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Review

Condition Monitoring of Electric Machines: Modern Frameworks and Data-Driven Methodologies

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Abstract: Electrical machines are at the centre of most engineering processes, with rotating electrical machines, in particular, becoming increasingly important in recent history due to their growing applications in electric vehicles and renewable energy. Although the landscape of condition monitoring in electrical machines has evolved over the past 50 years, the intensification of engineering efforts towards sustainability, reliability, and efficiency, coupled with breakthroughs in computing, has prompted a data-driven paradigm shift. This paper explores the evolution of condition monitoring of rotating electrical machines in the context of maintenance strategy, focusing on the emergence of this data-driven paradigm. Due to the broad and varying nature of condition monitoring practices, a framework is also offered here, along with other essential terms of reference, to provide a concise overview of recent developments and to highlight the modern challenges and opportunities within this area. The paper is purposefully written as a tutorial-style overview for the benefit of practising engineers and researchers who are new to the field or not familiar with the wider intricacies of modern condition monitoring systems.

Keywords: condition monitoring; data-driven; rotating electrical machines; maintenance strategy

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Academic Editor: Davide Astolfi

Received: 14 January 2025
Revised: 10 February 2025
Accepted: 12 February 2025
Published: 13 February 2025

Citation: Doorsamy, W. Condition Monitoring of Electric Machines: Modern Frameworks and Data-Driven Methodologies. *Machines* **2025**, *13*, 144. https://doi.org/10.3390/machines13020144

1. Introduction

Rotating electrical machines are ubiquitous in all manner of modern engineering applications. Most of these applications employ machines, particularly at lower ratings, that are adequately robust, effective, and reliable when compared to their availability requirements, such that condition monitoring is not required [1]. However, there are many applications where the reliability of rotating electrical machines is critical to the function they serve, necessitating condition monitoring. In recent decades, there has been a significant increase in these types of applications in growth sectors such as renewable energy [2], industrial automation [3], and electric vehicles [4].

This growth in demand for condition monitoring in rotating electrical machines, coupled with related technological advancements in sensing, communications, and computing, has led to increased research and development in this field, particularly with data-driven approaches. Consequently, the field has garnered widespread interest and a corresponding increase in the research literature, but much of this continues to be in directions that are not particularly useful to industry [5]. Although there have been some notable surveys in recent history, such as [5–9], this issue extends to many other general surveys that have emerged more recently. A factor contributing to this misalignment with industry needs and the inability to effectively position new developments is the lack of a common framework and consistent 'terms of reference' for condition monitoring of machines. The aim of this paper is twofold: to present a framework, within the context of maintenance strategy, that systematically characterises modern condition monitoring systems; and to concisely present some of the most recent developments in data-driven condition monitoring of electrical machines, outlining the foremost opportunities and challenges. Thus, the study contributes a framework to support research and development, as well as the selection and evaluation of condition monitoring techniques for rotating electrical machines. Additionally, the review of the recent literature, including seminal works and other important surveys, together with an analysis of opportunities and challenges, offers archival value for researchers and practitioners and identifies potential avenues to catalyse future research in this field.

This paper is organised as follows. The next section gives an overview of the evolution of condition monitoring, contextualises its role within a wider maintenance strategy, and presents a generalised framework that encompasses systematic characteristics based on this evolution and context. Thereafter, faults and failure mechanisms are discussed together with a review of condition monitoring methods that focuses on data-driven methods. The future outlook for data-driven condition monitoring is then discussed before a brief conclusion.

2. Background

2.1. Evolution of Condition Monitoring

Modern condition monitoring is a product of several decades of experience, innovation, and technological advancement. The earliest generation of modern equipment monitoring through telemetry systems dates back to the 1930–1940s, where the need for progressive methods for maintenance planning, i.e., the ‘Waddington effect’, became apparent [10]. This paved the way for the emergence of the concept of ‘continuous monitoring’ and supervisory control and data acquisition (SCADA) during the 1950–1970s, where more emphasis was not only placed on automation but also on monitoring as part of the maintenance strategy [11]. The proliferation of transducers and advancement of data acquisition systems in the 1970–1980s [12] afforded further development and widespread expansion of equipment monitoring systems. In recent decades, condition monitoring has undergone another paradigm shift with advancements in communications and computing, where the widespread adoption of the Internet-of-Things (IoT) and data analytics has seen more industries modernising their asset management practices, not only to exploit strategic business opportunities but also as an essential organisational function.

Condition monitoring of rotating electrical machines is distinct within the general area of equipment condition monitoring, evolving in its own right, due to the ubiquity of these machines and their vital importance in several sectors of industry, such as utilities, transport, manufacturing, etc. In general, monitoring becomes less essential for lower-rated machines, e.g., active power $P < 20$ kW, except for those serving critical functions [1]. Ultimately, the decision to monitor the machine is based on weighing the associated costs against the significance of losing the machine and/or the function it provides. Although this trade-off will always need to be evaluated for specific cases, monitoring costs have reduced over time, leading to further uptake. The aforementioned advancements offer more cost-effective approaches, whether through dedicated machine condition monitoring systems or integrating machine monitoring into the wider plant-wide monitoring/expert system.

2.2. Asset Management Context

While the benefits of monitoring rotating electrical machines are often emphasised in the literature, its role within the wider context of asset management is often overlooked. Although a condition monitoring system itself may be highly effective in performing its function, this does not equate to efficient asset management when viewed from a strategic perspective. For this reason, condition monitoring should be considered as support to, and dependent on, the overall maintenance strategy [13]. Simply put, the selection and evaluation of the condition monitoring approach to be deployed is based on the requirements analysis arising from the maintenance strategy. The description of asset management, offered by [14], refers to the "organisation's objectives into asset-related decisions, plans and activities risk-based approach". Asset management thus determines the requirements for condition monitoring based on the risk assessment [15], e.g., production impact due to machine unavailability, and it is the condition monitoring system that informs the maintenance decision making. Typically, a modern condition monitoring system will comprise what are referred to here as monitoring and assessment functions (as depicted in Figure 1). The asset management strategy determines the type and level of assessment needed, which in turn defines the monitoring requirements. The assessment function of the condition monitoring system does not only provide feedback on the condition of the machine, but may also provide crucial information for failure mode and effect analysis (FMEA), and defining safety levels [16]. In rotating electrical machines, the assessment function may extend beyond diagnosing current problems to estimating future degradation, that is, prognostics [17]. Furthermore, non-destructive evaluation (NDE), which is inclusive of non-destructive inspection (NDI) and non-destructive testing (NDT), needs mentioning here as a field that historically parallels condition monitoring in the context of assessment management, particularly in the case of in-service NDE [18]. More specifically, while in-service NDE plays a seemingly distinct role in identifying or locating specific problems with the asset, there is an overlap with this role and the assessment function of condition monitoring systems. The synonymity of in-service NDE with certain condition monitoring techniques proposed for electrical machines is evident in some of the literature, as in [19–21], where these terminology have been used interchangeably.

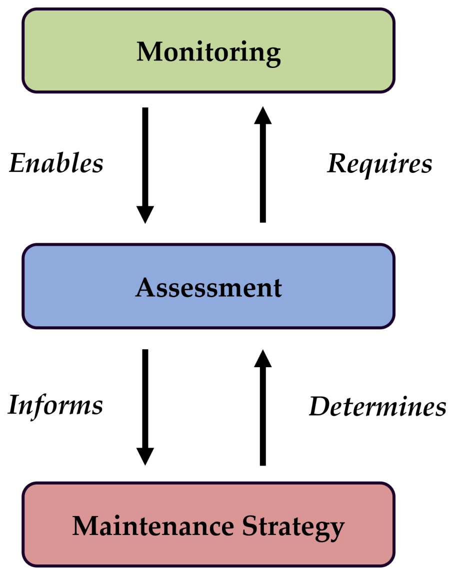

Figure 1. Condition monitoring in the context of maintenance strategies.

