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Review

A Review of the Intelligent Condition Monitoring of Rolling Element Bearings

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Abstract: Bearing component damage contributes significantly to rotating machinery failures. It is vital for the rotor-bearing system to be in good condition to ensure the proper functioning of the machine. Over recent decades, extensive research has been devoted to the condition monitoring of rotational machinery, with a particular focus on bearing health. This paper provides a comprehensive literature review of recent advancements in intelligent condition monitoring technologies for rolling element bearings. Fundamental monitoring strategies are introduced, covering various sensing, signal processing, and feature extraction techniques for detecting defects in rolling element bearings. While vibration-based monitoring remains prevalent, alternative sensor types are also explored, offering complementary diagnostic capabilities or detecting different defect types compared to accelerometers alone. Signal processing and feature extraction techniques, including time domain, frequency domain, and time–frequency domain analysis, are discussed for their ability to provide diverse perspectives for signal representation, revealing unique insights relevant to condition monitoring. Special attention is given to information fusion methodologies and the application of intelligent algorithms. Multisensor systems, whether homogeneous or heterogeneous, integrated with information fusion techniques hold promise in enhancing accuracy and reliability by overcoming limitations associated with single-sensor monitoring. Furthermore, the adoption of AI techniques, such as machine learning, metaheuristic optimisation, and deep-learning methods, has led to significant advancements in condition monitoring, yielding successful outcomes with improved accuracy and robustness in various studies. Finally, avenues for further advancements to improve monitoring accuracy and reliability are identified, offering insights into future research directions.

Keywords: review; condition monitoring; rolling element bearing; fault diagnosis; vibration; information fusion; feature extraction; intelligent algorithms

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1. Introduction

Rolling element bearings (REBs) in rotating machinery are essential parts in machine operation [1]. They facilitate the rotational motion required while reducing friction between moving parts. It is common, however, that these components naturally develop defects over time. REB defects may be caused by many factors including but not limited to inadequate lubrication, external contaminants, and use in incorrect operating conditions. Damage to bearing components accounts for about 45% of rotating machinery failures [2] and, therefore, ensuring REBs in good condition is vital to the proper functioning of the machine.

Many studies have been conducted on the condition monitoring of rotating machinery to identify a variety of issues including REB defects [3]. The condition monitoring of certain parameters allowed for the scheduled maintenance and replacement of REBs to be conducted when the defect was incipient [4]. This can help to achieve the maximised

usage of components and significantly reduced costs associated with the purchase of REBs. Additionally, the revenue that may be lost due to machine downtime caused by unnecessary scheduled maintenance can be significantly limited.

There are many common condition monitoring approaches such as vibration, acoustic emission (AE), infrared thermography, and wear-debris-based monitoring [4]. Of the various approaches, vibration-based monitoring has been researched extensively in the context of condition monitoring of machinery. It utilises accelerometers appropriately positioned on or within the machine to detect vibrations that are produced as a result of machine operation and defects. The signals obtained in the time series can then be processed in various ways to make the fault extraction and classification process easier. Mollasalehi categorised the techniques available for the fault diagnosis of bearings as being data-driven or model-based [5]. Data-driven or signal-based techniques include various methods available for analysis of a signal in the time, frequency, or time–frequency domain. Model-based techniques involve the design of a model based on various assumptions, relevant theory, and geometrical properties to accurately portray a system's operation.

Granted the single-sensor approach to condition monitoring has been successful, but it is greatly advantageous to utilise multiple sensors. Information fusion is a method in which data from various sources are combined to obtain a better interpretation [6]. Fusion of data has become increasingly common in various disciplines and has found its way into condition monitoring applications [7]. Depending on the sensors used and the application, one or more levels of fusion may be used to improve the accuracy and reliability of condition monitoring. Certain sensor types may also be susceptible to environmental factors causing failure or distortions in the output. The use of a hybrid condition monitoring approach is able to overcome this by utilising a heterogeneous sensor system.

Utilising artificial intelligence (AI) in the condition monitoring of rotational machinery has been a highly researched area over the past decade leading to the use of various intelligent algorithms for classification and optimisation tasks. The implementation of AI-incorporated algorithms is robust, highly adaptable, and also reduces the requirement of strong fundamental knowledge and experience in condition monitoring, making it desirable for many operators [8]. Most intelligent algorithms used to detect defects are focused on their application to data-driven systems. Some researchers have also highlighted the potential of using model-based systems to train machine-learning classifiers as it would be impractical to acquire the amount of data required for this purpose from the machine [9].

The monitoring of rotational machinery, particularly bearing condition, has been a significant area of research over the past few decades. Despite the availability of several literature review papers published in recent years [10–13], there remain areas such as information fusion techniques and intelligent classifiers that have not received adequate attention. This paper aims to bridge this gap by providing a comprehensive literature review of recent advancements in intelligent condition monitoring technologies for rolling element bearings. Special emphasis is placed on feature extraction techniques, information fusion methodologies, and the application of intelligent algorithms. The primary contributions are focused on answering the following questions:

- What are the main approaches for sensing and signal processing to extract features for bearing faults? How can signal integrity be enhanced and uncertainty reduced?
- What kinds of information fusion techniques are being used to improve the reliability of bearing fault diagnosis?
- How are intelligent algorithms driving rapid advancements in bearing monitoring and diagnosis? What are the frontier intelligent techniques and the challenges associated with them?

For this review, relevant papers were primarily sourced from ScienceDirect, Google Scholar, and IEEE Xplore digital library. The keywords used in the search included basic terms like "rolling bearing", combined with additional terms relevant to this review's scope, such as "condition monitoring", "fault diagnosis", "sensing", "signal processing", "feature extraction", "information fusion", "intelligent", "machine learning", and "deep

learning". The initial search yielded a very large number of papers, which were then manually screened to refine the selection based on journal reputation, paper quality, and relevance to the scope of this review.

The structure of this paper is as follows. Section 2 introduces the fundamentals of bearing condition monitoring and various sensing strategies. Section 3 discusses signal processing and feature extraction techniques. Section 4 reviews different levels of information fusion. Section 5 focuses on intelligent algorithms and applications, including machine learning, metaheuristic optimisation, and deep-learning approaches. Finally, conclusions and future perspectives are presented in Section 6.

2. Fundamentals and Sensing Strategies

2.1. Defect Frequencies of Rolling Element Bearings

A typical rolling element bearing contains an inner race, outer race (usually fixed), rolling elements, and a cage [14], as shown in Figure 1a [15]. As there is constant contact between the rolling element and the races during operation, the REB can exhibit signs of wear and develop various defects over time, such as spalls, pits, and cracks [16]. Defects can occur in any of the components of the REB. When a defect is developed, it will generate a series of pulses of vibration that repeat periodically at a rate specific to the type of defects [17], as indicated in Figure 1. The frequency at which these defects come into contact with other moving parts can be calculated using the geometry of the bearing and the shaft's rotational frequency. These theoretical defect frequencies (TDFs), including the ball pass frequency of the inner race (BPFI), ball pass frequency of the outer race (BPFO), ball spin frequency (BSF), and fundamental train frequency (FTF), can be calculated using Equations (1)–(4) below, where n is the number of rolling elements, f_r is the shaft frequency, d is the rolling element diameter, D is the pitch diameter of bearing, and θ is the contact angle [18]. For special cases where both the inner race and outer race are rotating, f_r is the relative frequency difference between the inner and outer race. It must also be noted that the ball spin frequency (BSF) represents the frequency at which the ball makes contact with only one of the races and therefore the harmonics of this TDF will also need to be observed [19].

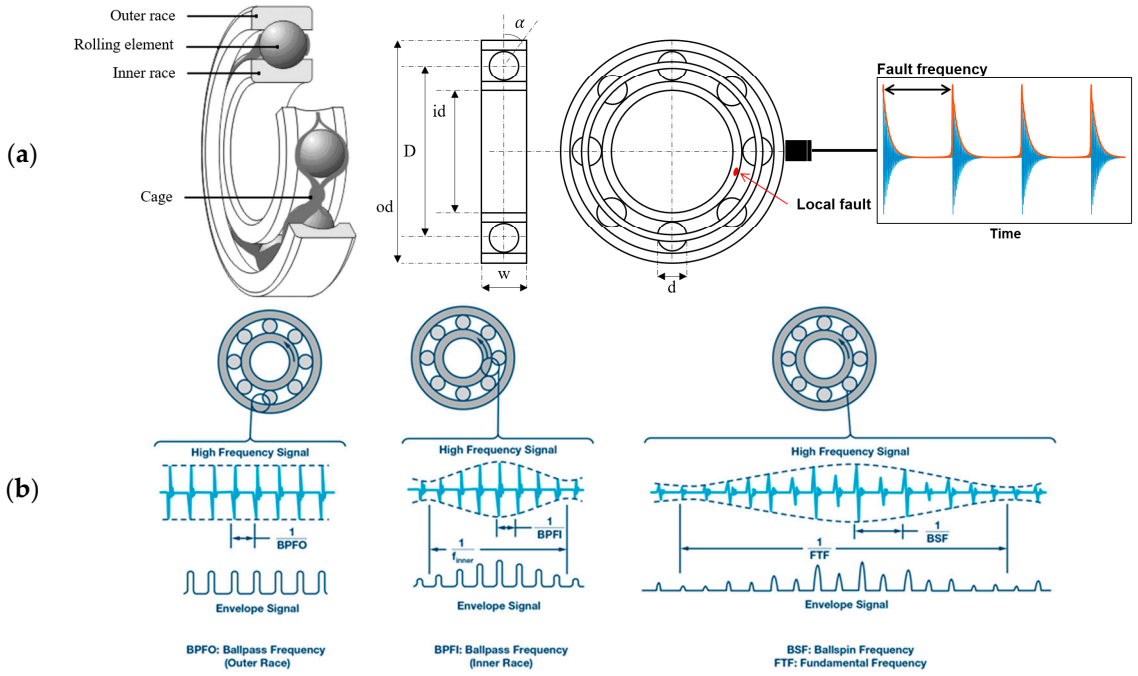


Figure 1. (**a**) Bearing geometry and impact signal ([15]); (**b**) Typical envelope signatures due to defects in outer race, inner race, and a rolling element ([17]).

$$BPFO = \frac{nf_r}{2}\left(1 - \frac{d}{D}\cos\theta\right) \quad (1)$$

$$BPFI = \frac{nf_r}{2}\left(1 + \frac{d}{D}\cos\theta\right) \quad (2)$$

$$BSF = \frac{Df_r}{2d}\left(1 - \left(\frac{d}{D}\cos\theta\right)^2\right) \quad (3)$$

$$FTF = \frac{f_r}{2}\left(1 - \frac{d}{D}\cos\theta\right) \quad (4)$$

The condition monitoring of machinery is of considerable importance to various industry sectors due to the possible reduction in costs and increase in safety that can be achieved. Over the past few decades, several notable innovations and general improvements have been made in the field.

