].

### 3.1. Development of Vibration based Techniques for Condition Monitoring

This condition monitoring is an important characteristic of renewable energy systems, particularly in the situation of wind turbine technology [80]–[82]. The development of these vibration based techniques of condition monitoring for wind turbines describes a full history of advancements and innovations [83]. This journey extends from basic fault detection methods to sophisticated vibration analysis techniques. It reflects the research for reliable, efficient, and proactive maintenance strategies in the renewable energy sector [27]. This section provides a background of vibration based techniques of condition monitoring, which includes the history of wind turbine technology, the evolution of condition monitoring practices, and the significance of vibration based monitoring in the context of renewable energy. Researchers explored the milestones, technological revolutions, and transformative impact of vibration based methodologies in enhancing the reliability and longevity of wind turbine systems.

The application of vibration based techniques of condition monitoring has expanded significantly. The technique has been refined to detect a wide range of faults, such as bearing degradation, gear wear, and blade defects. Various signal processing methods, such as time-domain analysis, frequency-domain analysis, and time-frequency analysis, are employed to extract meaningful information from the vibration data. Advanced algorithms and machine learning techniques are also being integrated into condition monitoring systems to improve fault detection accuracy and reduce false alarms.

## 3.2. Advancements in Vibration based Techniques

In the realm of wind turbine health monitoring, a variety of traditional and cutting-edge condition monitoring approaches have been employed for early fault diagnosis. They showcased the effectiveness of vibration based techniques [37], [45], [84]. These approaches encompass sophisticated signal processing methods for analyzing vibration data obtained from both healthy and damaged gearboxes [57], [85]. Examples are variable amplitude Fourier series and wavelet analysis. The importance of artificial intelligence techniques in smart grid and renewable energy systems were highlighted to emphasize the role of this technology in shaping wind turbine systems [86], [87]. Furthermore, a comparative study on vibration based techniques of condition monitoring algorithms was conducted for wind turbine drive trains, to demonstrate the continuous evolution of monitoring practices in wind turbine technology [88]. Additionally, an intensive review of signal-based and model-based monitoring techniques of wind turbines was provided to highlight the continuous expansion of fault diagnosis and lifetime prognosis methods [39].

## 3.3. Significance of Vibration based monitoring

The significance of vibration based monitoring in the context of renewable energy, particularly in wind turbine technology, is well documented. An active vibration based structural health monitoring system was demonstrated for wind turbine blades, to showcase the practical implications of vibration based monitoring [86], [89]. The application of vibration analysis extends beyond gearbox assessment, to include some studies delving into the detection of irregularities in time-domain-reflected vibrations using Supervisory Control and Data Acquisition (SCADA) systems [34], [90]. Efforts to enhance monitoring accuracy include the development of robust algorithms integrating dynamic threshold techniques and echoing state network modelling, to leverage SCADA-acquired vibration data for wind turbine gearbox surveillance [58], [91]. Meanwhile, the pursuit of innovative methods for detecting and diagnosing rotor imbalance underscores the multifaceted nature of vibration analysis. This encompasses pitch misalignment, yaw inconsistencies, and mass imbalance [51], [63]. The utilization of vibration analysis is not only limited to fault detection but also extends to the estimation of immediate shaft speed recovery, to demonstrate its versatility in addressing various operational challenges [92], [93].

## 3.4. Evolution of Vibration based Techniques of Condition Monitoring

The history of wind turbine technology has grown significantly over the past 15 years, including some advancements in design and functionality. Many researches demonstrated the effectiveness of vibration based techniques of condition monitoring in wind turbine systems. For example, a study has shown how vibration analysis can detect bearing faults at an early stage [53]. This allowed for timely maintenance and preventing of severe damage [94]. Other study has focused on the detection of gear wear and misalignment, which are common issues in wind turbines [95]. These case studies showed the practical application of vibration based techniques of condition monitoring systems and highlighted their benefits in real-world scenarios [15]. From 2010 to 2024, the field of wind turbine vibration based techniques of condition monitoring have seen a significant increase in the number of published reviews. This surge reflected the growing importance of sustainable energy and the serious need for effective maintenance strategies to ensure the reliability and longevity of wind turbines [21]. **Figure 6** shows the trend in the number of published reviews on specifically vibration based techniques of condition monitoring of wind turbines from 2010 to 2024. Also, **Table 5** summarizes a chronological brief description on the research conducted in this field. Vibration techniques have proven the effective accelerometer in condition monitoring and reduced downtime by 12%. At the same time, acoustic methods improved fault detection by 15%. Combining methods boosted power output stability by 10%.

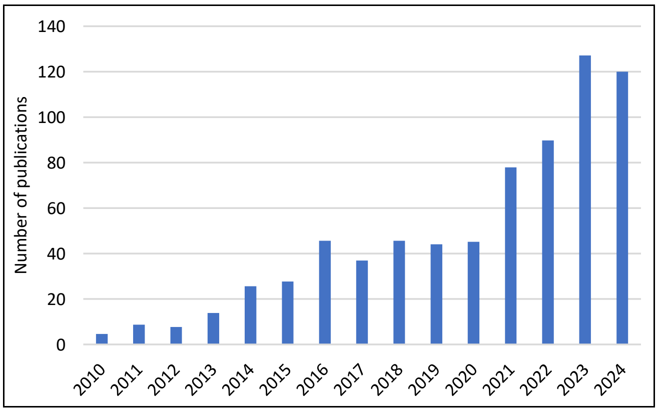


**Figure 6.** Number of published reviews in wind turbine vibration based techniques of condition monitoring from 2010 to 2024

**Table 5.** Critical analysis of published reviews in wind turbine vibration based techniques of condition monitoring from 2010 to 2024

| Ref. | Year | Brief Description/Topics | Critical Analysis | Gaps Identified |
|---|---|---|---|---|
| [96] | 2010 | Promises vibration analysis for structural health monitoring to reduce downtime and failures. | Early study emphasizing potential, but lacks implementation and validation details. | Need for real-world validation in reducing downtime. |
| [25] | 2011 | Overview of drivetrain condition monitoring for wind turbines. | Highlights drivetrain's importance; lacks focus on blade and tower monitoring. | Expansion needed on multi-component vibration analysis. |
| [97] | 2012 | Vibration as a tool for blade fault diagnosis. | Focus on blade faults; lacks consideration for gearbox faults. | A gap in comprehensive systems covering all components. |
| [27] | 2013 | Reviews multiple condition monitoring technologies, including vibration methods. | Provides a broad overview but limited critical assessment of vibration-specific methods. | Limited analysis of effectiveness across turbine subsystems. |
| [88] | 2014 | Compares algorithms for detecting gear and bearing degradation in drivetrains. | Effective in algorithm comparison but lacks insight into hybrid approaches. | Gap in combining vibration data with other signals for higher accuracy. |
| [98] | 2015 | Emphasizes vibration analysis for improving gearbox reliability. | Gearbox-specific focus; lacks consideration for integration with SCADA data. | Need for studies integrating SCADA and vibration for enhanced monitoring. |
| [99] | 2016 | Vibration-based system for early gearbox defect diagnosis. | Valuable for early detection but lacks comprehensive multi-algorithm comparison. | Research gap in comparing different vibration-based algorithms for robustness. |
| [100] | 2017 | Comparative study on data-driven algorithms for blade monitoring using vibration signals. | Effective comparative analysis but focused on blades only; lacks broader turbine application. | Broader focus needed on drivetrain and structural components. |
| [101] | 2018 | Vibration-based monitoring for structural damage using over 1 year of data. | Long-term data use is valuable but lacks AI integration. | Gaps in AI and machine learning application for real-time structural health monitoring. |
| [102] | 2019 | Automated framework for gearbox failure diagnosis using vibration and AI. | Introduces AI but is limited to gearbox diagnosis, missing blade and tower diagnostics. | Need for integrated systems addressing all turbine components. |
| [103] | 2020 | Automatic fault diagnosis for condition monitoring using vibration analysis. | Highlights automation, yet lacks detailed comparison with manual methods. | Insufficient analysis of cost-effectiveness and reliability of automated methods. |
| [104] | 2021 | Cloud-based real-time vibration and temperature monitoring for early fault detection. | Advances smart maintenance but lacks focus on cybersecurity in cloud systems. | Gaps in ensuring data security and reliability in cloud-based monitoring. |
| [105] | 2022 | Reviews signal-based and model-based techniques for fault diagnosis and lifetime prognosis. | Comprehensive overview but lacks detail on combining signal-based and model-based approaches. | Needs studies on hybrid methods for lifetime prognosis accuracy. |
| [106] | 2023 | Case study on condition monitoring at Gibara II wind farm. | Real-world case study valuable for field insights but lacks generalization for other locations. | Limited in providing universal conclusions across turbine sites. |
| [41] | 2024 | A case study where standard diagnostics failed to prevent gearbox downtime. | Critically highlights limitations of standard diagnostics, suggesting a need for advanced techniques. | Gap in developing fault-tolerant diagnostic methods to minimize severe failures. |

While vibration based techniques of condition monitoring are highly effective, it can be further enhanced by integrating it with other monitoring techniques. For instance, combining vibration analysis with acoustic emissions and oil analysis can deliver a more complete understanding of the turbine's health. Acoustic emissions can detect crack beginning and propagation, whereas oil analysis can identify wear particles and contamination in the lubricant. The condition monitoring systems can offer additional holistic approach to fault detection and diagnosis by integrating these techniques. These examples demonstrate how different faults can be detected and diagnosed using vibration analysis.

