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AI-Based Predictive Maintenance Techniques for Bearings: Emerging Research Trends and Engineering Solutions

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Abstract

Bearings are essential components across a wide range of mechanical systems, facilitating smooth motion with minimal energy dissipation. Therefore, their maintenance and health monitoring are critical for ensuring system reliability and operational safety. With the increasing integration of advanced digital technologies into industrial processes, condition monitoring systems have become indispensable for the early detection of bearing wear and damage, allowing interconnected machines to gather vast amounts of data and convert it into actionable insights. While extensive datasets offer significant opportunities for analysis, they are often subject to noise, biases, and inconsistencies that complicate the development of accurate physical models, particularly in complex, dynamic systems. Machine learning has emerged as a powerful tool for extracting meaningful insights from large-scale datasets, enabling automated detection, classification, and prediction of bearing faults without the need for explicit programming, thereby reducing the necessity for human intervention.

This thesis provides a thorough review of peer-reviewed scientific literature alongside currently available engineering solutions in the field of intelligent bearing fault diagnosis. In this context, it critically examines existing technologies in relation to the established body of knowledge, identifying and analysing any gaps that may exist between these domains. By investigating potential factors contributing to such disparities, this work offers informed projections for future developments in intelligent bearing fault diagnosis.

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Chapter 1

1 Introduction

Bearings are fundamental components in a wide array of mechanical systems, serving to reduce friction and facilitate smooth rotational or linear motion. Their reliable operation is crucial for maintaining the efficiency and safety of these systems, as any degradation in bearing performance can lead to increased energy consumption, unexpected downtime, and even catastrophic failures. Consequently, the maintenance and continuous health monitoring of bearings have become indispensable practices in modern industry, particularly as mechanical systems become more complex and interconnected. With the rapid integration of advanced digital technologies, condition monitoring systems are increasingly equipped with capabilities to detect early signs of bearing wear and damage, enabling proactive maintenance strategies that reduce operational risks and costs.

This critical role of bearings and the importance of early fault detection and diagnosis are discussed in detail in Section 2, including the challenges posed by the ongoing process of industrial digitalization. As interconnected machines and sensors become more prevalent, they generate vast amounts of operational data, which serve as a valuable resource for monitoring and diagnosing bearing health. However, this influx of data introduces new challenges, such as noise, biases, and inconsistencies, which complicate the development of accurate physical models, particularly within complex and dynamic systems. Traditional diagnostic approaches, as explored in Section 3, struggle to cope with these challenges, limiting their effectiveness in real-world applications and highlighting the need for more robust methods. To address these limitations, Section 4 explores the application of artificial intelligence (AI) as a transformative approach in bearing fault diagnosis. Through a decision tree framework developed to categorize and systematically label various publications, this section lays the groundwork for a structured discussion of AI-driven techniques in the field. This framework supports the literature review by organizing research findings and enabling a critical evaluation of emerging trends and innovations in intelligent fault diagnosis.

Section 5 presents the findings of the literature review, based on approximately 150 selected articles. The analysis highlights recent advancements in the field and identifies emerging trends, providing a comprehensive overview of key developments and potential directions for future research. To bridge the gap between theory and practice, Section 6 examines how leading companies utilize AI-based approaches for bearing fault diagnosis, leveraging insights from real-world applications while adhering to confidentiality boundaries. Finally, Section 7 brings the thesis to a close by synthesizing the key findings, comparing theoretical advancements against current industry practices, and highlighting disparities between research and implementation where they exist. This concluding section also acknowledges the study's limitations and proposes future research directions for developing more adaptive and resilient diagnostic solutions.

By addressing these areas in a structured, comprehensive manner, this thesis provides a thorough understanding of current methodologies while establishing a foundation for advancing intelligent bearing fault diagnosis. It contributes to the field by highlighting actionable insights and fostering innovations to enhance diagnostic accuracy and predictive maintenance in complex industrial environments.

Chapter 2

2 Bearings: Critical Role and the Importance of Monitoring

In mechanical systems, bearings play a crucial role in facilitating smooth rotational or linear motion, directly influencing overall efficiency and safety. These components operate by transferring the primary load through rolling contact elements rather than sliding contact, resulting in much lower friction compared to the starting friction typically observed in sleeve bearings. Bearing performance and service life depend not only on their design and materials but also on regular diagnostics and maintenance practices. Till this very day, skilled engineers are essential in almost all aspects of bearing diagnostics, from inspecting contact surfaces for wear to selecting critical diagnostic features and optimizing maintenance strategies. For larger bearings, such as those used in wind turbines, diagnostics become even more critical due to unique stresses and high remanufacturing potential. In these cases, engineers evaluate whether remanufacturing is a viable option, offering a sustainable solution that lowers costs, prolongs service life, and enhances reliability. However, accessing experienced bearing analysts remains a challenge due to the specialized knowledge required, which is often acquired over years of experience.

2.1 Bearings in Mechanical Systems

Bearings are designed to handle pure radial loads, pure thrust loads, or a combination of both. Depending on the type of load (static or dynamic) and other operational factors, such as friction, heat, corrosion resistance, kinematic issues, material properties, lubrication, machining tolerances, assembly, and usage; the designer selects a specific bearing configuration. Bearings can be broadly categorized into four main types based on structural design: Ball Bearings, Roller Bearings, Plain Bearings, and Magnetic and Fluid Bearings. Each type has unique characteristics suited to specific applications, load capacities, and motion requirements.

1. ***Ball bearings***

   Using spherical balls as rolling elements, these provide smooth, low-friction rotation. They are primarily designed for radial loads, although some types can handle moderate axial loads, with certain designs specifically engineered for axial loads alone.

   a) ***Deep Groove**:* Designed with deep grooves to support both radial and moderate axial loads, commonly used in electric motors and pumps.
   b) ***Angular Contact**:* Featuring angled contact surfaces, these support both radial and higher axial loads, suitable for high-speed applications like turbines.
   c) ***Self-Aligning**:* The spherical outer raceway allows for slight misalignment, making them suitable for applications such as conveyor systems.
   d) ***Thrust**:* Exclusively for axial loads, making them unsuitable for radial loads, commonly used in applications like swivel chairs and turntables.

   Applications: Electric motors, fans, automotive components, and high-speed machinery that requires smooth, low-friction motion.

2. ***Roller bearings***

   Employing cylindrical, tapered, or barrel-shaped rollers, these bearings provide a larger contact area than spherical ball types. This design supports higher radial loads, making them ideal for heavy-duty applications.

   a) ***Cylindrical:*** Uses straight cylindrical rollers to support high radial loads, commonly found in gearboxes and heavy machinery.
   b) ***Tapered:*** With conical rollers, these support both radial and axial loads, frequently used in vehicle wheel hubs and gearboxes.
   c) ***Spherical:*** Barrel-shaped rollers offer self-alignment, suitable for heavy loads and applications with potential misalignment, such as mining equipment.
   d) ***Needle:*** Compact and using long, thin rollers, needle types are ideal for high-load capacities in space-limited applications like automotive transmissions.
   e) ***Thrust:*** Built to handle heavy axial loads, often found in crane hooks and industrial machinery.

   Applications: Heavy machinery, mining equipment, automotive transmissions, and industrial applications needing high load capacity.

3. ***Plain bearings (Sleeve Bearings)***

   Also known as sleeve or journal bearings, these contain no rolling elements and rely on a sliding motion between two surfaces, typically lubricated to reduce friction. Simple and durable, they are highly effective in high-load, low-speed applications. Historically, this is one of the oldest bearing configurations.

   a) ***Sleeve:*** Cylindrical in shape, allowing a shaft to slide within the bearing surface, suitable for high-load, low-speed applications.
   b) ***Flange:*** Featuring a flange on one side to support axial positioning and prevent shaft movement, useful in applications requiring precise positioning.

   Applications: Agricultural machinery, heavy-duty equipment, hinges, and applications with continuous or heavy loads where low-speed operation is typical.

4. ***Magnetic and fluid bearings***

   Operating without direct contact, these advanced bearings provide virtually frictionless motion. Ideal for high-speed and high-precision applications where minimal friction and wear are crucial.

   a) ***Magnetic:*** Uses magnetic fields to suspend the load without physical contact, suitable for applications requiring extremely low friction and high-speed capabilities, such as turbines and compressors.
   b) ***Fluid:*** Employs a thin layer of liquid or gas to support the load, reducing friction and wear, especially in high-speed applications.

   Applications: High-speed turbines, compressors, precision instruments, and computer hard drives where frictionless motion is essential for optimal performance.

Focusing hereafter on the first two categories, which are the most commonly employed families of bearings, we use a deep groove ball bearing, as illustrated in Figure 1 provided by [1], to show the nomenclature typically used, along with the essential components of these systems. These components include the outer ring, inner ring, balls or rolling elements, and the separator (or cage). In some lower-cost bearings, the separator may be omitted; however, it plays an important role in preventing rubbing contact by keeping the rolling elements separated. Each of these parts can degrade and ultimately fail, either individually or in combination with the other components, with each part exhibiting distinct failure modes. This underscores the complexity involved in analysing such a system.

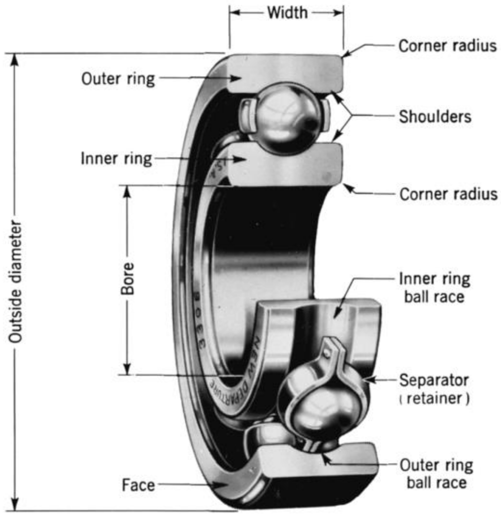

Figure 1: Nomenclature of a ball bearing.

2.2 Bearing Failure Modes and Causes

As previously mentioned, during the design process, bearing specialists consider factors such as fatigue loading, friction, heat, corrosion resistance, kinematics, material properties, lubrication, machining tolerances, assembly, usage, and other elements that affect operational performance, all of which contribute to a relatively low failure rate. According to [2], an estimated 10 billion bearings are produced worldwide each year, of which only a small fraction fail. As shown in Figure 2, approximately 9.5% are replaced for preventive reasons, prior to failure, suggesting that only around 0.5% are replaced due to actual failure.

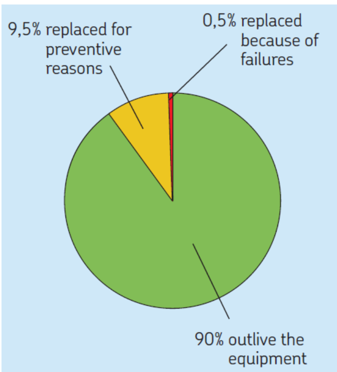

Figure 2: Bearing life and failure estimate from SKF Groop.

To better understand these anomalies and support effective maintenance practices, the ISO 15243-2017 standard (which aligns closely with SKF's classification) provides a structured framework for classifying bearing failure modes, specifically addressing failures that occur while the bearing is installed in the asset/machine and during its operational life. This classification excludes manufacturing defects, such as missing parts, focusing instead on failures arising from operational and environmental stresses. The ISO standard identifies six primary failure mode categories, each with specific subcategories for more detailed classification. These include:

1. ***Rolling Contact Fatigue (RCF):*** Involves subsurface-initiated and surface-initiated cracks caused by cyclic loading, poor lubrication, or contamination. Both phenomena will be discussed in detail later.
2. ***Wear:*** Divided into abrasive wear, caused by contaminants eroding surfaces, and adhesive wear, in which sliding contact transfers material, causing smearing or galling.
3. ***Corrosion:*** Includes moisture corrosion from water entering the bearing, fretting corrosion due to micro-movements, and false brinelling from vibration causing localized wear.
4. ***Electrical Erosion:*** Covers excessive current erosion from high-intensity currents melting surfaces, and current leakage erosion from low currents creating craters and surface wear.
5. ***Plastic Deformation:*** Includes overload deformation from excessive static load or improper handling, causing indentations and scratches, and particle indentations from contaminants in the lubricant, potentially leading to surface-initiated fatigue.
6. ***Cracking and Fracture:*** Includes fractures caused by excessive stress, fatigue fractures from repeated cyclic loading, and thermal cracking resulting from heat buildup leading to surface cracks.

Each category provides a comprehensive framework, allowing for specific classification of the observed failure modes. This standardized approach aids in consistent identification and diagnosis across industries, providing a unified basis for analysing bearing performance and failure mechanisms.

In general, according to SKF, bearing failure modes are distributed as follows:

- 1/3 fail due to fatigue
- 1/3 fail due to lubrication issues (e.g., incorrect lubricant, incorrect lubrication intervals)
- 1/6 fail due to contamination (e.g., ineffective seals)
- 1/6 fail for other reasons (e.g., improper handling and mounting, unexpected loading conditions, inadequate fits).

Whatever the reason for replacement, considerable costs are associated with such activities. Additionally, any degradation in bearing performance can increase energy consumption, lead to unexpected downtime, and in cases of failure, however rare, result in severe consequences, including damage to secondary components and, more importantly, pose a risk to human life [3]. The time from initial damage to a bearing becoming unserviceable varies significantly, taking just seconds in high-speed applications or extending to months in large, slow-rotating machines.

Therefore, early detection through condition monitoring and regular inspection enables timely replacement during scheduled maintenance, helping to prevent costly unscheduled downtime and extensive damage. Recognizing these benefits, companies are increasingly investing in predictive maintenance strategies that leverage advanced analytics and artificial intelligence to improve bearing health predictions. These technologies allow for proactive maintenance decisions, enabling issues to be addressed before they escalate and thereby optimizing equipment reliability and lifespan.

2.3 Condition Monitoring for Fault Detection, Diagnosis and Prognosis

Condition monitoring refers to the continuous or periodic assessment of machinery to evaluate its operational state and performance, primarily aimed at gathering data on the current status of equipment without necessarily diagnosing specific faults. Advances in sensors (Figure 3 illustrates an example of a “Smart Sensor”.), sensor networks, and computing systems have strengthened the appeal for data-driven approaches, establishing them as the foundation for predictive maintenance.