2.2. Condition Monitoring Approaches

According to Jablonski [20], condition monitoring systems can include a number of tasks, namely, fault detection, diagnosis, severity assessment, root cause analysis, prognosis, and prescription. Fault detection involves determining whether or not a fault is present in a machine. This task can sometimes be accomplished through methods as simple as monitoring a statistical indicator's magnitude to see if a set threshold is reached. Fault diagnosis often refers to identifying what type of fault is present in a machine element. It is also used to describe the process of identifying which machine element is faulty. Unlike fault detection, the fault diagnosis task more often involves advanced signal processing techniques. It must be noted that this naming convention is not strictly adhered to by all researchers and the terms detection and diagnosis are used interchangeably by some. Severity assessment, as the name implies, involves attaining additional information regarding the prominence of the fault [21]. Root cause analysis tackles another aspect of condition monitoring attempting to identify the primary cause inducing the detected fault [20]. Fault prognosis is carried out to avoid unexpected failures by estimating the remaining useful life of components [22]. Prescription or prescriptive analytics involves providing recommendations on maintenance actions that can be taken for machine condition monitoring [20].

Condition monitoring tasks can be achieved through various approaches. Different sensors have been employed for the measurement of natural phenomena which can hold valuable information on the equipment being monitored. Some common approaches are explained in the following subsections.

2.2.1. Vibration-Based Monitoring

Vibration-based monitoring is considered the most mature condition monitoring approach and has been widely used for several decades. The presence of defective components in rotating machinery produces vibrations that are substantially different from what is generated by the machine in a healthy condition. In REBs, the periodic contact of the defective component (i.e., a rolling element, inner race, or outer race) with other surfaces during operation typically generates strong impulses at a higher frequency compared to other machine vibrations. These vibration signals can be collected using an accelerometer mounted on the machine near the component being monitored. Accelerometer measurements often have a high-frequency response typically around 10 kHz to 20 kHz [23]. Many signal processing methods have been utilised for the extraction of defect-related features in the different domains.

2.2.2. Acoustic Emission-Based Monitoring

Acoustic emission (AE) is defined as the propagation of transient elastic waves as a result of the contact of surfaces during operational motion [24]. Upon direct contact of the

defect with another component, AEs are released which can be picked up using the AE sensor. The signals from AE sensors have a much higher frequency response from around 100 kHz up to several MHz [25]. Choudhury and Tandon [26] investigated the use of AE sensors for the detection of different sizes of defects in REB. By counting occurrences of the case when the voltage exceeded a set threshold, roller and inner race defects were able to be detected. Elforjani and Mba [27] found that AE signals can be used for the detection of incipient defects and their propagation and also to estimate the size. Caesarendra et al. [28] reported that it was able to detect defects much earlier using AE signals, although there was a trade-off between accuracy and computational time. Such advantages made the use of AE-based monitoring a viable alternative to vibration-based monitoring.

A common concern in using AE signals is the extreme computation burden due to the very high sampling rate required. A time synchronous resampling technique with spectral averaging was used in the extraction of condition indicators of low-speed bearings using AE signals at a lower sampling frequency [29]. A study by Liu et al. [30] utilised a compressive sampling technique on AE signals and extracted features based on their energy to assess the state of the bearing. The extracted features were consistent with the features from a raw uncompressed signal.

2.2.3. Thermal-Based Monitoring

Thermal-based monitoring aims to detect abnormal heat patterns caused by malfunction in rotating machinery [31]. The sensors used are primarily infrared cameras, but thermocouples can also be utilised. Infrared cameras capture the energy from the monitored structure in the infrared wavelength of the electromagnetic spectrum allowing for the collection of images indicating surface temperature distribution [32]. Condition monitoring using infrared thermography typically involves the use of image processing and machine-learning methods. This approach is non-intrusive in nature as the infrared cameras can be easily set up while the machine is still in operation, leaving its process unaffected. The drawbacks of this approach include the high cost of infrared cameras, the requirement of additional space and setup, and being sensitive to environmental factors [25].

Janssens et al. [33] used infrared imaging to detect various defects in rotating machinery including rotor imbalance, defects present on the outer raceway of bearings, and also bearing lubrication levels. The detection of the lubrication levels and outer raceway faults was carried by obtaining the mean of the Gini coefficient, standard deviation, and second-order moment of pixels for all frames. Liu et al. [34] employed a convolutional neural network (CNN) on infrared images for the classification of rotor bearing system defects. Mehta et al. [35] used infrared thermography for the classification of bearing defects. It was found that the SVM classifier had a better performance in comparison to other classifiers tested for this application.

2.2.4. Other Approaches

There are several other sensors which can be utilised for the condition monitoring of bearings [7]. Online oil monitoring with oil quality or wear debris sensors has been utilised for the monitoring of machine issues such as lubrication degradation and wear state [36,37]. Ultrasonic detection involves monitoring sound waves at frequency levels of 20 kHz to 100 kHz [38]. It can be employed for the early detection of bearing defects and also lubrication levels [39]. Current signature monitoring is used for the monitoring and detection of incipient bearing failures in induction motors through the analysis of stator current signals [40], in which an algorithm to analyse electric current signals was proposed as a suitable alternative to vibration signals to detect bearing faults. This approach is non-invasive and can monitor multiple components in motor-driven systems. Microphones have also been employed for non-contact acoustic monitoring of bearings with success [41]. This is achieved by measuring pressure variations or sound from the environment. In addition, employing the inherent electrical impedance of rolling element bearings to detect bearing damage is also an alternative measurement method [42]. The impedance is a direct

property of the bearing which is related to the resistance and capacitance of a bearing. These electrical properties are influenced by variations in the surface properties of rolling bearings such as surface roughness and damage, and the elastohydrodynamic (EHL) contacts as a function of the lubrication film thickness. It has been shown that electric impedance analysis is capable of diagnosing the presence of surface damage in rolling bearings, and even its extension in an early stage of the damage occurrence [42,43]. Nevertheless, impedance-based bearing condition monitoring technologies are still under investigation and have not been widely used in the industry.

A summary of the commonly used bearing condition monitoring sensors is listed in Table 1.

2.3. Influence of Sensor Integrity

The quality of sensors and signals used in the condition monitoring of machinery can greatly influence the trustworthiness of detection and diagnosis [44]. It is crucial to ensure the reliability of the information acquired from sensors. In many cases, monitoring sensors are installed at harsh and difficult-to-access locations, such as on off-shore wind turbines; thus, physical inspection of the sensors on site is a big challenge. Sensor issues affecting signal integrity can occur due to various reasons including faulty mounting, background noise, saturation, and sudden impact. Girondin et al. [45] stated that mechanical shocks and the loosening of accelerometers were the cause of random peaks and asymmetries in signals affecting helicopter health and usage monitoring systems. While the study was unable to detect the occurrence of mechanical shocks, asymmetries were detected using enhanced skewness indicating transducer looseness. Similarly, Abboud et al. [46] investigated the issue of accelerometer detachment. It was found that asymmetry affected the random part of the vibration signal, so cepstrum pre-whitening was used to remove the deterministic content of the signal. An indicator that compared the number of outliers on the set positive and negative thresholds was used for the detection of the sensor issue. An alternative approach for the detection of accelerometer mounting issues was taken by Randall and Smith [23], which involved the use of multiple sensors mounted on the structure. Discrepancies between accelerometer resonances could indicate a problem with mounting. This method, however, requires all other sensors to be mounted correctly, otherwise it can be difficult to identify faulty mounting. Song et al. [47] developed a method for checking signal quality and the detection of defective conditions. This involved the use of histograms from segments of a signal without any distortions from equipment operating at normal conditions. Recently, Kannan et al. analysed some common signal integrity issues in vibration monitoring, such as sensor saturation, signal distortion, and sensor loosening and detachment, and proposed a method to detect the occurrence of vibration signal integrity issues using a one-class support vector machine [48]. It can be integrated in a bearing condition monitoring system as an effective preprocessing step for increased reliability and accuracy and reduced measurement uncertainty.

Table 1. Commonly used sensing strategies and characteristics.

Sensing Strategy	Sensor Type	Signal Type	Basic Principles	Advantages	Limitations	Applications
Vibration Analysis	Accelerometers	Acceleration Signals	Measures acceleration to detect changes in vibration patterns caused by bearing faults	High sensitivity to faults, well-established methodology	Sensitive to noise, requires high-frequency data acquisition	General bearing fault diagnosis, early fault detection
Vibration Analysis	Velocimeters	Velocity Signals	Measures the speed of vibrations, used for analysing low-frequency vibrations	Suitable for low-frequency analysis, less sensitive to noise	May miss high-frequency fault features	Fault detection in slow-rotating machinery
Acoustic Emission	Acoustic Emission Sensors	Acoustic Emission Signals	Detects high-frequency stress waves generated by defects in bearings	Highly sensitive to small defects, useful for early detection	Requires specialised equipment, complex signal interpretation	Detection of incipient faults and crack propagation
Infrared Thermography	Infrared Cameras	Thermal Images	Measures temperature variations on bearing surfaces	Non-contact, suitable for detecting thermal anomalies	Limited to detecting thermal effects, influenced by external factors	Monitoring bearing temperature, detecting lubrication issues
Electrical Methods	Current Sensors	Motor Current Signals	Analyses changes in motor current signals caused by bearing faults	Non-intrusive, can monitor multiple bearings simultaneously	Less sensitive to small defects, affected by load variations	Monitoring electric motors and generators
Electrical Methods	Voltage Sensors	Voltage Signals	Detects voltage fluctuations due to bearing faults in motor systems	Effective for monitoring electrical machinery	Requires stable operating conditions, sensitive to external electrical noise	Diagnosis of faults in electric motors and drives
Impedance Measurement	Impedance Analysers	Impedance Signals	Measures electrical impedance variations due to bearing faults and EHL contacts	Sensitive to changes in material properties, non-destructive	Requires specialised equipment, influenced by electrical interference	Monitoring material degradation and detecting insulation faults
Oil Analysis	Oil Quality Sensors	Oil Condition Signals	Analyses contaminants and debris in lubrication oil	Can identify wear particles and contamination	Requires oil sampling, influenced by oil properties and operating conditions	Monitoring bearing wear and lubrication status
Strain Measurement	Strain Gauges	Strain Signals	Measures deformation in bearing components due to applied forces	Direct measurement of load effects, sensitive to small changes	Requires direct attachment to the bearing, can be intrusive	Monitoring load and stress on bearing components
Noise Measurement	Microphones	Noise Signals	Detects noise patterns and variations due to mechanical defects	Non-contact, capable of detecting early-stage faults	Sensitive to environmental noise, complex signal analysis	Monitoring noise levels and detecting bearing anomalies

3. Signal Processing and Feature Extraction Techniques

Signal processing and feature extraction techniques are used to uncover relevant monitoring information from a source. Many of the vibration signal processing and feature extraction techniques are applicable to most temporal signals such as the AE signal. Alternative methods of analysis are needed for different condition monitoring approaches such as temperature-based monitoring where feature extraction typically involves some form of image processing [49].

