Vibration-based Data-driven Fault Diagnosis of Rotating Machines Operating Under Varying Working Conditions: A Review and Bibliometric Analysis

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Abstract

The intelligent fault diagnosis of rotating machines has been significantly advanced by learning-based techniques in recent years. However, the performance of these techniques can drastically decrease under varying working conditions (VWC). This paper investigates the root causes of these decreased capabilities by analyzing the impact of VWC on each of the key steps in intelligent fault diagnosis for rotating machines. In addition, techniques proposed in the literature to mitigate these effects are reviewed and assessed for their relevance in industrial applications. A bibliometric study is also conducted to understand the evolution of research in this field over the past two decades. Beyond providing a synthesis of the existing literature, this review is intended for researchers, engineers, and industry professionals seeking to implement robust fault diagnosis systems under varying operational conditions. It offers insights on when and how these techniques can be effectively applied, depending on specific industrial scenarios and assumptions.

1. Introduction

Vibration analysis is one of the most commonly used approaches for fault diagnosis of rotating machines. Since the development and widespread availability of specialized instrumentation, vibration signals have successfully been used for early detection and characterization of mechanical faults, thus increasing the safety and reliability of rotating machines. Over the years, a multitude of physics-based, data-driven, or hybrid techniques have been proposed and demonstrated noteworthy diagnosis capabilities. More recently, the field has been further advanced by the advent of Industrial Internet of Things (IIoT) sensors providing large amounts of vibration data autonomously, partly enabling the use of intelligent Machine Learning (ML) techniques.

However, most of these techniques often rely on the assumption of constant operating conditions. As industrial systems and manufacturing processes get increasingly more complex, this assumption is often untrue, resulting in decreased diagnosis performance. Consequently, techniques adapted to the challenges of VWC are needed. This paper offers a comprehensive understanding of the development of such techniques. The challenges induced by VWC are examined at each stage of the diagnosis process, from data acquisition to health state classification. We identified two primary challenges: the non-stationary nature of vibration signals in machines under varying conditions, and the significant distribution shifts due to VWC, which challenge the standard assumption that data in data-driven models are independent and identically distributed.

Many reviews on the topic of intelligent fault diagnosis of rotating machines have been proposed, some offering a broad perspective (Tiboni et al. (2022); Wei et al. (2019)), and many others reviewing the utilization of ML techniques (Tama et al. (2022); R. Zhao et al. (2019)). Some focused on techniques tailored for a specific component (Rai & Upadhyay (2016); T. Wang et al. (2019)) or a specific signal processing technique (Isham et al. (2019); Yan et al. (2014)). The topic of varying working conditions is often mentioned as a major challenge (Fink et al. (2020)) but few works are dedicated to the topic, ex-

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cept (Choudhury et al. (2021), Lin & Zhao (2014)) and D. Liu et al. (2023)) who reviewed diagnosis techniques for varying speeds specifically, and (Kan et al. (2015)) who reviewed prognostics techniques for non-stationary and non-linear rotating systems. Besides that, reviews on Transfer Learning (TL), such as (C. Li et al. (2020)), often present TL as a mitigation to the challenges of varying working conditions, but no review encompassing all the research effort on the topic of fault diagnosis of rotating machines operating under varying working conditions was found by the authors.

In this context, the present study addresses the following research questions:

Q1: How did fault diagnosis of machines operating under varying working conditions evolve in terms of publications and sources in the past 20 years?

Q2: What are the challenges specific to the fault diagnosis of machines operating under varying working conditions?

Q3: What are the steps needed to perform fault diagnosis of machines operating under varying working conditions?

Our contribution aims to provide researchers and practitioners with a comprehensive understanding of the literature related to the fault diagnosis of rotating machines operating under varying working conditions while giving a technical description of the methods commonly utilized.

The rest of this paper is organized as follows, Section 2 presents the methodology used to conduct the review. In Section 3 the results of the bibliometric review are presented, followed by a technical review of the techniques proposed for the fault diagnosis of rotating machines operating under VWC.

2. METHODOLOGY

In this section we will present the methodology utilized for conducting the systematic review, based on the guidelines of the PRISMA method (Liberati et al. (2009)). This includes two main steps: data collection, and method for data analyses.