Figure 3: Sensor-integrated bearing unit for machine tool spindles, manufactured by NTN Corporation, equipped with three types of sensors for load, temperature, and vibration measurement. Additionally, the unit includes a built-in generator as an independent power source and a wireless module for wireless data transmission.

While fault detection, diagnosis, and prognosis all play critical roles in condition monitoring, they serve distinct but complementary purposes:

- ***Fault Detection*** involves identifying whether a fault exists by monitoring machinery for deviations from expected operating conditions. It typically relies on recognizing unusual patterns or anomalies that may signal potential issues. A commonly used technique for fault detection is novelty detection, a method in machine learning and statistics designed to identify new or unusual data points that differ significantly from the normal data previously seen by a model. Novelty detection, also known as anomaly detection or outlier detection in some contexts, is particularly effective in fault detection because it flags any behaviour that deviates from the established "normal" patterns, allowing the system to identify potential faults as soon as they emerge.
- ***Fault Diagnosis*** goes a step further by analysing these detected anomalies to determine the specific type, location, and severity of the fault. Diagnosis requires more detailed data and often combines multiple data sources to accurately classify and understand the root cause of the fault.
- ***Prognosis*** focuses on predicting the remaining useful life (RUL) of machinery and estimating the time to failure for critical components. It involves analysing trends and historical data to anticipate when maintenance or replacements may be needed, supporting proactive decision-making and reducing the risk of unexpected breakdowns.

Together, detection, diagnosis, and prognosis form a cohesive approach: fault detection provides early warnings through novelty detection techniques, diagnosis identifies and characterizes the specific fault to enable targeted maintenance actions, and prognosis ensures timely interventions by forecasting the progression of faults and their impact on equipment performance.

2.3.1 Types of Data for Bearing Condition Monitoring

The most common types of data gathered during bearing condition monitoring include:

- ***Vibration data:*** Vibration analysis is one of the primary methods for monitoring bearing condition. Sensors measure vibrations to detect irregularities, and analysis of the vibration signature can reveal issues such as imbalance, misalignment, and bearing wear. Vibration data serves both fault detection and diagnosis purposes, as deviations may indicate the presence of a fault, while deeper analysis helps classify the fault type.

- ***Temperature data:*** Monitoring the temperature of bearings provides insights into operational health. Elevated temperatures may indicate issues like poor lubrication, excessive friction, or misalignment. However, temperature is generally sensitive only to severe failures, so other signals, such as vibration and acoustic signals, are preferable for fault diagnosis and prognostic analysis. Temperature data primarily assists in fault detection.
- ***Lubrication and oil analysis data:*** Regular analysis of bearing lubricant is crucial for health monitoring. This includes assessing viscosity, contamination levels (e.g., water, dirt), and wear particles. Techniques such as spectrometry and particle counting are commonly used to evaluate oil quality and detect degradation. This data can support both detection and diagnosis by identifying early warning signs and revealing specific degradation patterns.
- ***Acoustic emission data:*** Acoustic emission sensors capture sound waves generated by bearings during operation. Variations in these signals can indicate fault conditions such as surface wear or cracking. Acoustic emission data assists in both detection and diagnosis, helping identify and classify faults through sound patterns.
- ***Current and power consumption data:*** Monitoring the electrical current and power consumption of the motor driving the bearings can provide insights into load and performance. Anomalies may suggest increased friction or other issues, supporting fault detection and contributing to a more accurate diagnosis when combined with other data sources.
- ***Speed and load data:*** Tracking rotational speed and load on bearings is essential for understanding operating conditions. Deviations from normal values may signal potential issues and primarily serve for fault detection.
- ***Operational environment data:*** Environmental factors such as humidity, temperature, and particulate matter can impact bearing performance. Monitoring these conditions helps assess risks to bearing health, providing contextual data that supports fault detection.
- ***Historical performance data:*** Analysing historical data, including past maintenance records and operational performance, helps identify trends and guide monitoring strategies. Historical data can aid in both detection and diagnosis by revealing patterns that signify common fault progression over time.

2.3.2 Addressing Condition Monitoring Challenges

In condition monitoring, various types of data are analysed either individually or in combination to create a comprehensive, multidimensional view of bearing health. This data provides valuable insights for detecting and diagnosing machine conditions, particularly in data-driven approaches such as AI applications.

Handling large and complex datasets introduces challenges like sensor noise, biases, and inconsistencies. Publicly available datasets help address these issues by providing structured data that describe bearing behaviour under various operating conditions, including fault conditions. By leveraging such datasets, researchers can improve and develop machine learning models for fault detection and diagnostics. There are several publicly available datasets for rolling bearing research, each with distinct characteristics. The Case Western Reserve University (CWRU) dataset is a classic choice for fault diagnosis, offering vibration data from bearings with various faults in controlled lab conditions, though it lacks real-world variability. In contrast, the Paderborn University dataset expands on this with a diverse range of faults, including naturally occurring damage, making it more representative for classification tasks. For prognostics and degradation studies, the XJTU-SY dataset focuses on the full lifespan of bearings, recording vibration data until failure, making it ideal RUL predictions. Similarly, the PRONOSTIA dataset from the FEMTO-ST Institute emphasizes degradation under multiple loads, making it another strong choice for RUL tasks. The IMS dataset, collected during endurance tests, captures fault progression, although it is limited by its relatively uniform operating conditions. The SEU dataset provides insights into single-point damage under varying speeds, bridging the gap between controlled and diverse fault scenarios. Meanwhile, the C-MAPSS dataset, though initially designed for turbofan engines, has been adapted for bearing prognostics due to its comprehensive time-series data. For benchmarking and competitions, the PHM 2012 Challenge dataset offers degradation data suitable for both fault diagnosis and life prediction tasks. For more sensor-rich environments, the Rotating Machinery Fault Dataset (RMFD) combines vibration and acoustic data for a holistic approach to fault analysis. Lastly, for applications in renewable energy, the Wind Turbine Bearing Data provides realistic operational data from large bearings, ideal for fault detection in slow-rotating systems.

Public rolling bearing datasets have been pivotal in advancing research in fault detection, diagnostics, and prognostics. However, their application in AI-driven solutions faces several challenges that can impact the development, training, and deployment of models, particularly in real-world industrial scenarios.

Challenges of public bearing datasets include:

- ***Not realistically representative:*** Many datasets, such as CWRU, Paderborn, and PRONOSTIA, are generated in controlled lab environments. Although this approach provides consistency, it does not reflect the complexity of industrial scenarios, including factors like environmental noise, uneven loading, and fluctuating operating conditions. Additionally, these datasets often focus on a single bearing type or size, limiting their generalizability to diverse designs or materials.
- ***Limited operating conditions:*** Parameters like speeds, loads, and temperatures are often kept fixed in datasets such as IMS and XJTU-SY, which do not reflect the dynamic nature of industrial applications. This static nature hinders models from adapting to varying real-world scenarios.
- ***Imbalance and unrealistic fault representation:*** Fault data in datasets like CWRU and SEU is often skewed, with a heavy focus on healthy bearings or specific fault types, while rare or gradual faults are underrepresented. This imbalance limits the diversity needed for robust model training. Furthermore, many faults are introduced artificially (e.g., via electrical discharge machining), which may not accurately reflect naturally occurring fault patterns critical for real-world applicability.
- ***Data quality and preprocessing issues:*** Public datasets often lack metadata, such as sensor calibration and environmental details, which reduces their effectiveness in diverse contexts. Preprocessing steps, such as filtering and normalization, are inconsistent, leading to difficulties when combining datasets. The presence of noise in datasets like IMS adds realism, but its absence in others can lead to overly optimistic model performance.
- ***Volume and diversity constraints:*** Many datasets, including CWRU and Paderborn, are relatively small and focus primarily on vibration signals. This limits their suitability for large-scale AI models, particularly those requiring multi-sensor data (e.g., acoustic emissions or temperature). Such limitations restrict the ability of models to generalize to real-world variability.
- ***Flexibility and transferability challenges:*** Models trained on a single dataset often overfit to its specific conditions and struggle to generalize to new datasets or real-world scenarios.

Differences in sensor placement, type, and experimental setups introduce inconsistencies and biases, further hindering transferability.

- ***Ethical and practical limitations:*** Industrial datasets are often proprietary and not publicly available, limiting the development of AI models tailored for real-world applications. Public datasets fail to capture the full range of industrial scenarios, and there is a lack of standardized methodologies to adapt models effectively.
- ***Benchmarking and validation gaps:*** Public datasets often fail to provide standardized evaluation metrics, making it difficult to benchmark and compare AI models across studies. Furthermore, cross-dataset validation is seldom performed, leaving the generalizability of models largely unexplored. Limited documentation on preprocessing methods and experimental conditions further complicates validation efforts, as it affects reproducibility and the ability to effectively evaluate models.

Addressing these challenges will enable public rolling bearing datasets to support the development of robust, scalable AI models for fault detection, diagnostics, and prognostics in industrial applications.

Chapter 3

3 Classical Approaches and Related Issues

Accurate fault detection and diagnosis in bearings is critical for ensuring the reliability and optimal performance of rotating machinery. This chapter examines key classical approaches in the field, encompassing both empirical methods for estimating bearing life, highlighting the inherent complexity of predicting bearing behaviour under varying operating conditions, and traditional techniques for fault detection and diagnosis. These approaches are discussed along with their limitations, providing a foundation for understanding the challenges that drive the need for more advanced diagnostic solutions.

3.1 Bearing Fatigue and Empirical Methods for Life Estimation

The contact geometry and motion of rolling elements against the inner and outer raceways produce contact stresses and interactions that are too complex to be fully characterized by Hertz's theory. These dynamic loading conditions give rise to the phenomenon of Rolling Contact Fatigue (RCF). Unlike classical structural fatigue, contact fatigue involves alternating subsurface shear stresses generated by the geometry and motion of the rolling elements. With increasing load cycles, surface and subsurface plastic strain accumulate, eventually leading to crack initiation. RCF is fundamentally a material failure caused by the repeated application of stresses to a small volume of material. Even under optimal operating conditions, when the bearing is kept clean, well-lubricated, properly mounted, effectively sealed against contaminants, and operated within moderate temperature ranges, failure ultimately occurs due to surface fatigue.

Given the unique nature of Rolling Contact Fatigue, several critical differences from classical fatigue prevent the direct application of traditional fatigue principles.

The most important distinctions are as follows:

- ***Complex, multiaxial stress state:*** The state of stress at contact points in RCF is complex and multiaxial, governed by Hertzian contact mechanics. Unlike most classical fatigue mechanisms, RCF typically involves multiaxial fatigue, necessitating the application of a multiaxial fatigue criterion.
- ***Absence of an endurance limit:*** Contact fatigue lacks an endurance limit. While the fatigue lives of components under cyclic torsion or bending are limited, rolling contact fatigue lifespans are significantly greater, often spanning tens to hundreds of millions of cycles.
- ***High Hydrostatic Stress Component:*** RCF involves a significant hydrostatic stress component, which is generally absent in classical fatigue under tension-compression or bending.
- ***Localized Stress Volume:*** Fatigue damage in RCF occurs in a very small volume of stressed material, with typical bearing contact widths ranging from 200 to 1000 µm.
- ***Non-Proportional Loading History:*** In contrast to classical fatigue, the loading history at a point below the surface in RCF is non-proportional; the stress components do not vary in a consistent ratio over time. Notably, the peaks of normal stresses do not align with the peaks of shear stress, resulting in a complete reversal of shear stress while normal stresses remain compressive.
- ***Constantly changing principal axes:*** In non-conformal contacts, the principal stress axes change direction continuously throughout each stress cycle, causing the planes of maximum shear stress to shift as well. This complexity makes it challenging to identify the planes where maximum fatigue damage occurs.
- ***Residual stresses*****:** When the elastic limit is exceeded during the initial application of load, residual stresses are introduced. However, subsequent load cycles remain within the elastic limit, further complicating the fatigue behaviour.

The two primary RCF mechanisms are subsurface-originated spalling and surface-originated pitting, both of which release particles from the race or rolling element in the load zone, creating craters that act as stress concentrators. These mechanisms often compete, with the dominant failure mode depending on several factors, including surface quality, lubricant cleanliness, and material integrity.

- ***Surface-originated pitting:*** This failure mode, as illustrated in Figures 4a and 4b (adapted from [4]), occurs when surface defects, such as dents or scratches, are present. Cracks initiate at surface stress concentrators and propagate at shallow angles (15–30 degrees) to the surface. The role of a lubricating fluid, which may be driven into the crack through hydraulic effects, is also significant. As the crack reaches a critical length or depth, it branches toward the surface, resulting in the detachment of a small volume of material and the formation of a pit, causing the bearing to become noisy and operate with increased roughness. This failure mechanism is commonly observed in gears, where substantial sliding occurs between contacting surfaces.

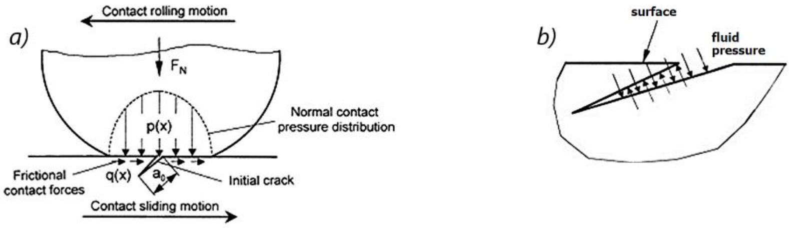

Figure 4: Illustration of surface-initiated crack growth in a moving lubricated contact, showing the distribution of contact forces and the role of fluid pressure in crack propagation.

- ***Subsurface-originated spalling*:** This mechanism occurs when microcracks develop below the surface at material inhomogeneities, such as non-metallic inclusions, and propagate toward the surface to form a spall (Figure 5 adapted from [5]). These cracks typically initiate in the region of maximum subsurface shear stress. Factors that promote subsurface-originated spalling include smooth bearing surfaces, the presence of non-metallic inclusions, and the absence of surface shear. This mechanism is particularly prevalent in rolling element bearings with smooth surfaces operating under Elasto-Hydrodynamic Lubrication (EHL) conditions.