## 3.5. Applications and Extensions of Vibration based Techniques of Condition Monitoring

Investigations into seasonal daytime vibrations highlight the significant impact of wind on wind turbine vibration dynamics. This underscores the importance of considering environmental factors [107]. This environmental perspective was further explored in studies examining the outside dynamic responses of rooftop vertical axis wind turbine structures. It demonstrated a holistic approach to understanding vibration behavior [66], [108]. These findings collectively suggest that external environmental factors have a marked influence on vibration dynamics. This supports the case for integrated environmental analysis in turbine monitoring. However, inconsistencies arise in terms of data quality and complexity. Practical implementation is challenged by the high dependency on reliable environmental data and increased computational demands while broader studies argue for holistic perspectives. This shed light on the ongoing efforts to tackle technical and scientific challenges in wind turbine status monitoring [109]. While considering external factors like wind, as a high holistic perspective on wind turbine vibration dynamics, challenges remain concerning data quality dependency and analysis complexity. Nonetheless, the implications are still significant, including enhanced maintenance strategies, performance optimization, and cost reduction in wind turbine operations and maintenance.

# 4. Existing Techniques used in Vibration based Techniques of Condition Monitoring

Vibration analysis is an active device for condition monitoring of wind turbines [110]. It detects irregularities, faults, as well as potential disasters. By studying mechanical vibrations, abnormalities may be recognized. Also, capacity faults may be predicted and renovation activities can be scheduled correctly [27], [111]. The vibration based techniques of condition monitoring represented a cornerstone within the protection and health evaluation of wind turbine systems [112]. This method leverages the critical vibrational signatures emitted by using numerous components at some point of operation. It affords valuable understandings into the fitness and overall performance of those complex machines. Vibration based strategies of condition monitoring includes putting sensors on machinery to degree vibrations, then reading the records to come across abnormalities, and after that taking motion to save you breakdowns. **Figure 7** shows the manner of vibration based total techniques of condition monitoring.

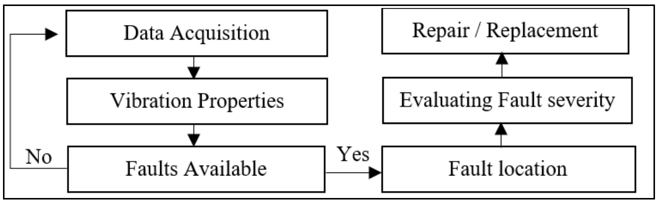


**Figure 7.** Vibration based techniques of condition monitoring process of wind turbine

Vibration analysis encompasses a range of techniques from basic signal acquisition to sophisticated data analytics. They facilitate fault detection, diagnosis, and prognosis in wind turbines [43]. As one of the most widely used approaches in condition monitoring, vibration analysis enables the proactive detection of potential faults to prevent sudden failures and downtime. This vibration analysis is needed for maintaining efficient wind turbine operations [9]. Commonly used techniques include energy spectral density analysis and frequency-domain amplitude spectrum analysis [54], [113]. These methods provide valued visions, as they are evidenced by studies employing vibration signal spectrum analysis to monitor the state of rotating machinery [114] and using a spectral modification to detect bearing defects [115].

However, challenges such as data complexity, computational demands, and false alarms complicate the application of these vibration based condition monitoring techniques [30], [61]. The growing integration of multi-sensor fusion techniques showed a good potential for addressing these issues. This could be done by combining data sources (e.g., vibration, torque, and electrical signals) in order to enhance predictive model accuracy and reduce error rates. This integration offers a significant improvement over the traditional single-sensor approach. However, questions are raised regarding the standardization of fault diagnostics protocols across varied sensor types and data sources. Additionally, while advanced techniques such as envelope spectral analysis are employed to diagnose faults under different wind speeds [116], [117], studies reported variability in outcomes, revealing inconsistencies in the effectiveness of these methods under different operational conditions.

These observations highlight areas in standardizing vibration based techniques for various wind turbine models and operational environments [55]. Research could focus on establishing generalizable, adaptive models capable of accommodating the complex, and variable conditions typical of wind turbine systems. This approach holds promise for enhancing the reliability, efficiency, and operational lifespan of wind turbines [45], [92], which leverages advanced signal processing, data analytics, and machine learning. The ongoing need for harmonized protocols that balance predictive accuracy with computational efficiency remains a central challenge in advancing the field. The main technologies used for vibration based techniques of condition monitoring are discussed as follows:

## 4.1. Signal Acquisition and Processing

In wind turbine condition monitoring, vibration signals are collected using accelerometers that are strategically placed in critical areas, such as the gearbox, bearings, and blades [35]. These accelerometers convert mechanical vibrations into electrical signals. The collected signals undergo essential steps like preprocessing, filtering, and digitization to remove noise and enhance data quality, ensuring accurate fault diagnosis [45]. They are then analyzed in both time and frequency domains. Proper signal conditioning and preprocessing are needed to reduce artefacts and improve the reliability of condition monitoring systems [19].

In practical applications of vibration based fault detection in wind turbines, signal processing techniques showed importance in identifying and addressing component issues before they escalate. For example, wavelet packet decomposition is applied in gearbox fault monitoring to process vibration signals across various frequency bands. This pinpoints effectively early signs of wear and pitting on gear teeth [98]. The Fast Fourier Transform, discussed in the next section, has also been extensively used in diagnosing bearing faults to detect specific frequency spikes tied to particular faults even in complex operational environments where transient events are common [55], [100]. Similarly, envelope analysis, discussed later in this section, is effective in identifying blade defects such as cracks or delamination due to environmental stresses [102]. Figure 8 shows the process of this signal-processing technique.

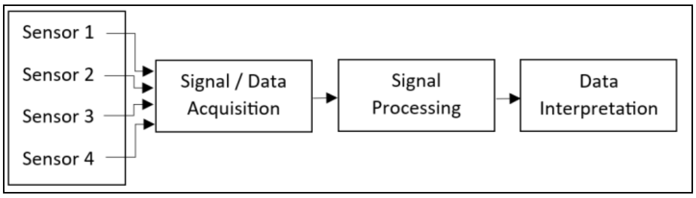


**Figure 8.** Concept of signal processing technique

Additional signal processing techniques, such as Wavelet Transform and Principal Component Analysis, are needed to enhance fault detection and diagnosis in wind turbine systems. The Wavelet Transform is particularly valuable for analyzing transient signals that may be missed by stationary frequency methods. It is applied effectively in isolating power quality disturbances and identifying transient behaviours in electrical systems [31]. On the other hand, Principal Component Analysis aids in data-driven fault diagnosis by reducing data dimensionality to focus on relevant fault features [106].

In practical wind turbine maintenance, vibration signals from accelerometers are essential for identifying early signs of wear in components like bearings, blades, and gearboxes. For example, pre-processing and filtering eliminate noise enhance and improve the reliability of the data used in real-time diagnostics. This processing allows to predict failures and address issues proactively, as well as improving turbine uptime and reducing emergency repairs. Siemens Gamesa uses signal acquisition systems to monitor turbine health, enabling early detection of issues that could cause costly outages.

## 4.2. Time and Frequency Domain Analysis

The cornerstone of vibration based monitoring lies in frequency domain analysis, particularly through Fast Fourier Transform (FFT) and spectral analysis techniques [57]. Spectral analysis is a way to analyze the vibration data based on the Fourier transform [30], [31]. These methods facilitate the decomposition of vibration signals into time or frequency components, aiding in the identification of fault-related frequencies and harmonics [20], [113]. Monitoring the vibration signatures of different components in the frequency domain helps in identifying potential faults and assessing the overall health of the wind turbine [57]. It enables early detection of faults, and identification of fault frequencies, and provides valuable awareness for effective maintenance strategies, ultimately contributing to the reliability and longevity of wind turbine systems. **Figure 9** shows the Time and Frequency Domain Analysis process.

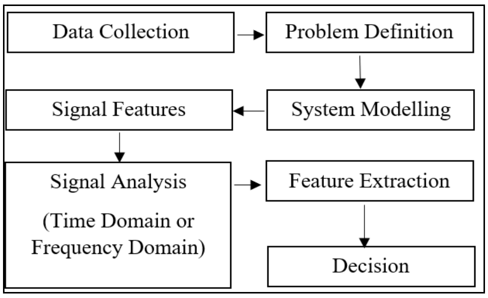


**Figure 9.** Time and frequency domain analysis process

Time and frequency domain analysis is widely applied in industry to decompose vibration signals in order to enable early detection of abnormal patterns. Fast Fourier Transform (FFT), for example, isolates fault frequencies in turbine bearings and gearboxes, to intervene before faults escalate. General Electric (GE) employs frequency domain analysis in its turbines to isolate vibration frequencies that correlate with specific faults, such as bearing or gearbox damage.