In asset management, the main maintenance strategies are condition-based maintenance (CBM), reliability-centred maintenance (RCM), time-based maintenance (TCM), and corrective maintenance (CM) [22]. These strategies are broadly categorised as shown in Figure 2, where CBM and RCM are typically deployed in predictive maintenance strategies, RCM and TCM are deployed in preventative maintenance strategies, and CM is deployed in reactive maintenance strategies. The key factors that determine which strategy is most appropriate are the process or system in which the machine is deployed and the machine or component itself. For instance, where the condition of the machine or component is considered critical—e.g., due to low or no redundancy—and is deployed in a highly critical process or system, RCM is the most suitable maintenance approach, where maintenance is prioritised, and machine faults must be closely monitored, assessed, and managed; while the maintenance strategy may specify distinct condition monitoring requirements, this may adapt to changes in operational experience, priorities, and risk, which means that organisations can draw tremendous benefit from condition monitoring systems that are more flexible. This is a sought-after feature in modern condition monitoring systems and is discussed later.

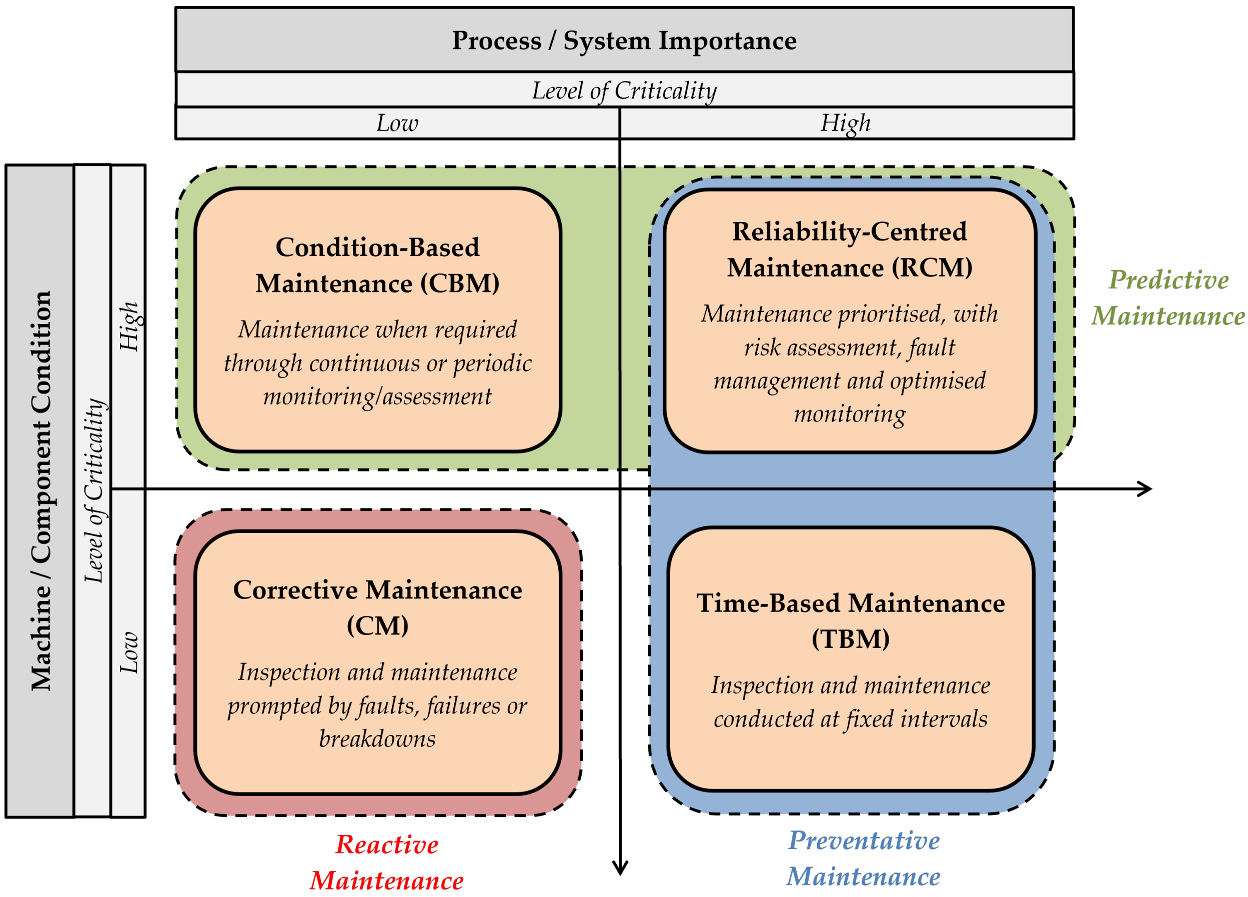

Figure 2. Categorisation of maintenance strategies.

2.3. Framework and Terms of Reference

The landscape for condition monitoring of electrical machines is vast and continuously evolving. Currently, there is no modern framework that adequately encapsulates this evolution and provides a means of systematically contextualising new research and unambiguously positioning the specific area of incremental progress. Thus, the generalised framework offered here (in Figure 3) proposes a basic system architecture for condition monitoring comprising monitoring and assessment layers. These layers link to the asset management strategy at the higher level (Figure 1) and represent different functions at the level of the condition monitoring system. The monitoring layer encompasses the system components that perform all of the functions from measurement to information extraction. The subsequent layer utilises this information to carry out the assessment. It should be highlighted that the framework is specific yet sufficiently generic such that it suitably characterises the vast range of condition monitoring approaches and different combinations thereof. For example, this framework characterises the condition monitoring approach, whether it is a technician using a handheld device to manually determine vibration or an automated fault classifier based on motor current signature analysis.

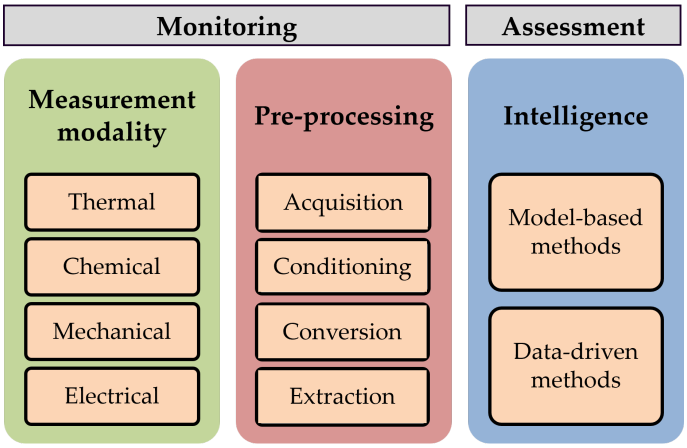

Figure 3. Generalised framework for condition monitoring.

There is also some key terminology associated with the framework that enables a common basis for developing condition monitoring systems for electrical machines. Measurement modality refers to the primary source of information, that is, the machine parameters or signals—e.g., current, temperature, and speed—that are being monitored. This determines the pre-processing requirements, which poses limitations on how often measurements can be taken, and whether monitoring is performed online or offline, ultimately influencing the type and extent of the assessment. In condition monitoring of electrical rotating machines, the measurement modality can be broadly classified into different types, such as thermal, chemical, mechanical, and electrical. The modality of the detector, or transduction process, may in some cases be linked to the machine's state that is being monitored/measured through this categorisation, although these may not necessarily be the same—e.g., vision sensing with an event-based camera [23] can be considered a mechanical measurement modality, like an accelerometer-based method, when used to monitor vibration.