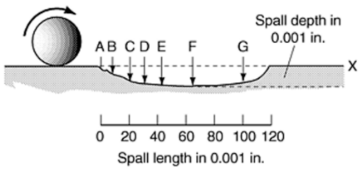

Figure 5: Anatomy of a race spall in a ball bearing.

It is commonly understood that material fatigue is caused by dynamic stressing during cyclic loading. However, there is no general agreement on the parameters that best explain this phenomenon. Brändlein proposed three primary hypotheses: maximum shear stress, distortion energy, and alternating shear stress. However, it should be noted that crack initiation and propagation result from the combined effect of the entire subsurface stress field, not from a single stress component. The field stresses are all proportional to one another, including the stresses mentioned above, meaning that any of these can serve as an indicator of the overall stress field magnitude. In this context, maximum surface pressure could also be considered relevant. In pursuit of a reliable formula for predicting bearing life, Lundberg and Palmgren assumed that a subsurface crack initiates at a particular depth when the maximum orthogonal shear stress occurs at a weak point in the material. They further assumed these weak points to be stochastically distributed within the material. By applying Weibull's statistical strength theory to the stressed volume in the case of pure Hertzian contact, they derived the probability of survival for that volume against subsurface fatigue, emphasizing that failure was primarily governed by crack initiation. This work ultimately led to the well-known load-life equation (3.1), shown below:

$$L_{10} = \left({}^{C}\!/_{R} \right)^{p} \quad (3.1)$$

where

- L_{10} is the basic rating life (in millions of revolutions) at 90% reliability, meaning that only 10% of bearings will fail before reaching a life $L < L_{10}$
- C is the basic dynamic capacity, the load (R) that if applied results in a life of one million cycles with a 10% failure probability
- P is the equivalent dynamic load
- p is the load-life exponent

The formula was later refined according to ISO 281/1 – 1997 and subsequently enhanced by SKF in its current version (3.2), which considers not only loads but also important factors such as reliability, lubrication conditions, contamination, and the fatigue load limit:

$$L_{na} = a_1 \cdot a_{SKF} \cdot \left(\frac{C}{P}\right)^p \qquad (3.2)$$

where

- L_{na} represents the rating life in millions of cycles, calculated by assuming a damage probability equal to n
- a_1 is the life adjustment factor
- a_{SKF} is the SKF life modification factor

All the above-mentioned considerations and results are generally used during the design process, allowing the designer, with a certain margin of safety, to assess whether the selected bearing will meet the expected service life.

However, this deterministic approach does not account for complex, real-world variables such as fluctuating operational conditions, environmental factors, and material wear, all of which influence bearing degradation. Consequently, the rating life equation is not typically integrated directly into machine learning models for predicting bearing failure. Integrating such deterministic models into neural networks could potentially enhance prediction accuracy and reliability. Nonetheless, there is currently a gap in the literature regarding the integration of the bearing rating life equation with neural network architectures for failure prediction. This presents an opportunity for future research to develop hybrid models that combine the strengths of physics-based equations and data-driven techniques, potentially leading to more robust and interpretable bearing failure predictions.

3.2 Traditional Techniques for Fault Detection and Diagnosis

During operating conditions, factors such as contamination, poor lubrication, misalignment, extreme temperatures, poor fitting, and shaft unbalance are leading causes of premature bearing failures, often resulting in increased vibration. In noise-sensitive applications, bearing vibration remains an essential factor as it correlates with quality; quiet operation reflects both the health and precision of the rolling contact surfaces. Consequently, bearing manufacturers have developed vibration monitoring methods as effective tools for assessing bearing quality and condition.

As discussed earlier, vibration measurements acquired during condition monitoring serve three primary purposes in bearing analysis: detection, diagnosis, and prognosis. Each purpose plays a distinct role in addressing bearing health, from identifying early defects to diagnosing specific faults and predicting the remaining useful life of the bearing. To achieve these goals, various signal processing techniques, including broadband vibration analysis, frequency spectrum analysis, and envelope spectrum analysis, are applied to extract meaningful insights from vibration data.

- ***Detection:*** The most basic form of assessment, detection utilizes Overall Vibration Level Measurement to monitor general vibration levels across wide frequency ranges, such as 10–1000 Hz or 10–10,000 Hz. By capturing overall vibration activity, this approach provides an initial indication of potential defects. In systems with minimal vibrations from sources other than bearings, parameters like the Crest Factor (peak-to-RMS ratio) can reveal early-stage (incipient) defects, while high RMS levels often suggest more severe issues. Although this method offers limited diagnostic detail, it is highly valuable for trend analysis; by plotting vibration levels over time, operators can detect signs of deterioration, facilitating proactive maintenance scheduling. Additionally, these measurements can be compared to vibration standards for different equipment types to assess overall machine health.
- ***Diagnosis:*** For a more precise identification of vibration sources and fault types, Frequency Spectrum Analysis is used. Unlike broadband measurements, frequency spectrum analysis isolates specific frequencies, enabling the detection of characteristic frequencies associated with particular bearing defects, such as inner or outer raceway faults or rolling element damage. By providing clearer identification of the fault's origin, this technique distinguishes bearing-related issues from external sources like unbalance or misalignment. Frequency spectrum analysis enhances diagnostic accuracy, supporting targeted maintenance efforts and reducing downtime.
- ***Prognosis:*** Prognosis aims to predict the bearing's remaining useful life and anticipate possible failure modes, critical for optimizing maintenance schedules and preventing unexpected breakdowns. This phase often relies on Envelope Spectrum Analysis, an advanced technique that highlights high-frequency bursts in the vibration signal, which may otherwise be masked by lower frequencies or background noise. Envelope spectrum analysis is particularly useful for identifying early-stage defects through impulsive events associated with emerging faults. Prognosis may also incorporate both real-time data and historical records of similar bearing faults to estimate the optimal timing for intervention. By forecasting the bearing's service life, prognosis supports effective maintenance planning, ensuring repairs or replacements are performed before failure occurs.

To fully appreciate the diagnostic potential of vibration analysis, whether for detection, diagnosis, or prognosis, it is essential to explore the fundamental sources of vibration in rolling bearings. The following section examines the primary causes of vibration and the characteristic frequencies they produce, as outlined and illustrated in [6].

3.2.1 Vibration Causes in Bearings

Rolling contact bearings are complex dynamic systems, whose components i.e. rolling elements, inner raceway, outer raceway and separator interact to generate complex vibration signatures. As mentioned, multiple times, although rolling bearings are manufactured using high-precision machinery under strict cleanliness and quality controls, they will still have some degree of imperfection, which generates vibration as the surfaces interact through a combination of rolling and sliding. Nowadays, although the scale of surface imperfections are in the order of nanometres, significant vibrations can still be produced in the entire audible frequency range (20Hz - 20kHz). The level of the vibration will depend upon many factors including the energy of the impact, the point at which the vibration is measured and the construction of the bearing.

The primary sources of bearing vibration are listed and explained below:

- ***Variable compliance vibrations*** are caused by the changing load distribution among the rolling elements as the bearing rotates. This shifting load leads to elastic deformation at the contact points between the balls and raceways, resulting in periodic vibration with a base frequency determined by how often the balls pass through the load zone. Under radial load, these movements form a two-dimensional path (locus) in a radial plane, while under misalignment, they follow a three-dimensional path. This base frequency, along with additional higher-frequency vibrations, contributes to the overall bearing vibration. For example, in a single-row radial ball bearing with an inner ring speed of 1800 rev/min, a typical ball pass rate is 100 Hz, with higher-frequency vibrations reaching over 500 Hz.
  Variable compliance vibration is significantly influenced by the number of rolling elements supporting the load; the more balls that share the load, the less pronounced the vibration becomes. Moreover, variable compliance vibration levels can be higher than those produced by surface roughness and waviness. However, in applications where vibration control is critical, these vibrations can be reduced to a negligible level by using ball bearings with the appropriate level of axial preload.
- ***Geometrical imperfections***, inherent to the manufacturing process, are a significant source of vibration in bearings. These imperfections can be categorized into three distinct types, with the first two distinguished by comparing the wavelength to the width of the rolling element-raceway contacts.

- ***Surface roughness:*** Microscopic peaks and valleys (asperities) create high-frequency vibration, particularly when the lubricant film is insufficient, leading to increased wear, noise, and heat generation. Surface roughness, characterized by relatively short wavelengths, produces vibration predominantly at frequencies above 60 times the rotational speed of the bearing, causing the high-frequency part of the vibration spectrum to appear as a series of resonances.
- ***Waviness:*** Larger-scale variations in the surface, appearing as waves, produce lower-frequency vibration and can affect load distribution, contributing to premature wear and fatigue. Waviness, characterized by relatively long wavelengths, can produce vibration at frequencies up to approximately 300 times the rotational speed but is usually predominant at frequencies below 60 times the rotational speed.
- ***Discrete defects:*** Individual flaws such as scratches, dents, or pits generate localized vibrations and significantly impact bearing performance, often leading to premature failure. Unlike surface roughness and waviness, which are inherent to the manufacturing process, these discrete defects result from external factors such as assembly errors, contamination, operation, mounting, or inadequate maintenance. Bearing manufacturers use simple vibration measurements on finished products to detect these defects, which typically produce impulsive vibrations with a high peak-to-RMS ratio (Figure 6). In cases with multiple defects, individual peaks may be harder to distinguish, but the overall RMS vibration level is significantly higher than that of a bearing in good condition.

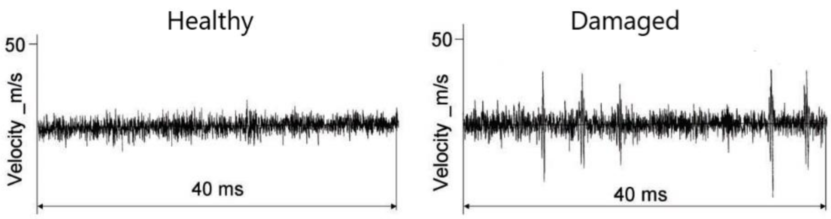

Figure 6. Adapted from [6].

3.2.2 Bearing Characteristic Frequencies

Rolling bearings generate fundamental frequencies that can be derived from relatively simple formulas, yet these frequencies cover a wide frequency range and can interact to produce complex vibration signals. This complexity is often further increased by additional sources of vibration from mechanical, structural, or electromechanical components within the equipment.

For a bearing with a fixed outer ring and rotating inner ring, from the bearing geometry the fundamental frequencies are derived as follows:

$$f_{C/o} = f_r/2\left[1 - cos\alpha\, {}^{d}/_{D}\right] \qquad (3.3)$$

$$f_{C/i} = f_r/2\left[1 + cos\alpha\, {}^{d}/_{D}\right] \qquad (3.4)$$

$$f_{b/o} = Z\, f_{C/o} \qquad (3.5)$$

$$f_{b/i} = Z\, f_{C/i} \qquad (3.6)$$

$$f_b = \frac{D}{2d} f_r \left[1 - \left(cos\alpha\ {}^{d}/_{D}\right)^2\right] \qquad (3.7)$$

where

$f_r = inner\ ring\ rotational\ frequency$

$f_{C/o} = fundamental\ train\ (cage)\ frequency\ relative\ to\ outer\ raceway$

$f_{C/i} = fundamental\ train\ frequency\ relative\ to\ inner\ raceway$

$f_{b/o} = ball\ pass\ frequency\ of\ outer\ raceway$

$f_{b/i} = ball\ pass\ frequency\ of\ inner\ raceway$

$f_b = rolling\ element\ spin\ frequency$

$D = pitch\ circle\ diameter$

$d = diameter\ of\ roller\ elements$

$Z = number\ of\ rolling\ elements$

$\alpha = contact\ angle$

The previously introduced equations assume that no sliding occurs during rolling motion. However, in practice, this ideal motion is rarely achieved. Due to various factors, the rolling elements often experience a combination of rolling and sliding. Consequently, the actual characteristic defect frequencies may differ slightly from those predicted by the equations, depending significantly on the type of bearing, operating conditions, and fits. Typically, the characteristic frequencies of the bearing are not integer multiples of the inner ring's rotational frequency, which helps to distinguish these frequencies from other sources of vibration. Since most vibration frequencies are directly proportional to rotational speed, it is essential to collect vibration data at consistent speeds when comparing vibration signatures. This aspect represents a significant challenge in AI applications, as extensively demonstrated and addressed in various publications, including [7]. Variations in speed can shift the frequency spectrum, leading to inaccuracies in both amplitude and frequency measurements. In variable-speed equipment, spectral orders are sometimes used, where all frequencies are normalized relative to the fundamental rotational speed. This process, known as order normalization, designates the fundamental rotational frequency as the first order.
In addition to analysing spectral orders, the bearing speed ratio, a measure obtained by dividing the ball pass frequency by the shaft rotational frequency, serves as a valuable indicator of bearing performance. This ratio is influenced by bearing loads and clearances, providing insights into operating conditions. When the bearing speed ratio falls below expected values, it may signal insufficient loading, excessive lubrication, or inadequate radial internal clearance, all of which can lead to higher operating temperatures and potential premature failure. Conversely, a higher than anticipated bearing speed ratio may suggest excessive loading, too much radial internal clearance, or insufficient lubrication.

An example of how the bearing speed ratio can help identify potential issues is illustrated in Figure 7 (Adapted from [6].), which displays the vibration acceleration spectrum measured axially on the end cap of a 250kW electric motor. In this case, type 6217 radial ball bearings were subjected to an unexpectedly high axial load. This excessive load occurred because the non-locating bearing could not slide within the housing, likely due to thermal expansion (thermal loading). For a nominal shaft speed of 3000 revolutions per minute (rev/min), the estimated outer raceway ball pass frequency (fb/o) was calculated to be 228.8 Hz, resulting in a predicted bearing speed ratio of 4.576. However, measurements revealed an actual outer raceway ball pass frequency of 233.5 Hz, resulting in a bearing speed ratio of 4.67; a 2%

increase from the expected value. This deviation indicates the presence of an additional axial load, which would not have been apparent without analysing the bearing speed ratio.