## 4.3. Time-Frequency Analysis

Time-frequency analysis techniques, such as the wavelet transform and Hilbert-Huang transform (HHT), offer advantages in capturing transient and non-stationary signals [11], [20], [30], [57]. As shown in **Figure 10**, the Hilbert-Huang transform is the result of empirical mode decomposition (EMD) and Hilbert spectral analysis (HSA) [118]. Other techniques of time-frequency analysis are the Short-Time Fourier Transform, Cepstral Analysis, Time-Frequency Distribution, Wavelet Packet Transform, and Empirical Mode Decomposition that can be established for detecting blade damage and imbalance in wind turbine blades [60], [119]. Empirical mode decomposition and Hilbert-Huang transform are adaptive signal processing techniques that can decompose non-stationary and nonlinear vibration signals into intrinsic mode functions (IMFs), facilitating the analysis of complex vibration patterns associated with turbine faults [120]. A combination of these time-frequency analysis techniques is often employed to ensure a comprehensive understanding of the vibration signals. This multi-faceted approach enhances the ability to detect and diagnose various mechanical issues, contributing to the overall reliability and performance of wind turbine.

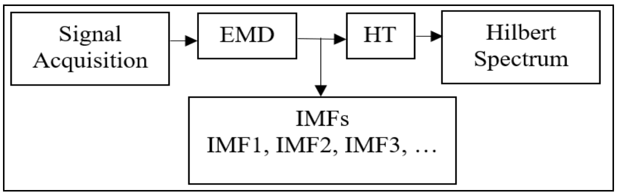


**Figure 10.** Hilbert-huang transform process

Time-frequency analysis, including wavelet and Hilbert-Huang transforms, is especially useful for handling non-stationary signals from wind turbines. They identify complex fault signals like blade imbalances. This addresses performance issues that would otherwise go undetected, especially in variable operational environments. Vestas uses wavelet transform-based time-frequency analysis to monitor the transient signals of wind turbines.

## 4.4. Envelope Analysis and Demodulation

Envelope analysis and demodulation techniques focus on extracting fault-related modulations from vibration signals [19], [30]. They are essential techniques in the field of vibration based techniques of condition monitoring, particularly in the context of wind turbines, which are subjected to various environmental and operational conditions, making it critical to monitor their health for optimal performance and to prevent unexpected failures [121]. Envelope analysis involves extracting the envelope of a signal, which represents the variation in amplitude over time. It is applied to vibration signals acquired from sensors placed on critical components such as bearings, gearboxes, and generators for identifying low-frequency modulation components associated with faults like gear tooth damage, bearing defects, and other machinery anomalies [64]. The demodulation process is closely related to envelope analysis and involves separating the high-frequency vibration signal from the low-frequency modulation components [113]. As a result, demodulation helps in isolating the specific fault-related information embedded in the signal. This separation allows for a more detailed analysis of the fault characteristics, making it easier to identify the root cause of the vibration anomaly. Bearing faults often exhibit amplitude modulations related to defects [53], [122]. **Figure 11** shows the demodulation flow chart.

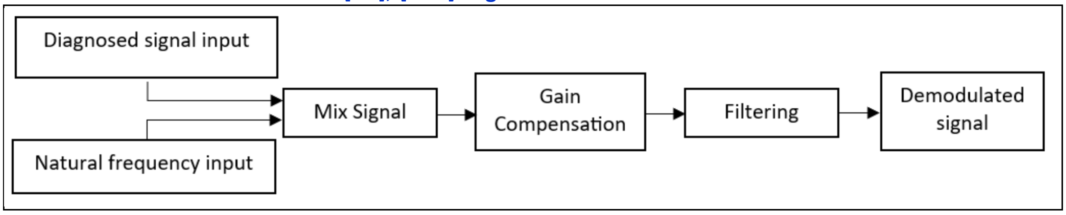


**Figure 11.** Demodulation analysis process

Envelope analysis has practical utility in isolating fault-related modulations within vibration signals. It is needed to identify bearing and gearbox defects. That is, it is used to detect amplitude variations that signify wear and address issues before they lead to catastrophic failures, in order to preserve turbine functionality and safety. Companies like SKF apply envelope analysis to monitor bearings in wind turbines.

## 4.5. Statistical and Pattern Recognition Techniques

Statistical methods and pattern recognition algorithms, including principal component analysis and artificial neural networks, aid in extracting fault signatures and identifying abnormal patterns within vibration data [65], [123]. These algorithms are integral to vibration analysis, mainly in machinery condition monitoring and fault diagnosis. The statistical techniques include descriptive statistics, probability distributions, hypothesis testing, regression analysis, and time series analysis. This provides the distribution, central tendency, and relationships within vibration data. The pattern recognition algorithms facilitate the extraction of meaningful features from vibration signals and the detection of anomalies or faults. They include supervised and unsupervised machine learning (ML) methods, as shown in **Figure 12**.

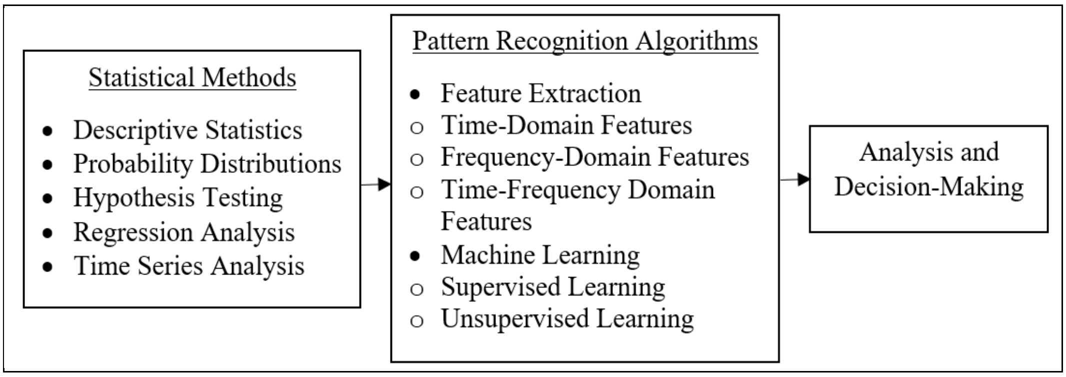


**Figure 12.** Statistical and pattern recognition processes

In real-world applications, Principal Component Analysis (PCA) statistical methods simplify vibration data for fault detection. However, machine learning algorithms can classify fault types. These techniques enhance condition monitoring systems by providing quick and accurate diagnostics for efficient decision-making and maintenance prioritization. Pattern recognition is applied by IBM's Watson IoT platform to monitor turbine health using algorithms.

## 4.6. Integration of Multiple Sensor Data

The wind turbines are equipped with various sensors, including accelerometers, strain gauges, temperature sensors, and oil condition sensors. Integrating data from multiple sensors provides a more comprehensive view of the turbine's health and performance, allowing for early detection of faults and abnormalities [31], [123]. Data fusion techniques combine information from different sensors to improve fault diagnosis accuracy and reliability. For example, combining vibration data with temperature measurements can help identify overheating bearings or gearbox components [47]. Multi-sensor integration, as shown in **Figure 13**, elevates wind turbine reliability, paving the way for sustainable and efficient energy generation.

By combining data from multiple sensors (such as accelerometers and temperature sensors) a holistic view of turbine health is gained. This integration enables more precise fault detection, identifies overheating issues and indicates component degradation, to extend component life. Siemens Wind Power integrates multiple sensor types to monitor the health of turbine components.

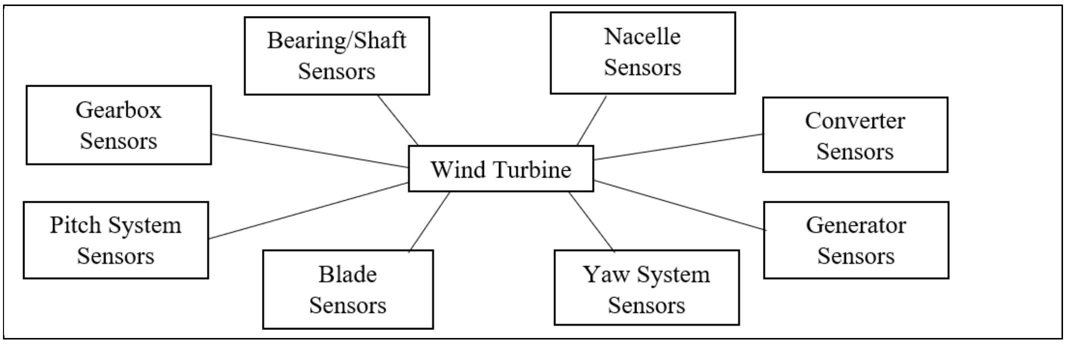


**Figure 13.** Wind turbine components and related sensors

## 4.7. Remote Monitoring and Internet of Things (IoT) Integration

Remote monitoring involves the continuous surveillance of wind turbine components from a centralized location. This approach leverages advanced wireless sensors, communication technologies, and cloud-based platforms to enable real-time data collection, analysis, and decision-making, ultimately enhancing the reliability and performance of wind energy systems [64]. Cloud computing platforms provide scalable storage and processing capabilities. They are used for analyzing large volumes of vibration data collected from multiple wind turbines. Cloud-based analytics tools can perform advanced data analytics tasks, like trend analysis, pattern recognition, and predictive maintenance modelling. They are using machine learning algorithms and big data techniques [124]. Recent advancements include the integration of vibration monitoring into IoT platforms, to enable remote monitoring and real-time data analysis [15], [123]. The integration of IoT technology in condition monitoring of wind turbine takes this approach to a higher level. IoT enables the collection and transmission of data from various sensors and devices in real-time. This provides a comprehensive overview of turbine health [121], as shown in **Figure 14**.