Vibration signals are commonly analysed in the time domain, frequency domain, or time–frequency domain, each presenting their own advantages and drawbacks [12]. When signals recorded are visualised with respect to time, it is said to be in the time domain. Alternatively, the frequency domain allows for the analysis of the same signals with respect to frequency and appears as impulses. The time–frequency domain allows for a representation capturing signal changes over both time and frequency. A taxonomy of the most common signal processing and feature extraction methods is illustrated in Figure 2 [50].

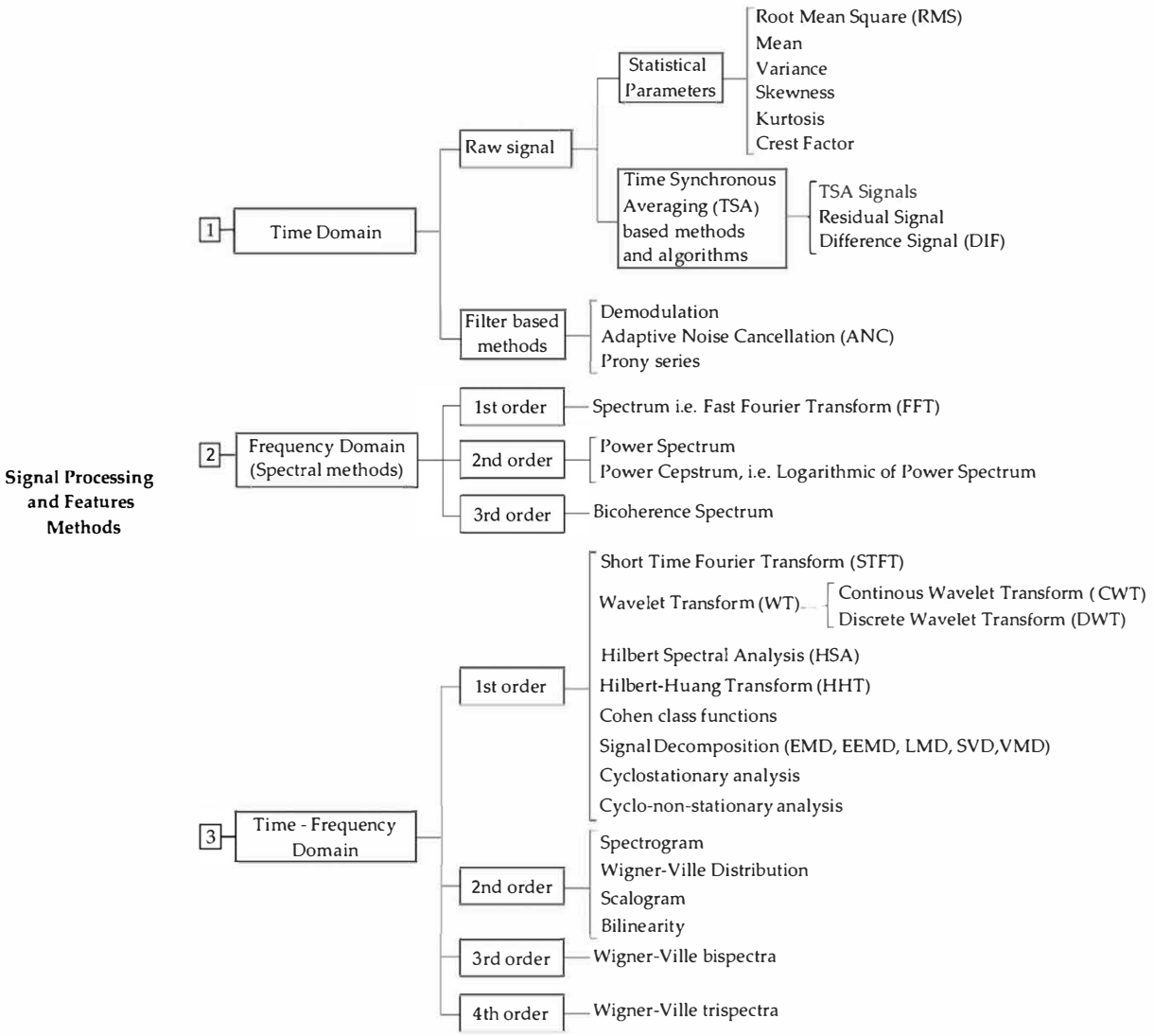


Figure 2. A taxonomy of the most common signal processing and feature extraction methods (adapted from [50]).

3.1. Time Domain Methods

Temporal analysis techniques are typically used to provide insight into the variation in conditions in the machinery and identify the presence of defects. There are several features,

including the root mean square (RMS), crest factor, kurtosis, and skewness, that can be extracted from the time domain to obtain information on the signal. These are shown in Equations (5)–(8), respectively, where μ is the mean, σ is the standard deviation, and x is a vector of n samples [5].

$$MS = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} \tag{5}$$

$$CF = \frac{\max|x_i|}{\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}} \tag{6}$$

$$K = \frac{\sum_{i=1}^{n}(x_i - \mu)^4}{n\sigma^4} \tag{7}$$

$$S = \frac{\sum_{i=1}^{n}(x_i - \mu)^3}{n\sigma^3} \tag{8}$$

A faulty bearing compared to one that is in good condition has a higher RMS value which can be expected to increase with the development of the fault [51]. The RMS of the vibration signal can be used as a basic indication technique for the presence of faults. However, it is inferior to other methods for the detection of incipient faults. The impact caused by the contact of the defect to the raceway or rolling elements can be calculated using the crest factor. The change in the pattern of vibration on signals due to this defect is reflected in the increase in this feature's magnitude [52]. The equation is simply the ratio of the peak value to RMS. Kurtosis has been identified as a good indicator of bearing health as healthy bearings have a Gaussian amplitude distribution with a kurtosis value of three regardless of speed or loading conditions [53]. It is much better at detecting incipient faults when compared to RMS; however, it has poor stability [54]. The asymmetry of the vibration signal is measured using skewness to tell if it is negatively or positively skewed [10]. Bearings in a healthy operating condition have signals with a near-zero skewness. Goyal et al. [55] present several other statistical indicators that can be used for condition monitoring. With a reasonably high sampling rate, the output of the sensor can be analysed in near-continuous time, making the features extracted more accurate.

The features mentioned above and many others have been successfully used in identifying the presence and even the type of fault. Heng and Nor [56] used plots of kurtosis vs. crest factor to distinguish the type of fault in the bearing. However, this method did not work for all cases tested, only giving accurate results for defective REBs at a shaft speed of 1000 rpm. Sreejith et al. [57] used two features, kurtosis and normal negative log-likelihood, as inputs to a neural network. From this, they were able to distinguish different bearing faults accurately. Fu et al. [54] proposed an adaptive fuzzy C-means clustering method using time domain-based features with which bearing health could be accurately computed. The clustering algorithm used crest factor, skewness, kurtosis, RMS, and variance as the feature matrix [54]. Samanta and Al-Balushi [44] developed a method where the features RMS, kurtosis, variance, skewness, and normalised sixth central moment were used as inputs for an artificial neural network (ANN) with some preprocessing. From this, they were able to determine whether the bearing tested was healthy or defective.

It is generally agreed that time-domain analysis techniques are favoured when a fast result is required. It eliminates the need for using complicated signal processing methods and features can be extracted from the same domain they are collected in. This makes it a preferred method for use with various intelligent algorithm-related techniques and has helped to achieve accurate results. Additionally, basic assumptions can also be made on the types of faults present in the REB based on the general shape of the vibration signal in the time domain. In the vibration signal of a bearing with an outer race fault (ORF) as shown in Figure 1b, prominent impulses can be noticed periodically with a near-uniform amplitude. The difference in time between these impulses equals the inverse of the ball pass frequency of the outer race (BPFO). A bearing with an inner race fault (IRF) generates

a signal which oscillates in amplitude periodically. This period aligns with the inverse of the shaft frequency, and the spacing between impulses corresponds to the inverse of the ball pass frequency of the inner race (BPFI). A ball fault (BF) in an REB can be expected to have a similar wave pattern as that of an IRF with the oscillation of amplitudes. The period at which this occurs corresponds to the inverse of the fundamental train frequency (FTF, i.e., the frequency at which the roller cage enters and exists the load zone). The distance between every second impulse relates to the inverse of the BSF as one impulse is produced for contact with each raceway (i.e., inner and outer race). Therefore, it is also possible to visually determine the presence of a fault and the type of defect the bearing may possess. However, this would require someone with expertise in the field and the identification of a fault may not always be so straightforward.

The use of analysis methods in the time domain has the advantage of simplicity in calculations and being able to process signals directly as collected thus lowering the time taken for processing [54]. Despite the development of more advanced signal processing techniques, these time-based statistical features are still used for some cases as other domain analysis methods may present some disadvantages. Analysis methods in the time domain, however, are still considered inferior to others due to their low accuracy and sensitivity [54].

3.2. Frequency Domain Methods

Frequency domain analysis methods are common in the fault diagnosis of bearings and are extensively used by many researchers [58]. The frequency domain is very useful in identifying the occurrence of impulses in periodic intervals. In order to convert the vibration signal from the time domain to the frequency domain, the Fourier transform is computed typically through the fast Fourier transform (FFT).

Envelope analysis, also known as the high-frequency resonance technique (HFRT), is a commonly used method for the diagnostics of REBs that allows for periodic impulses to be better visualised [18]. Envelope analysis works by first obtaining the frequency spectrum for the raw signal. From this, a frequency range is chosen for the amplitude demodulation process by using a bandpass filter to remove the other frequencies present. The Hilbert transform is a prominent technique used for this amplitude demodulation due to the advantages it presents over other analogue methods [19]. The Hilbert transform denoted by $\hat{x}(t)$ is the representation of phase shifting Fourier components on its frequency spectrum by $\pm\pi/2$ [59]. The signal $x(t)$ is convoluted with the function $1/(\pi t)$; this is mathematically represented in Equation (9).

$$\hat{x}(t) = \frac{1}{\pi}\int_{-\infty}^{\infty} \frac{x(\tau)}{t-\tau} d\tau \tag{9}$$

The band selected for demodulation is often from a higher frequency range where structural resonance amplifies the defect-related impulses [19]. The analytic time signal is found, and the modulus is computed. Using the Fourier transform once again, the envelope spectrum is obtained which can be analysed for information pertaining to bearing health. The ideal selection of a demodulation range will allow for certain frequencies to be uncovered. These frequencies may correspond to the shaft frequency, TDFs, and their harmonics as discussed in Section 2. This process is depicted in Figure 3. The correlation of the peaks in the envelope spectrum with a TDF and its harmonics can confirm the presence of a defect in the REB used. The use of HFRT has been considered by many as a common benchmarking method in the identification of bearing health conditions.