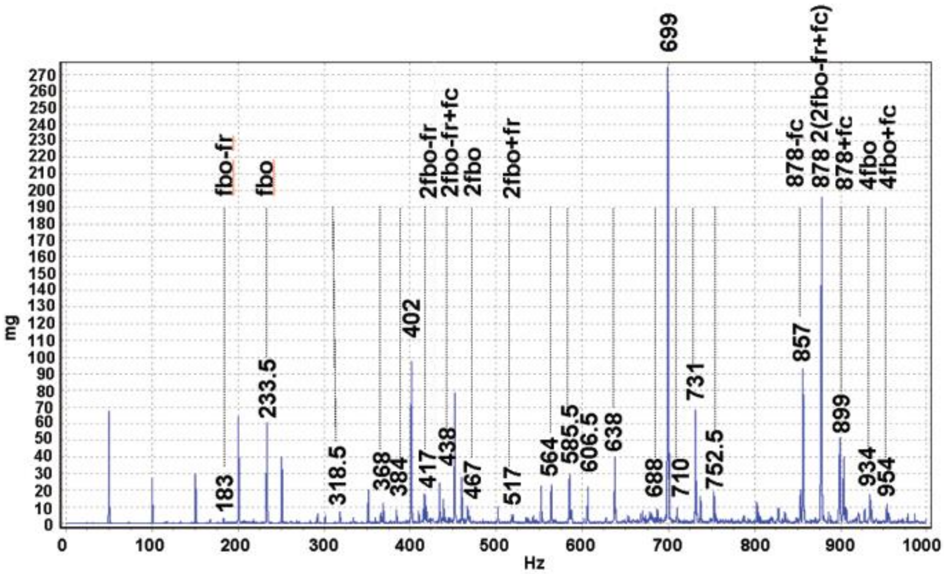

Figure 7. Axial vibration acceleration spectrum on end cap of a 250kW electric motor.

Ball pass frequencies can be generated as a result of elastic properties of the raceway materials due to variable compliance or as the rolling elements pass over a defect on the raceways. The frequency generated at the outer and inner ring raceway can be estimated roughly as 40% and 60% of the inner ring speed times the number of rolling elements respectively.

Despite these estimates, bearing vibration signals are rarely straightforward due to the complex interactions among various bearing components. This complexity, however, can serve as a useful diagnostic tool for detecting surface deterioration or damage on the rolling elements. In particular, surface imperfections on raceways and rolling elements, often introduced during the manufacturing process, interact to produce additional discrete frequencies and sidebands, as summarized in Table 1. These imperfections combine, adding layers of complexity to the vibration spectrum, especially when multiple defects are present.

Analysing these vibration signals is challenging because the characteristic frequencies generated by imperfections often blend with each other, and background noise or other sources of vibration can mask defect frequencies, particularly in the early stages of damage. Nonetheless, advancements in diagnostic algorithms have enabled more effective detection of bearing faults by analysing vibration signatures on the bearing housing.

These methods leverage both the characteristic defect frequencies and the “ringing frequencies” (i.e. natural frequencies) of the bearing.

Surface Defect		Frequency
Component	**Imperfection**	
Inner raceway	Eccentricity Waviness Discrete defect	f_r $nZf_{C/i} \pm f_r$ $nZf_{C/i} \pm f_r$
Outer raceway	Waviness Discrete defects	$nZf_{C/o}$ $nZf_{C/o} \pm f_r$ $nZf_{C/o} \pm f_{C/o}$
Rolling element	Diameter Variation Waviness Discrete defect	$Zf_{C/o}$ $2nf_b \pm f_{C/o}$ $2nf_b \pm f_{C/o}$

Table 1. Frequencies related to surface imperfections. From [6]

The list below outlines the main types of bearing defects and other sources of vibration, detailing how each type influences the characteristic frequencies in bearing systems and contributes to the overall vibration profile.

- ***Raceway defect:*** A discrete defect on the inner raceway generates high-energy pulses at the ball pass frequency, which vary in amplitude as the defect moves in and out of the load zone. This creates amplitude modulation at the inner ring's rotational frequency, resulting in sidebands around the carrier frequency in the frequency domain. As the defect grows, additional sidebands appear, potentially replacing the ball pass frequency with peaks spaced at the inner ring rotational frequency.
  In contrast, a discrete defect on the stationary outer raceway produces consistent pulse amplitudes, appearing as a single peak in the frequency domain. However, with an unbalanced rotor, the signal may also be modulated at the inner ring rotational frequency. If a defect is present on a rolling element, it moves in and out of the load zone at the fundamental train frequency, generating sidebands around the ball pass frequency. Inner

raceway defects tend to produce lower amplitude signals than outer raceway defects due to a more complex transmission path from the defect to the sensor location, making outer raceway defects easier to detect.

- ***Rolling element defect:*** Defects on rolling elements can generate vibrations at frequencies that are twice the ball spin frequency, along with its harmonics, as well as at the fundamental train frequency. When a defect strikes both the inner and outer raceways, it often generates a frequency twice the ball spin frequency. However, this frequency can be lower if the ball is outside the load zone or if energy is lost as the signal travels through structural parts. Defects oriented along the axis of the ball may be more challenging to detect, as they don't always strike both raceways. When multiple rolling elements have defects, combined frequencies (sums of the ball spin frequencies) may occur, and larger defects may also produce vibrations at the fundamental train frequency.
- ***Cage defect:*** Cages in bearings typically rotate at around 0.4 times the inner ring speed and, due to their low mass, generally produce minimal vibration unless there is a manufacturing defect. Unlike raceway defects, cage failures do not usually trigger specific ringing frequencies, making them harder to detect through envelope spectrum analysis. When cage wear or deformation begins, often from inadequate lubrication, random bursts of vibration and a wide range of frequencies can occur. As the cage deteriorates further, increased sideband activity may appear around other fundamental frequencies. Excessive clearance can also cause vibration at the fundamental train frequency (FTF), leading to impact forces between the rolling elements and cage pockets.
- ***Other sources of vibration:*** Contamination is a common cause of bearing wear and premature failure, often due to foreign particles entering the bearing during handling or operation. This contamination generates vibrations that vary in intensity and may be hard to detect initially, depending on the type of particles. Contaminants damage rolling surfaces and produce vibrations across a wide frequency range. In early stages, the vibration signals crest factor may increase, though this is difficult to detect in the presence of other vibration sources. In grease-lubricated bearings, initial vibrations may be high as the grease is distributed throughout the bearing, but these vibrations generally degrade as the bearing continues to operate. Low-noise greases are often used in noise-sensitive applications.

3.2.3 Limitations of Vibration Analysis

Despite its widespread application, vibration analysis has several limitations. The intricate vibration patterns encountered during condition monitoring often arise from the interaction of multiple vibration sources, making interpretation complex without skilled analysts. Experienced vibration analysts are typically required to accurately distinguish and assess the characteristic signatures of bearing defects, such as variations in the amplitude and frequency of fundamental vibration signals. Although vibration monitoring software can assist by demodulating signals and generating an envelope spectrum for early detection, it has limitations. Certain defect types, such as cage failures, may not excite specific natural frequencies, making them more difficult to detect.

Furthermore, simple broadband vibration measurements, while useful for general monitoring, offer limited diagnostic capability and may not provide an early warning for incipient damage. This dependency on human expertise to interpret complex signals, identify subtle indicators of deterioration, and make informed maintenance decisions highlights the inherent challenges of relying solely on vibration analysis for fault detection.

Chapter 4

4 AI in Bearing Fault Diagnosis: A Decision Tree Approach for Classification and Analysis

The Industrial Internet of Things (IoT) and data-driven techniques have transformed the manufacturing landscape by enabling interconnected machines to gather vast amounts of data and turn it into actionable insights. While large data volumes offer valuable opportunities, they also introduce challenges such as noise, biases, and inconsistencies that hinder the development of accurate physical models, complicating the representation of complex, dynamic systems. Additionally, many physics-based models struggle to integrate online measured data, limiting their effectiveness and adaptability. Traditional diagnostic methods remain heavily dependent on human expertise, ranging from basic visual and auditory inspections to more advanced tasks like signal analysis. However, accessing experienced analysts can be difficult due to the specialized knowledge required, which is often developed over years of practice. Even when available, human analysts may find it challenging to process the vast, multidimensional datasets generated by modern acquisition systems.

This chapter undertakes a detailed investigation into the application of Artificial Intelligence (AI) in bearing fault diagnosis, specifically through a decision tree framework designed to systematically categorize and label relevant research, as illustrated in Table 2. This structured framework supports a comprehensive literature review, enabling a critical evaluation of emerging trends and innovations in intelligent fault diagnosis. The following chapter is organized into four sections, each dedicated to a major branch of the decision tree, providing a detailed examination of AI-driven techniques and their contributions to bearing fault diagnosis.

Main Category	Subcategory	Classification Label	Article reference from 2020 to 2024
Machine Learning Path	Supervised Learning	SVM-based Bearing Fault Diagnosis	
		Tree-based Bearing Fault Diagnosis	
		k-NN-based Bearing Fault Diagnosis	
		Ensemble-based Bearing Fault Diagnosis	
		Regression-based Bearing Fault Diagnosis	
		Supervised Generative Models in Bearing Fault Diagnosis	
		Other ML-based Bearing Fault Diagnosis	
	Unsupervised Learning	Clustering in Bearing Fault Diagnosis	
		Pattern Deviation Detection in Bearing Fault Diagnosis	
		Dimensionality Reduction in Bearing Fault Diagnosis	
		Unsupervised Generative Models in Bearing Fault Diagnosis.	
	Semi-Supervised Learning	Graph-Based Semi-Supervised Bearing Fault Diagnosis	
		Self-Training Semi-Supervised Bearing Fault Diagnosis	
		Generative Semi-Supervised Bearing Fault Diagnosis	
		Semi-Supervised Generative Models in Bearing Fault Diagnosis.	
Deep Learning Path	Traditional Neural Networks (NNs)	Traditional NN-based Bearing Fault Diagnosis	
	Advanced Deep Learning	CNN-based Bearing Fault Diagnosis	
		RNN-based Bearing Fault Diagnosis	
		Autoencoder-based Bearing Fault Diagnosis	
		Few-Shot Learning in Bearing Fault Diagnosis	
		Transfer Learning in Bearing Fault Diagnosis	
		Foundation Models in Bearing Fault Diagnosis	
Hybrid Methods Path	ML/DL + Signal Processing	Hybrid ML + Signal Processing in Bearing Fault Diagnosis	
		Hybrid DL + Signal Processing in Bearing Fault Diagnosis	
	ML/DL + Optimization Algorithms	Hybrid ML + Optimization in Bearing Fault Diagnosis	
		Hybrid DL + Optimization in Bearing Fault Diagnosis	
	ML/DL + Reinforcement Learning	Hybrid ML + Reinforcement Learning in Bearing Fault Diagnosis	
		Hybrid DL + Reinforcement Learning in Bearing Fault Diagnosis	
	ML/DL + Generative Models	Hybrid ML + Generative Models in Bearing Fault Diagnosis	
		Hybrid DL + Generative Models in Bearing Fault Diagnosis	
	AI + Physics-based Models	Hybrid AI + Physics-based Models in Bearing Fault Diagnosis	
		Hybrid AI + Sensor Fusion in Bearing Fault Diagnosis	
Other AI Methods Path	Fuzzy Logic	Fuzzy Logic in Bearing Fault Diagnosis	
	Expert Systems	Expert Systems in Bearing Fault Diagnosis	
	Bayesian Networks	Bayesian Networks in Bearing Fault Diagnosis	
	AI-Driven Maintenance Scheduling	AI-Driven Maintenance in Bearing Fault Diagnosis	
	Genetic Programming	Genetic Programming in Bearing Fault Diagnosis	
	Neuro-Fuzzy Systems	Neuro-Fuzzy Systems in Bearing Fault Diagnosis	

Table 2. Literature review classification table.

4.1 Machine Learning Path in Bearing Fault Diagnosis

Machine learning techniques are well suited for structured data and are effective for moderate-sized datasets, making them versatile tools for bearing fault diagnosis. Models can be trained on labelled or unlabelled data, and these methods are typically interpretable, which is valuable in industrial applications where understanding the reasoning behind predictions is crucial for informed decision-making. Depending on the type and availability of data, a range of approaches are available.

1. ***Supervised learning*** relies on labelled data to train models, allowing them to recognize and classify fault patterns in bearings by learning a mapping between inputs and their corresponding outputs. In the context of bearing fault diagnosis, supervised learning encompasses a variety of approaches:
   - ***Support Vector Machines (SVM)****:* SVM models determine the optimal boundaries between classes, making them effective in distinguishing between different fault conditions.
   - ***Decision Trees/Random Forests****:* Decision Trees segment data into branches based on features, while Random Forests combine multiple decision trees to enhance prediction robustness and accuracy.
   - ***k-Nearest Neighbors (k-NN)****:* A proximity-based method that classifies a new sample based on its closest data points (neighbours) in the dataset.
   - ***Ensemble Methods*** *(e.g., AdaBoost, Gradient Boosting):* These techniques combine multiple weak models, such as decision stumps or shallow trees, to form a stronger predictive model. Ensemble methods improve fault prediction accuracy and resilience to noise.
   - ***Regression Models*** *(Logistic, Ridge, etc.):* Regression models predict continuous or discrete outcomes, with logistic regression commonly used for binary classification in fault diagnosis.
   - ***Supervised Generative Models*** *(e.g., GANs, VAEs, Conditional Variational Autoencoders (CVAEs)):* These models use labelled data to generate synthetic data, aiding in fault classification and enhancing model training through synthetic data augmentation.

- ***Other algorithms**:* Includes supervised learning algorithms that do not fit within the categories above, such as probabilistic models like Naive Bayes.

2. ***Unsupervised learning*** aims to uncover hidden patterns or groupings within unlabelled data, making it useful for anomaly detection by grouping similar fault conditions in bearing fault diagnosis. This category includes:
   - ***Clustering** (e.g., K-Means, Hierarchical):* Groups data into clusters based on similarity without any predefined labels, identifying potential fault patterns.
   - ***Pattern Deviation Detection** (e.g., Isolation Forest, Outlier Detection):* Detects abnormal or rare instances (outliers) in the data, assisting in early fault detection.
   - ***Dimensionality Reduction** (e.g., PCA, t-SNE):* Reduces the number of features in the data to improve model efficiency while preserving essential information.
   - ***Unsupervised Generative Models** (e.g., GANs, VAEs, Gaussian Mixture Models):* Use unlabelled data to detect patterns, create new data instances, or identify anomalies.