2.1. Data collection

Web of Science (WoS) was used to construct the initial publication corpus. Although other data sources such as Scopus or Google Scholar were considered, Web of Science is widely regarded as a reference (Moral-Muñoz et al. (2020)) and was deemed sufficient for our analysis. WoS was queried using the following keywords: ”fault diagnosis” AND ”vibration” AND ((”time-varying” OR ”varying” OR ”different” OR ”non-stationary”) AND (”speed*” OR ”working condition*” OR ”load*” OR ”operational condition*”)). The keyword ”rotating machines” was not included as many papers do not explicitly mention it but rather mention specific components such as the rolling element bearing. The screening process of the initial corpus of papers is illustrated in Figure 1.

Criterion	Example values
Type of VWC	Speed, Load, Environmental
Asset type	Rolling element bearing, Gearbox, Rotor...
Feature extraction type	Time-frequency analysis, Order tracking
Feature extraction details	Short-term Fourier Transform, Computed order tracking
Classification / Decision	Neural Network, Support Vector Machine
Speed information	Yes, No
Dataset used	CWRU, PRONOSTIA...

Table 1. Criteria used for analysis.

2.2. Analytic method

Each of the items in the corpus was examined and hand-labeled using an empirically-designed set of 8 criteria of interest given in Table 1. Even though author-defined or journal-defined keywords could have been used to accomplish the same result, hand-tagging drastically reduces the risk of false positives and mislabeling, it also serves as a common ground for analysis. On top of that, some of the terms regularly used in the literature can be ambiguous if not given a proper context.

Additionally, VOSviewer and CiteSpace were used to conduct an automated discovery of the keywords, citation, authors and journals networks.

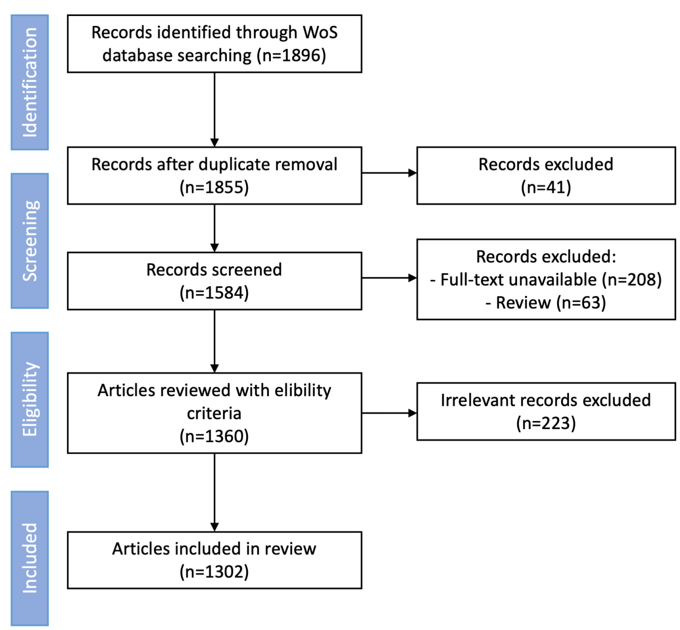

Figure 1. Methodology for the selection of the articles to be included in the review.

3. BIBLIOMETRIC ANALYSIS

3.1. Papers

The fault diagnosis of rotating machines operating under varying working conditions literature has received a lot of interest in the past few years (Figure 2). Indeed, the majority of all publications included in this study were published in the past 5 years.

Figure 2 illustrates the growing interest in data-driven methods, where in the recent years more than half of all collected papers proposed a data-driven fault diagnosis scheme.

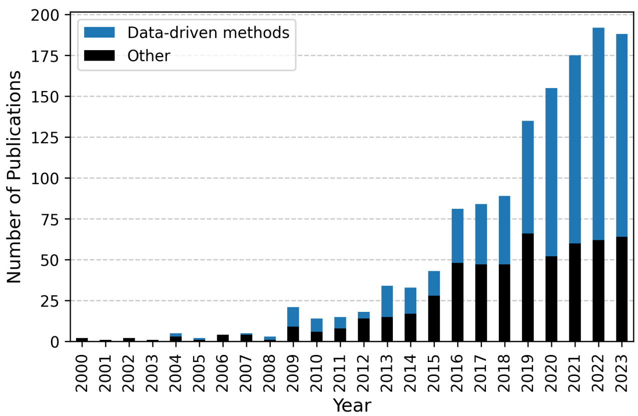

Figure 2. Number of publications per year since 2000.