The pre-processing component of the monitoring layer in the framework refers to everything from signal acquisition to the conversion and extraction techniques used. This makes an important distinction between the monitoring and assessment layer, where this boundary is often blurred in the literature. This is because the assessment approach is, in many instances, directly related to the pre-processing. However, in modern condition monitoring, these must be differentiated for the purposes of distinctly identifying novelty and comparatively evaluating new research and developments in the area. The assessment layer can be thought of as the component of the condition monitoring system that carries out the inference about the state of the electrical machine, or component/s thereof. In modern condition monitoring, the inference typically leads to three types of assessment—i.e., detection, diagnosis, or prognosis—which convey varying levels of fault information and, in some prognostic assessments, the remaining useful life of machine components. This layer thus carries out the 'intelligence' function where the inference itself can range from a simple checking of a parameter against a threshold or limit to a more complex prognosis. The level of intelligence in this layer therefore varies according to the level of underlying knowledge about the machine that is codified into the inference, where the inference, or assessment, can be automated or carried out by a human. There are many instances where existing terminology inadequately captures the aforementioned distinctions in modern condition monitoring of electrical machines. For example, the spectrum-based methods reviewed in [24] are all based on signals, utilise time, time–frequency, or frequency–domain methods, and employ models for inference about the state of the machine which are based on underlying knowledge of the machine's physics. Therefore, broadly classifying these approaches as signal-based methods, and differentiating them from 'model'- and 'knowledge'-based approaches is somewhat imprecise. Furthermore, modern strategies can and do use spectrum techniques to extract signal features for carrying out assessments based on historical data and not on the modelled physics of the machine. Similarly, Akbar et al. [25] separately categorise spectral and vibration analysis as 'conventional' techniques, which fails to make the distinction between the modality and pre-processing technique where conventional vibrational analysis utilises spectral techniques. Therefore, the presented framework provides a more accurate way of characterising measurement, pre-processing and assessment techniques, and a more sensible approach to classifying the condition monitoring strategy according to the assessment method.

Assessment methods can be broadly classified as model-based or data-driven. The main strength of model-based methods is perhaps the source of its main limitations. Although a well-defined model of the physical component or process in the machine enables a more effective assessment of its state, the availability of such models and domain knowledge limits the application flexibility and assessment range of these methods. Therefore, model-based methods are also key to the fundamental development of condition monitoring in electrical rotating machines as they typically offer new insights into modelling fault mechanisms and, in some cases, novel measurement modalities and pre-processing techniques. Data-driven assessment approaches overcome this dependence on physical modelling by using historical data, potentially extending their application flexibility and assessment range. However, this key strength over model-based methods is also a source of limitations with data-driven approaches where historical data, particularly fault data, are not readily available. Some of the key considerations and trade-offs between model-based and data-driven assessment are paving the way for different avenues of research and development in the condition monitoring of electrical rotating machines. Examples of these are as follows:

- Model-based assessment relies on codified domain knowledge in well-defined representations of physical processes/mechanisms, while data-driven assessment typically depends on historical data.
- Research efforts have intensified into data-driven strategies more recently because they seemingly offer the potential to further progress modern condition monitoring goals such as incipient fault detection/diagnosis, holistic and integrated assessments, as well as online, continuous, and real-time monitoring.
- While data proliferation, owing to related technological advancements, lends itself to data-driven approaches, it also brings about several new challenges, which are discussed later.

It should be noted that methods employing a combination of model-based and data-driven techniques are sometimes referred to as hybrid methods. Although the framework depicted in Figure 3 does not explicitly mention these methods under a different category, they can be characterised according to how the actual assessment is carried out. For example, physics-informed machine learning is an example of a hybrid method [26], where the assessments are still based on available data but within the constraints of the physical knowledge of the machine.

3. Review and Analysis

3.1. Scope

Considering the extensive array of measurement modalities and pre-processing techniques used in monitoring, as well as the proliferation of research into assessment methods, recent developments in this area are too vast to concisely review. Therefore, the approach taken concisely formulates a roadmap by focusing its scope on an illustrative selection of data-driven methods that push the boundaries of the assessment layer. Further details of the selection criteria for the examples is given Section 3.3. An overview of fault and failure mechanisms in electrical rotating machines is given in the next section to better contextualise the reviewed methods within the assessment layer. This is because the differentiation of the capabilities, and the evaluation of the suitability, of the condition monitoring technique should be based on the faults and failure modes specific to machine for which the technique is intended.

3.2. Faults and Failure Mechanisms

There are various types of faults and failure modes in electrical rotating machines. Depending on the machine type, size, and application, the type, distribution, and frequency of faults vary. Generally, faults and failure modes tend to be classified at the component level, e.g., rotor and stator windings, air-gap, rotor bars, end rings, slip rings, permanent magnets, brushes, shaft, cores and laminations, bearings, peripherals/assembly, load, and auxiliaries [27]. Bearing and stator winding failures are the most common modes of failure in machines; however, bearing failure is more prominent in machines rated up to 4 kV, and stator winding failures account for the largest share among failure modes in higher-rated machines [28]. This is because windings suffer insulation degradation due to thermal, thermo-mechanical, and mechanical ageing, as well as partial discharges, particularly in conventional machines rated 3.3 kV and above and 400 V and above for inverter-fed motors [29]. Much of the research efforts on online, non-invasive, and incipient fault diagnostics have focused on rotor faults, such as broken rotor bars, and bearing faults; while some researchers have proposed online methods for assessing winding insulation health, such as some of the promising new broadband frequency techniques [30], they are yet to be proven in industry and therefore offline methods continue to be used more widely [31]. Machine applications are also a driving force behind innovation in condition monitoring, where advancements in fault detection and diagnosis extend beyond the machine's components. In recent history, this is especially true for wind energy and electric vehicle applications where monitoring extends to faults and failure modes associated with intertwined critical electrical and mechanical subsystems [32,33].

The trend in broadening the scope of the monitoring and assessment capabilities of condition monitoring systems stems from long-standing goals of online and incipient fault diagnosis in predictive maintenance. However, the latter goal is often overlooked in the literature, where failures can occur through cascading fault mechanisms. For example, while bearing defects may cause eccentricity leading to failure, bearing wear and failure can also be triggered through a succession of other faults, or 'fault tree' [34,35], like insulation wear, localised heating, etc. This makes incipient fault diagnosis quite challenging, where the goal is not only to detect faults early but to diagnose them at an early stage of the fault tree. Thus, although diagnosis may provide additional assessment information over detection as to the fault location and type, it may not necessarily alleviate uncertainty around the severity and root cause of the fault. It is worth again highlighting the essential role of modality in constraining the subsequent layers of the overall condition monitoring system, thereby ultimately determining what assessment is possible. For example, current [7,36] and magnetic flux (axial and stray) [37] modalities offer the potential for assessing type, location, and severity for a wider variety of faults than is possible with mechanical and thermal modalities. That being said, data-driven methods are being shown to better exploit the information capacity of certain modalities, such as sound [38], to enhance overall assessment capability. This further emphasises the need to distinguish approaches within the layers of the presented framework where the overall fault assessment capabilities vary with different combinations of techniques.

3.3. Data-Driven Methods

Data-driven methods essentially refer to the category of techniques that use statistical or machine learning models to carry out assessment—i.e., detection, diagnosis, or prognosis. Due to growing interest in data-driven condition monitoring, several reviews of related work have recently been completed [25,39–43]. However, the proliferation of research in this area, coupled with the lack of a suitable framework to systematically position and comparatively evaluate new developments, has rendered concise and focused reviews in the area rarities. This is evident in the recent groundswell of studies on machine learning techniques applied to bearing fault diagnosis, as there are several open-source datasets available [44], where deep learning ablation and optimisation studies have been used to improve classification accuracy; while these studies may significantly contribute to setting new benchmarks for a particular technique, they do not necessarily equate to new condition monitoring approaches or strategies. Therefore, only a selection of examples is offered here with the aim of demonstrating some of the most recent research offering progressive data-driven methods in the assessment layer of condition monitoring systems for electrical rotating machines.