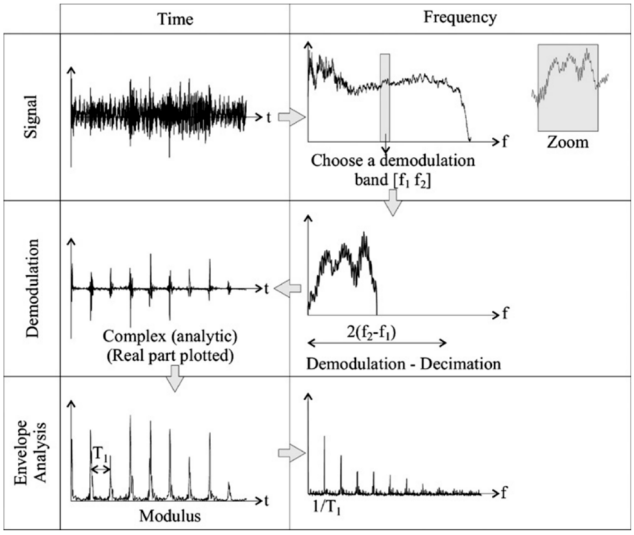


Figure 3. HFRT procedure (from [19]).

There have been several studies which attempt to find an optimised demodulation band selection technique for use with HFRT. Bechhoefer and Menon [60] investigated a helicopter's oil cooler fan bearing damage detection. Various envelope windows were tested manually to identify the optimal frequency band by incrementally changing the lower frequency and bandwidth within a specified range. A demodulation band range was selected which was optimal for the different defect frequencies present in the data. Boškoski and Urevc [61] proposed a two-step fault detection method for bearings. First, the likelihood of a defect was determined using spectral kurtosis. The bandpass filter maximising spectral kurtosis value was then used in envelope analysis to isolate defect-related frequencies. Spectral kurtosis and envelope kurtosis were used by Bechhoefer et al. [60] for bandwidth selection in the envelope analysis of bearing data. In this study, an average energy algorithm was employed to measure the selected window performance. In a recent work, a real-coded genetic algorithm was developed with a novel fitness function and crossover selection method to automate the optimal selection of bandpass filter parameters for envelope analysis [62], which allowed for the distinction of defect-related frequencies for REBs in an automated way.

In addition to the computational burden for the selection of optimal demodulation band, there are also some other drawbacks that can be expected in frequency domain analysis, including the occurrence of slip causing variations in TDF, interference from additional vibration sources like bearing looseness, and multiple faults making it difficult to discern certain frequencies [63]. The popularity of developing metrics for performance measurement may have inspired the use of metaheuristic optimisation algorithms in condition monitoring. The selection of optimal demodulation bands without the need for operator input can be achieved using metaheuristic optimisation techniques and will be further discussed.

It has been noted that when the measurement signal is contaminated by complex interference noise, the conventional envelope approaches, including both the envelope spectrum and the square envelope spectrum, often fail to effectively reveal the characteristic frequencies of rolling bearing faults [64]. Certain feature enhancement or noise reduction techniques are required for preprocessing, such as signal adaptive decomposition in the time–frequency domain, bandpass filtering, and blind deconvolution. Borghesani and Shahriar [65] proposed a new envelope spectrum, i.e., the log-envelope, to allow for a variance-free hypothesis test for cyclostationary components. Based on the simplified Box–Cox transform, Chen et al. [64] constructed generalised envelopes (GEs) from the analytical signal as a family of signal demodulation tools, and then proposed a spectrum family named generalised envelope spectra (GESs) to reveal cyclostationarity. The Box–Cox

transformation establishes a relationship between logarithmic operation and exponentiation operation. Simulation studies showed that the GESs with various transformation parameters (p) exhibit different capabilities and characteristics under different interference noises. An enhanced demodulation spectrum called PES (product envelope spectrum) was developed to combine the performance advantages of different GESs, which can achieve a stronger cyclostationarity detection capability than individual GES. A schematic diagram of the product envelope spectrum is shown in Figure 4 [64].

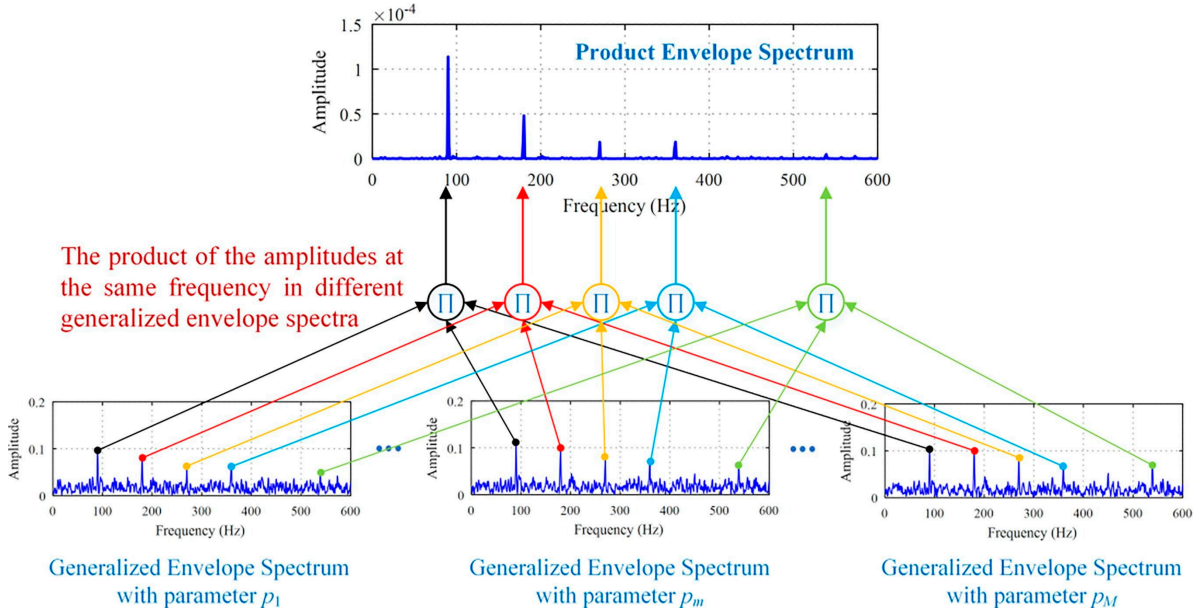


Figure 4. Schematic diagram of the product envelope spectrum.

3.3. Time–Frequency Domain Methods

Signals produced by some machinery can be expected to operate at varying speeds and the analysis methods used would need to account for their nonstationary nature. Some examples of rotational machinery with nonstationary REB signals include helicopters and wind turbines. The time and frequency analysis methods discussed above can only show features in their respective domains [66]. Signals that are considered nonstationary require alternate analysis methods known as time–frequency analysis, such as short-time Fourier transform (STFT), Wigner–Ville distribution (WVD), wavelet transform (WT), and Hilbert–Huang transform (HHT).

STFT uses Fourier transform in small time windows segmenting the signal as it can be assumed that the signal is stationary for a short duration [66]. The variation in the signal with time can be distinguished by analysing the local Fourier spectrum for each frame. Some benefits of using STFT is the lack of cross term interference as can be expected in WVD and its fast implementation. However, due to fixed window function and length, STFT is not adaptable. A high time resolution cannot be achieved when a fine frequency resolution is and vice versa [67]. It was one of the first time–frequency analysis methods developed and has therefore been used in several condition monitoring studies [68–70].

The WVD is a bilinear time–frequency method on which many others are based. Unlike STFT, a window function is not used in WVD, allowing for a much higher time–frequency resolution. Multi-component signals consist of auto terms and cross terms. Cross terms are the unwanted oscillations in the signal whose interference affects the effectiveness of the distribution [71]. The presence of cross terms can cause overlapping on auto terms and make time–frequency features appear indistinct [66]. Liu et al. [72] propose the auto term window method based on WVD analysis for bearing fault diagnosis where the effects of the cross terms are suppressed and auto terms boosted.

As the window size is fixed when it slides along the time in STFT, it is not able to provide good time and frequency resolution at the same time. The wavelet transform (WT) was developed to overcome the problem [73], which uses windows of different sizes for different frequencies and thus is capable of studying high-frequency components with a sharper time resolution than the low-frequency components [74]. WT converts the time domain signals into a group of wave-like signals, from which the original data can be reassembled using the weighting coefficient of each signal (i.e., wavelet coefficients) [75]. WT-based methods have been widely used in bearing condition monitoring. Zhang et al. [76] introduced a time–frequency analysis method based on continuous wavelet transform (CWT) and multiple Q-factor Gabor wavelets (MQGWs) to extract bearing diagnostic information. They found that the resolution of the CWT time–frequency map can be greatly increased, and the diagnostic information can be accurately identified. An intelligent fault diagnosis method of rolling bearing based on wavelet transform (WT) and an improved residual neural network (IResNet) was reported by Liang et al. [77], which resulted in better robustness under noisy labels and environments.

The HHT is an adaptive non-parametric analysis method which involves the use of empirical mode decomposition (EMD) and the Hilbert spectrum. Although the instantaneous frequency for mono-component signals can be computed easily, real applications typically deal with multi-component signals which need to first be decomposed into mono-components. These mono-components or intrinsic mode functions (IMFs) are extracted using EMD through a process called iterative sifting [66]. Signals can be approximated by an IMF series. The HHT method calculates the instantaneous frequency from the IMF phase's local derivative enhancing signal local properties, thereby making it capable of achieving a high time–frequency resolution. It is adaptive in the representation of signals that are arbitrary and also does not have interference from cross terms, making HHT a very effective method [66]. HHT has been widely used in the field of fault diagnosis and has specifically been applied in the detection of bearing faults [78].

To deal with the challenges of unsteady vibration signals collected under varying speeds, a number of nonstationary signal processing approaches for bearing fault diagnosis have been developed, including the spectrum analysis-based methods, such as order tracking, cyclic spectrum correlation, and generalised demodulation, and the time–frequency analysis methods, such as the postprocessing methods and chirplet transform-based methods [79]. Gu et al. employed an angular domain resampling technology to transform the time-domain vibration signals under varying speeds into relatively steady angular-domain vibration signals [80]. Li et al. proposed an oscillatory time frequency concentration (OTFC) approach [81] for the adaptive extraction of the time-varying bearing fault signature, which demonstrated a superior performance than the conventional methods. Li et al. presented a time–frequency ridge estimation (TFRE) method [82] for gear and bearing fault diagnosis at time-varying speeds, which included a cost kernel function and search edge detection principle. This approach is adaptively modelled and can run automatically without parameter setting and adjustment. Furthermore, there are also approaches to addressing this problem by using the artificial feature extraction- and deep learning-enabled intelligent diagnosis methods [79].

In addition to those described, many other methods have been used for condition monitoring applications including local mean decomposition [83] and energy separation algorithms [84]. A detailed review of the time–frequency analysis methods can be found in [66].

4. Information Fusion

The condition monitoring output obtained from a single source might suffer reliability issues as the information could be corrupted due to sensing problems or even sensor failure. This may occur because of harsh environmental and operational conditions or by selecting a sensor not well suited to the application. Therefore, the use of multiple sensors can allow for the construction of a more robust condition monitoring system.