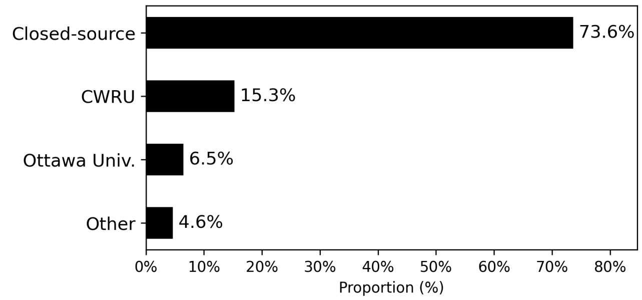

Figure 3. Distribution of the most commonly used datasets for the fault diagnosis of rotating machines operating under variable working conditions.

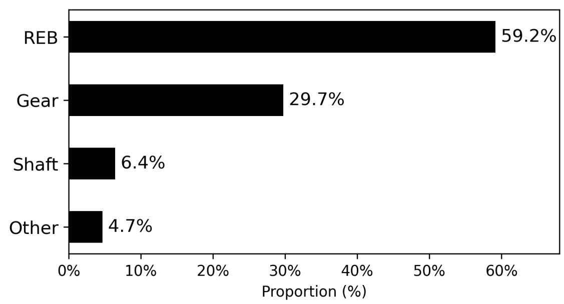

Figure 4. Distribution of the most commonly studied mechanical components in the literature.

3.2. Datasets

With the rise of data-driven methods, it is essential to take interest in the datasets most often used in the literature. It is especially important since the lack of large-scale databases of vibration data is often recognized as a major pitfall of the current fault diagnosis research (Sun et al. (2023)). The open datasets most often encountered in the literature are summarized in Table 2.

Based on this table, the small number of available datasets must be noted in light of the vast variety of mechanical systems found in industrial environments. Moreover, one can see that the representation of truly variable and dynamically changing working conditions is largely lacking. This might explain why, when examining the distribution of datasets used in fault diagnosis literature (focused on variable working conditions), most experimental setups employed to validate the methods are ad-hoc closed-source datasets, as shown in Figure 3. This significantly hinders the proper evaluation and comparison of data-driven methods, and limits the assessment of the generalization capabilities and the applicability of the proposed methods to real industrial applications.

3.3. Mechanical components under study

Rotating machines can experience a multitude of mechanical faults, depending on their structure and function. In the literature, we find several key mechanical components often studied, as they were found to be the most common cause of machine breakdown in the field. The distribution of said components is given in Figure 4.

Evidently, there is a large interest in the study of Rolling Element Bearings (REBs), this finding is consistent with the industrial setting as REB faults are often cited as the most common mechanical failure among rotating machines (G. Singh & Ahmed Saleh Al Kazzaz (2003)).

3.4. Keywords

An automated keywords discovery has been conducted with VosViewer and is illustrated by Figure 5. These keywords offer an initial understanding of the underlying topics and challenges related to the intelligent fault diagnosis of rotating machines operating under VWC.

Dataset	Test component	Accelerometers and sampling frequency	Faults	Working conditions
Case Western Reserve University (CWRU (2021))	Bearing	1 per bearing Sampled at 12kHz and 48 kHz	Artificial inner and outer raceways	Multiple static loads
Paderborn University (Lessmeier et al. (2016))	Bearing	1 per bearing Sampled at 64 kHz	Artificial and accelerated lifetime test inner and outer raceways	Multiple static speed and load
Center for Intelligent Maintenance Systems (Qiu et al. (2006))	Bearing	2 per bearing Sampled at 20 kHz	Run-to-failure inner, outer raceways and rolling element	Fixed
Southeast University (Shao et al. (2019))	Gearbox	1 on the motor 3 per gearbox Sampled at 50 kHz	Artificial chipped or missing tooth, root and surface fault	Multiple static speed and load
Ottawa University (H. Huang et al. (2018))	Bearing	1 per bearing Sampled at 200 kHz	Artificial inner and outer raceways	Dynamic variations in speed
Ottawa University (Sehri & Dumond (2024))	Bearing	1 per component Sampled at 42 kHz	Artificial inner and outer raceways, unbalance, misalignment, bowed and broken rotor	Dynamic variations in speed
Society for Machinery Failure Prevention Technology (MFPT (2013))	Bearing	1 per bearing Sampled at 97.656 kHz and 48.828 kHz	Artificial inner and outer raceways	Multiple static loads Fixed speed
Xi'an Jiaotong University (B. Wang et al. (2020))	Bearing	2 per bearing Sampled at 25.6 kHz	Run-to-failure outer, inner raceways, rolling element, cage	Multiple static speed and load
Pronostia (Nectoux et al. (2012))	Bearing	2 per bearing Sampled at 25.6 kHz	Unknown run-to-failure faults	Fixed
PHM data challenge (2009)	Gearbox	2 at each end of the gearbox Sampled at 66.6 kHz	Artificial missing, chipped tooth	Multiple static speed and load

Table 2. Datasets regularly used for the evaluation of fault diagnosis of rotating machines methods.