The examples presented in Table 1 were selected based on the following criteria. Only research using data-driven techniques was considered, thereby excluding articles that propose model-based methods. The search criteria required articles to be explicit about the applicability of their proposed techniques to rotating electrical machines. The most recent articles were considered, and the pool of potential research was limited to ten articles from 2023 up to the time of writing. Although research articles that have garnered the most interest (top cited) were used as a sorting mechanism, diversifying the set of examples according to measurement modality, fault type, and data-driven method was given precedence. This approach is based on the proliferation of bearing vibration monitoring studies mentioned earlier. As the vast majority of recent articles focusing on this measurement modality are essentially ablation studies, the selection of these articles was only considered where there was a significant difference in monitoring and assessment approach—e.g., assessment layer using a physics-informed neural network or transfer learning, as opposed to using a similar convolutional neural network approach with slightly different parameters to demonstrate higher classification accuracy with a specific benchmarked dataset.

Table 1. Summary of selected research in data-driven condition monitoring of rotating electrical machines.

Reference	Fault	Method	
		Monitoring Layer	**Assessment Layer**
[23]	Bearing	Event-based vision sensor, image-shaping, data augmentation and denoising	Convolutional Neural Network (CNN)
[45]	Bearing	Accelerometer, vibration, discrete Fourier transform (DFT)	Physics-Informed Residual Network

Table 1. *Cont.*

Reference	Fault	Method Monitoring Layer	 Assessment Layer
[46]	Bearing	Infrared thermal camera (thermography), image-shaping and pre-processing	CNN with Transfer Learning (TL)
[47]	Rotor bar, stator winding	Stator currents and speed, Ramanujan Periodic Transform	Digital twin with health indicator
[48]	Stator winding	Infrared thermal camera, image-shaping and pre-processing	CNN
[49]	Rotor permanent magnet	Stator current, short-time Fourier transform (STFT)	k-nearest neighbours (kNN) and multilayer perceptron (MLP)
[50]	Bearing	Torque, stator current and voltage, normalisation and cosine similarity	Graph Neural Network (GNN)
[51]	Driven-equipment faults (pump)	Torque, stator current and voltage, frequency spectrum estimation	CNN–Long short-term memory (LSTM)
[52]	Stator winding, eccentricity, permanent magnets	Search coil, magnetic flux, frequency spectrum estimation	Random Forest
[53]	Rotor permanent magnets	Stator currents, Fast Fourier Transform (FFT)	CNN with TL

The selected research given in Table 1 is organised here in terms of the presented framework where the various components or layers of the condition monitoring system are separated. This is to demonstrate how framing of these condition monitoring approaches enables better comparison and assessment of their suitability, applicability, capability, and even novelty. For example, although the proposed method presented in [23] is similar in terms of the bearing fault type and CNN assessment layer to many other recent research articles, its monitoring layer uses event-based vision sensing that produces very different data to the typical accelerometer-based vibration monitoring techniques. Similarly, both of the proposed approaches in [46,48] employ thermal monitoring, or more specifically thermography in these cases, together with CNN-based techniques in their assessment layer, but they each focus on very different machine components and fault types—i.e., bearing and stator winding faults.

4. Prospects for Driven-Driven Condition Monitoring

4.1. Opportunities

4.1.1. Online, Real-Time, and Automated Assessment

Condition monitoring of rotating electrical machines has always had some level of automation, where even the earliest systems could automatically take a measurement and provide a basic assessment. Modern condition monitoring systems are automated in this sense, but their layers, particularly the assessment layer, can have varying degrees of automation. As mentioned above, the assessment can range from basic threshold checking, which is still relevant in modern condition monitoring [54], to a more advanced prognosis [55], with different levels of information pertaining to the type, location, and severity of the fault, as well as the remaining useful life of the components. Therefore, the goal of fully automating assessments—many of which continue to be carried out by human experts in practice—is a catalyst for further research and development in data-driven methods. For example, large language models (LLMs) are fast becoming an interesting prospect for building large-scale foundation models in industrial settings [56]. LLMs offer a practical means, when used in conjunction with data-driven condition monitoring techniques in the assessment layer, to further automate assessment tasks, as presented in [57]. Automated data-driven assessment has the potential to unlock several other benefits such as improved scalability and flexibility [58], and real-time assessment, particularly when deployed in online and continuous monitoring systems [59].

4.1.2. Fault Detection, Diagnostics, and Prognostics

Much has been discussed about the different levels of assessment and fault types. This is because recent research has demonstrated the potential of data-driven methods to enhance assessment at each level—i.e., detection, diagnosis, and prognosis—as well as widen the range of fault types that can be assessed. Model-based assessments typically developed around specific modalities, whereas data-driven assessments are based on features of the available data. Data-driven methods therefore have the flexibility to combine modalities/sensory data and provide multimodal assessment, thereby extending the range of fault types that can be assessed by a single model-based system [39,60].

While the fault detection category of assessment has undergone a wide range of advancements through different data-centric methods, the most recent strides in this area have been with the provision of online, real-time, and continuous assessment. The change in terminology used in recent literature from fault detection to anomaly detection delineates this progressive shift towards a particular set of characteristics within this assessment category. Real-time anomaly detection has featured in other applications [61,62], but is now also emerging in fault detection as these methods, unsupervised learning techniques in particular [63], are equipped to handle continuous data streams and make fast automated assessments without the need for extensive offline processing. The concept of digital twins in machine condition monitoring has also received a lot of attention lately as it promises to take advantage of several of the aforementioned benefits of data-driven methods, coupled with breakthroughs in computing capacity to develop high-fidelity models for online, real-time, and continuous monitoring and fault detection [47]. Research in this area is expected to continue to grow with prospects for improved digital twin models and architectures for interoperable digital twins, where monitoring may benefit from machine models seamlessly interacting with models of other equipment in its operating context. Fault diagnosis is the category of assessments that has arguably benefited the most from data-driven methods, where supervised machine learning techniques have been leveraged to classify faults using labelled historical data [64]. Similarly, data-driven techniques have opened new possibilities in the fault prognosis assessment category with extensive progress in modelling component degradation to predict remaining useful life and forecast failures [65].

Despite these recent strides in data-driven assessment methods, an ongoing challenge, which will be discussed further in the next section, is to extend the online, continuous, and real-time capabilities of modern fault detection to diagnostic and prognostic assessments that can help with root cause analysis and FMEA. This is an area of future research and development that is expected to bring about assessment depth, such as fault type, severity, and location, in online, real-time, and streaming applications.

4.1.3. System Integration

The flexibility, scalability, and increasing ubiquity of data-driven methods are seemingly converging towards the development of systems that can exploit all the aforementioned opportunities. This offers the chance to truly integrate condition monitoring into plant management, where fleet-wide monitoring [66], and even multi-plant management requiring assessment of a combination of factors, such as maintenance, production, safety, resources, etc. [15], are becoming more realistic prospects. An example of recent work that represents this latest direction in data-driven methods is given in [67], which seeks to integrate monitoring and control systems to optimise overall operational efficiency using data-driven approaches. Figure 4 provides a simplified example of system-level integration to illustrate this concept that combines monitoring, control, and analytics across flexible and scalable layers of intelligence—i.e., a lower monitoring/control layer for x to n machines/components, an analytics layer for y to p processes/functions, and an upper layer for system-level analytics.