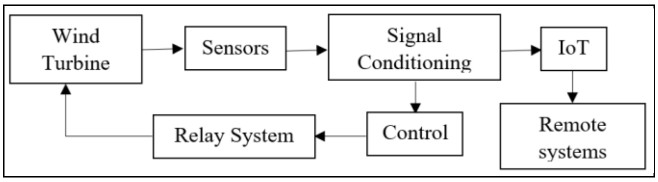


**Figure 14.** Wind turbine monitoring with IoT

IoT integration in real wind turbine monitoring systems facilitates remote diagnostics through continuously transmitting the vibration data to centralized platforms. This setup supports real-time analysis, responds quickly to anomalies, and reduces the need for frequent on-site inspections. Envision Energy incorporates IoT in its wind turbine fleet for remote monitoring

## 4.8. Prognostics and Health Management (PHM)

Vibration based prognostics and health management aim to predict component degradation and estimate the remaining useful life based on their existing health condition and operational history [47], [125]. These techniques utilize some advanced data analytics, including statistical modelling, machine learning, and physics-based models. They forecast potential failures and prioritize maintenance activities, as shown in **Figure 15**. By predicting failures before they occur, Prognostics and Health Management systems enable proactive maintenance strategies, minimize downtime, reduce repair costs, and extend the lifespan of critical components [125]. Prognostics takes vibration based monitoring to the next level by not only detecting current issues but also predicting the future health of critical components. This involves employing some advanced analytics, machine learning algorithms, and predictive modelling to assess the degradation of components and estimate their remaining useful life [126].

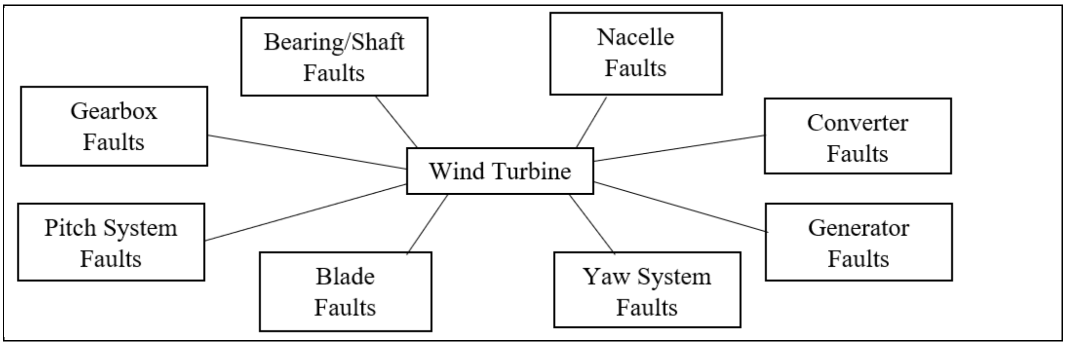


**Figure 15.** Wind turbine components faults

PHM systems predict component degradation and estimate remaining useful life. This is invaluable in operational turbines. The PHM systems enable proactive maintenance planning to reduce downtime and optimize resource allocation. GE Renewable Energy uses PHM systems to estimate the remaining useful life of critical turbine components based on the current vibration and operational data.

## 4.9. Machine Learning and Artificial Intelligence Integration

Machine learning and artificial intelligence algorithms are increasingly integrated into condition monitoring systems for wind turbines [48]. These algorithms can analyze vast amounts of vibration data collected from sensors installed on the turbine components. Supervised learning algorithms can be trained on labelled data to classify vibration patterns associated with different types of faults, such as bearing wear, gearbox damage, or blade imbalance [109]. Unsupervised learning techniques, such as clustering and anomaly detection, can identify abnormal vibration patterns that may indicate emerging faults or degradation in turbine components. Reinforcement learning algorithms can optimize maintenance strategies by learning from past maintenance actions and their outcomes, thus improving the efficiency of maintenance operations over time [127]. The human-cyber-physical system (HCPS) concept, shown in **Figure 16**, is one of the machine learning and artificial intelligence techniques of upcoming wind turbines [128]. This includes an artificial intelligence that directly controls the wind turbine operation in quasi-real-time.

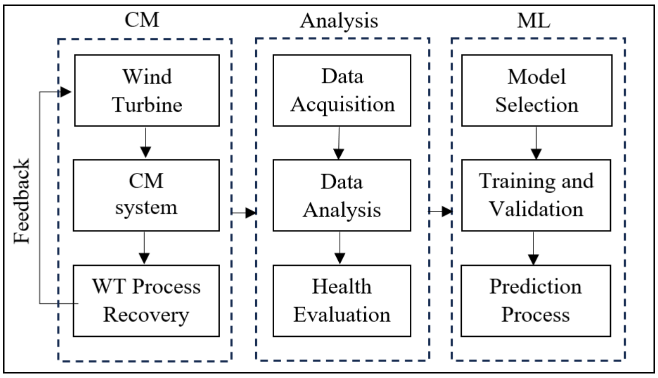


**Figure 16.** Condition monitoring with machine learning and artificial intelligence concept

Machine learning and artificial intelligence in condition monitoring analyze extensively the vibration datasets. They detect patterns associated with specific faults. In practice, artificial intelligence algorithms predict component wear and enable pre-emptive repairs. Siemens uses machine learning algorithms in their turbine monitoring systems in order to detect unusual vibration patterns associated with specific faults.

## 4.10. Condition-Based Maintenance

Condition-based maintenance strategies use real condition monitoring information to optimize maintenance schedules and prioritize maintenance activities based on the actual health condition of wind turbine components [21], [129]. Condition-based maintenance enables predictive and proactive maintenance actions, such as bearing replacements, gearbox overhauls, or blade inspections, before failures occur [130]. By avoiding unnecessary maintenance tasks and focusing resources on critical components, Condition-based maintenance strategies can reduce maintenance costs, extend equipment lifespans, and maximize turbine uptime and performance. **Figure 17** shows the workflow of the Condition-based maintenance strategy.

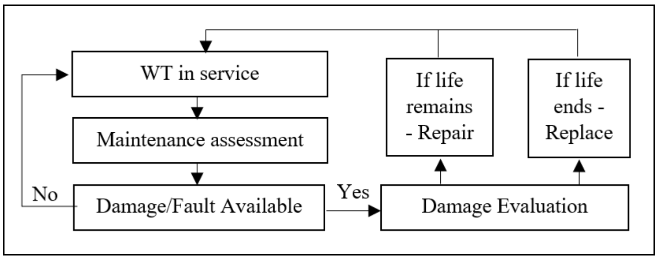


**Figure 17.** Workflow of condition-based maintenance strategy

Condition-based maintenance strategies control real-time data in order to schedule repairs based on actual equipment conditions rather than fixed intervals. This tailored approach reduces unnecessary costly maintenance and, at the same time ensures turbines operate at optimal efficiency with more sustainable energy production. Suzlon Energy implements condition-based maintenance on its wind turbines by monitoring real-time vibration data for guiding maintenance scheduling.

## 4.11. Eigensystem Realization Algorithm (ERA)

Eigensystem Realization Algorithm is basically a system identification technique. It is employed to extract the modal parameters (such as natural frequencies, mode shapes, and damping ratios) of a system from measured data. It is based on the realization theory of linear time-invariant systems and relies on the singular value decomposition of the system's response matrix [131]. In the context of condition monitoring of wind turbine, Eigensystem Realization Algorithm can be applied to the vibration data collected from the sensors that are installed on the turbine system. Eigensystem Realization Algorithm can identify the natural frequencies and mode shapes of the turbine blades, tower, and other components by analyzing the collected vibration signals. Any variations in these average parameters over time can indicate structural damage, fatigue, or other matters affecting the turbine's performance [59]. **Figure 18** shows Eigensystem Realization Algorithm process.

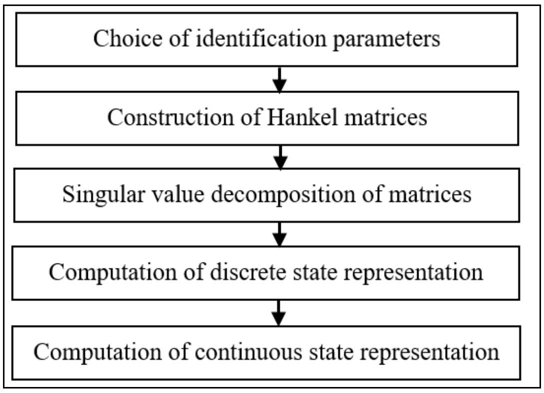


**Figure 18.** Eigensystem realization algorithm process

ERA is used in industry to monitor the structural integrity through extracting modal parameters from vibration data. In wind turbines, ERA helps to detect shifts in structural dynamics, indicate wear or damage in blades and towers, and finally enable early intervention before significant structural failures occur. The National Renewable Energy Laboratory (NREL) employs ERA to track structural changes in their turbine towers and blades.