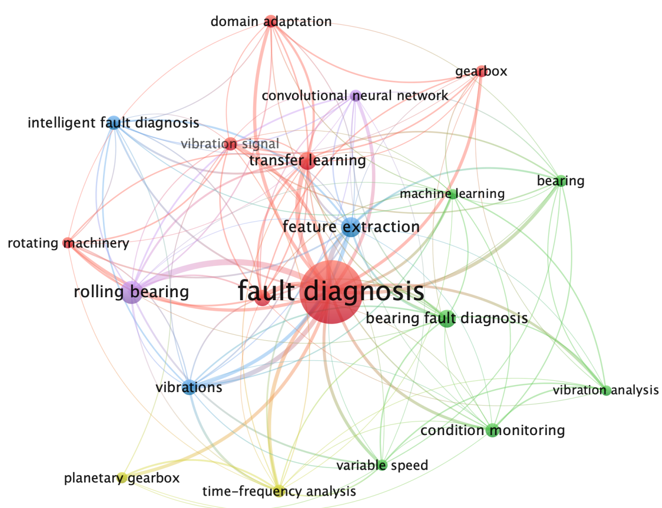

Figure 5. Automated keyword discovery generated using VosViewer.

Indeed, common keywords related to the broader fault diagnosis literature can be found, such as “feature extraction” or “machine learning”. However, the presence of keywords such as “time-frequency analysis” or ”transfer learning” hint to methods specific to the VWC case.

This network allows for the identification of central themes, such as ”fault diagnosis” and its strong connections to ”feature extraction” and ”machine learning.” Prominent objects of study like ”rolling bearing” and ”gearbox” are also evident. Crucially, keywords such as ”variable speed,” ”time-frequency analysis,” ”transfer learning,” and ”domain adaptation” highlight the specific challenges and specialized methodologies pertinent to diagnosing faults under varying working conditions (VWC). Examining these relationships provides an initial understanding of the main topics, common components studied, and key trends in addressing VWC.

4. PROBLEM STATEMENT

The goal of vibration-based fault diagnosis of rotating machines is typically to identify vibratory signatures that are symptomatic of a mechanical fault and infer a diagnosis. To do so, a multitude of signal processing and data-driven techniques have been proposed over the years. However, constant working conditions are often assumed, which is far from guaranteed in real industrial applications. Indeed, mechanical systems often operate under varying working conditions, depending on their task and environment. Most often, the variations in working conditions manifest themselves as varying speed, varying load changes in the environment of the machine. In the following, the effects induced by each of these variations will be discussed.

Speed variations are the most commonly addressed type of working condition in the literature, given their prevalence in industrial settings. While many condition monitoring systems are designed to collect acceleration signals at constant speeds, this is not always feasible in practice. A notable example is a wind turbine, which experiences natural variations in speed due to changing wind conditions.

The typical fault frequencies found in rotating machinery are closely associated with the rotational frequency of the shaft. As such, when the shaft speed varies over time, the fault frequencies inevitably exhibit similar variations. This dynamic change in fault frequencies significantly complicates the task of identifying defective components. Consequently, this complexity renders a vast array of signal processing techniques, which are typically effective in constant-speed environments, inadequate and ineffective for addressing scenarios where the shaft speed is not constant.

Changes in the load managed by machinery can also significantly influence vibration characteristics. Different loads modify the mechanical stresses and strains on machine components, thus altering the vibration signals. Traditional vibration monitoring assumes that shifts in vibration signals stem from mechanical defects, so a fluctuating load can lead to erroneous diagnoses. For instance, dynamic loading in gearboxes has a strong influence on mesh stiffness effects, which significantly alters the waveform of the resulting vibration signals.

Finally, environmental noise is a very common challenge in vibration-based fault diagnosis, as it hides the signal of interest and prevents early detection of mechanical failures. A common assumption of most denoising techniques is that the noise is normally distributed. However, environmental or process-related noise having impulsive characteristics can be encountered, notably in mining processes such as crushing or milling. Many fault detection techniques rely on finding an informative frequency band which contains weak impulsive characteristics, often symptomatic of a fault. The presence of impulsive noise can mislead the frequency band identification process, thereby missing the fault.