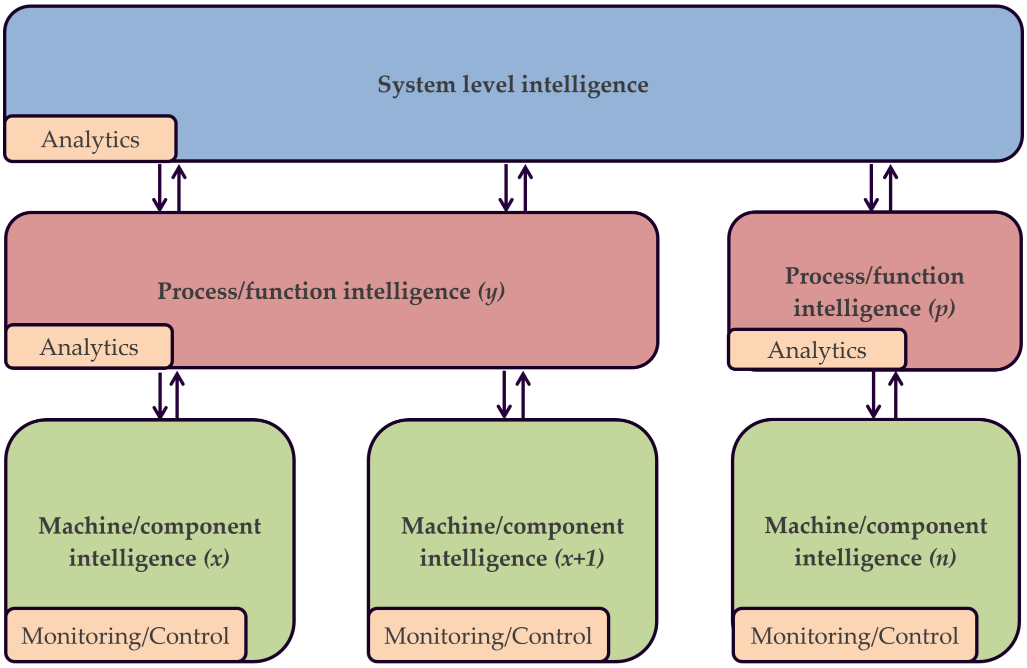

Figure 4. Example of modern condition monitoring architecture for exploiting system-level integration.

4.2. Challenges

4.2.1. Data Availability and Reliability

Unlike model-based methods, the reliability of data-driven models is highly dependent on the availability of reliable data. Supervised learning techniques can be used to train models to accurately classify a wide variety of incipient faults, but the historical data must be suitably labelled and contain all of the nuanced patterns that characterise these faults. The accuracies and ranges of fault classification models are also dependent on the suitability of the extracted features. Furthermore, the performance of models trained in one context cannot be guaranteed, especially when there are significant differences in the design, manufacture, and operating regimes of certain machines. The availability of fault-type data is also often limited in practice, where fault conditions occur sparsely during the life of a machine, leading to the challenge of data imbalance. The focus of recent research in this area has thus shifted away from conventional supervised learning techniques, turning to ensemble, resampling, transfer learning, semi-supervised, and unsupervised learning approaches, amongst others, that may address these ongoing challenges [68–73]. However, there is still much work to be performed in terms of improving the assessment capabilities of these methods, particularly with fault severity and root cause analysis. Research aimed at addressing data availability and reliability is therefore expected to continue to grow, as these issues form an especially critical stumbling block to the practical implementation and widespread adoption of data-driven assessment methods.

4.2.2. Model Transparency and Interpretability

With all the advancements in condition monitoring of electrical machines, a vast range of model-based and data-driven assessment methods are now available. These methods are based on models that differ in complexity and transparency. Traditional model-based approaches typically offer transparent, or 'white-box', models, whereas most data-driven models are not transparent, or 'black-box' models, having been built using machine learning techniques. This lack of transparency in models poses a significant challenge to interpretability, which in turn may hinder trust, serviceability, compatibility, and adaptability. An understanding of the inner workings of the assessment model plays a crucial role in evaluating how well it is able to capture fault characteristics and degradation trends in its decision-making process, making the results more intelligible and trustworthy [74]. Similarly, models with low interpretability make it difficult to troubleshoot problems with the condition monitoring system [75], especially if several of these models are interconnected. The black-box nature of data-driven models also complicates the assessment of how compatible they are with existing components/subsystems, or how adaptable they will be to new components/subsystems; while there have been some recent efforts to improve model interpretability, such as model-agnostic methods and model embedding, it still remains a significant obstacle to the wider uptake of data-driven methods for condition monitoring [75,76].

4.2.3. Systems Design, Deployment, and Operation

Fully exploiting the highlighted opportunities offered by modern data-driven condition monitoring means confronting several practical challenges with system design, deployment, and operation, particularly when adopting these approaches at scale. Despite the vast amount of research literature on data-driven condition monitoring, there is still a lack of technical literature, including standards, that deal with these practical issues. This is owing not only to a lack of maturity with some of these technologies but also to the aforementioned challenges where comparative evaluations with 'legacy' systems are not yet available. Consequently, the uncertainties surrounding the design, deployment, and operation of data-driven condition monitoring systems may hinder uptake, as there is a need to consider all of the issues to properly assess initial investment versus long-term gains.

The issue of data ontology relates to other challenges discussed here, such as data availability and reliability, but warrants several design, deployment, and operational considerations in its own right [77]. Due to the data-centric nature of modern condition monitoring approaches, industrial-scale implementations typically require a complete rethink of how data are managed [78]. This includes considering the design architecture of the data pipeline based on the current and future asset management needs. For example, the decision of which functions within the different layers of the condition monitoring system—such as storage, pre-processing, and assessment of sensor data—should be implemented locally to the machine through edge computing, or via cloud computing, or some combination of both; this not only affects costs, efficiency, and performance in the short term but can also determine scalability, flexibility, and compatibility in the long term. These decisions are largely based on the condition monitoring requirements in the context of the maintenance strategy as discussed in Section 2.2. The data transmission (latency, throughput, etc.), data storage (local and/or remote capacities), and data handling (compute resources) needs therefore follow a comprehensive definition of these requirements through considering, inter alia, the number, types, and frequency of measurements; where and what quantity of raw data will be stored, pre-processed, and processed; whether the processing of data will be carried out online, continuously, and in real-time; assessment model workflows including training, retraining, visualisation, analytics, etc.; integration with other control or management systems.

While there is some general guidance available on the management of data assets within the area of asset management [79], and some good examples of recent research that consider practical issues with data in condition monitoring [80–82], this is a challenge area with many opportunities for future interdisciplinary research. Similarly, there are also several other wider issues surrounding design, deployment, and operation challenges in data-driven condition monitoring that may benefit from future interdisciplinary research—e.g., human factors in engineering [83,84], and efficiencies [85].

5. Conclusions

The demand for condition monitoring of rotating electrical machines has risen together with their ever-widening role in engineering applications, particularly in areas such as renewable energy, industrial automation, and electric vehicles. This groundswell of interest in condition monitoring, coupled with advancements in sensing, communications, and computing, has led to a rapid increase in research and development in the field. Despite the resulting proliferation in the literature on the topic, there are very few resources that bridge the gap between academic research and industrial needs. Therefore, this paper gives a tutorial-style overview of the field that discusses the evolution of condition monitoring, offers a structured framework for modern condition monitoring systems in the context of maintenance strategy, and concisely examines recent advancements, challenges, and opportunities. The generalised framework links maintenance strategy to a modern condition monitoring system architecture, thereby enabling systematic characterisation, selection, analysis, and evaluation of techniques in line with the requirements of the monitoring application. Focusing on data-driven methods, the selective review of recent progress illustrated how the framework can be used to systematically characterise emerging techniques and provide insights into areas of incremental progress. Building on this, the research and development prospects in data-driven condition monitoring were discussed. The assessment layer was identified as a key area for exploiting the benefits of data-driven methods, with opportunities for enhancing flexibility, scalability, integrability, and interoperability of condition monitoring systems. Some key future research and development challenges were also identified, specifically in the areas of data availability and reliability, model transparency and interpretability, and systems design, deployment, and operation.