Researchers have explored the use of homogeneous and heterogeneous sensor systems in the condition monitoring of machinery. The monitoring reliability can be enhanced through information fusion that combines information from various sources in order to acquire a better interpretation of the data available. According to Khaleghi et al. [6], the challenges faced with information fusion include the disparity of data, data correlation, data imperfection, and data inconsistency. Information fusion is commonly categorised into three levels of abstraction, i.e., measurements, characteristics, and decisions [85]. These are also known as data-level fusion, feature-level fusion, and decision-level fusion, as discussed below.

4.1. Data-Level Fusion

Data-level fusion involves the direct combination of information from multiple sources before feature extraction and classification. Typically, all sensors used in this fusion measure the same phenomena [86].

Wang et al. [87] used signals from multiple accelerometers for the fault diagnosis of rotational machinery. The signals were initially transformed into a two-dimensional (2D) image which was a combined representation of each sensor's output. Feature extraction and fault classification were then conducted using a bottleneck layer optimised CNN. The proposed method was validated using data from a wind power test rig, demonstrating superior performance compared to a single-sensor approach. Xia et al. [88] also utilised data-level fusion for machinery fault diagnosis using a CNN. This involved extracting one-dimensional temporal data from each accelerometer mounted on the machine and combining them into a matrix. The resulting 2D matrix was then fed to the CNN for fault diagnosis. Testing on REB and gearbox data showed very good results. While data-level fusion is typically conducted with homogeneous sensors due to waveform similarity, heterogeneous sensors have also been utilised in combination. Jing et al. [89] applied information fusion using a deep CNN for planetary gearbox fault diagnosis. They combined standardised data segments from an accelerometer, microphone, current sensor, and optical encoder into a single data sample before using them with the deep CNN. Despite the disparity in physical quantities measured by the sensors, the information was fused for a unified input to the classifier, though not in the traditional sense. While this means information is combined at the data level, the authors noted that fusion also occurred at other levels, though not explicitly mentioned. In addition, this approach notably surpassed the performance of a single-sensor approach in testing. Guan et al. [90] constructed a fusion strategy called normalized pulse energy kurtosis through combing the characteristics of the Teager energy operator and kurtosis to make full use of channel information in different directions and positions to enrich the signal representation. The softmax function was used to calculate the weight of each sensor signal.

Data-level fusion yields rich information, enabling high accuracy, but it retains a larger volume of data compared to other fusion levels [7]. This may pose a challenge when computational efficiency and time are critical. However, with the growing availability of more powerful processing units, this concern is less significant for smaller condition monitoring setups. It is also worth noting that fusion at the lowest level could compromise the integrity of the condition monitoring decision if the integrity of a single-sensor output is compromised.

4.2. Feature-Level Fusion

In contrast to data-level fusion, feature-level fusion entails extracting pertinent characteristics from the acquired data. These features from each sensor are subsequently amalgamated at an intermediate level before integrating into condition monitoring systems. While the sensors employed for fusion at this level need not be commensurate, the chosen features must accurately represent crucial aspects of signal responses relevant to the conditions.

Chen and Li [91] collected time and frequency domain features from accelerometers mounted at various locations on the machinery tested. These features were fused using a multiple two-layer sparse autoencoder. The resulting fused features were used to train a deep belief network for fault classification. This approach was validated with test data, showing a high accuracy. It was also suggested that the method could be expanded for use with different sensor types. Tao et al. [92] utilised vibration signals from multiple accelerometers for the fault diagnosis of REBs. This involved the extraction of features from the time domain signals of every accelerometer. A deep belief network was then employed with the extracted features as input vectors, resulting in a suitable classifier for fault diagnosis. In comparison to a single-sensor approach, the method showed a better performance in the classification of REB defects. Vanraj et al. [93] employed signals from an accelerometer and microphone for classifying gear conditions. Feature extraction involved the use of EMD, the Teager–Kaiser energy operator, and a combination of both. The extracted statistical features were sorted based on relevance using a sequential floating forward selection algorithm. Using the selected feature vectors, k-nearest neighbour (KNN) was utilised to successfully classify faults.

Su et al. introduced the knowledge-based features for fault diagnosis of rolling bearings [94]. They developed a knowledge-informed deep network-based (KIDN) method based on deep CNN to extract and fuse knowledge-based and data-driven features. The knowledge-based features encompass the fault-related statistical features in the time domain (including skewness, kurtosis, and RMS, etc.) and frequency domain characteristics such as the fault spectrum energy obtained by using the Hilbert transform and FFT. A framework of a knowledge-informed deep network is illustrated in Figure 5. It involves two feature extraction modules, i.e., data-driven feature extraction and knowledge-based feature extraction. A feature fusion layer is defined to fuse the data-driven features extracted from the dense layer of the CNN network and the knowledge-based features, and then the new concatenated feature vector will be used as a fused feature map for fault classification. Leveraging the two types of features is believed to be capable of providing rich information for system fault diagnosis and thus resulting in improved robustness and accuracy.

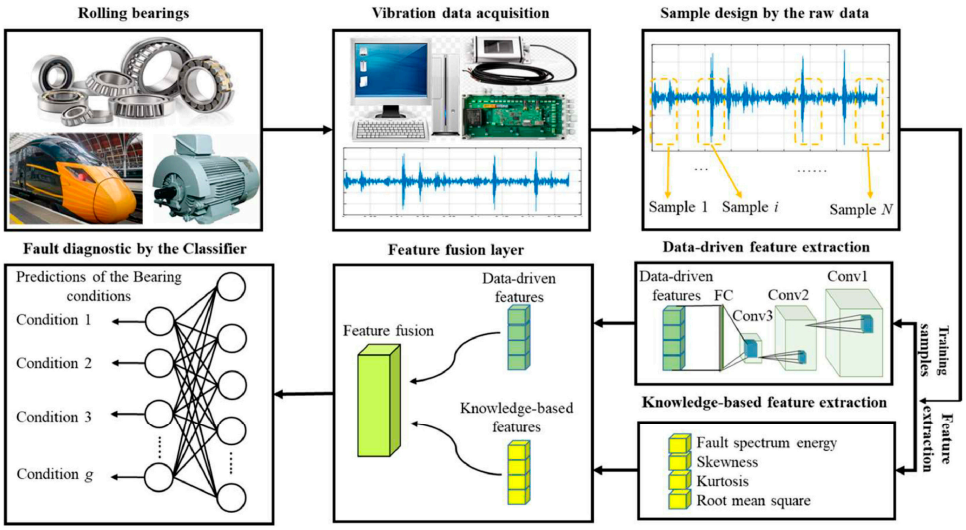


Figure 5. The framework of a knowledge-informed deep network with feature extraction and fusion modules [94].

While the use of feature-level fusion does deal with a smaller amount of data in comparison to data-level fusion, the trade-off is the potential loss of other useful information contained in the raw signal [7].

4.3. Decision-Level Fusion

Decision-level fusion represents the highest level of fusion, where sensor information is acquired, features are extracted, and the condition monitoring system makes a local decision for each sensor used. These local decisions are then combined to derive a global decision on the state of the machinery. Compared to lower and intermediate levels, fusion at this level results in the greatest loss of information [7]. Decision-level fusion is often used for, though not exclusively, heterogeneous sensor systems as a means to interpret sensor data recording various phenomena.

In a study by Niu et al. [86], both current and vibration signals were employed for motor fault diagnosis. Selected features were extracted from these signals and fed into different classifiers. The optimal selection of decision vectors was achieved by feature correlation, aiming for the best fusion performance with the fewest number of classifiers. The decision-level fusion was then conducted using a multi-agent classifier fusion algorithm. Comparisons with fault diagnosis from a single sensor demonstrated the superior performance of the proposed method. Safizadeh and Latifi [95] monitored REB health through accelerometers and load cell signals. They observed that load cells were good at distinguishing healthy bearings from defective ones but struggled to differentiate between different types of faults. The accelerometer on the other hand was highly effective in this but faced challenges in distinguishing healthy bearings with some outer race defects. To address this, they employed a waterfall fusion process model for decision-level fusion of the two sensors, achieving successful detection of each tested bearing fault condition.

Zhong et al. [96] also conducted decision-level fusion for the fault diagnosis of an automotive engine. The feature extraction and individual fault classification were from the air ratio, ignition pattern, and engine sound signals. These classifications were integrated using a probabilistic ensemble method, with the varying reliability and sensitivity of different signals to defects considered by assigning appropriate weighting to each signal. Validation demonstrated an improved performance compared to a single classifier approach. Stief et al. [97] utilised vibration, acoustic, and electric signals for the diagnosis of mechanical and electrical faults in induction motors. Features from each signal were dimensionally reduced using Principal Component Analysis (PCA) and the principal components were used with a two-stage Bayesian method. The local stage involved using Gaussian Naïve Bayes classifiers for the fusion and classification of each sensor's principal components. On the global stage, local decisions were integrated using a global confusion matrix to derive an overall diagnosis result. This method demonstrated success in detecting various faults under different environmental and loading conditions.

While fusion at the decision level generally enhances reliability and accuracy in fault classification, conflicting results can pose a challenge in diagnosis. Although instances of disagreement are rare, they can be more misleading in condition monitoring systems with fewer sensors. Using a greater number of sensors may provide insight into which sensor classification is unreliable through a majority vote; however, this approach is not always feasible and does not entirely resolve the issue. Furthermore, external factors that distort sensor signals are likely to affect other sensors of the same type, compromising the validity of such an approach. Consequently, this remains an ongoing research concern [98]. Mey et al. [99] proposed an approach for monitoring drive trains using both vibration and AE sensors. Data from each transducer were fed into a separate multilayer perceptron, and the resulting activations were employed in a combined classifier. This method was claimed to remain functional even if one of the sensors fails, as classification results can be based on the functioning sensor.

4.4. Multi-Level Fusion

Typically, information fusion occurs at a single level, as most scenarios do not necessitate multiple levels of fusion. However, despite its potential complexity, multi-level fusion can significantly enhance the condition monitoring performance.

Han et al. [100] introduced a fault diagnosis method for rotational machinery using a dual CNN. The data-level fusion of accelerometer signals in both the time domain and frequency domain was performed separately. Representative features were subsequently extracted and fused to achieve classification. The method was evaluated on bearing and gearbox datasets, with an enhanced performance demonstrated. Zhang et al. [101] used a hierarchical adaptive CNN for fault diagnosis of a centrifugal blower test rig. Initially, signal segments of the same sensor type were fused at the data level. Subsequently, features were extracted through automatic and manual procedures for the fused vibration and other sensor signals, respectively. Feature-level fusion was then performed using a kernel PCA from which fault classification was achieved with a multilayer perceptron. Yan et al. [102] proposed a method for the multi-level fusion of information to facilitate the fault diagnosis of a computer numerical control (CNC) machine tool. Features were extracted in the time domain, frequency domain, and from EMD using data from the machine's internal information source and externally mounted sensors. Kernel PCA was used for the fusion of features, from which sensitive features were used as input to separate classifiers. Classifier results were then integrated at the decision level with a fuzzy comprehensive evaluation. This method was evaluated across various defect conditions, demonstrating good performance.