3. ***Semi-supervised learning*** leverages both labelled and unlabelled data to improve model performance, particularly when labelled data is scarce, making it valuable for bearing fault diagnosis.
   - ***Graph-Based Methods** (e.g., Label Propagation):* Uses a graph structure to propagate labels from labelled to unlabelled data points, enhancing performance on sparse datasets.
   - ***Self-Training Models**:* Models that iteratively label their most confident predictions and retrain on this expanded labelled set, increasing adaptability.
   - ***Semi-Supervised Generative Models** (e.g., GANs, VAEs, Ladder Networks):* Utilize both labelled and unlabelled data for representation learning or synthetic data generation, improving fault diagnosis accuracy.

4. ***Reinforcement Learning**:* A decision-making approach where agents learn optimal strategies by interacting with their environment and receiving feedback (rewards). It is applied in dynamic fault diagnosis, where maintenance decisions require continuous adaptation.

Machine learning based fault diagnosis methods rely heavily on human intervention for feature extraction. However, as frequently emphasized, signals are often non-stationary, and manually extracted fault features largely depend on expert experience and prior knowledge, making the feature extraction process challenging. Furthermore, machine learning models struggle to address these complexities effectively, limiting their diagnostic accuracy. Consequently, these models exhibit inadequate performance and fail to meet the modern requirements for fault diagnosis, which demand rapidity and high accuracy.

4.2 Deep Learning Path in Bearing Fault Diagnosis

Deep Learning involves complex neural networks with multiple layers that learn from large, unstructured datasets such as images, time-series data, or text. These models automatically extract relevant features, eliminating the need for manual feature engineering and improving their performance with increasing amounts of data. Deep learning is particularly powerful for recognizing patterns, making it ideal for applications like fault diagnosis, predictive maintenance, and anomaly detection. Although deep learning requires significant computational resources, advancements in hardware (e.g., GPUs) have made it more accessible and efficient. Common architectures include:

1. ***Traditional Neural Networks*** form the basis for deep learning architectures and consist of layers of interconnected neurons. Each neuron evaluates input data using weights and an activation function to produce an output, which is then passed to the next layer. This structure enables the network to learn patterns and relationships within structured data, making it effective for tasks like classification and pattern recognition.
    - ***Multilayer Perceptrons (MLPs)****:* Fully connected networks where neurons are organized into layers, with each neuron in one layer connected to all neurons in the next. MLPs are often used in bearing fault diagnosis to classify fault types and severity levels by learning patterns from vibration and acoustic signals.
    - ***Backpropagation Neural Networks (BPNNs)****:* A neural network trained using the backpropagation algorithm, optimizing weights through error minimization. BPNNs are applied in bearing fault diagnosis for accurately identifying and classifying different fault conditions by training on historical fault data.

- ***Feedforward Neural Networks (FNNs)**:* Neural network architecture where information flows in one direction, from input to output. FNNs are commonly used in bearing fault diagnosis to detect faults in a straightforward manner, processing structured data like vibration signals to identify anomalies.
- ***Deep Belief Networks (DBNs)**:* Probabilistic generative models with multiple layers of latent variables, often pre-trained layer by layer using Restricted Boltzmann Machines (RBMs). In bearing fault diagnosis, DBNs have been employed to detect complex fault patterns and enhance fault classification by modelling high dimensional feature spaces from sensor data.

2. ***Advanced Deep Learning*** employs architectures like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which are suited for high dimensional data, such as images and time-series signals. These models are valuable for tasks like fault classification and anomaly detection in bearing fault diagnosis.
    - ***Convolutional Neural Networks**:* Suited for image or 2D data analysis, CNNs are used in bearing fault diagnosis to analyse images of bearing surfaces or spectral representations, detecting surface defects and patterns indicative of faults.
    - ***Recurrent Neural Networks** (e.g., LSTMs):* Good for sequential data like time series, RNNs are employed in bearing fault diagnosis to capture temporal patterns in vibration and acoustic signals, aiding in early fault detection and trend analysis.
    - ***Autoencoders/Stacked Autoencoders**:* Used for unsupervised tasks like learning simplified representations of data or reducing noise in signals, autoencoders help identify subtle anomalies in bearing signals, enhancing fault detection sensitivity.
    - ***Few-Shot Learning Algorithms**:* Leverages neural networks to generalize from limited data, making few-shot learning valuable for bearing fault diagnosis when labelled fault data is scarce.
    - ***Transfer Learning**:* Extends a model trained on one task to another related task, allowing pre-trained models on limited datasets to be adapted for bearing fault diagnosis.
    - ***Foundation Models**:* Large models pre-trained on massive datasets, which can be fine-tuned for fault detection tasks in bearing diagnosis, benefiting from their broad feature representation abilities.

4.3 Hybrid Methods Path in Bearing Fault Diagnosis

Hybrid methods combine machine learning or deep learning with other techniques, such as signal processing, optimization, reinforcement learning, or physics-based models, enhancing the model's effectiveness for complex diagnostic tasks. These combinations enhance the diagnostic capabilities of AI models, making them more robust and adaptable to complex tasks where both data-driven insights and domain knowledge are essential.

1. ***ML/DL + Signal Processing***: Combines AI models with signal processing techniques to enhance feature extraction and data representation.
   - ***ML + Signal Processing:*** Combines traditional machine learning models with signal processing methods like Principal Component Analysis (PCA) or Fast Fourier Transform (FFT) to improve faut classification.
   - ***DL + Signal Processing:*** Combines deep learning architectures (e.g., CNNs) with signal processing techniques like Wavelet Transforms.

2. ***ML/DL + Optimization Algorithms:*** Integrates AI models with optimization techniques to refine model parameters for improved accuracy.
   - ***ML + Optimization Algorithms:*** Combines traditional machine learning models with optimization techniques like Genetic Algorithms (GA) or Particle Swarm Optimization (PSO) to enhance predictive accuracy and model performance in fault diagnosis.
   - ***DL + Optimization Algorithms:*** Integrates deep learning models with optimization algorithms, such as GA or PSO, to optimize parameters and improve fault detection capabilities in complex tasks.

3. ***ML/DL + Reinforcement Learning:*** Blends traditional ML/DL models with reinforcement learning for adaptive decision-making in real-time fault diagnosis.
   - ***ML + Reinforcement Learning:*** Pairs traditional machine learning models with reinforcement learning for tasks requiring dynamic optimization and decision-making, such as maintenance scheduling and adaptive fault response.
   - ***DL + Reinforcement Learning:*** Merges deep learning models with reinforcement learning to tackle complex decision-making processes, enhancing fault diagnosis capabilities through continuous learning and optimizing maintenance response time.

4. ***ML/DL + Generative Models**:* This approach combines machine learning or deep learning models with generative models, enhancing data quality and anomaly detection.
   - ***ML + Generative Models**:* Uses ML with generative models (e.g., GANs, Variational Autoencoders) to improve fault diagnosis through data augmentation or synthetic data generation.
   - ***DL + Generative Models**:* Combines DL with generative models to generate synthetic data or detect anomalies, improving model robustness and diagnostic accuracy.

5. ***AI + Physics-based Models**:* This approach integrates AI models with physics-based diagnostic techniques, combining data-driven insights with theoretical knowledge to improve diagnostic accuracy.
   - ***AI + Physics-based Models**:* Uses physical principles alongside AI to provide diagnoses that align with known mechanical properties. Examples include Finite Element Analysis (FEA), widely used for simulating stress and strain in mechanical components to predict failure points, as well as for analysing other physical phenomena, and Physically Informed Neural Networks (PINNs), which leverage physical laws to guide the model's predictions, ensuring robustness and adherence to realistic mechanical behaviour.
   - ***AI + Sensor Fusion**:* Combines data from multiple sensors to enhance fault detection accuracy through a more comprehensive dataset.

4.4 Other AI Methods Path

This path encompasses AI methods that fall outside traditional machine learning and deep learning categories, including rule-based systems, fuzzy logic, expert systems, and probabilistic reasoning approaches. These techniques are particularly valuable when managing uncertainty, integrating expert knowledge, or ensuring interpretability is paramount. Unlike ML and DL, which often rely heavily on large datasets for training, these approaches typically use predefined rules, logical reasoning, or evolutionary strategies to model complex systems. This makes them especially well-suited for environments where data is scarce, incomplete, or where human interpretability and direct integration of domain expertise are critical for effective fault diagnosis.

1. ***Fuzzy logic systems****:* A rule-based approach that mimics human reasoning by handling uncertainty and ambiguity. This flexibility makes it particularly effective in fault diagnosis scenarios where precise thresholds for decision-making are impractical or difficult to define.
2. ***Expert systems****:* These systems emulate human decision-making through predefined rules and logical structures derived from domain expertise, offering structured diagnostics based on human knowledge. Expert systems are particularly valuable in environments with scarce labelled data, as they rely on explicit knowledge representation rather than training.
3. ***Bayesian Networks****:* Probabilistic graphical models like Bayesian Networks are designed to manage uncertainty in fault diagnosis by using statistical measures to model relationships between variables. These networks update their predictions dynamically as new data becomes available, making them suitable for real-time diagnostic applications.
4. ***AI-Driven Maintenance Scheduling****:* This approach uses AI to optimize maintenance schedules based on fault detection and prediction. By analysing fault data and predicting potential failures, these systems enable proactive maintenance strategies, reducing downtime and maintenance costs.
5. ***Genetic Programming****:* An evolutionary algorithm that evolves computer programs to optimize diagnostic performance. Genetic programming is especially beneficial in creating solutions for complex problems where traditional methods struggle, such as developing unique fault classification models tailored to specific systems.
6. ***Neuro-Fuzzy Systems****:* Combining the adaptive learning capabilities of neural networks with the interpretability of fuzzy logic, neuro-fuzzy systems integrate human-like reasoning with machine learning to improve fault detection. This hybrid approach is particularly valuable when data uncertainty must be managed alongside automated learning.

Chapter 5

5 Literature Review Results and Findings

This chapter provides a comprehensive analysis of the literature reviewed, synthesizing findings from 150 articles that explore advancements in AI-driven bearing fault diagnosis. Using the decision tree framework for AI methods in bearing fault diagnosis introduced in the previous chapter, the selected studies are systematically categorized based on specific AI approaches. The provided labels offer a balanced level of precision, capturing key methodological distinctions without becoming overly complex or unmanageable.

5.1 Eligibility and Selection Criteria

In this section, we outline the eligibility and selection criteria used to identify articles for the literature review. This discussion provides a transparent and systematic framework for selecting relevant studies, detailing the rationale behind the selection criteria and their alignment with the review's objectives. The scope of the research is limited to English-language articles published between 2020 and 2024. A minimum of 30 articles per year was selected, resulting in a total of 150 articles. Notably, China emerged as the most significant contributor to this field, as displayed in Figure 8.

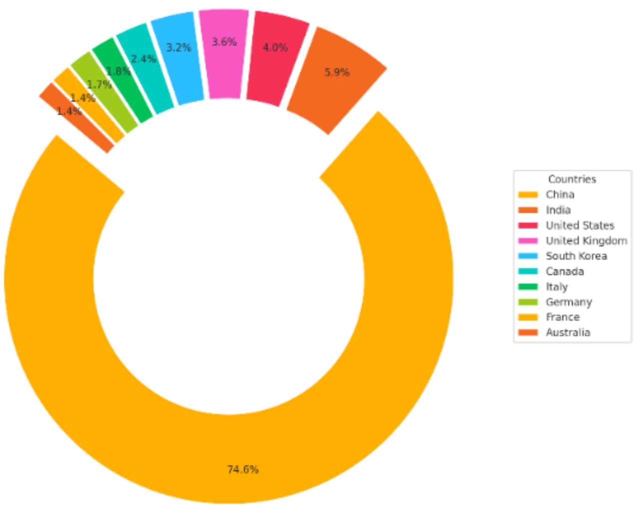

Figure 8. Top 10 countries by number of articles on bearing fault diagnosis.

The following digital databases were used for article selection:

- ***Google Scholar***
- ***ScienceDirect*** and ***Scopus*** (academic research platforms developed by ***Elsevier***)
- ***MDPI Open Access Journals***
- **IEEE Xplore**
- ***American Society of Mechanical Engineers (ASME)***

The search was conducted using the following keywords: "rolling bearing" OR "bearings" AND "fault diagnosis" AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network" OR "transfer learning"). This strategy provided sufficient flexibility while maintaining relevance to the topic. Articles that focused on bearing fault diagnosis and detection without incorporating AI were excluded to ensure the review aligned with its technological focus.

5.2 Presentation and Analysis of Results

This section presents the findings of the literature review, organized using the decision tree framework. For visual clarity, the results are divided into two parts: Table 3 covers the Machine Learning Path and Deep Learning Path, while Table 4 addresses the Hybrid Methods Path and Other AI Methods Path. It is important to note that each label assigned to an article represents the understood focus or key innovation of the study, rather than the sole approach or method used to address the problem. This structured approach highlights key trends, innovative techniques, and the distribution of research across AI methodologies in bearing fault diagnosis.

Before proceeding, it is important to emphasize that, generally speaking, all AI frameworks integrate multiple approaches and techniques. Consequently, the provided labels aim to strike a balance between precision and simplicity, capturing key methodological distinctions without becoming overly detailed or cumbersome. This premise is crucial for understanding why certain labels may not be accompanied by citations.