## 4.12. Natural Excitation Technique (NExT) ERA

Natural Excitation Technique (NExT) is another method for a system identification. It aims to approximately estimate the modal parameters of a system without relying on external excitation sources. It utilizes the natural excitation existing in the structure itself, such as wind-induced vibrations or ambient noise, to extract the modal properties [132], [133]. In condition monitoring of wind turbines, Natural Excitation Technique can be particularly useful because it doesn't require additional external forces to be applied to the turbine. This can be challenging and sometimes impractical in operational wind farms. Natural Excitation Technique can still identify the natural frequencies, damping ratios and mode shapes of the turbine system by analyzing the ambient vibrations and noise picked up by the sensors [133]. Changes in these modal parameters can then be indicative of structural changes or damage that may require maintenance or repair [134]. **Figure 19** shows the Natural Excitation Technique Analysis used for wind turbines.

The NExT technique controls ambient vibrations, such as wind-induced motion. It extracts modal properties of turbine components without external excitation. In practice, this method allows for continuous monitoring of structural health, as well as supporting preventive maintenance actions based on real-world operating conditions. Companies like Ørsted apply this technique to track changes in modal parameters.

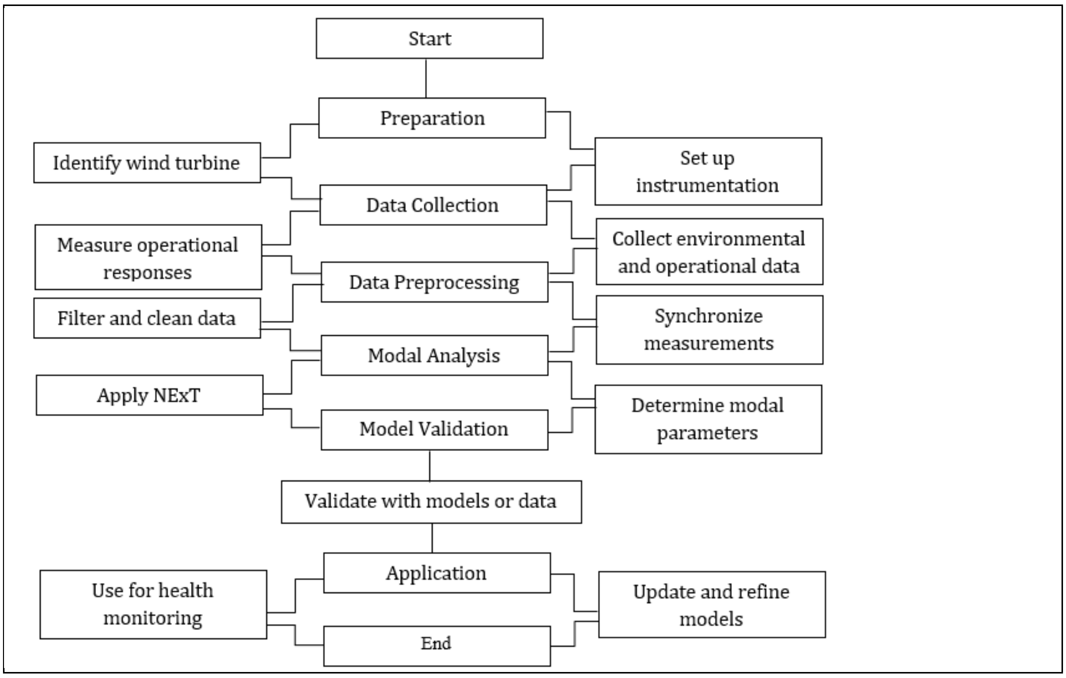


**Figure 19.** Natural excitation technique in wind turbine

## 4.13. Observer/Kalman Filter Identification (OKID)

The Observer/Kalman filter Identification is basically a timed-domain and data-driven modelling technique for system identification and fault detection in dynamic systems like wind turbines. It uses input-output data to estimate system dynamics and parameters, constructing mathematical models representing turbine behavior [135]. Observer/Kalman filter Identification facilitates model-based fault detection by predicting expected vibration responses and comparing them with measured data. Its adaptability and predictive maintenance capabilities enable it to anticipate and address issues, leading to optimizing maintenance efforts and maximizing turbine reliability. The Observer/Kalman filter Identification process chart is illustrated in **Figure 20**.

OKID applies model-based fault detection through estimating system dynamics and predicting expected vibration patterns. In industry, this technique identifies deviations from normal behaviour in turbine components. This is needed for maintaining high reliability in wind energy operations. The OKID technique is applied by companies like Goldwind to model turbine dynamics and predict expected vibration responses.

Vibration-based condition monitoring is a widely used technique for assessing the health of machinery and equipment. **Table 6** shows the strengths and limitations of these vibration based techniques of condition monitoring.

**Table 6.** Strengths and limitations of vibration based techniques of condition monitoring

| Technique | Strengths | Limitations | Potential Improvements |
|---|---|---|---|
| Signal Acquisition and Processing | Integrates vibration data with machine learning for fault classification. | Limited adaptability across different turbine models and environmental conditions. | Testing adaptability across diverse turbine models and environments. |
| Frequency Domain Analysis | Useful for analyzing environmental effects on turbine performance. | Only captures frequency information, missing transient faults. | Comparisons with time-frequency methods to improve fault detection. |
| Time-Frequency Analysis | Captures dynamic disturbances, addressing transient faults. | High computational demands, limiting real-time applicability. | Develop lower-computation methods or enhance real-time capabilities. |
| Envelope Analysis and Demodulation | Effective in identifying bearing faults. | Sensitive to noise, affecting reliability. | Combine with noise-robust techniques, like AI filters, for better fault isolation. |
| Statistical and Pattern Recognition | Reliable for fault classification in wind turbine pitch systems. | Limited scalability across diverse fault types. | Broader testing and IoT integration for faster data acquisition and response. |
| Integration of Multiple Sensor Data | Allows comprehensive health monitoring using vibration, torque, and electrical signals. | Data fusion challenges, leading to inconsistencies in fault detection. | Develop robust sensor fusion algorithms for diverse signal sources. |
| Remote Monitoring and IoT Integration | Enables remote tracking of turbine parameters, like speed and temperature. | Faces data security issues and slow response times. | Integrate with machine learning for predictive maintenance while ensuring data security. |
| Prognostics and Health Management (PHM) | Shows potential for long-term reliability and fault prediction. | Data acquisition challenges across various turbine models, limiting adaptability. | Develop PHM frameworks adaptable to real-time use, leveraging machine learning and sensor data. |
| Machine Learning and AI Integration | Optimizes turbine control systems, improving power generation. | High data requirements and model reliability concerns. | Standardize training data and explore models with reduced data dependency. |
| Condition-Based Maintenance (CBM) | Reduces maintenance costs, especially with support vector machine classification. | Lacks robustness for handling diverse fault types. | Explore hybrid models combining SVMs with other AI techniques for complex faults. |
| Eigensystem Realization Algorithm (ERA) | Sensitive parameter monitoring enhances structural health assessment. | Susceptible to false positives due to operational variability. | Refine algorithm for consistency across different environmental conditions. |
| Natural Excitation Technique (NExT) | Provides accurate modal identification of structural elements. | Limited to structural faults, less effective for operational issues like blade or gearbox faults. | Expand applicability to detect a wider range of faults, including non-structural issues. |
| Observer/Kalman Filter Identification | Effective for dynamic fault detection in turbine systems. | Computationally complex and challenging to implement in real time. | Simplify or optimize an algorithm for better real-time application. |

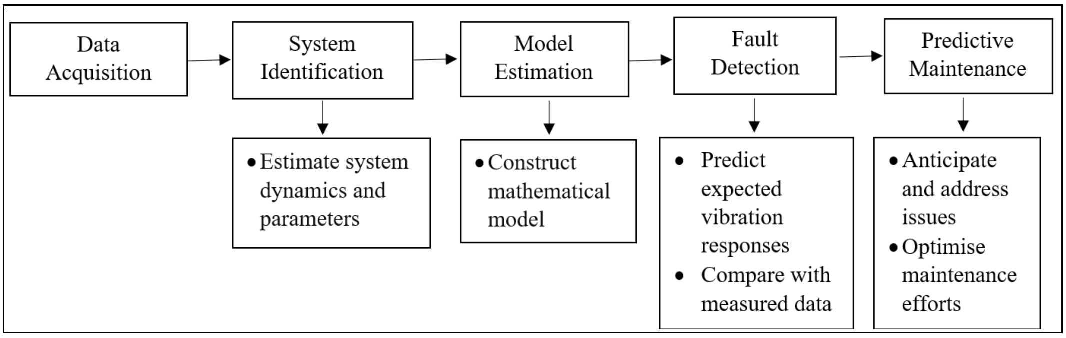


**Figure 20.** Observer/kalman filter identification process

Vibration based techniques of condition monitoring techniques for wind turbines have been extensively researched to improve reliability and reduce maintenance costs. Various methods, with time synchronous averaging, frequency domain analysis and bearing envelope analysis, have been evaluated on full-scale wind turbine drive trains [88]. While traditional techniques like vibration and oil analysis require multiple sensors and complex computations, cost-effective alternatives have emerged. One approach uses generator output power and rotational speed with continuous wavelet transform to detect faults in both fixed and variable-speed turbines [136]. Another study developed new techniques combining empirical mode decomposition, principal component analysis, and continuous wavelet transform with feature intensity level for early fault detection in turbine blades. Recent trends include acoustic emission for detecting incipient failures and optical fibered sensors for mechanical health monitoring of blades. These advancements aim to enhance wind turbine reliability and reduce downtime. For each of these techniques, **Table 7** summarizes published articles.