Funding: This research received no external funding.

Data Availability Statement: No new data were created or analysed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: The author declares no conflicts of interest.

References

1. Tavner, P.; Ran, L.; Penman, J.; Sedding, H. *Condition Monitoring of Rotating Electrical Machines*; The Institution of Engineering and Technology: London, UK, 2008.
2. Hussain, M.; Mirjat, N.H.; Shaikh, F.; Dhirani, L.L.; Kumar, L.; Sleiti, A.K. Condition Monitoring and Fault Diagnosis of Wind Turbine: A Systematic Literature Review. *IEEE Access* **2024**, *12*, 190220–190239. [CrossRef]
3. Carratù, M.; Gallo, V.; Iacono, S.D.; Sommella, P.; Grasso, A.B.F.; Ciani, L.; Patrizi, G. A Novel Methodology for Unsupervised Anomaly Detection in Industrial Electrical Systems. *IEEE Trans. Instrum. Meas.* **2023**, *72*, 17–24. [CrossRef]
4. Choudhary, A.; Fatima, S.; Panigrahi, B.K. State-of-the-Art Technologies in Fault Diagnosis of Electric Vehicles: A Component-Based Review. *IEEE Trans. Transp. Electrif.* **2023**, *9*, 2324–2347. [CrossRef]
5. Bellini, A.; Filippetti, F.; Tassoni, C.; Capolino, G.A. Advances in Diagnostic Techniques for Induction Machines. *IEEE Trans. Ind. Electron.* **2008**, *55*, 4109–4126. [CrossRef]

6. Nandi, S.; Toliyat, H.A.; Li, X. Condition Monitoring and Fault Diagnosis of Electrical Motors—A Review. *IEEE Trans. Energy Convers.* **2005**, *20*, 719–729. [CrossRef]
7. El Hachemi Benbouzid, M. A review of induction motors signature analysis as a medium for faults detection. *IEEE Trans. Ind. Electron.* **2000**, *47*, 984–993. [CrossRef]
8. Riera-Guasp, M.; Antonino-Daviu, J.A.; Capolino, G.A. Advances in Electrical Machine, Power Electronic, and Drive Condition Monitoring and Fault Detection: State of the Art. *IEEE Trans. Ind. Electron.* **2015**, *62*, 1746–1759. [CrossRef]
9. Zhang, P.; Du, Y.; Habetler, T.G.; Lu, B. A Survey of Condition Monitoring and Protection Methods for Medium-Voltage Induction Motors. *IEEE Trans. Ind. Appl.s* **2011**, *47*, 34–46. [CrossRef]
10. Ignizio, J.P. The Waddington Effect, C^4U-Compliance, and Subsequent Impact on Force Readiness. *Phalanx* **2010**, *46*, 17–24.
11. Fiedler, H.J.; Swarthout, R.W. Exploration of Utility Automation Applications Trough Supervisory Control. *IEEE Trans. Ind. Electron. Control. Instrum.* **1973**, *IECI-20*, 12–20. [CrossRef]
12. National Semiconductor. *Data Aquisition*; Handbook; National Semiconductor: Santa Clara, CA, USA, 1978.
13. *IEC 60050-192-06-28*; International Electrotechnical Vocabulary (IEV)—Part 192: Dependability. International Electrotechnical Commission: Geneva, Switzerland, 2015.
14. *ISO 55000*; Asset Management—Vocabulary, Overview and Principles. International Standards Organisation: Geneva, Switzerland, 2024.
15. Hesla, E.; Fowler, C.; Huber, J. Maintenance management in multiple plants: Examining various factors. *IEEE Ind. Appl. Mag.* **2006**, *26*, 88–94. [CrossRef]
16. Igder, M.A.; Rafiei, M.; Boudjadar, J.; Khooban, M.H. Reliability and safety improvement of emission-free ships: Systemic reliability-centered maintenance. *IEEE Trans. Transp. Electrif.* **2021**, *21*, 256–266. [CrossRef]
17. Yildirim, M.; Sun, X.A.; Gebraeel, N.Z. Sensor-driven condition-based generator maintenance scheduling—Part I: Maintenance problem. *IEEE Trans. Power Syst.* **2016**, *31*, 4253–4262. [CrossRef]
18. Papadakis, E.P. Future Growth of Nondestructive Evaluation. *IEEE Trans. Sonics Ultrason.* **1976**, *23*, 284–286. [CrossRef]
19. Qiao, W.; Lu, D. A Survey on Wind Turbine Condition Monitoring and Fault Diagnosis—Part I: Components and Subsystems. *IEEE Trans. Ind. Electron.* **2015**, *62*, 6536–6545. [CrossRef]
20. Shin, S.M.; Choi, B.H.; Kang, H.G. Motor Health Monitoring at Standstill Through Impedance Analysis. *IEEE Trans. Ind. Electron.* **2016**, *63*, 4422–4431. [CrossRef]
21. Peng, Y.; Huang, S.; Deng, B.; He, Y.; Guo, X.; Wang, H. Joint Scanning Electromagnetic Thermography for Industrial Motor Winding Defect Inspection and Quantitative Evaluation. *IEEE Trans. Ind. Inform.* **2021**, *17*, 6832–6841. [CrossRef]
22. Schneider, J.; Gaul, A.J.; Neumann, C.; Hograäfer, J.; Wellßow, W.; Schwan, M.; Schnettler, A. Asset management techniques. *Int. J. Electr. Power Energy Syst.* **2006**, *28*, 643–654. [CrossRef]
23. Li, X.; Yu, S.; Lei, Y.; Li, N.; Yang, B. Intelligent Machinery Fault Diagnosis with Event-Based Camera. *IEEE Trans. Ind. Inform.* **2024**, *20*, 380–389. [CrossRef]
24. Bossio, G.R.; Meira, M.; Bossio, J.M.; Verucchi, C.J.; Ruschetti, C.R. Full Spectrum for Rotating Electrical Machines Condition Monitoring and Fault Diagnosis: A Review. In Proceedings of the IEEE XX Workshop on Information Processing and Control (RPIC), Obera, Argentina, 1–3 November 2023 ; pp. 1–8.
25. Akbar, S.; Vaimann, T.; Asad, B.; Kallaste, A.; Sardar, M.U.; Kudelina, K. State-of-the-art techniques for fault diagnosis in electrical machines: Advancements and future directions. *Energies* **2023**, *16*, 6345. [CrossRef]
26. Wu, Y.; Sicard, B.; Gadsden, S.A. Physics-informed machine learning: A comprehensive review on applications in anomaly detection and condition monitoring. *Expert Syst. Appl.* **2024**, *255*, 124678. [CrossRef]
27. Frosini, L. Novel diagnostic techniques for rotating electrical machines—A review. *Energies* **2000**, *13*, 5066. [CrossRef]
28. Haq, S.U.; Trivedi, A.; Rochon, S.; Moorthy, M.T. Alternative Methods of Machine Online Condition Monitoring: Recommendations for Rotating Machines in the Petroleum and Chemical Industry. *IEEE Ind. Appl. Mag.* **2024**, *30*, 19–31. [CrossRef]
29. Lee, S.B.; Stone, G.C.; Antonino-Daviu, J.; Gyftakis, K.N.; Strangas, E.G.; Maussion, P.; Platero, C.A. Condition monitoring of industrial electric machines: State of the art and future challenges. *IEEE Ind. Electron. Mag.* **2020**, *14*, 158–167. [CrossRef]
30. Ruiz-Sarrio, J.E.; Antonino-Daviu, J.A.; Navarro-Navarro, A.; Biot-Monterde, V. A Review of Broadband Frequency Techniques for Insulation Monitoring and Diagnosis in Rotating Electrical Machines. *IEEE Trans. Ind. Appl.* **2024**, *60*, 6092–6102. [CrossRef]
31. Henao, H.; Capolino, G.A.; Fernandez-Cabanas, M.; Filippetti, F.; Bruzzese, C.; Strangas, E. Trends in Fault Diagnosis for Electrical Machines: A Review of Diagnostic Techniques. *IEEE Ind. Electron. Mag.* **2014**, *8*, 31–42. [CrossRef]
32. Badihi, H.; Zhang, Y.; Jiang, B.; Pillay, P.; Rakheja, S. A Comprehensive Review on Signal-Based and Model-Based Condition Monitoring of Wind Turbines: Fault Diagnosis and Lifetime Prognosis. *Proc. IEEE* **2022**, *110*, 754–806. [CrossRef]
33. Zhang, X.; Hu, Y.; Gong, C.; Deng, J.; Wang, G. Artificial Intelligence Technique-Based EV Powertrain Condition Monitoring and Fault Diagnosis: A Review. *IEEE Sens. J.* **2023**, *23*, 16481–16500. [CrossRef]
34. Shu, X.; Guo, Y.; Yang, W.; Wei, K.; Zhu, Y.; Zou, H. A Detailed Reliability Study of the Motor System in Pure Electric Vans by the Approach of Fault Tree Analysis. *IEEE Access* **2020**, *8*, 5295–5307. [CrossRef]