Main Category	Subcategory	Classification Label	Article Reference from 2020 to 2024
Machine Learning Path	Supervised Learning	SVM-based Bearing Fault Diagnosis	[8]
		Tree-based Bearing Fault Diagnosis	
		k-NN-based Bearing Fault Diagnosis	
		Ensemble-based Bearing Fault Diagnosis	[9], [10], [11]
		Regression-based Bearing Fault Diagnosis	
		Supervised Generative Models in Bearing Fault Diagnosis	
		Other ML-based Bearing Fault Diagnosis	[12]
	Unsupervised Learning	Clustering in Bearing Fault Diagnosis	
		Pattern Deviation Detection in Bearing Fault Diagnosis	
		Dimensionality Reduction in Bearing Fault Diagnosis	
		Unsupervised Generative Models in Bearing Fault Diagnosis.	[13]
	Semi-Supervised Learning	Graph-Based Semi-Supervised Bearing Fault Diagnosis	[14], [15], [16]
		Self-Training Semi-Supervised Bearing Fault Diagnosis	
		Semi-Supervised Generative Models in Bearing Fault Diagnosis.	[17]
Deep Learning Path	Traditional Neural Networks (NNs)	Traditional NN-based Bearing Fault Diagnosis	[18], [19], [20], [21], [22], [23]
	Advanced Deep Learning	CNN-based Bearing Fault Diagnosis	[24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [7], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50]
		RNN-based Bearing Fault Diagnosis	[51],[52], [53]
		Autoencoder-based Bearing Fault Diagnosis	[54], [55], [56], [57], [58]
		Few-Shot Learning in Bearing Fault Diagnosis	[59]
		Transfer Learning in Bearing Fault Diagnosis	[60], [61], [62], [63], [64], [65], [66], [67], [68], [69], [70], [71], [72], [73], [74], [75], [76], [77], [78], [79], [80], [81], [82], [83], [84], [85], [86], [87], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [98], [99], [100], [101], [102], [103], [104], [105] ,[106], [107]
		Foundation Models in Bearing Fault Diagnosis	

Table 3.

Main Category	Subcategory	Classification Label	Article Reference from 2020 to 2024
Hybrid Methods Path	ML/DL + Signal Processing	Hybrid ML + Signal Processing in Bearing Fault Diagnosis	[108], [109], [110]
		Hybrid DL + Signal Processing in Bearing Fault Diagnosis	[111], [112], [113], [114], [115], [116], [117], [118], [119], [120], [121], [122], [123], [124], [125], [126], [127], [128], [129], [130]
	ML/DL + Optimization Algorithms	Hybrid ML + Optimization in Bearing Fault Diagnosis	[131]
		Hybrid DL + Optimization in Bearing Fault Diagnosis	[132], [133], [134], [135], [136], [137], [138], [139], [140], [141], [142], [143]
	ML/DL + Reinforcement Learning	Hybrid ML + Reinforcement Learning in Bearing Fault Diagnosis	
		Hybrid DL + Reinforcement Learning in Bearing Fault Diagnosis	
	ML/DL + Generative Models	Hybrid ML + Generative Models in Bearing Fault Diagnosis	[144]
		Hybrid DL + Generative Models in Bearing Fault Diagnosis	[145], [146], [147], [148]
	AI + Physics-based Models	Hybrid AI + Physics-based Models in Bearing Fault Diagnosis	[149], [150], [151], [152], [153], [154]
		Hybrid AI + Sensor Fusion in Bearing Fault Diagnosis	[155]
Other AI Methods Path	Fuzzy Logic	Fuzzy Logic in Bearing Fault Diagnosis	[156]
	Expert Systems	Expert Systems in Bearing Fault Diagnosis	
	Bayesian Networks	Bayesian Networks in Bearing Fault Diagnosis	
	AI-Driven Maintenance Scheduling	AI-Driven Maintenance in Bearing Fault Diagnosis	
	Genetic Programming	Genetic Programming in Bearing Fault Diagnosis	
	Neuro-Fuzzy Systems	Neuro-Fuzzy Systems in Bearing Fault Diagnosis	

Table 4.

Transfer learning has undoubtedly emerged as the most researched topic in the field of intelligent fault diagnosis, as demonstrated by the analysis of 150 reviewed articles and depicted in the figure below. This trend is supported by other reviews on the topic conducted in the past five years, such as [157], [158] and [159], with the last citation going a step further by identifying this topic as a future prospect for promoting the applications of IFD in engineering scenarios in the coming years.

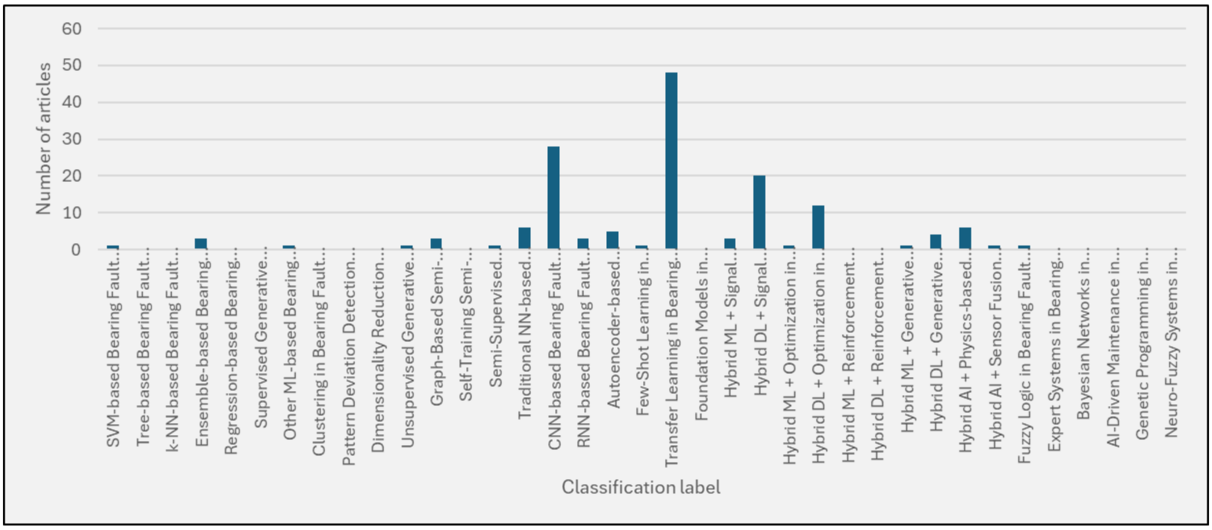

Figure 9: Research trend from 2020 to 2024.

Transfer learning is particularly effective in industrial scenarios with limited labelled data, where traditional ML and DL models struggle as it reduces reliance on large datasets and addresses distribution discrepancies commonly encountered in real-world applications. The lack of labelled data in industrial settings often arises from practical challenges, such as the risks of running machines in faulty conditions, the extended time required for machines to degrade before failure, and the wide range of operating conditions, including varying loads and speeds. These factors make it difficult to create comprehensive datasets, leading to poor performance of deep learning models trained on laboratory data due to significant differences in data distributions between training and testing environments. Unlike traditional learning processes that require building new models for each task and retraining them from scratch when data distributions change, transfer learning reuses pre-trained models. Figure 10 illustrates the basic layout of the standard transfer learning process.

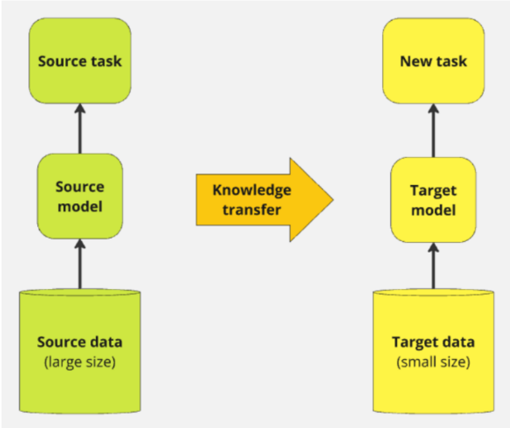

Figure 10. Transfer learning idea.

By retraining an existing model with a new dataset, it applies knowledge gained from an initial source task or data to a new, related target task or data, enabling integration of insights from multiple datasets, often achieving better performance, faster training, and mitigating overfitting. This is particularly useful in cases where diagnostic knowledge obtained from controlled laboratory experiments can be reused in real-world engineering scenarios, enabling models trained on such datasets to diagnose faults effectively, despite insufficient or inconsistent labelled data. As an example, Kumar et al. [81] leveraged a pretrained ResNetV2 as the base model within a transfer learning framework to develop an efficient strategy for feature extraction and selection, enabling accurate detection of bearing faults. Just recently, Guo et al. [106] proposed a lightweight residual network, ResNet-KTQD, specifically tailored for cross-domain fault diagnosis, demonstrating the adaptability of transfer learning techniques in addressing domain discrepancies and ensuring effective fault detection.

However, transfer learning has limitations. For optimal results, the source and target tasks should be similar, the data distributions between them should not differ significantly, and the same model type should be applicable to both tasks. Failure to meet these conditions can lead to negative transfer, which harms model performance. Addressing this requires careful evaluation of dataset similarities and techniques such as distant transfer to mitigate issues from dissimilar data distributions. To address the imbalance in the number of fault categories between the source and target domains, Li et al. [66] developed an adversarial transfer learning method based on a stacked autoencoder. He et al. [70] employed the CORrelation ALignment (CORAL) algorithm to minimize the marginal distribution discrepancy between the source and target domains. Similarly, Yang et al. [73] used the CORAL algorithm to align the data distributions of the source and target domains in their proposed approach. More recently, Li et al. [98] utilized Multi-Kernel Maximum Mean Discrepancy (MK-MMD), another domain adaptation technique, to narrow the distribution distance between the source and target domains, obtain domain-invariant features, and achieve the transfer diagnosis of rolling bearing faults across different devices.

Many studies combine transfer learning with convolutional neural networks, leveraging CNN's powerful feature extraction capabilities alongside transfer learning's adaptability to varying environments. Combining CNNs with transfer learning addresses common challenges associated with CNNs, such as their reliance on large datasets during training and inclination to overfitting, resulting in a robust and efficient solution for fault diagnosis. Lu et al. [60] proposed a generic intelligent bearing fault diagnosis system coupling a convolutional neural network with transfer learning to automatically identify and classify different bearing faults. Transfer learning was used to avoid overfitting problem of deep network. In 2021, Shao et al. [77] proposed a modified transfer CNN driven by thermal images to diagnose faults in a rotor-bearing system under varying working conditions, utilizing parameter transfer to enable the source-modified CNN to adapt to the target domain and address the challenge of limited available training data in the target domain.

Based on the literature reviewed, CNNs emerge as the second most researched topic in bearing fault diagnosis, following transfer learning. Since their introduction in 2016 as a promising solution for fault diagnosis, CNNs have been extensively studied. Well-suited for image and 2D data analysis, CNNs are employed in bearing fault diagnosis to analyse bearing surface images or spectral representations, effectively detecting surface defects and fault patterns. Zhao et al. [26], developed a normalized CNN for diagnosing rolling bearings under varying fault severities and configurations, addressing challenges such as data imbalance and variable working conditions. CNNs have demonstrated superior performance compared to traditional methods, particularly in identifying faults under complex conditions and at early development stages. Choudhary et al. [30], proved the superior performance of a LeNet-5-based CNN compared to both shallow and deep learning approaches incorporating artificial neural networks for bearing fault classification using thermal images. Kumar et al. [38] addressed the common challenge of identifying bearing defects from small samples in CNNs by enhancing the cost function with an additional sparsity term, which reduces unnecessary neuron activations in the hidden layers.

Another key observation from the review is the greater emphasis placed by academics on signal preprocessing over model optimization to address the issue of anti-noise. Preprocessing is a critical step in any data-driven approach, designed to remove noise and extract meaningful features from the data, ensuring that only relevant information is fed into the diagnostic system. This approach significantly enhances the system's resilience to noisy or low-quality input data. Chen et al. [111] utilized Cyclic Spectral Coherence (CSCoh) to preprocess vibration signals, resulting in superior discriminative feature representations of bearing health statuses across different operating conditions. More recently, Lin et al. [118] utilized the Modified Ensemble Empirical Mode Decomposition (MEEMD) scalar index to capture the condition of bearings.

In many cases, signal processing techniques are used in combination with autoencoders to leverage their respective strengths and mitigate their limitations. Traditional signal processing effectively removes structured, well-understood noise, while autoencoders excel in handling complex, nonlinear noise patterns, making them a powerful hybrid solution. As an example, Yang et al. [117] proposed a novel feature extraction method that combines a statistical algorithm, wavelet scattering network, and stacked auto-encoder network.

Chapter 6

6 Commercial Solutions: Overview and Analysis

Commercially available solutions play a pivotal role in translating theoretical advancements into practical applications for bearing fault detection, diagnosis, and prognosis. This chapter provides an overview of such solutions, focusing on those that explicitly incorporate artificial intelligence technologies. Each solution is described in terms of its functionality, applications, and potential advantages in real-world settings, with information sourced from companies' official websites and publicly disclosed documents to ensure accuracy and relevance. While this chapter focuses on AI-driven tools, it is important to acknowledge that many other solutions are available but are excluded here due to practical limitations rather than their significance. Observations and insights on the reviewed solutions will be provided at the end of the chapter to synthesize key takeaways and future directions. This chapter serves as a starting point for understanding the current state of AI-driven tools in the industry and lays the groundwork for discussions in the concluding chapter on their implementation, effectiveness, and the gap between commercial practices and theoretical advancements.

6.1 Commercial Solutions from the Industry

This section presents a carefully selected range of commercially available AI-driven solutions for bearing fault detection, diagnosis, and prognosis. Each tool or system is described in terms of its functionality and applications, illustrating the diverse ways artificial intelligence is being applied in real-world industrial settings to drive innovation.

6.1.1 ABB Ability™ Smart Sensor

ABB is a global leader in electrification, robotics, automation, and motion, offering innovative solutions aimed at enhancing industrial productivity and energy efficiency. Among ABB's solutions is the ABB Ability™ Smart Sensor, a wireless device designed to monitor the health of bearings and other rotating equipment. It provides insights into equipment performance and maintenance needs through a user-friendly interface, enabling informed decision-making and proactive maintenance.