From this, we can identify two main challenges induced by VWC, which are stated in the following.

4.1. Challenge 1: effects of VWC on the vibration signals

From what precedes, it can be concluded that vibration signals originating from machines operating under VWC are non-stationary. Extracting meaningful health information from such signals is a challenging task which necessitates ad hoc signal processing tools (Abboud et al. (2016)).

4.2. Challenge 2: effects of VWC on data distributions

As stated previously, intelligent ML-based diagnosis methods have received great attention recently as they achieve state-of-the-art performance. One key assumption of most ML algorithms is that training and testing data are sampled from the same underlying distribution. The intrinsic uncertainty of varying working conditions challenges this assumption, as it is often difficult to guarantee that the whole operating range of the machine has been well captured in the training data, especially as fault data are very difficult to obtain. Consequently, out-of-distribution (OOD) testing samples can appear, severely hindering the diagnosis capabilities of the ML systems, especially with Deep Learning (DL) models which could classify OOD samples into a class with high confidence. The OOD problem is well known and receives significant attention in theoretical ML research (J. Ren et al. (2019)). In the field of intelligent fault diagnosis, it has been recognized as a major challenge of the current ML techniques (Y. Lei et al. (2020)), with Transfer Learning regularly invoked as its mitigation (C. Li et al. (2020)).

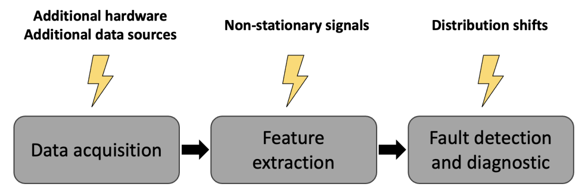

Figure 6. The diagnosis process and the challenges of VWC.

In the following Section, we will detail the commonly used fault diagnosis process and review the techniques proposed to alleviate the challenges described above.

5. DIAGNOSIS PROCESS UNDER VWC

The diagnosis process is traditionally comprised of 3 phases. The first one being data collection, during which the surveillance signals are collected. We will restrict here our analysis to vibration signals but other signals such as current, acoustic emission or temperature are often used as well. The second phase, feature extraction, aims to extract relevant machine health information from the acquired signals, typically using signal processing and statistical tools. The third and final step is health state recognition, where the extracted features are fed into a statistical classification model in order to infer the surveyed machine health states by detecting and characterizing eventual mechanical faults. The overall process and its associated challenges are illustrated in Figure 6.

In this section we will detail how the challenges of varying working conditions have been addressed in each of these phases.

5.1. Data acquisition

Vibration signals are often collected using piezoelectric accelerometers placed as close as possible to the component we wish to monitor. An optimal accelerometer placement is illustrated in Figure 7, although it must be noted that in real industrial applications such placement is often impossible as components are hidden by the housing and we must resort to sub-optimal placement. Some mechanical faults, such as the ones occurring in rolling element bearings, manifest themselves very high in the spectrum. Consequently, accelerometers with a high sampling rate must be preferred.

Beyond single-point accelerometers, alternative measurement schemes such as sensor arrays or multi-modal sensing (e.g., combining vibration with acoustic or thermal data) can provide richer diagnostic information, particularly for complex or high-dimensional structures. Such multi-channel data may then necessitate advanced signal processing techniques, includ-

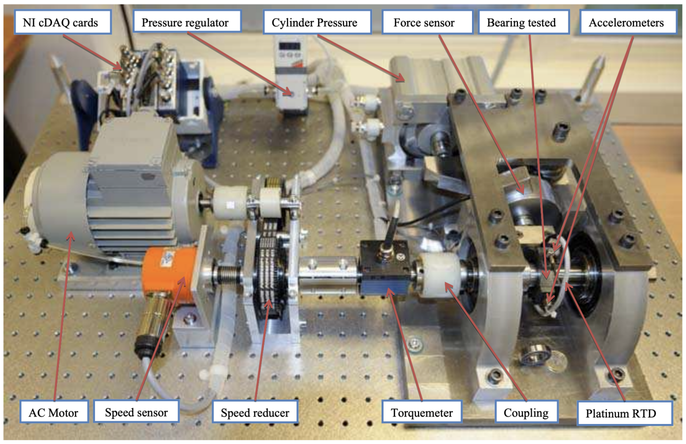

Figure 7. Experimental setup used for the PRONOSTIA dataset (Nectoux et al. (2012)).

ing operational modal analysis (OMA) adapted for varying conditions to effectively extract relevant fault signatures.