35. Filippetti, F.; Franceschini, G.; Tassoni, C.; Vas, P. Recent developments of induction motor drives fault diagnosis using AI techniques. *IEEE Trans. Ind. Electron.* **2000**, *47*, 994–1004. [CrossRef]
36. Thomson, W.T.; Fenger, M. Current signature analysis to detect induction motor faults. *IEEE Ind. Appl. Mag.* **2001**, *7*, 26–34. [CrossRef]
37. Zamudio-Ramirez, I.; Osornio-Rios, R.A.; Antonino-Daviu, J.A.; Razik, H.; de Jesus Romero-Troncoso, R. Magnetic Flux Analysis for the Condition Monitoring of Electric Machines: A Review. *IEEE Trans. Ind. Inform.* **2022**, *18*, 2895–2908. [CrossRef]
38. Kiranyaz, S.; Devecioglu, O.C.; Alhams, A.; Sassi, S.; Ince, T.; Avci, O. Exploring Sound Versus Vibration for Robust Fault Detection on Rotating Machinery. *IEEE Sens. J.* **2024**, *24*, 2895–2908. [CrossRef]
39. Gawde, S.; Patil, S.; Kumar, S.; Kamat, P.; Kotecha, K.; Abraham, A. Multi-fault diagnosis of Industrial Rotating Machines using Data-driven approach: A review of two decades of research. *Eng. Appl. Artif. Intell.* **2023**, *123*, 106139. [CrossRef]
40. AlShorman, O.; Irfan, M.; Masadeh, M.; Alshorman, A.; Sheikh, M.A.; Saad, N.; Rahman, S. Advancements in condition monitoring and fault diagnosis of rotating machinery: A comprehensive review of image-based intelligent techniques for induction motors. *Eng. Appl. Artif. Intell.* **2024**, *130*, 107724. [CrossRef]
41. Das, O.; Das, D.B.; Birant, D. Machine learning for fault analysis in rotating machinery: A comprehensive review. *Eng. Appl. Artif. Intell.* **2023**, *9*, e17584. [CrossRef] [PubMed]
42. Qi, R.; Zhang, J.; Spencer, K. A review on data-driven condition monitoring of industrial equipment. *Eng. Appl. Artif. Intell.* **2023**, *16*, 9. [CrossRef]
43. Surucu, O.; Gadsden, S.A.; Yawney, J. Condition Monitoring using Machine Learning: A Review of Theory, Applications, and Recent Advances. *Energy Syst. Appl.* **2023**, *221*, 119738. [CrossRef]
44. Zhang, X.; Zhao, B.; Lin, Y. Machine Learning Based Bearing Fault Diagnosis Using the Case Western Reserve University Data: A Review. *IEEE Access* **2021**, *9*, 155598–155608. [CrossRef]
45. Ni, Q.; Ji, J.; Halkon, B.; Feng, K.; Nandi, A.K. Physics-Informed Residual Network (PIResNet) for rolling element bearing fault diagnostics. *Mech. Syst. Signal Process.* **2023**, *200*, 110544. [CrossRef]
46. Choudhary, A.; Mian, T.; Fatima, S.; Panigrahi, B.K. Passive Thermography Based Bearing Fault Diagnosis Using Transfer Learning with Varying Working Conditions. *IEEE Sens. J.* **2023**, *23*, 4628–4637. [CrossRef]
47. Hu, W.; Wang, T.; Chu, F. Novel Ramanujan Digital Twin for Motor Periodic Fault Monitoring and Detection. *IEEE Trans. Ind. Inform.* **2023**, *19*, 11564–11572. [CrossRef]
48. Attallah, O.; Ibrahim, R.A.; Zakzouk, N.E. CAD system for inter-turn fault diagnosis of offshore wind turbines via multi-CNNs and feature selection. *Renew. Energy* **2023**, *203*, 870–880. [CrossRef]
49. Pietrzak, P.; Wolkiewicz, M. Demagnetization Fault Diagnosis of Permanent Magnet Synchronous Motors Based on Stator Current Signal Processing and Machine Learning Algorithms. *Sensors* **2023**, *23*, 1757. [CrossRef] [PubMed]
50. Li, T.; Sun, C.; Li, S.; Wang, Z.; Chen, X.; Yan, R. Explainable Graph Wavelet Denoising Network for Intelligent Fault Diagnosis. *IEEE Trans. Neural Netw. Learn. Syst.* **2024**, *35*, 8535–8548. [CrossRef] [PubMed]
51. Han, Y.; Zou, J.; Gong, B.; Luo, Y.; Wang, L.; Batlló, A.P.; Yuan, J.; Wang, C. The use of model-based voltage and current analysis for torque oscillation detection and improved condition monitoring of centrifugal pumps. *Mech. Syst. Signal Process.* **2025**, *222*, 111781. [CrossRef]
52. Du, B.; Huang, W.; Cheng, Y.; Chen, J.; Tao, R.; Cui, S. Fault Diagnosis and Separation of PMSM Rotor Faults Using Search Coil Based on MVSA and Random Forests. *IEEE Trans. Ind. Electron.* **2024**, *71*, 15089–15099. [CrossRef]
53. Skowron, M. Transfer Learning-Based Fault Detection System of Permanent Magnet Synchronous Motors. *IEEE Access* **2024**, *12*, 135372–135389. [CrossRef]
54. Chang, H.C.; Jheng, Y.M.; Kuo, C.C.; Hsueh, Y.M. Induction Motors Condition Monitoring System with Fault Diagnosis Using a Hybrid Approach. *Energies* **2019**, *12*, 1471. [CrossRef]
55. Magadán, L.; Suárez, F.; Granda, J.; delaCalle, F.; García, D. Robust prediction of remaining useful lifetime of bearings using deep learning. *Eng. Appl. Artif. Intell.* **2024**, *130*, 107690. [CrossRef]
56. Li, Y.; Wang, H.; Sun, M. ChatGPT-like large-scale foundation models for prognostics and health management: A survey and roadmaps. *Reliab. Eng. Syst. Saf.* **2024**, *243*, 109850. [CrossRef]
57. Wang, H.; Li, C.; Li, Y.-F.; Tsung, F. An Intelligent Industrial Visual Monitoring and Maintenance Framework Empowered by Large-Scale Visual and Language Models. *IEEE Trans. Ind.-Cyber-Phys. Syst.* **2024**, *2*, 166–175. [CrossRef]
58. Cheng, J.H.; Lu, C.L.; Zhang, G.; Wang, B.; Fang, J. Design of Motor Intelligent Monitoring and Fault Diagnosis System Based on LoRa. *IEEE Trans. Appl. Supercond.* **2021**, *31*, 0601904. [CrossRef]
59. Dong, H.; Ma, H.; Wang, Z.; Man, J.; Jia, L.; Qin, Y. An Online Health Monitoring Framework for Traction Motors in High-Speed Trains Using Temperature Signals. *IEEE Trans. Ind. Inform.* **2023**, *19*, 1389–1400. [CrossRef]
60. Liu, D.; Cui, L.; Wang, H. Rotating Machinery Fault Diagnosis Under Time-Varying Speeds: A Review. *IEEE Access* **2023**, *23*, 29969–29990. [CrossRef]