These vibration based techniques of condition monitoring techniques play a very important role in industrial maintenance by detecting faults in machinery before they escalate into costly failures. In this comparative analysis, these techniques are compared considering their performance, advantages, disadvantages, suitability, and computational costs, as shown in **Table 8**.

# 5. Progressions in Vibration based Techniques of Condition Monitoring

The field of vibration based techniques of condition monitoring of wind turbines has witnessed significant progress due to advancements in vibration analysis [60]. Ensuring the best performance and safety of wind turbines is needed for renewable energy generation [110], [111]. vibration analysis acts as an essential diagnostic means for monitoring the health and functionality of these complex systems. Over the years, vibration analysis has revolutionized the detection, analysis, and prediction of potential turbine failures, leading to more efficient maintenance strategies and increased reliability [9], [15]. The core principle behind vibration analysis in condition monitoring of wind turbines involves detecting and interpreting mechanical vibrations within the turbine structure [137]. Analyzing these vibrations offers a clear understanding of the overall health condition of turbine components, and enables proactive maintenance to minimize downtime.

## 5.1. Integration of Advanced Sensor Technologies

Recent advancements in vibration analysis for wind generators include the combination of recent advanced sensor technologies. Traditional vibrational monitoring structures generally depended on primary sensors to capture facts [31], [138]. However, the advent of high-precision accelerometers, stress gauges, and different advanced sensors has drastically better the information collection abilities [19], [123]. These sensors provide better sampling rates and increased sensitivity. This enables the monitoring of multiple factors concurrently and taking into consideration extra accurate and complete assessments of turbine vibrations. Additionally, the implementation of new wireless sensor networks has streamlined facts collection tactics. It enabled real-time monitoring of turbine vibrations and facilitated non-stop statistics transmission to centralized monitoring systems [139]. These improvements allow for prompt detection of abnormalities, fashion evaluation, and statistics-pushed decision-making with none constraints of bodily wiring. These enhancements encompass the development of state-of-the-art sensors and data acquisition structures, which give excessive-resolution vibration records [140]. Such advancements have enabled greater unique fault detection and analysis in machinery, as well as decreasing downtime and upkeep costs extensively.

**Table 7.** Description and critical analysis of published articles about vibration based techniques of condition monitoring techniques

| Ref. | Techniques used | Brief Description/Topics | Critical Analysis |
|---|---|---|---|
| [141] | Signal Acquisition and Processing | A method was presented for the health monitoring of wind turbine blades using vibration signal analysis and machine learning techniques for fault classification. | Establishes an initial integration of vibration data and machine learning, focusing on blade health. However, lack of exploration of performance across different turbine models and environmental conditions, indicating a gap in testing the adaptability of this approach. |
| [142] | Frequency Domain Analysis | Frequency-domain analysis of wind turbine performance in complex terrain was used to examine power spectral density and frequency response. | Useful for analyzing environmental effects on turbine performance, but is limited by its frequency-only focus. Flaws arise in comparing results with time-frequency methods, as the latter may capture transient faults that frequency analysis alone misses. |
| [143] | Time-Frequency Analysis | Time-frequency analysis was used to quantify and compare the time-varying power quality disturbances introduced by different wind turbine generator types. | Highlights advantages over frequency-only methods by capturing dynamic disturbances. However, time-frequency methods require high computational power, an identified gap for real-time applications. Further comparison with machine learning techniques could enhance predictive accuracy. |
| [144] | Envelope Analysis and Demodulation | Narrowband envelope analysis can effectively identify bearing faults in direct-driven wind turbines. | While highly effective for bearing fault detection, envelope analysis is sensitive to noise, limiting its reliability. Contrary findings on noise interference suggest a gap in combining this with noise-robust techniques, such as AI filters, for improved fault isolation. |
| [145] | Statistical and Pattern Recognition Techniques | A pattern recognition method was proposed for fault analysis of wind turbine pitch systems to improve reliability. | Demonstrates reliability in fault classification but lacks scalability across diverse fault types, indicating a need for broader testing. Combining pattern recognition with real-time IoT could enhance data acquisition and fault resolution speed. |
| [146] | Integration of Multiple Sensor Data | The use of multi-sensor data was explored to monitor the health condition of wind turbine systems, including vibration, torque, and electrical signals, | Highlights the benefits of multi-modal data but suffers from data fusion challenges. Contradictory findings show inconsistencies in fault detection accuracy when integrating sensor types, indicating a gap in robust sensor fusion algorithms for diverse signal sources. |
| [147] | Remote Monitoring and IoT Integration | A system was described for remote monitoring and control of wind turbine parameters like speed, vibration, and temperature using IoT. | Useful for remote fault tracking but limited by data security and response times. Integrating machine learning with IoT for predictive maintenance could address gaps in real-time decision-making while maintaining data security. |
| [148] | Prognostics and Health Management (PHM) | The challenges and opportunities in applying prognostics and health management (PHM) to wind turbine components were discussed | PHM shows potential for long-term reliability, though challenges in data acquisition from diverse turbine models limit effectiveness. Gaps remain in developing PHM frameworks adaptable to real-time applications, leveraging machine learning and sensor data integration. |
| [149] | Machine Learning and AI Integration | A comprehensive review of how AI and machine learning algorithms were used to optimize wind turbine control systems and improve wind power generation. | Illustrates the potential of AI for optimizing control systems but raises concerns about data requirements. Contradictory findings on AI model reliability indicate a need for standardization in training data, as well as lower data-dependency models. |
| [150] | Condition-Based Maintenance | A condition-based care policy for wind turbines using support vector machine classification can reduce maintenance costs. | SVM application shows promising cost reductions but lacks robustness across diverse fault types. Exploring hybrid SVM models combined with other AI approaches may close gaps in handling complex, multi-type faults within turbines. |
| [151] | Eigensystem Realization Algorithm (ERA) | The parameter sensitivity of the Eigensystem Realization Algorithm (ERA) was examined for estimating the structural parameters of a MW-size wind turbine. | ERA's sensitivity enhances structural monitoring but can lead to false positives. Contradictory findings on accuracy in various operational settings suggest a need for refining the algorithm to handle environmental variability in wind farms. |
| [132] | Natural Excitation Technique (NExT) | An improved Natural Excitation Technique (NExT) method was presented for more accurate modal identification of structures compared to the traditional NExT method. | The improved NExT offers precision in modal identification but has limited application to non-structural faults. Research gaps exist in expanding its applicability to detect operational faults, such as blade or gearbox issues. |
| [62] | Observer/ Kalman Filter Identification (OKID) | The Kalman filter and Luenberger estimator-based observers were presented for fault diagnosis in the pitch system of a wind turbine. | Effective in dynamic fault detection, but observer techniques are complex and computationally intensive. Contradictory results on real-time application feasibility indicate a need for algorithm simplification or optimization for practical use. |

**Table 8.** Comparison of vibration based techniques of condition monitoring

| Technique | Performance | Advantages | Disadvantages | Suitability | Costs |
|---|---|---|---|---|---|
| Signal Acquisition and Processing | Direct measurement of vibration signals | Direct insight into machine behaviour | Limited to basic fault detection | Simple systems with known faults | Low to moderate |
| Frequency Domain Analysis | Analysis of frequency components in signals | Good for identifying specific frequencies. | Limited ability to detect transient faults | Systems with known fault frequencies | Moderate |
| Time-Frequency Analysis | Captures time-varying spectral content. | Suitable for non-stationary signals | Computationally intensive | Systems with dynamic operating conditions | Moderate to high |
| Envelope Analysis and Demodulation | Focuses on amplitude variations over time | Effective for detecting amplitude modulation | Sensitive to noise and signal distortions | Systems with clear fault signatures | Moderate |
| Statistical and Pattern Recognition Techniques | Utilizes statistical models for fault detection | Robust to noise and signal variations | Requires extensive training data | Systems with diverse fault patterns | Moderate to high |
| Integration of Multiple Sensor Data | Fusion of data from various sensors | Enhances fault detection accuracy | Complexity in sensor synchronization | Complex systems with multiple failure modes | Moderate to high |
| Remote Monitoring and IoT Integration | Real-time monitoring from remote locations | Enables proactive maintenance strategies | Dependency on network connectivity | Distributed systems or inaccessible locations | Moderate |
| Prognostics and Health Management (PHM) | Predicts the remaining useful life of machinery | Allows for predictive maintenance scheduling | Relies on accurate degradation models | Critical systems requiring high uptime | Moderate to high |
| Machine Learning and AI Integration | Utilizes algorithms to learn from data | Adaptability to changing operating conditions | Complexity in model interpretation | Systems with complex fault patterns | High |
| Condition-Based Maintenance | Maintenance triggered by equipment conditions | Cost-effective compared to time-based methods | Requires accurate condition monitoring | Systems with predictable failure modes | Low to moderate |
| Eigensystem Realization Algorithm (ERA) | Accurate estimation of modal parameters | Accurate with noisy data, handles both deterministic and stochastic inputs | Requires high-quality data, sensitive to model assumptions | Systems with controlled testing and high accuracy | Moderate to high |
| Natural Excitation Technique (NExT) | Provide less precise estimates | Doesn't require external excitation sources, suitable for operational monitoring | Relies on ambient excitation, less accurate than controlled excitation methods | Systems with controlled excitation is impractical | Low to Moderate |
| Observer/Kalman Filter Identification (OKID) | System identification technique for fault detection | Effective for identifying system dynamics | Requires accurate modelling of the system | Systems with well-defined dynamic models | Moderate to high |