Additional hardware can help alleviate the effects of VWC. Tachometers, for instance, can be useful to circumvent the challenges induced by varying speeds. Process data can also be used to distinguish between working conditions. For instance, in (Ruiz-Cárcel et al. (2016)), process data were used to distinguish between the operating states of a motor-compressor, including the temperature, the inlet tank pressure or the air flow among others. A similar approach was used in (Pawlik et al. (2025)) where a tachometer signal, a current signal and the temperature were used alongside the vibration signal to distinguish between working conditions. However, it must be noted that additional hardware might negate one of the strengths of vibration-based fault diagnosis which is its cost effectiveness, only requiring very inexpensive and easy-to-install accelerometers.

Given that acquiring vibration data from rotating machines in real industrial application is a very challenging task, especially fault examples, most publications use publicly available datasets summarized in Table 2 or custom experimental setups. As stated previously, the prevalence of the use of custom laboratory experimental setups is clear. This is partly due to the fact that most publicly available datasets do not usually portray variable working conditions.

Despite the availability of public datasets, it's important to note that vibration data available in real industrial settings often differ significantly from idealized datasets, where all fault modes in all working conditions are equally represented. Considering realistic data availability scenarios is crucial for developing techniques that are truly applicable in the field.

5.2. Feature extraction

Extracting meaningful health information from vibration signals of machines operating under VWC is a difficult task which often requires the use of dedicated signal processing methods. Indeed, many of the effects of VWC manifest themselves as amplitude modulation and frequency modulation, which can easily be mistaken for a fault.

In this section, we will review the most commonly used techniques to address this problem and give some application examples. A summary of the effects of VWC and is given in Table 3. The methods proposed to alleviate the effects of varying speed are presented first, since they are by far the most often considered in the literature.

5.2.1. Variable speed case

Variations in rotating speed cause frequency modulation (FM) effects and amplitude modulation (AM) effects in the resulting signals. Specific signal processing tools that can help attenuate these effects are reviewed in this section.

5.2.1.1 Removing FM effects

Under speed variations, the periodicity of most vibratory events of interest are no longer constant in time. However, they are still linked to the main shaft rotation, thus constant in the angular domain. As such, analyzing the signal in the angular domain can help overcome the challenges of varying speed.

Using the Order Tracking (OT) method, the vibration can be transformed from the time domain to the angular domain to produce an order (multiple of the rotating frequency) spectrum.

Early implementations of OT used analog instrumentation with variable sampling rate depending on the rotation speed of the main shaft, but required costly and complex equipment which hindered the viability of the solution. Computed Order Tracking (COT) proposes to acquire the signals at constant time increments and then resample it based on a tachometer signal. Being fully digital, COT was proven to be much more usable in real industrial applications. In practice, angular resampling allows the use of traditional cyclostationary analysis tools, as vibrations signal under limited speed variations are angle-cyclostationary. A typical example of COT use can be found in (Randall & Antoni (2011)) where the COT method is employed to remove the effects of small speed fluctuations and enhance a rolling element bearing signal, enabling the use of envelope analysis.

An example of the use of COT is given in Figure 8, where a vibration signal of a machine under run-up is presented. The OT operation allows to identify distinct peaks in the squared

VWC Type	Key Impact/Challenge on Diagnosis
Varying Speed	Signal non-stationarity (FM/AM effects), shifting fault frequencies, smeared spectra, making standard frequency analysis difficult.
Varying Load	Amplitude modulations, altered mechanical stresses/strains, load-induced vibration changes can be mistaken for faults.
Environmental Noise (Impulsive/ Non-Gaussian)	Obscured fault signatures, impulsive noise characteristics can mimic fault signatures, misleading fault indicators (e.g., kurtosis).
General Data Distribution Shifts (due to any VWC)	Degradation of diagnostic models trained under different conditions, violation of the Independent and Identically Distributed (i.i.d.) assumption, emergence of Out-of-Distribution (OOD) samples.

Table 3. Overview of VWC: Types and Key Challenges.

envelope spectrum which are indicative of a rolling element fault, while the squared envelope spectrum of the time-domain signal is smeared and doesn't allow the identification of a fault.

The COT technique is very useful to allow the utilization of classical diagnosis tools in the context of varying rotating speed, however some limitations must be acknowledged. For instance, the ease of acquisition of vibration signals compared with other types of surveillance signals makes it a prime option for scalable fault diagnosis technology. But COT's need for additional hardware able to accurately measure the rotation speed then negates one of the main advantages of vibration-based fault diagnosis. Consequently, significant interest has been directed towards order tracking solutions with no tachometer requirement.