61. Flusser, M.; Somol, P. Efficient anomaly detection through surrogate neural networks. *Neural Comput. Appl.* **2022**, *34*, 20491–20505. [CrossRef]
62. Razzak, M.I.; Imran, M.; Xu, G. Big data analytics for preventive medicine. *Neural Comput. Appl.* **2022**, *9*, 4417–4451. [CrossRef] [PubMed]
63. Ahmad, S.; Lavin, A.; Purdy, S.; Agha, Z. Unsupervised real-time anomaly detection for streaming data. *Neurocomputing* **2017**, *262*, 134–147. [CrossRef]
64. Kudelina, K.; Asad, B.; Vaimann, T.; Rassõlkin, A.; Khang, A.K.H.V. Methods of condition monitoring and fault detection for electrical machines. *Energies* **2021**, *14*, 7459. [CrossRef]
65. Magadán, L.; Suárez, F.J.; Granda, J.C.; delaCalle, F.J.; García, D.F. A Robust Health Prognostics Technique for Failure Diagnosis and the Remaining Useful Lifetime Predictions of Bearings in Electric Motors. *Appl. Sci.* **2023**, *13*, 2220. [CrossRef]
66. Kande, M.; Isaksson, A.J.; Thottappillil, R.; Taylor, N. Rotating electrical machine condition monitoring automation—A review. *Machines* **2017**, *5*, 24. [CrossRef]
67. Wang, H.Z.Z.; Liu, X.; Gaudoin, O.; Xie, M. Joint optimization of condition-based production and maintenance with mutual production-deterioration dependencies. *Reliab. Eng. Syst. Saf.* **2025**, *256*, 110679.
68. Ali, M.Z.; Shabbir, M.N.S.K.; Zaman, S.M.K.; Liang, X. Single- and Multi-Fault Diagnosis Using Machine Learning for Variable Frequency Drive-Fed Induction Motors. *IEEE Trans. Ind. Appl.* **2020**, *56*, 2324–2337. [CrossRef]
69. Swana, E.F.; Doorsamy, W.; Bokoro, P. Tomek Link and SMOTE Approaches for Machine Fault Classification with an Imbalanced Dataset. *Sensors* **2022**, *22*, 3246. [CrossRef]
70. Zhang, C.; Tan, K.C.; Li, H.; Hong, G.S. A Cost-Sensitive Deep Belief Network for Imbalanced Classification. *IEEE Trans. Neural Netw. Learn. Syst.* **2019**, *30*, 109–122. [CrossRef] [PubMed]
71. Guo, L.; Lei, Y.; Xing, S.; Yan, T.; Li, N. Deep Convolutional Transfer Learning Network: A New Method for Intelligent Fault Diagnosis of Machines with Unlabeled Data. *IEEE Trans. Ind. Electron.* **2019**, *66*, 7316–7325. [CrossRef]
72. Chen, X.; Yang, R.; Xue, Y.; Huang, M.; Ferrero, R.; Wang, Z. Deep Transfer Learning for Bearing Fault Diagnosis: A Systematic Review Since 2016. *IEEE Trans. Instrum. Meas.* **2023**, *72*, 3508221. [CrossRef]
73. Russell, M.; Wang, P.; Liu, S.; Jawahir, I.S. Mixed-Up Experience Replay for Adaptive Online Condition Monitoring. *IEEE Trans. Ind. Electron.* **2024**, *71*, 1979–1986. [CrossRef]
74. Li, Y.; Sun, Y.; Li, Z.; Chen, X.; Yang, L. Interpretable Spectra PCA for Condition Monitoring of Rotating Machinery: Theoretical and Experimental Investigations. *IEEE Trans. Instrum. Meas.* **2024**, *73*, 35387122. [CrossRef]
75. Chen, G.; Yuan, J.; Zhang, Y.; Zhu, H.; Huang, R.; Wang, F. Enhancing Reliability Through Interpretability: A Comprehensive Survey of Interpretable Intelligent Fault Diagnosis in Rotating Machinery. *IEEE Sens. J.* **2024**, *12*, 103348–103379. [CrossRef]
76. Sharma, J.; Mittal, M.L.; Soni, G. Condition-based maintenance using machine learning and role of interpretability: A review. *Int. J. Syst. Assur. Eng. Manag.* **2024**, *15*, 1345–1360. [CrossRef]
77. Hendriks, J.; Azarm, M.; Dumond, P. Structured Data Ontology for AI in Industrial Asset Condition Monitoring. *J. Sens. Actuator Netw.* **2022**, *13*, 23. [CrossRef]
78. Cocconcelliand, M.; Capelli, L.; Cavalaglio Camargo Molano, J.; Borghi, D. Development of a Methodology for Condition-Based Maintenance in a Large-Scale Application Field. *Machines* **2018**, *6*, 17. [CrossRef]
79. *ISO 55013*; Asset Management—Guidance on the Management of Data Assets. International Standards Organisation: Geneva, Switzerland, 2024.
80. Zhou, B.; Svetashova, Y.; Gusmao, A.; Soylu, A.; Cheng, G.; Mikut, R.; Waaler, A.; Kharlamov, E. SemML: Facilitating development of ML models for condition monitoring with semantics. *J. Web Semant.* **2021**, *71*, 100664. [CrossRef]
81. Saki, M.; Abolhasan, M.; Lipman, J. A Novel Approach for Big Data Classification and Transportation in Rail Networks. *IEEE Trans. Intell. Transp. Syst.* **2020**, *21*, 1239–1249. [CrossRef]
82. Chen, Q.; Cao, J.; Zhu, S. Data-Driven Monitoring and Predictive Maintenance for Engineering Structures: Technologies, Implementation Challenges, and Future Directions. *IEEE Internet Things J.* **2023**, *10*, 14527–14551. [CrossRef]
83. van Oudenhoven, B.; Van de Calseyde, P.; Basten, R.; Demerouti, E. Predictive maintenance for industry 5.0: Behavioural inquiries from a work system perspective. *Int. J. Prod. Res.* **2022**, *66*, 7846–7865. [CrossRef]
84. Khamaj, A.; Ali, A.M.; Saminathan, R.; Shanmugasundaram, M. Human factors engineering simulated analysis in administrative, operational and maintenance loops of nuclear reactor control unit using artificial intelligence and machine learning techniques. *Heliyon* **2024**, *10*, e30866. [CrossRef] [PubMed]
85. Frederiksen, R.D.; Bocewicz, G.; Radzki, G.; Banaszak, Z.; Nielsen, P. Cost-Effectiveness of Predictive Maintenance for Offshore Wind Farms: A Case Study. *Energies* **2024**, *17*, 3147. [CrossRef]