The solution includes both hardware and software, described as follows:

- ABB Ability™ Smart Sensor (shown in Figure 11a): A battery-operated device capable of recording signal data such as temperature, vibrations, magnetic field measurements, and ultrasonic sounds.
- The acquired data is transmitted to the Cloud-based ABB Ability™ platform, where it can be accessed in three ways, as listed below and schematically shown in Figure 11b:
    1) ABB Ability™ Smart Sensor App,
    2) ABB Ability™ Digital Powertrain portal,
    3) Customer cloud and network system

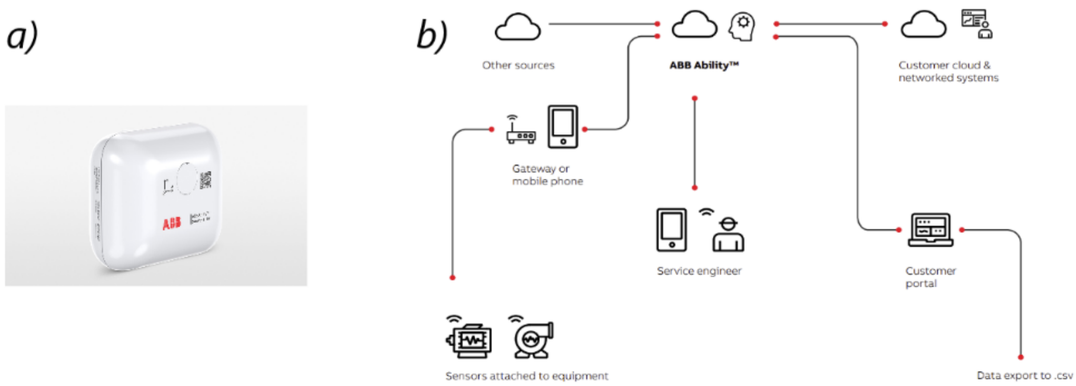

Figure 11. Adapted from ABB.com.

Although ABB publicly declares the use of AI in its solutions, including its Genix suite and its collaboration with Microsoft to enhance AI functionalities, there is no publicly disclosed information on how AI is utilized to process the acquired data in the ABB Ability™ Smart Sensor, as the methodologies remain proprietary.

6.1.2 Amazon Monitron and Amazon Lookout for Vision

Amazon, a multinational technology company, is renowned for its e-commerce platform and advanced cloud computing services, including AI-powered industrial solutions. Among its industrial AI offerings, Amazon provides Amazon Monitron and Amazon Lookout for Vision, two innovative solutions designed to enhance predictive maintenance and quality control in industrial settings.

- ***Amazon Monitron*** is an end-to-end machine learning-based condition monitoring solution designed to detect abnormal conditions in industrial rotating equipment. It enables the implementation of predictive maintenance programs to reduce unplanned downtime. Amazon Monitron includes purpose-built sensors for capturing vibration and temperature data, gateways that automatically transfer data to the AWS Cloud, and an application for system setup, analytics, and notifications to track equipment condition. The solution employs a ML model to monitor equipment vibrations, detecting changes in vibration patterns that may indicate potential faults. The ML approach is refined over time using feedback provided by technicians, enhancing its ability to predict similar abnormalities in the future. This ML model is complemented by an ISO threshold model, which analyses vibration magnitude to assess machine health. Figure 12 (adapted from Amazon.com) illustrates a sensor reading of an unhealthy asset.

Figure 12.

By integrating these advanced methods, Amazon Monitron delivers effective predictive maintenance solutions to optimize equipment reliability and reduce operational disruptions.

- ***Amazon Lookout for Vision*** is a computer vision-based service designed to streamline defect detection and maintain high standards in industrial manufacturing. It detects defects such as scratches, dents, and missing components, improves production quality through real-time issue identification, and enhances operational efficiency by reducing reliance on manual inspections and enabling better analysis of defect trends.

  This solution identifies anomalies in images using two types of machine learning models, which users can select based on their specific needs:

  - ***Image Classification Model***: Determines whether an image contains an anomaly or not, providing a binary classification (normal or anomalous) along with a confidence score.
  - ***Image Segmentation Model***: Identifies the location of anomalies within an image, highlighting defective areas with color-coded masks according to the type of defect.

Once that the model has been selected Amazon Lookout for Vision follows a structured workflow for defect detection. Users first prepare labelled datasets of normal and defective components, uploading data from local storage, Amazon S3, or Amazon SageMaker Ground Truth manifest files. The system then automatically selects the most appropriate algorithms to train the model, evaluating its performance using metrics such as Precision, Recall, and F1 score. During inference, the trained model analyses input images to identify anomalies. Classification models return a binary prediction indicating whether the image is normal or defective, while segmentation models provide detailed anomaly masks, highlighting defect locations and types. Once trained, models can be deployed on AWS IoT Greengrass-compatible edge devices, enabling on-site anomaly detection without continuous cloud connectivity, reducing bandwidth costs and supporting real-time analysis.

Although Amazon Lookout for Vision specializes in anomaly detection, it can be integrated with Amazon Rekognition Custom Labels for more detailed, multi-class defect classification. This integration enables users to identify specific defect types beyond binary classification and gain detailed insights into production quality issues, enhancing corrective action planning. Combining Lookout for Vision’s anomaly detection capabilities with Rekognition’s advanced image analysis and defect categorization delivers robust solutions for industrial manufacturing.

6.1.3 IBM Maximo® Application Suite

IBM is a technology and consulting company renowned for its pioneering advancements in AI, cloud computing, and analytics to drive business transformation. IBM Maximo® Application Suite (MAS) is an integrated lifecycle management solution designed to streamline the maintenance, inspection, and reliability of critical equipment like bearings by leveraging generative AI, advanced analytics, and the Internet of Things.

Within the IBM Maximo® Application Suite, Maximo Health and Maximo Predict are complementary tools that enable comprehensive equipment management by addressing distinct aspects of equipment performance and maintenance:

- ***IBM Maximo Health****:* Consolidates data from various sources, including third-party IoT sensors, to monitor the current condition of equipment. It provides insights into equipment health, facilitating condition-based maintenance strategies.
- ***IBM Maximo Predict****:* Utilizes machine learning to analyse historical and real-time data, predicting potential future failures and optimizing maintenance schedules.

By integrating IoT sensor data (e.g., vibration and temperature readings) from bearings, MAS monitors real-time conditions. Machine learning models detect anomalies or patterns indicative of wear or failure, and predictive analytics forecast the remaining useful life of bearings, enabling timely maintenance and preventing unexpected downtimes.

6.1.4 NSK Bearing Doctor

NSK is a leading manufacturer of bearings and precision machinery, offering innovative solutions to enhance the performance and reliability of industrial equipment. The NSK Bearing Doctor is a software-based diagnostic tool, enhanced with AI capabilities, designed to assist users, such as engineers, maintenance professionals, and designers, in managing bearings effectively throughout their lifecycle.

Its key aspects include:

- ***Optimized Bearing Selection****:* Assisting users in selecting the most suitable bearings based on specific operational parameters such as load, speed, and temperature, while providing access to NSK's comprehensive catalogue of bearing products tailored for diverse industrial applications.

- ***Diagnostic and Prediction**:* The system collects and analyses operational data, such as vibration, noise, and temperature, to identify anomalies and diagnose issues like excess heat or noise. It provides actionable recommendations for corrective actions, including guidance on proper lubrication intervals and suitable lubricants to prolong bearing life. Using advanced predictive analytics, the system forecasts potential failures and tracks performance trends in real time, enabling condition-based maintenance and alerting users to necessary interventions before critical failures occur. Enhancing this capability, the NB-4 Compact Bearing Monitor (shown in Figure 13) evaluates bearing conditions using vibration and acceleration measurements across multiple axes through its integrated sensor. The monitor assesses key parameters such as frequency, amplitude, and time-domain trends to identify irregularities. Its compact design, which includes a dedicated vibration sensor, allows for precise real-time monitoring, even in space-constrained setups, ensuring reliable condition assessments.
- ***Accessible Tools and Interface**:* The user-friendly interface, accessible on mobile devices, ensures quick navigation and ease of use for on-site bearing management. Additionally, users benefit from comprehensive educational resources, including manuals and technical articles, as well as seamless integration with other NSK tools for a comprehensive equipment management approach.

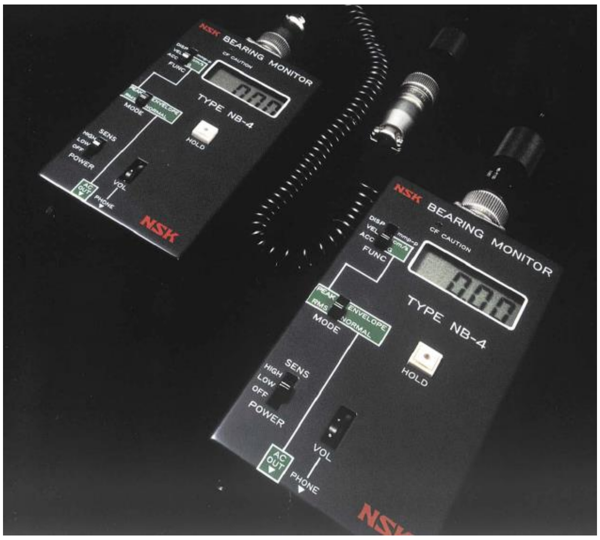

Figure 13. Adapted from NSK.com.

6.1.5 NTN Corporation

NTN is a global leader in precision machinery and components, renowned for its innovative bearings and advanced condition monitoring solutions. By integrating state of the art sensing technologies with machine learning, AI, and IoT, NTN delivers comprehensive tools for condition monitoring, fault detection, and predictive maintenance across a range of industries. Sophisticated algorithms like vibration spectrum analysis, random forest classification and outlier detection contribute to high-precision defect identification and remaining useful life predictions, even in complex environments. Through seamless compatibility with industrial IoT platforms, NTN enables centralized monitoring, big data analysis, and data-driven decision-making, ensuring optimized operations and enhanced reliability.

NTN offers customers a variety of products and services, including:

- ***Sensor Integrated Bearings**:* NTN's Sensor Integrated Bearing Units (as shown in Figure 3) incorporate advanced sensors to monitor load, temperature, and vibration directly from the bearing's raceway surface, ensuring high accuracy and early anomaly detection. These units also feature a built-in generator for independent power supply and wireless modules for seamless data transmission, simplifying integration into IoT environments. The technology supports both real-time condition monitoring and machine control, enabling predictive maintenance and reduced downtime. Data from these units can be directly integrated with industrial IoT platforms like Edgecross™, facilitating comprehensive data analysis and storage for big data applications.
- ***Talking Bearings™**:* Similar to Sensor Integrated Bearings, Talking Bearings™ include vibration, temperature, and rotation sensors along with wireless communication and independent power systems. These innovative bearings continuously transmit condition data, enabling remote and continuous monitoring without additional sensing equipment.
- ***Portable Vibroscopes**:* For on-site maintenance, NTN offers portable devices that interface with tablets or smartphones. These tools quickly measure and record vibration data, providing rapid diagnostics to detect bearing abnormalities based on predefined criteria.

- ***WindDoctor™***: WindDoctor™ is NTN's specialized condition monitoring system for wind turbines. It processes vibration and operational data to provide real-time diagnostics and remote monitoring, enabling early detection of anomalies and efficient maintenance scheduling. This system (Figure 14 adapted from [160]) tailored to reduce maintenance costs and improve equipment availability for power generation companies by integrating fault detection and remaining life estimation algorithms.

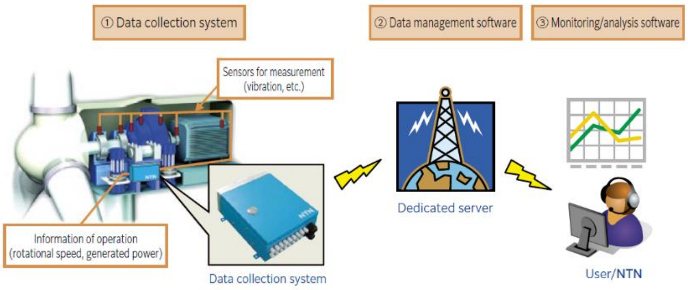

Figure 14. Wind doctor system configuration.

Among the publicly disclosed documents, in the recent 89th NTN Technical review 2022-2023 where the company highlights the latest technological advancements, product developments, and research findings, there are some explicit references to some of the approaches used in condition monitoring and bearing diagnosis:

- Signal processing techniques:
  - ***Noise Filtering***: Removes unwanted noise using statistical filters to improve signal clarity.
  - ***Ultrasonic Echo Analysis***: Utilized for detecting periodic changes in ultrasonic reflection intensity (URI) for early fault diagnosis.
  - ***Autocorrelation Analysis***: Applied to time-domain ultrasonic data for identifying consistent rolling patterns and grease conditions.
  - ***Adaptive Signal Enhancement***: Improves the signal to noise ratio (S/N) for diagnosing low dN (speed-diameter product) environments.
  - ***Bandpass Filtering***: Filters specific frequency bands to extract key vibration signal features for analysis.
  - ***Statistical Feature Extraction for AI Models***: Time-Domain Features (RMS, maximum value, peak factor), Frequency-Domain Features (Spectral kurtosis, skewness), Cepstral-Domain Features (Envelope-processed RMS and other quantitative metrics).

- ***AI-Based Algorithms***:
    - ***Machine learning – Regression methods***:
        - ***Kernel Ridge Regression (KR)***: A regression technique that uses kernel functions to model nonlinear relationships between features and outputs.
        - ***Random Forest Regression (RF)***: Ensemble-based regression method that aggregates multiple decision trees for accurate predictions.
    - ***Deep Learning Models***:
        - ***Deep Neural Networks (DNNs)***: Employs architectures with multiple hidden layers (e.g., 4-layer DNN) for regression and classification tasks.
        - ***Convolutional Neural Networks***: Converts vibration acceleration spectrograms into image-like representations for feature extraction and classification.
        - ***Feature Fusion Network (FFN)***: Combines multimodal data (vibration, acoustic, temperature) into a single predictive framework, enhancing diagnostic accuracy and RUL prediction

6.1.6 Schaeffler Group

The Schaeffler Group specializes in precision components for automotive, industrial, and aerospace applications, including bearings, with a focus on reliability and efficiency. Schaeffler also offers a comprehensive solution for both condition monitoring and smart lubrication: the OPTIME Ecosystem. The OPTIME Ecosystem (schematically shown in Figure 15, adapted from Schaeffler.com) comprises various elements that work together to minimize unplanned downtime. The Schaeffler OPTIME solution is a scalable system that integrates wireless sensors (provided by Schaffler), a cellular gateway, and digital services powered by proprietary Schaeffler algorithms. The wireless sensors monitor key parameters, such as vibration and temperature, on machines and devices. The collected data is transmitted to the Schaeffler Cloud via the gateway, where it is analysed using advanced algorithms. Actionable insights and error diagnoses are then provided to users through intuitive mobile and web-based interfaces, enabling effective and clear machine condition monitoring.