The main challenge of Tacho-less Order Tracking (TOT) is then to estimate the Instantaneous Angular Speed (IAS) directly from the acceleration signal, circumventing the need for a dedicated instrument. Two main ways of doing so can be found in the literature.

The first way of extracting the IAS from the vibration signal is based on time-frequency analysis by tracking harmonics in a time frequency representation (TFR). A typical early example of this can be found in (Kwok & Jones (2000)), where an adaptive STFT was used to produce a TFR, and a multistate hidden Markov model (HMM)-based post-estimation enabled the tracking of the instantaneous frequency. Other techniques adopt more advanced TFA methods, such as in (M. Zhao, Lin, Wang, et al. (2013)), where the Chirplet Transform was used to estimate the instantaneous frequency and a Vold-Kalman Filter extracted the IAS. In (H. Huang et al. (2018)), a multiple curve extraction scheme is proposed using the STFT and achieved good performance on the fault diagnosis of bearings operating under unknown rotational speed but noted that a more advanced TFA technique could improve their results. Such advanced techniques can be found in (P.-P. Yuan et al. (2025)), where a spline-kernelled chirplet transform and multi synchrosqueezing technique was used to produce a TFR with a very good time-frequency resolution. Other techniques propose to track multiple harmonics instead of a single one in order to make use of all vibratory components susceptible of being present in the signal, such as the ones emitted by shafts or gears. A fairly recent example of this approach is the multi-order probabilistic approach (Leclère et al. (2016)). This approach extracts the IAS by considering the TFR as a probability density function map of the fundamental rotation frequency.

The second way of extracting the IAS is based on the instantaneous phase demodulation of harmonics. An early example can be found in (Bonnardot et al. (2005)), where a harmonic of the gear meshing frequency was used to obtain the IAS in the case of limited speed fluctuations. A more recent method which uses a multi-order approach to instantaneous phase demodulation can be found in (Peeters et al. (2022)).

A comprehensive review of TOT can be found in (S. Lu et al. (2019)), and a performance comparison of different approaches can be found in (Peeters et al. (2019)). The ability of TOT to circumvent the need for an additional speed signal is its greatest strength, however inferring the rotating speed of the machine directly from the vibration signal is difficult to achieve robustly. Moreover, a significant challenge lies in assessing the accuracy of these estimations in real applications where the true speed is unknown. This challenge was addressed in (D. Peng et al. (2023)) where through the use of several indicators, such as the sparsity of the order spectrum, the quality of the candidate IAS were assessed, effectively improving the IAS selection.

In data-driven fault diagnosis, OT has been used as a preprocessing technique in data-driven methods in order to mitigate the effects of speed variations. For instance in (Z. Lei et al. (2023)), COT was used as prior knowledge for few-shot fault diagnosis of rolling element bearings operating under variable rotating speeds. Similar approaches can be found in (D. Liu et al. (2021)), (Kim et al. (2024)) or (Gu et al. (2020)).