## 5.2. Innovations in Signal Processing and Digital Twins

Innovation in vibration analysis for condition monitoring of wind turbines has been driven by means of the requirement for more correct and early detection of faults. Advanced signal processing methods, like wavelet transforms and experimental mode decomposition [140], were used to improve the capacity to identify and isolate faults in complicated machinery [43], [48], [49]. Furthermore, using virtual twins has grown to be awesome in vibration evaluation for wind turbines. Digital twins are virtual imitations of bodily belongings that simulate their conduct in actual time [152]. By combining sensor information with computational models, those virtual twins can mirror the real turbine overall performance, and permit non-stop monitoring, overall performance optimization, and scenario trying out without disrupting operational turbines. This technology helps a deeper knowledge of vibration dynamics and facilitates predictive upkeep strategies [18]. Additionally, advancements in signal processing techniques have contributed to the more specific and green analysis of vibration statistics. They are extracting valuable information from complicated vibration alerts and enhancing fault detection and prognosis accuracy [43], [48], [49].

## 5.3. Machine Learning and AI in Predictive Maintenance

Machine learning (ML) and artificial intelligence (AI) enable predictive upkeep via analyzing large quantities of vibration statistics. They pick out patterns and are expecting ability faults before they arise [48], [109]. AI algorithms can understand oblique adjustments in vibration styles, and correlate them with regarded failure modes, after which generate early warnings or protection pointers. This proactive method minimizes downtime and optimizes turbine performance [16]. The integration of ML and AI has caused the development of autonomous vibration based totally techniques of condition monitoring structures capable of real-time condition monitoring. The use of deep learning knowledge of models became confirmed in automatically diagnosing faults with nominal human involvement [153]. The application of system machine learning algorithms, which include neural networks and guide vector machines, becomes highlighted in studying vibration facts to predict machinery health [72], [76], [153]. These algorithms may be learnt from historical information, to pick out styles and anomalies which could suggest imminent disasters. Hybrid models combine multiple gadgets gaining knowledge of strategies. Neural networks and fuzzy logic hybrid systems showed enhanced fault diagnosis capabilities [153]. These advancements have collectively enhanced the precision, efficiency, and reliability of condition monitoring systems, as well as ensuring the sustained health and performance of critical machinery across industries. Recent advancements in vibration based techniques of condition monitoring have significantly improved the fault detection and diagnosis in industrial machinery. The integration of machine learning and artificial intelligence has revolutionized these techniques, and enabled more accurate and reliable monitoring systems [154]. Deep learning approaches have revealed promise in analyzing vibration signals for fault diagnosis in rotating equipment [155]. These data-driven methods offer computational efficiency and can handle complex problems, and making them particularly useful for bridge health monitoring [140]. Vibration analysis remains the most effective method for predictive maintenance, as it allows for the detection of developing bearing defects before they cause further damage [53], [156]. The combination of vibration based monitoring techniques with machine learning has led to quick digital transformation in keeping the continuous performance of existing structures [157].

# 6. Challenges in Vibration based Techniques of Condition Monitoring

Vibration based techniques of condition monitoring is a critical step of ensuring the structural integrity and optimal performance of wind turbines [21], [59]. These massive structures harness wind energy, converting it into electricity, but they also face numerous challenges, particularly in the realm of vibration analysis [138]. The nonstationary, stochastic nature of wind turbine vibrations complicates fault diagnosis and requires advanced analysis techniques like spectrogram and bi-spectrum analyses [76], [158]. Offshore wind turbines present additional difficulties due to their remote locations, making data transfer and maintenance costly and time-consuming [159]. Reliability-centered maintenance strategies, including accurate condition monitoring systems, are needed for improving availability and reducing energy costs [30]. However, existing commercial monitoring systems often rely on techniques from other industries, which may not be fully adapted to wind turbine specifics. To address these challenges, researchers are exploring innovative approaches, such as integrating event-based alerts with SCADA data for more effective condition monitoring [159], [160]. As the wind energy sector grows, developing reliable and cost-effective monitoring techniques remains a priority [11]. Researchers worked on understanding these challenges in maintaining the functionality and safety of wind turbines [30], [61], [65]. **Table 9** shows some of these challenges.

**Table 9.** Summary of vibration based techniques of condition monitoring challenges

| Category | Challenges |
|---|---|
| Environmental factors | Environmental variability and high operational loads |
| Structural complexity | Complex mechanical structures and nonlinear behavior |
| Operational challenges | Limited accessibility, and fault diagnosis and prognosis |
| Data and analysis | Data analysis and interpretation, sensor placement and reliability |
| Cost and resource management | Cost and resource constraints |

One of the primary obstacles in vibration analysis for wind turbines is the complex nature of the data. These machines operate in varying environmental conditions, resulting in diverse vibration patterns influenced by wind speed, turbulence, direction, and other atmospheric factors [55]. Analyzing these multifaceted statistics needs for state-of-the-art algorithms and gear capable of discerning regular operational vibrations from those indicating capability faults or damages in the functioning zones of the power curve.

Moreover, wind turbines are subjected to incessant dynamic loading due to the fluctuating wind forces [52]. This continuous stress can lead to fatigue in materials, causing wear and tear that manifest as changes in vibration patterns [117]. Identifying these subtle alterations amidst the background noise of normal operational vibrations is a significant challenge for effective condition monitoring [64]. Another hurdle in vibration evaluation is the sheer size and top of wind turbines. Offshore wind turbine, particularly, pose logistical challenges for information collection and analysis. Accessibility problems arise, making it difficult to install and maintain vibration monitoring system. Monitoring structures should be long lasting enough to withstand harsh environmental conditions whilst also being easily serviceable in faraway locations [58], [138]. Furthermore, the structural complexity of wind turbines adds some other layer of issue [22]. These machines comprise numerous components, together with blades, gearboxes, turbines, and bearings, every with its vibration signature [23]. Distinguishing among vibrations originating from different components and determining the foundation reason of abnormalities requires advanced analytical strategies and understanding [43]. Additionally, the presence of fake alarms or ambiguous vibration signatures can impede accurate diagnostics. Factors consisting of adjustments in wind situations or operational modes can result in transient vibrations that may mimic fault signs. Distinguishing between those brief vibrations and actual faults may be very important to save you useless downtime and renovation charges [65]. Integration and standardization of monitoring systems pose any other project in the area of vibration primarily based strategies of situation monitoring [161]. Wind turbine manufacturers regularly use extraordinary monitoring technology and protocols, ensuing in compatibility issues and making information interpretation and contrast throughout specific generators a frightening project. Addressing these challenges is needed to ensure the longevity, reliability, and safety of wind turbine in generating easy and sustainable power [30], [61].

To address the challenges in vibration-based condition monitoring for wind turbines, researchers and industry practitioners have been exploring several potential solutions and innovative approaches. **Table 10** shows these proposed solutions and approaches:

**Table 10.** Potential solutions and approaches to address the challenges in vibration-based condition monitoring for wind turbines

| Challenge Category | Proposed Solutions/Approaches |
|---|---|
| Complex Vibration Data | Using wavelet transform, empirical mode decomposition (EMD), and variational mode decomposition (VMD) to separate fault-induced vibrations from operational signals [140]. |
| Sensor Technology & Accessibility | Implementing wireless accelerometers and fiber optic sensors for more accurate data capture [64].<br>Positioning sensors on specific turbine components to isolate fault signals [49]. |
| Data Interpretation & False Alarms | Leveraging machine learning algorithms like deep learning and neural networks to analyze large datasets, reduce false alarms, and improve diagnostic accuracy [71]. |
| Data Transfer for Offshore Turbines | Utilizing 5G and edge computing to enable faster data transfer and real-time processing for remote monitoring and efficient response in offshore wind turbines [64]. |
| Maintenance and Resource Management | Applying predictive models to estimate component lifespan, optimize maintenance schedules, reduce downtime, and extend the operational life of turbine parts [92]. |
| Standardization & System Integration | Developing unified data formats and diagnostic criteria for better cross-comparison and benchmarking across turbines from different manufacturers [91]. |

# 7. Trends in Vibration based Techniques of Condition Monitoring

Vibration primarily based techniques of condition monitoring of wind turbines have visible sizeable advancements in latest years, driven with the aid of the increasing want for reliable and green renewable energy resources. Modern trends on this area emphasized the combination of new advanced sensor technology, like wireless accelerometers and MEMS sensors, which provide better sensitivity and actual-time statistics acquisition. Additionally, the implementation of machine learning algorithms and synthetic intelligence has revolutionized the evaluation of vibration facts, allowing more correct fault detection and predictive upkeep. These technologies facilitate the early identification of issues consisting of imbalance, misalignment, and bearing wear, thereby lowering downtime and maintenance prices. The flow toward cloud-based monitoring structures additionally allows for the centralized evaluation of statistics from more than one turbine, improving the capacity to carry out fleet-extensive health tests [162]. Those developments make contributions to the improved reliability, performance, and lifespan of wind turbine operations.