While the fusion of information across multiple levels may offer certain advantages, it is essential to evaluate whether its application is truly necessary, as single-level fusion approaches often attain a sufficiently high performance to be considered reliable. Additionally, the adoption of multi-level fusion techniques could introduce added complexities to the condition monitoring system, potentially yielding only marginal improvements in performance. Although the utilisation of multi-level fusion techniques in machinery condition monitoring has not been extensively studied, it may be justified in specific use-case scenarios where its benefits outweigh the associated complexities.

5. Intelligent Algorithms and Applications

Algorithms incorporating artificial intelligence, commonly known as intelligent algorithms, offer highly adaptable and robust tools that mitigate the need for extensive fundamental knowledge and experience in condition monitoring, rendering them desirable for many operators [8]. According to Liu et al. [8], fault diagnostics of rotating machinery primarily involves pattern recognition, a task for which AI is particularly well-suited. The intelligent algorithms discussed in this section for the condition monitoring of rotational machinery are categorised as either machine-learning classifiers or metaheuristic optimisation techniques. In addition, the recent rapid development of deep-learning approaches related to bearing fault diagnosis is also included. A brief comparison of various intelligent approaches is listed in Table 2. Due to the complexity of rotating machineries and variable working conditions, there are different issues and challenges in bearing fault diagnosis, such as time varying conditions, measurement uncertainties, actual fault labels beyond the known labels, being without prior knowledge of the bearing fault location for a system with multiple bearings, complex fault patterns, and real-time fault detection. Each challenge may require special considerations in selecting the most effective methodologies and techniques. A taxonomy of methods in terms of addressing some typical challenges of bearing fault diagnosis is summarised in Table 3.

Table 2. Various intelligent approaches for bearing condition monitoring and diagnosis.

Category	Technique	Principles	Advantages	Limitations	Applications	Publications
Machine Learning	Support Vector Machine (SVM)	SVM finds the optimal hyperplane that maximises the margin between classes in high-dimensional space.	Effective for high-dimensional data; Robust to overfitting in many cases.	Requires proper kernel selection; Limited performance with large datasets.	Fault classification using vibration data; Distinguishing between different fault types.	[103–105]
Machine Learning	Random Forest (RF)	RF uses an ensemble of decision trees trained on various sub-samples of the dataset, and averages to improve prediction accuracy.	Handles large datasets well; Robust to overfitting due to averaging.	Computationally intensive for large trees; Can become biased if some classes dominate.	Classifying complex and non-linear fault patterns; Identifying feature importance for fault diagnosis.	[106,107]
Machine Learning	k-Nearest Neighbours (k-NN)	k-NN classifies a data point based on the majority class among its k-nearest neighbours in the feature space.	Simple and intuitive; No training phase required.	Computationally expensive for large datasets; Sensitive to irrelevant features and noisy data.	Fault classification with small and simple datasets; Quick diagnostics in real-time systems.	[108,109]
Deep Learning	Convolutional Neural Network (CNN)	CNNs use convolutional layers to automatically extract spatial features from raw data and learn hierarchical representations.	Excellent at feature extraction from raw data; High performance in image and signal processing.	Requires large datasets and computational resources; Less interpretable than traditional methods.	Bearing fault diagnosis using vibration signal images; Automatic feature extraction and classification.	[110,111]
Deep Learning	Recurrent Neural Network (RNN)	RNNs handle sequential data and learn temporal dependencies by using feedback loops in the network architecture.	Effective for time-series data; Captures temporal dependencies and dynamics.	Prone to vanishing gradient problems; Requires careful tuning and long training times.	Fault diagnosis from sequential vibration data; Monitoring time-evolving fault characteristics.	[112]
Deep Learning	Autoencoder	Autoencoders learn to encode input data into a lower-dimensional representation and then reconstruct the original input.	Useful for unsupervised learning; Can handle unlabelled data for anomaly detection.	Reconstruction quality depends on network complexity; Less effective for supervised classification.	Unsupervised feature learning and anomaly detection; Identifying new or unknown fault types.	[113]
Deep Learning	Transfer learning	Transfer knowledge from related tasks to improve fault diagnosis.	Reduces need for large labelled datasets, improves model generalisation.	Requires related source and target domains.	Fault diagnosis with limited labelled data.	[114]

Table 2. *Cont.*

Category	Technique	Principles	Advantages	Limitations	Applications	Publications
Deep Learning	Transformer	Leverage self-attention mechanisms to capture complex dependencies.	Handles long-range dependencies, parallelisable training.	Requires large datasets, high computational cost.	Fault diagnosis with complex sequential data.	[115,116]
Metaheuristic Optimisation	Genetic Algorithm (GA)	GAs simulate the process of natural selection to optimise feature selection and classification parameters.	Effective for global optimisation; Can handle complex, non-linear problems.	Computationally expensive; Requires careful tuning of parameters.	Optimising feature selection for fault diagnosis. Finding optimal classification parameters.	[62]
Metaheuristic Optimisation	Particle Swarm Optimisation (PSO)	PSO mimics the social behaviour of birds or fish to find the optimal solution by sharing information among individuals in a swarm.	Fast convergence to optimal solutions; Simple to implement and understand.	May converge to local optima; Performance sensitive to parameter settings.	Optimising neural network weights for fault classification; Feature selection and parameter tuning.	[117]
Metaheuristic Optimisation	Ant Colony Optimisation (ACO)	ACO simulates the foraging behaviour of ants to find optimal paths and solutions by reinforcing successful trails.	Effective for combinatorial optimisation problems; Can explore large solution spaces efficiently.	Slower convergence compared to other methods; Performance dependent on heuristic design.	Optimising fault diagnosis rules and decision-making; Feature selection and optimisation.	[105]

Table 3. Taxonomy of methods addressing major challenges of bearing fault diagnosis.

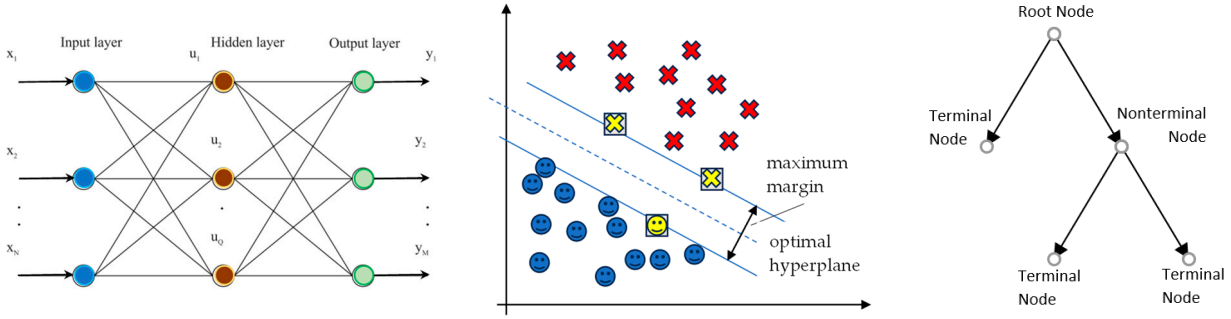
Challenges	Methods/Techniques	Publications
Time-Varying Conditions	Order tracking, angular domain resampling, oscillatory time frequency concentration, time–frequency ridge estimation, adaptive filter, transformer, autoencoder	[79–82]
Measurement Uncertainties	Information fusion, robust statistical methods, noise-tolerant SVM, KNN	[48,111,118,119]
Unknown Fault Labels	Unsupervised learning, clustering, semi-supervised learning, autoencoder, transfer learning, domain adaptation, generative adversarial network (GAN), digital twins	[113,120,121]
Multiple Bearings (Unknown Locations)	Sensor fusion—data fusion, feature-level fusion, blind source separation	[122]
Complex Fault Patterns	Ensemble methods—random forest, hybrid SVM-KNN, CNN-LSTM	[119,120]

5.1. Machine Learning and Deep-Learning Approaches

AI has found extensive application in the classification of REB faults. Following the extraction of features using suitable signal processing techniques, a classifier is employed for the automatic identification of various machine conditions, eliminating the requirement for an experienced technician. Machine learning, as a key component of AI, refers to the specific approach of training algorithms to learn patterns and make predictions or decisions from data without being explicitly programmed for each task, providing the ability for AI systems to learn and improve from experience without human intervention [123].

There are three main types of machine-learning algorithms, namely supervised, unsupervised, and reinforcement learning algorithms. Supervised learning utilises collected data along with their correct class labels to train the algorithm to distinguish between classes from new data [124]. Unsupervised learning clusters data based on patterns discovered and is typically used to uncover previously unknown information without explicit guidance [125]. Reinforcement learning involves learning the behaviour necessary to perform optimally in a dynamic environment [126]. In the context of condition monitoring, the identification of different conditions in data primarily involves supervised learning methods.

ANNs, or artificial neural networks, are predominantly utilised in supervised learning applications. ANNs consist of multiple interconnected nodes arranged into three layers: input, hidden, and output [127], as depicted in Figure 6a. The nodes in the input layer relay information from sensors to the hidden layers and do not perform computation [128]. Nodes that do not deal with the input or output of data belong to the hidden layer. ANNs can have multiple hidden layers, where computation occurs. The output layer comprises nodes that convey the computational results from the ANN as output. The input value of each node is multiplied by the connection, which adjusts the input's impact in the algorithm.



(**a**) (**b**) (**c**)

Figure 6. (**a**) The general structure of an ANN; (**b**) Principle of SVM: Segregation of two classes in two-dimensional space with an optimally placed hyperplane; (**c**) Decision tree schematic.

Various ANN models have been prominently employed in the fault diagnosis of REBs. Jia et al. [129] proposed a method for the automated design of feature extraction algorithms in the bearing fault diagnosis using a four-layer local connection network. Vibration signals from the input layer were analysed by a normalised sparse autoencoder to learn useful features in the local layer. From this, shift-invariant features were identified in the feature layer, allowing the algorithm to differentiate between various conditions in the output layer. Chen et al. [130] recognised that feature extraction can be time-consuming and require a deep understanding of signal processing. They presented a method where the fault diagnosis of bearings was achieved with a multi-scale CNN and long short-term memory (LSTM) model. Two CNNs were used for the automatic extraction of features from raw vibration signals. A stacked LSTM network was then used for classifying bearing health conditions. Ali et al. [2] used a four-layer ANN for the classification of bearing defects. Features were extracted from the time domain, and the EMD method was also employed.

Effective IMFs for bearing fault diagnosis were selected using a statistic criterion. The selected features were then used to train the ANN for fault classification.