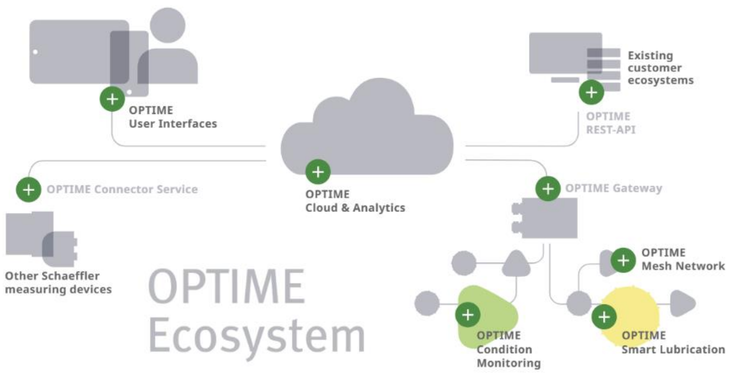

Figure 15.

6.1.7 SKF

SKF is a global leader in bearing technology and services, offering solutions for rotating equipment performance and predictive maintenance. SKF provides hardware and software systems to support condition monitoring practices, enabling the detection and diagnosis of issues as they occur.

Portable monitoring devices include the SKF QuickCollect sensor, a Bluetooth-enabled handheld device designed to collect vibration and temperature data. It is user-friendly and connects to apps like SKF QuickCollect, which quickly evaluates machine health by setting alarm thresholds and assessing machine condition according to industry standards. Alternatively, it integrates with the SKF Enlight ProCollect app, offering a comprehensive suite for in-depth condition monitoring, including data collection, analysis, and management within maintenance workflows. For a more comprehensive vibration data collection and analysis, SKF offers the SKF Microlog Analyzer dBX. This system allows simultaneous tri-axial measurements and employs SKF's fastest vibration analysis method, Multi-Point Acquisition (MPA). The system effectively interfaces with SKF's condition monitoring software, such as SKF @ptitude Analyst and SKF @ptitude Observer, enabling in-depth data analysis and efficient management.

- ***SKF @ptitude Observer*** focuses on real-time monitoring and diagnostics with advanced vibration analysis tools like FFT and Power Cepstrum. It employs Protean Diagnosis (diagnostic tool developed by SKF) for automatic fault detection, statistical alarm calculations, and adaptive alarming to reduce false positives. The platform excels in transient analysis with specialized graphing tools like Bode and Nyquist plots, enabling detailed evaluation during machine startup and shutdown. Additionally, it offers historical trend analysis and multi-layer alarms for comprehensive machine condition monitoring.

- ***SKF @ptitude Analyst*** specializes in advanced diagnostics and post-processing, featuring tools like acceleration enveloping (gE) for bearing fault detection, Harmonic Activity Locator (HAL) for prioritizing fault likelihoods, and Cyclic Time Average (CTA) for gear fault diagnostics. It leverages Digital Signal Processing (DSP) for in-depth spectral analysis, including waterfall plots and derived points for virtual data modelling. With event capture capabilities, statistical alarm calculations, and transient data integration, it enables predictive maintenance and detailed root cause analysis.

For continuous monitoring, SKF Axios offers a simple, wireless, and scalable end-to-end predictive maintenance solution. Developed in collaboration with Amazon Web Services (AWS), SKF Axios combines SKF's expertise in rotating machinery and predictive maintenance with AWS' industrial AI services to provide a cost-effective, cloud-based condition monitoring system. SKF Axios includes its own sensors capable of collecting and analysing 3-axis vibration and temperature data to detect equipment anomalies and notify users of abnormal conditions, with detailed information displayed through a dedicated app. When such conditions are detected, users receive alerts to take timely maintenance actions, preventing potential failures. Historical trend data forms the foundation of its machine learning algorithms, enabling smarter and more accurate anomaly detection as more data is gathered.

Moving to computer vision solutions, according to Evolution Technology Magazine from SKF, SKF has developed an AI-powered computer vision system to evaluate bearing damage automatically aiding in diagnostics and extending component life. The system uses a neural network image-recognition algorithm trained on thousands of images from SKF's archives. Unlike traditional machine-vision methods, it operates effectively in real-world conditions, handling imperfect angles and cluttered backgrounds. The AI tool identifies areas of interest, classifies damage type and severity, and focuses on failure modes that account for 80% of service issues, as defined by ISO 15243:2017. Figure 16 illustrates examples of input images containing bearing damage (left) and the resulting output (right), where the AI tool displays the detected damage in the form of bounding boxes with their corresponding ISO failure mode classification.

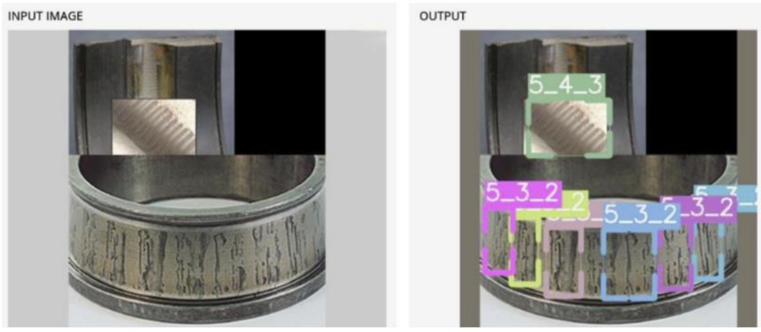

Figure 16. Adapted from Evolution Technology Magazine from SKF.

Training involved tagging images with failure modes and testing the algorithm against expert evaluations to refine its accuracy. Since its deployment, it has begun assisting customer support teams and remanufacturing personnel, with the system continually learning alongside experienced staff. Future plans include offering the tool as cloud-based software, allowing users to upload bearing images for instant analysis and decision-making on remanufacture suitability. SKF is also exploring integration with condition monitoring and machine control systems to automate root-cause analysis and address reliability challenges more effectively.

6.1.8 STMicroelectronics

STMicroelectronics is a global semiconductor company that designs and produces innovative electronic solutions for embedded systems. It offers a comprehensive solution for motor fault detection and classification, focusing on predictive maintenance. Using STM32 microcontrollers and NanoEdge AI Studio software, users can develop machine learning models to detect and classify motor faults, including bearing issues, enabling real-time monitoring and early detection of potential failures to enhance equipment reliability and reduce downtime. The solution integrates a 3-axis accelerometer featured on the STEVAL-PROTEUS1 wireless smart sensor evaluation board and NanoEdge AI Studio, which processes the sensor data to provide real-time analysis and decision-making in embedded systems. NanoEdge AI Studio allows developers to create optimized tinyML libraries for anomaly detection, outlier detection, classification, and regression with minimal data and no advanced AI expertise, enabling flexibility in edge AI applications. NanoEdge AI Studio performs both learning and inference directly on STM32 microcontrollers, streamlining the development process, reducing time and cost, and supporting various sensors and physical inputs such as acceleration, pressure, and temperature.

Key features include:

- ***Custom Library Generation**:* Create libraries optimized for accuracy, confidence, inference time, and memory footprint.
- ***Integrated Tools**:* Includes sampling finders, dataloggers, emulators, and tools for performance validation and testing.
- ***Scalability**:* Compatible with STM32 microcontrollers, including Cortex-M0-based devices, with native support for STM32 boards.

By combining STMicroelectronics' hardware and software innovations, NanoEdge AI Studio provides a robust platform for developing advanced predictive maintenance solutions in embedded systems.

6.2 Observations and Insights on Commercial Solutions

Since companies do not publicly disclose the specifics of their AI implementations, understanding the extent and manner of its use in the discussed solutions remains challenging. Commercial solutions for bearing fault monitoring increasingly leverage artificial intelligence to enhance functionality and improve accuracy. Machine learning algorithms are central to these systems, offering capabilities such as automated fault detection, anomaly detection, fault classification, and Remaining Useful Life prediction. By analysing operational data such as vibrations, temperature, acoustic emissions, and visual inputs, these systems enable predictive maintenance strategies and help optimize equipment performance. A notable feature of these ML-based approaches is their ability to improve over time through feedback mechanisms. Technicians provide insights into detected anomalies, which refine the ML models, enhancing their ability to predict similar abnormalities in the future. In parallel, these ML models can be complemented by an ISO threshold model that evaluates vibration magnitude to assess machine health, offering an additional layer of analysis independent of technician input. This combination of approaches strengthens the system's ability to facilitate proactive maintenance and health monitoring. Often integrated into embedded or edge devices, ML models enable real-time monitoring, which supports timely anomaly detection and equipment health assessments.

Despite the effectiveness of these systems, their implementation often faces challenges such as integration complexity, cost issues, and computational demands. Many tools rely on predefined fault libraries and statistical models to generate actionable insights. While useful in standard conditions, these approaches can struggle to adapt to novel or complex fault scenarios. Advanced methods such as convolutional neural networks (CNNs) are occasionally applied for tasks like identifying damage patterns through visual analysis, but their adoption remains rare due to computational and data requirements. Techniques like transfer learning and domain adaptation are gaining significant attention for their potential to improve model robustness across diverse operating conditions but are not yet widely implemented. Access to diverse and realistic datasets is also crucial for advancing ML models. Companies manufacturing condition monitoring systems, particularly bearing manufacturers, often possess proprietary datasets collected under varied and realistic operating conditions. These datasets provide a competitive edge by enabling more refined and context-specific AI models, but restricted access limits broader research advancements and inhibits collaboration between academia and industry.

To strengthen their capabilities further and align more closely with academic advancements, commercial solutions could focus on:

- ***Model Interpretability***: AI-generated insights must be clear, actionable, and easily understood by non-expert users. Incorporating explainable AI techniques can help achieve this, fostering trust and usability in industrial applications.
- ***Integration and Standardization***: Seamless integration of AI systems into existing maintenance workflows, coupled with adherence to established industrial standards, is essential for enabling broader adoption and compatibility across diverse operational environments.
- ***Scalability and Affordability***: Designing solutions that are adaptable to diverse industrial scales and budget friendly.
- ***Advancing AI Methods***: Incorporating techniques like transfer learning, domain adaptation, and deep learning to enhance performance across variable conditions and data environments.

By addressing these areas, commercial solutions have the potential to become more robust, adaptable, and aligned with both practical industrial requirements and cutting-edge academic innovations.

Chapter 7

7 Conclusions

In this thesis, we reviewed the applications of artificial intelligence in bearing fault detection, diagnosis, and prognosis, along with commercial engineering solutions in the field. After reviewing around 150 articles and examining some of the most prominent commercial solutions that explicitly mention the use of AI, two major aspects emerged: a general lack of labelled data from real industrial settings, and a noticeable gap between academically proposed solutions and the actual AI implementations in industrial practice, partly due to companies not publicly disclosing the specifics of their AI methodologies.

The **lack of labelled** data from real industrial settings arises from practical constraints such as the risks associated with running machines in faulty conditions, the extended time required for degradation, and the variability in operating conditions. These challenges hinder the creation of representative datasets and lead to poor performance of deep learning models trained on laboratory data, as distribution discrepancies often arise between training and testing environments. Proprietary datasets collected under real-world operating conditions provide a competitive edge, though restricted access limits broader research progress. While public datasets are widely used to advance research, they face issues such as limited realism, imbalance in fault representation, quality inconsistencies, and insufficient diversity and transferability. Addressing these data limitations is essential for the development of robust, scalable AI models capable of supporting industrial fault diagnostics.

Regarding the **gap between academic and industrial solutions**, a review of the literature shows that deep learning and hybrid approaches are widely employed in bearing fault monitoring. Transfer learning has emerged as a particularly effective solution in scenarios with limited labelled data, addressing distribution discrepancies between controlled experiments and real-world applications. Notably, this technique has become a focal point of research, as it allows pre-trained models to adapt to new domains, proving invaluable when operational data is imbalanced or scarce. However, while transfer learning shows great promise for improving model robustness across diverse operating conditions, it appears to be not explicitly mentioned in industrial solutions. Convolutional Neural Networks, often paired with transfer learning, have demonstrated high effectiveness in the research context of bearing fault diagnosis. This combination addresses CNNs reliance on large datasets and mitigates the risk of overfitting, creating robust and efficient solutions. CNNs, which excel at analysing images and 2D data, have been employed for examining bearing surface images and spectral representations, effectively identifying surface defects and fault patterns. Their role in image segmentation further demonstrates their versatility, as they can extract spatial and hierarchical features critical for fault analysis. For example, the 89th NTN Technical Review (2022–2023) explicitly highlighted CNNs applications in this context, underscoring their relevance in both academic and industrial advancements. Despite their potential, CNNs and other advanced methods remain limited in industrial solutions. Based on publicly disclosed information, these systems seem to primarily rely on classic machine learning algorithms, rather than advanced methods such as CNNs, for tasks like anomaly detection, fault classification, and Remaining Useful Life (RUL) prediction. These approaches are effective under standard conditions but often struggle to adapt to novel or complex fault scenarios. Additionally, many systems rely on predefined fault libraries and statistical models to generate actionable insights, often requiring human feedback and intervention for tasks like data interpretation, system tuning, and decision-making in complex scenarios. To further enhance their robustness and adaptability, commercial solutions could focus on improving model interpretability, standardization, scalability, and integration into existing workflows. Explainable AI techniques, for instance, can facilitate understanding of AI-generated insights, fostering trust and usability.

In conclusion, transfer learning and CNN-based methodologies have emerged as indispensable tools for advancing intelligent fault diagnosis. While transfer learning has primarily been explored in academic research, its potential indicates promising applications in industrial settings, particularly for adapting AI models to diverse operating conditions and improving their robustness. Advancing the application of these methodologies, along with other deep learning techniques, is crucial for addressing data-related limitations and enhancing performance across variable environments. Additionally, the sharing of industrial datasets could significantly strengthen data-driven applications, enabling the creation of more efficient, accurate, and flexible condition monitoring solutions. Bridging the gap between academic and industrial solutions requires further investigation into the development of scalable, easily integrable, and interpretable AI-driven approaches, which would ultimately enhance the reliability and safety of mechanical systems.

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