## 7.1. Role of Big Data and IoT

Big Data techniques are increasingly essential in the condition monitoring of wind turbines. They address the challenges of managing the massive volumes of data generated by modern sensor technologies [163], [164]. With data output reaching around 2 TB monthly, these Big Data techniques enable efficient processing and analysis of vast datasets. They facilitate the detection of system deterioration and optimize maintenance scheduling [164]. The real-time monitoring and online analysis of wind turbine conditions are possible by combining Big Data with advanced sensors, such as Macro Fiber Composites. Both enhance the ability to track equipment health continuously [165].

Recent advancements extend beyond Big Data to include machine learning and data mining strategies. They are transforming predictive maintenance and health assessment for both individual wind turbines and larger wind farms [38]. These smart analytics, in combination with Big Data processing, significantly improve fault diagnostics, provide early failure predictions, and enhance overall system reliability and economic performance [124]. As condition monitoring technologies progress, the AI based algorithms are becoming essential for processing the complex datasets generated by turbine sensors and refining the accuracy and efficiency of predictive models [38]. The integration of advanced sensor technology has substantially enhanced data collection capabilities within vibration based monitoring of wind turbines [19], [31], [64], [123]. IoT and cloud-based systems are revolutionizing data collection, processing, and remote access. They enable real-time monitoring, predictive analytics, and proactive maintenance planning from virtually any location [166]. This shift allows to rely on early-warning systems that reduce the need for on-site inspections [121].

The AI and IoT technologies are expected to drive the evolution of autonomous, real-time monitoring systems. AI algorithms will further optimize predictive maintenance models by offering more precise forecasts of potential faults, based on both historical and live vibration data [17], [18]. These algorithms are particularly those that continuously learn from incoming data. Additionally, advancements in IoT enabled sensors will continue to improve the depth and quality of data collected and allow for more granular insights into turbine health and performance. As these tools advance, the industry-wide anticipation will shift significantly towards condition-based maintenance strategies [16], [167], [168].

## 7.2. Potential Impact of New Technologies on Condition Monitoring

Recent advancements in condition monitoring of wind turbine have focused on various technologies and approaches. Vibration analysis, oil debris analysis, and acoustic emission are established condition monitoring techniques for detecting failures in components like gearboxes and bearings [23], [169]. SCADA data has gained attention for cost-effective condition monitoring, with approaches including trending, clustering, and normal behavior modeling [34], [50], [160]. Initial experiences with condition monitoring systems have revealed challenges such as the 3/revolution effect due to tower shadow and wind shear, leading to the development of enhanced time synchronous average algorithms [59], [170]. Emerging technologies for structural health monitoring include optical fiber sensors embedded in blades and radiography inspection methods [22], [169]. Both signal-based and model-based approaches are being explored for fault diagnosis and lifetime prognosis, with ongoing research focusing on improving the reliability and availability of wind turbines [39], [60].

New technologies are revolutionizing the field of vibration based techniques of condition monitoring for wind turbines, leading to increased reliability, reduced downtime, and enhanced performance in the renewable energy sector [9], [171]. The refinement of signal processing algorithms, frequency analysis, time-domain analysis, and spectral analysis techniques provides a deeper understanding of the complex vibration patterns in wind turbines [31], [172]. The implementation of digital twins enables simulation and predictive analysis based on real-time vibration data, aiding in optimizing performance and predicting potential failures [127], [173]. These technological advancements contribute meaningfully to the efficiency and effectiveness of condition monitoring, as well as ensuring the longevity and reliability of wind turbines [152].

## 7.3. Future Directions

Condition monitoring of wind turbines has become increasingly important as the wind energy sector keeps growing, with a focus on reducing operation and maintenance costs while improving reliability [11]. Current condition monitoring of wind turbine techniques includes vibration analysis and acoustic emission detection [169]. Time-frequency analysis tools like wavelets are widely used due to the variable-speed nature of wind turbines [169]. Emerging trends in condition monitoring of wind turbine include optical fiber sensors for structural health monitoring, radiography inspection, and Wi-Fi networks for cost-effective communication [59], [169]. The industry is moving towards more advanced turbine designs and reliable, cost-efficient monitoring techniques to enhance availability and reduce maintenance costs [174], [175]. Future challenges involve addressing weaknesses in current condition monitoring of wind turbine practices and defining research priorities to meet the evolving technological and market demands of the wind industry [11], [175].

The current state of vibration based techniques of condition monitoring for wind turbines highlights notable technological advancements and identifies several critical gaps requiring further research and development [15]. Recent studies have aimed at refining signal processing techniques, integrating machine learning algorithms, and enhancing remote monitoring capabilities in vibration based techniques of condition monitoring for wind turbines. Specifically, advanced signal processing methods like envelope analysis and demodulation have proven essential in bearing fault detection [45], [92]. Moreover, the role of machine learning in fault classification and estimating remaining useful life is becoming increasingly prominent. However, significant challenges persist, such as the need for improved fault diagnostics and severity assessments [19]. Standardization of diagnostic protocols and thresholds remains inconsistent [91]. The computational complexity, especially in remote monitoring, is a considerable challenge [58], [64]. Future research should focus on developing enhanced methodologies for fault severity assessment, as well as establishing standardized diagnostic protocols, advancing real-time analytics and edge computing, and integrating robust multi-sensor fusion techniques [15], [43], [44], [61]. Large-scale field tests and validation studies are also important to verify the efficacy and reliability of these techniques under different operating conditions and wind turbine types [19].

# 8. Conclusions and Recommendations

## 8.1. Conclusions

The literature overview on vibration based techniques of condition monitoring of wind turbines well-known shows that this approach is both powerful and important to make sure the reliability and performance of wind strength structures. Vibration based monitoring allows early detection of mechanical faults, together with bearing wear, gearbox issues, and blade imbalances, thereby mitigating the risk of unexpected failures and decreasing renovation costs [68]. The potential to display actual-time vibrations and analyze patterns allows for predictive renovation techniques, which might be critical in optimizing turbine performance and lengthening operational lifespans.

Comparatively, vibration based totally monitoring stands proud in opposition to other situation monitoring strategies inclusive of oil analysis, thermal imaging and acoustic emission. While every technique has its merits, vibration based totally monitoring offers an extra direct and quantifiable approach for detecting mechanical anomalies. It presents continuous, real-time records which can be analyzed to are expecting any capability disasters, not like other techniques which can be greater situational or much less complete in their diagnostics.

The important analysis of the reviewed techniques highlights several trends. Developments in sensor generation, data acquisition, and machine learning algorithms advanced significantly the accuracy and efficiency of vibration primarily based monitoring structures. However, challenges continue to be in integrating those systems with current turbine infrastructure and coping with the bigger volumes of generated information. The variability in turbine designs and operational situations also complicates the standardization of vibration monitoring practices.

## 8.2. Recommendations for Future Research:

- Integration with Predictive Analytics: Future research needs to focus on enhancing the integration of vibration data with advanced predictive analytics and machine learning models. This will improve fault detection accuracy and enable more precise forecasting of component failures.
- Standardization and Benchmarking: Developing standardized protocols and benchmarks for vibration monitoring across different turbine models and manufacturers will facilitate better comparison and validation of monitoring systems and techniques.

- Sensor Technology Advancements: Continued research into the development of more durable, cost-effective, and high-resolution sensors will further enhance the capabilities of vibration based monitoring systems.
- Data Management and Interpretation: Addressing the challenges associated with managing and interpreting large volumes of vibration data is important. Research should explore efficient data processing methods and algorithms to extract actionable insights and reduce data overload.
- Integration of AI and IoT for real-time for autonomous fault detection in wind turbines and focusing on accurate predictive models that adapt to varying conditions. Efforts should consider data standardization, interoperability, and cybersecurity to support robust and scalable implementation.
- Integration with Other Monitoring Techniques: Combining vibration based monitoring with other condition monitoring techniques, such as acoustic emission and thermal imaging, could provide a more comprehensive approach to condition assessment and failure prediction.
- Field Studies and Real-world Validation: Conducting field studies and real-world validation of advanced vibration monitoring systems will help assess their practical effectiveness and reliability in diverse operational environments.

The future research can further enhance the effectiveness of vibration based condition monitoring by addressing these areas and contributing to the advancement of wind turbine technology and the broader wind energy industry.

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# Authors' Declaration

**Authors' contributions and responsibilities** - A. H. A. designed the framework of this paper and was a major contributor in writing the manuscript. K. C. V. was a major contributor in sections 2, 3 and 4. V. V. K. was also a major contributor in revising the manuscript and improving sections 5, 6, 7 and 8. All authors read and approved the final manuscript.

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