SVM is another supervised learning technique commonly used in classification problems. In SVM, data are segregated in a multidimensional space using a hyperplane to classify different machine conditions [131]. The SVM aims to maximise the distance between the hyperplane and the support vectors of each class to find the best possible solution. These support vectors are the data points nearest to the hyperplane, which influence its orientation and position to effectively separate data classes. It must be noted that not all data can be linearly separated. In such cases, the data are to be mapped to a higher dimension where linear separation of the support vectors is possible. Figure 6b shows an example of two classes, circles and crosses, being separated with an optimal hyperplane [132]. The support vectors that define the maximum margin of the two groups are indicated with squares.

Although SVM was initially developed for binary classification problems [132], it has since been adapted to handle multi-class classification tasks using approaches like one-versus-one or one-versus-rest [133]. This adaptability makes SVM suitable for fault diagnosis in rotating machinery, where multiple health conditions are common. For instance, Yang et al. [103] applied SVM to diagnose bearing faults using vibration signals. They utilised both fractal dimensions and statistical features extracted from the data for SVM training. This method achieved a better classification performance compared to using only fractal dimensions or statistical features. Wang et al. [104] also used SVM for bearing fault diagnosis. They first extracted features from accelerometer signals using generalised refined composite multiscale sample entropy. Then, dimensionality reduction was performed on the feature set using the supervised isometric mapping algorithm. Finally, the reduced feature set was used with an optimised SVM for bearing health classification.

SVM has also been adapted for the detection of anomalies by training the model on a single class that is considered normal. The process is termed a one-class support vector machine (OCSVM) and is achieved by maximising the margin between the single data class and the origin in a higher dimensional feature space [134]. This method has been used by some researchers such as Fernández-Francos et al. [135] in the context of bearing fault diagnosis. Vibration signals from bearings operating under normal conditions were used to train an OCSVM for the identification of faulty bearings. Subsequently, fault type identification was achieved by employing envelope spectrum analysis. Kannan et al. [118] presented a novel information fusion approach to efficiently utilise homogeneous and heterogeneous sensor signals in bearing condition monitoring. OCSVM was employed to extract features corresponding to signal integrity issues; thus, an integrity score can be dynamically assigned to data depending on its perceived signal quality. Decision-level fusion was accomplished through a majority voting system using the integrity scores derived and the separate classification results. It was demonstrated that a more reliable classification prediction was achieved using this approach.

Decision trees or classification trees are quite simple in comparison to other supervised learning algorithms. They are models which represent the possible outcomes of a test in a tree-like structure and classifies records based on their likelihood of belonging to a certain class [136]. The root node representing the whole population is split into multiple sub-nodes which can be categorised as either terminal or nonterminal nodes. Nonterminal nodes are nodes that are further split into sub-nodes representing the outcome of the decision for which the node is responsible and terminal nodes are nodes that do not split. A schematic representation of a decision tree is shown in Figure 6c.

Decision trees are considered weak learners and, because of this, it is common to use them as part of an ensemble classification. An ensemble of decision trees is called a random forest (RF) where multiple decision trees are used to make predictions independently of one another [137]. These classifications are then combined through a voting procedure to, ideally, increase the predictive accuracy in comparison to a single decision tree [138]. Cerrada et al. [139] monitored the vibrational behaviour for the diagnosis of faults in spur

gears using concepts of RF with a GA. Various features were first extracted from the time and frequency domain of the vibration signal. Wavelet packet transform was also used on the raw signal getting each wavelet coefficient's energy which were considered features. A data matrix was constructed from the features and the selection process was set to run iteratively (i.e., one GA iteration then one RF training phase). Once the optimal feature subset was selected and the GA execution terminated, the classifier was then retrained with this subset. The classifier performance was then tested, and a good accuracy was achieved. Seera et al. [106] proposed a classification model using RF and a fuzzy min-max neural network for the diagnosis of REB faults. The features for input were extracted from the raw vibration signal using both power spectrum and sample entropy methods. Tests showed that using a combination of these features gave the highest accuracy compared to each method individually. The proposed model was also compared to other models proving that it had the highest accuracy and lowest standard deviation. Vakharia et al. [107] conducted a fault diagnosis on a bearing using vibration signals. With a feature ranking technique called ReliefF, significant features extracted from the time domain and discrete wavelet transform were selected for use with the RF classifier. The selected features in combination with the classifier performed well in the diagnosis of bearing faults.

KNN is a non-parametric technique that works by using an input vector with the K closest training samples in feature space, which has been used for health condition classification [108,109]. It is a multi-class classifier and needs no prior training. However, manual tuning is still needed to locate the k nearest neighbours for each testing sample via a global search when diagnosing [140]. A recent development to improve the performance is the adaptive nearest neighbour reconstruction (ANNR) [140], which can take advantage of both parameter- and case-based diagnosis methods. There are several other supervised machine-learning classifiers that can be implemented for machinery health classification including Naïve Bayes and discriminant analysis [141–145]. The use of supervised learning in the classification of machinery condition is generally preferred due to the model being trained to perform extremely well for a particular application.

5.2. Metaheuristic Optimisation Techniques

Another common use of intelligent algorithms is in the optimisation of parameters to obtain a suitable solution. Metaheuristic optimisation techniques have been of great interest to researchers in the field for tasks that require an ideal solution to be found within a large search space. The ability to measure the performance of different combinations of parameters against a certain criterion allows for the automatic selection of an optimal solution without the need for significant experience in the domain. This makes it desirable for diagnostic tool users who lack experience and a deeper understanding of bearing fault behaviour. Many of these optimisation techniques are based on concepts found in nature.

Evolutionary algorithms are a category of metaheuristic optimisation inspired by the concept of natural selection and are often applied to search for an optimal solution to a specific problem. The most popular evolutionary algorithm is the GA and its general operation is described in [62]. Some studies have explored the use of GA for the optimisation of the demodulation band for the envelope spectrum. In order to optimally demodulate resonance for REB fault diagnosis, Zhang and Randall [146] first used a fast kurtogram to roughly estimate the parameters. GA was then used for further optimisation of the parameters obtained allowing for faster convergence than directly using GA for the selection of the ideal bandpass filter. Wang et al. [147] conducted a study involving the detection of a sun gear crack in a planetary gearbox through envelope analysis. Through the development of an index measuring fault-related components to non-fault-related components in the envelope spectrum, GA was used to search the frequency range for an optimal subband. Kang et al. [148] also used a GA for the selection of optimal bandpass filter parameters in the condition monitoring of bearings. Unlike other studies, the parameters were coded with real numbers from 0 to 1 as opposed to binary values. The use of a real-coded GA is said to be advantageous for continuous parameter space variables [149]. For this reason, it can be

inferred that this approach generally allows for a higher accuracy in the representation of the optimal bandpass filter and that less storage will be needed [150]. The fitness score used was a ratio of residual-to-defect frequency components which was said to give insight into the degree of defectiveness [148]. The use of the fitness score as an indicator to determine defect severity, however, is not ideal. This is because the score for the same signal and, by extension, the bearing defect size can be expected to vary when the GA converges at a local or global optimum which could cause confusion. Swarm intelligence is another category of metaheuristic optimisation that is inspired by the collective behaviour of a population with no centralised structure controlling individuals. Common types of algorithms that use the concept of swarm intelligence are particle swarm optimisation (PSO) and ant colony optimisation. The uses of these algorithms are similar to that of GA.

Metaheuristic optimisation techniques have also been used with classification algorithms for the optimisation of parameters or structure of the classifier. In [151], Yan and Jia conducted fault diagnosis by using an optimised SVM for classification. Features were extracted in multiple domains and the Laplace score was used to determine which of these were to be used to reduce unnecessary or redundant characteristics. The selected features were then used as an input to an SVM whose parameters were optimised using PSO for the classification of bearing faults. Unal et al. [117] used an optimised ANN for the fault diagnosis of REBs from vibration signals. A GA was used to optimise the structure of the ANN, increasing the performance of fault classification. This was demonstrated by using GA in the optimal selection of the hidden layer number, number of neurons, and mean square error. In a study conducted by Li et al. [105], an optimised SVM was used for fault diagnosis in REBs. This was achieved by using an improved ant colony optimisation algorithm for the suitable selection of SVM parameters.

5.3. Deep-Learning Approaches

Deep learning is a sub-field of machine learning. It seeks to capture and model hierarchical representations within data by utilizing multiple layers of information processing units arranged in a hierarchical architecture [152]. This approach enables the classification and prediction of patterns through successive transformations and abstractions of the data. Deep-learning approaches have made significant advancements in the last decade in a wide range of applications, including bearing condition monitoring and fault diagnosis. The number of publications keeps increasing dramatically in recent years. Table 4 lists the annual number of articles for the years 2016–2024 from the website of ScienceDirect by using the terms of "deep learning", rolling bearing, and fault diagnosis to search. There are several comprehensive review papers on this topic published recently, including the work in [152–157].

Table 4. Number of articles found from ScienceDirect using the terms of "deep learning", rolling bearing, and fault diagnosis.

Year	2016	2017	2018	2019	2020	2021	2022	2023	2024 (up to June)
Articles	3	15	41	72	157	237	345	398	387

The widely explored deep-learning techniques include convolutional neural networks (CNNs), recurrent neural networks (RNNs) and long short-term memory (LSTM), autoencoders, generative adversarial networks (GANs), deep belief networks (DBNs), transformer networks, etc. CNNs are widely used for feature extraction and classification from time-series data and images derived from vibration signals. They are effective in handling large amounts of data and capturing spatial hierarchies in input features. Eren et al. [110] presented an intelligent system using an adaptive 1D CNN classifier that combines the feature extraction and classification blocks of a conventional pattern recognition approach in a specialised structure. Zhang et al. [111] proposed a model based on adaptive multivariate variational mode decomposition (AMVMD) and multi-scale CNN for the compound fault

diagnosis of rotating bearings. The multi-scale CNN was used to extract and recognise the denoising feature vectors in a deeper level, aiming to remove the interference of high-frequency environmental noise. With a goal of monitoring multiple bearings, Deng et al. proposed a framework called MgNet (Multi-granularity Network) to complete the fault diagnosis and location of a multi-bearing system via the vibration signal of an auxiliary bearing [122]. This framework is based on Conv1D and multi-granularity information fusion and claimed to achieve strong feature extraction ability and robustness.

Autoencoders can learn features and representations from monitoring data and detect anomalies in an unsupervised way. They are able to compress input data into a lower-dimensional representation and then reconstruct it. Liang and Zhou [113] utilised a semi-supervised learning method built upon the autoencoder with joint loss-based learning to fully utilise a large amount of unlabelled data together with limited labelled data to enhance fault detection performance. It offers the advantage of being easily implemented with fewer hyperparameters to be tuned. To solve the problem of low diagnostic accuracy for the bearing under strong noise conditions, Gao et al. proposed a method for weak fault feature extraction and diagnosis [112]. They used a multi-channel continuous wavelet transform (MCCWT) to transform the original temporal signals into a new representation with several channels and fewer network parameter requirements and a convolution-feature-based RNN (CFRNN), in which a recurrent unit combining several residual blocks and a LSTM block was proposed to mine the temporal features and the local vibration characteristics simultaneously.

Fault diagnosis methods based on deep learning need a lot of labelled data to train the network; however, it is usually difficult to collect enough fault data under the same working conditions for the training. Hou et al. [114] proposed a diagnosis method via simulation data driving transfer learning without target fault data to solve this problem. The simulation data are generated based on the bearing parameters, operating conditions, and normal baseline data collected from the target bearing. The envelope spectra of the simulation signals are used as the input to train a deep neural network with multi-head attention to identify fault types of the target bearing. A frame of procedures of the proposed diagnosis method for transfer learning is shown in Figure 7 [114]. The authors noted that the proposed method still suffers weakness in transfer diagnosis without target domain fault data as it is hard to map the simulated fault data features to the real fault data at different fault degrees; therefore, further research is still needed. Another approach to overcome the problem of sample imbalance is to build accurate and reliable digital twin models of faulty rolling bearings. Qin et al. constructed a multi-DOF bearing fault dynamics model for generating the vibration responses and employed a frequency-domain bi-directional long short-term memory (Bi-LSTM) cycle generative adversarial network (CycleGAN) named FBC-GAN to construct the frequency-domain coupling mapping relationship between the multipart vibration responses and the measured signals [121]. The developed digital twin model was used to generate the high-quality bearing fault samples with an arbitrary working condition, so as to update the imbalanced dataset for balancing the different types of bearing signal samples.

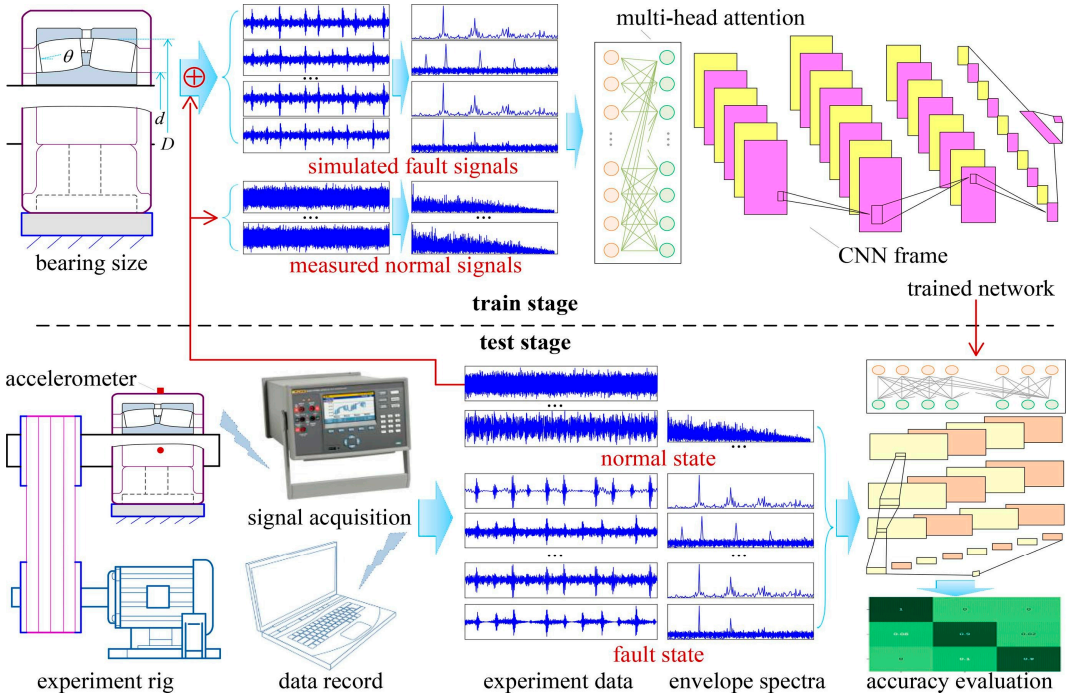


Figure 7. Frame of procedures of the proposed diagnosis method for transfer learning [114].

Transformers are the most recent development and gaining popularity for their ability to handle sequential data without the limitations of RNNs [154]. Transformer is basically an encoder–decoder structure, employing self-attention mechanisms to capture long-term dependencies in time-series data. The overall structure of a vanilla transformer is shown in Figure 8 [115]. To deal with the time-varying conditions where the speed is non-steady, Chi et al. [116] developed a vibration–speed fusion network by utilising a transformer with a self-attention module to extract vibration features and a sparse autoencoder (SAE) network to extract sparse features from the speed pulse signal. It enables the fusion of different signals in a high-dimensional vector space with a high degree of model interpretability. Du et al. [119] employed a transformer deep neural network to optimise the weight parameters of the SPBO-SDAE model for collecting the most essential features of the data. In comparison with the traditional methods and some other deep-learning methods, this approach showed a higher fault diagnostic accuracy and better generalisation performance. The proposed SPBO-SDAE-Transformer network has been tested using data with Gaussian noise added to simulate the actual complex and high-noise working conditions, and it demonstrated a good robustness and strong ability to deal with the actual complex working conditions. Hou et al. [115] designed a transformer-based rolling bearing fault diagnosis model called Diagnosisformer. This model consists of data processing, a multi-feature parallel fusion encoder, cross-flipped decoder, and classification head. Significantly different from the vanilla transformer, the Diagnosisformer applies the fault data features computed by multi-head self-attention as keys and values and the encoder output *X*enc as a query for the cross-attention mechanism computation. Diagnosisformer was claimed to improve the feature extraction ability and parallel computing ability greatly, and achieved high diagnostic accuracy and fast convergence speed [115]. Dong et al. proposed a multi-sensor data fusion-enabled lightweight convolutional double regularisation contrast transformer for aerospace bearing fault diagnosis with small samples [158]. In this approach, a lightweight Diwaveformer architecture was constructed as the backbone of contrast learning. Their case studies showed that transformer-based architectures exhibit substantial enhancements in fault recognition rate in comparison with the typical CNN architecture.

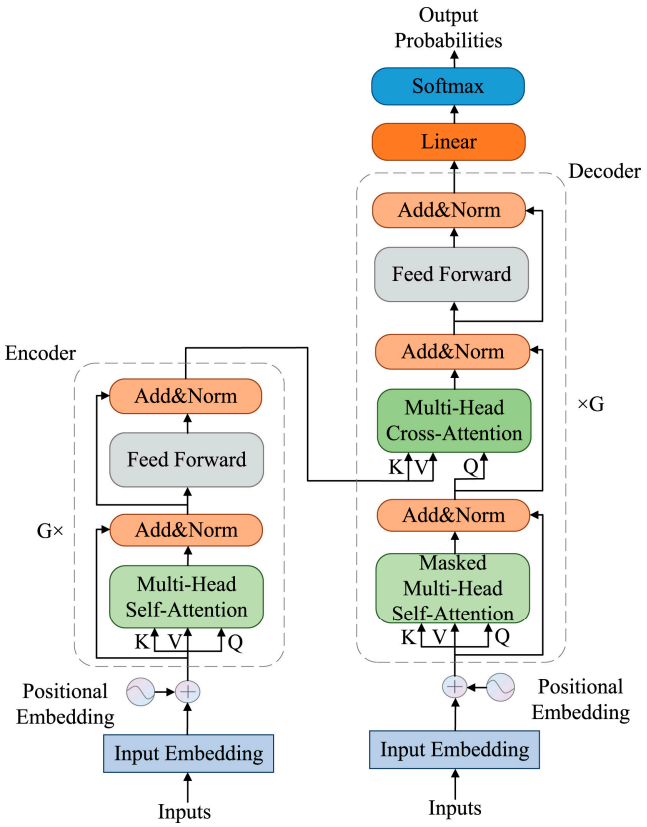


Figure 8. Overview of a vanilla transformer architecture [115].

Deep-llearning techniques for the monitoring and diagnosis of rolling bearing faults are undergoing rapid development. There is a continuous stream of new research publications introducing innovative technologies and methodologies. This area of study holds substantial promise, offering significant opportunities for future developments. The evolving nature of these approaches highlights their potential to revolutionise fault diagnosis and enhance the reliability and efficiency of machinery maintenance practices. As the field progresses, it is anticipated that further breakthroughs will continue to emerge, pushing the boundaries of what is achievable in bearing fault diagnosis through deep learning.

6. Conclusions and Future Perspectives

The significance of condition monitoring in rotational machinery is well-documented in the literature. A wide range of sensing, signal processing, feature extraction, and classification techniques have been developed for detecting defects in rolling element bearings. While vibration-based monitoring remains prevalent, the utilisation of other sensor types has proven advantageous, often offering complementary diagnostic capabilities or detecting different types of defects compared to accelerometers alone. Techniques such as time domain, frequency domain, and time–frequency domain analysis provide different perspectives for signal representation, whereas each reveals unique insights relevant to condition monitoring. Multisensor systems, whether homogeneous or heterogeneous, integrated with information fusion techniques can enhance accuracy and reliability by addressing the limitations associated with single-sensor monitoring. Additionally, the adoption of AI techniques, including machine learning, metaheuristic optimisation, and especially recent deep-learning approaches, has facilitated significant advancements in condition monitoring and achieved successful outcomes in various studies.

Meanwhile, there are several areas where advancements can be made to improve monitoring accuracy and reliability, such as in the following aspects.

- The envelope spectrum has proven to be an efficient benchmarking technique in the defect detection and diagnosis of bearings. The selection of an optimal frequency band for demodulation is crucial for this. While various techniques have been explored, many are time-consuming or require specialised expertise. New envelope spectrum approaches, such as the log-envelope and product envelope spectrum, have shown an improved performance. Further research leveraging metaheuristic optimisation and deep learning for automatic demodulation band selection and multi-band integration could enhance efficiency in this area.
- AI-based fault diagnosis techniques have become prominent due to their rapid development in the ability to significantly enhance the accuracy, efficiency, and reliability. Machine-learning classifiers are often used for diagnostic tasks due to their ability to achieve high accuracy without extensive domain knowledge. The classifier can be trained well for fault identification through the extraction of relevant features pertaining to the bearing health condition from historic data. It would be more practical for a signal integrity assessment technique to work on a variety of issues so it can be used as a standard preprocessing step to fault diagnosis. Research in the area will benefit from the development of a classification model that accurately captures the nonrigid nature of the decision boundary of signals to efficiently segregate anomalies.
- Multi-sensor monitoring systems were found to be advantageous as they increased the general reliability of fault detection and diagnosis. The use of heterogeneous sensors in conjunction can also aid in further increasing the reliability. While information fusion of different sensors has been achieved on different levels, it is most common for decision-level fusion to take place. However, conflicting results in sensor diagnoses can occur due to misclassification in learning models or sensor integrity issues, highlighting the need for further research to address these challenges.
- There are significant opportunities to employ innovative deep-learning technologies to address challenges in bearing fault diagnosis, such as the time-varying conditions, unlabelled and imbalanced data, complex fault patterns, and real-time detection for the fault types and locations. It is important to design the deep learning-based diagnosis systems that are lightweight, computationally efficient, and fast in execution. In addition, a deep understanding of the mechanics and physics of fault-related features is vital for the success of these monitoring systems.

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