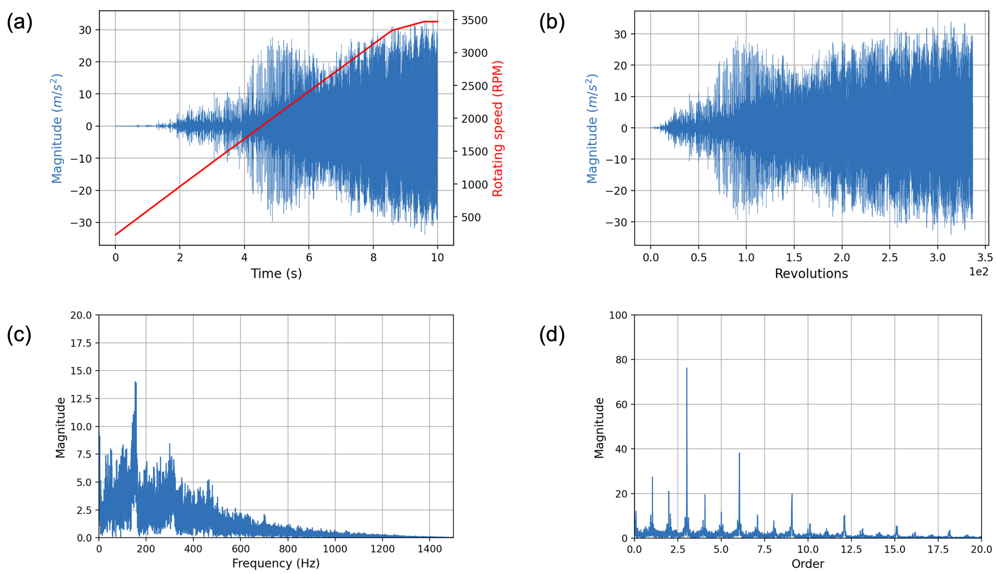

Figure 8. Use of OT to diagnose a rolling element bearing fault under varying rotating speed. (a) Time-domain signal (b) Angular resampled signal (c) Squared envelope spectrum of the time-domain signal (d) Squared envelope spectrum of the angular resampled signal.

5.2.1.2 Removing AM effects

Apart from FM, speed variations also induce AM effects, which are less studied but present significant challenges. AM can indeed result from both speed variations and faults. Therefore, removing AM effects risks eliminating fault-related symptoms, while leaving them unchecked can lead to mistaking speed-related AM effects for a fault.

Two main ways of removing AM effects can be found in the literature. The first approach proposes to estimate the envelope of the signal to estimate the speed-related AM effects, and use it to normalize the signal. This approach was used in (Urbanek et al. (2017)). In a similar fashion, in (Schmidt & Heyns (2020)), the square root of the moving median of the squared envelope was computed to normalize the AM signal. However, these envelope-based methods can remove fault-related contributions as they are contained in the envelope, which constitutes a significant shortcoming.

The other type of approach uses the assumption that the AM effects are proportional to the square of the rotating speed, and uses the speed signal to normalize the signal. An example of this approach can be found in (D. Wei et al. (2019)).

Normalizing vibration signals in data-driven fault diagnosis can help improve the performance of models across varying speed conditions. In (D. Wei et al. (2019)), the speed AM normalization was used before training a Convolutional Neural Network to diagnose rotor cracks. In (Rao et al. (2024)), a piecewise power fitting method was used to estimate and normalize the AM effects before using the normalized data to train an Autoencoder to detect rolling element bearing faults.

5.2.1.3 Time-frequency analysis

From what precedes, one obvious challenge when performing fault diagnosis of rotating machines under speed variations is to analyze the time-varying frequency content of the vibration signal and extract its local properties in the presence of strong noise.

Time-frequency analysis (TFA) aims to answer this need by building a time-frequency representation (TFR), able to represent the evolution of a signal's frequency content with respect to time.

A key property of TFA is given by Heisenberg's uncertainty principle : for a continuous time signal $x(t)$ in $L^2(\mathbb{R})$, Heisenberg's uncertainty principle, also referred to as Gabor's limit, states that $x(t)$ joint time and frequency resolution cannot be arbitrarily precise at any given point. As such, tradeoffs must be made in order to obtain a satisfying TFR within the limitation of the uncertainty principle.

In this context, we will discuss the 3 main techniques for TFA commonly used in the literature, that is linear TFA, quadratic TFA and mode decomposition.

OT type	Component	References
COT	Gearbox	K. Feng et al. (2017) H. Li et al. (2009) A. Singh & Parey (2019) A. Singh & Parey (2017) J. Yang et al. (2019) M. Zhao, Jia, et al. (2018) Y. Li, Ding, et al. (2018)
	Bearing	Barbini et al. (2018) Y. Yang et al. (2013) Tang et al. (2020) Ming et al. (2016) Y. Li, Wei, et al. (2018) Bouhalais et al. (2018) X.-h. He et al. (2016) Y. Guo et al. (2012) Y. Wang et al. (2017) Mishra et al. (2016) Z. Liu et al. (2021)
TOT	Gearbox	J. Wang et al. (2018) Bonnardot et al. (2005) Yi et al. (2020) Z. Feng, Qin, & Liang (2016) Z. Feng, Chen, & Liang (2016) X. Jiang & Li (2016)
	Bearing	Khan & Kim (2016) Siegel et al. (2012) J. Wang et al. (2019) J. Wang et al. (2016) Y. Wang et al. (2019) Gu et al. (2020) B. Chen et al. (2018) T. Wang et al. (2014) Y. Li et al. (2023) X. Wang et al. (2020) Niu et al. (2019) L. Wang et al. (2019) M. Zhao, Lin, Xu, & Lei (2013) S. Guo et al. (2020) Kumar et al. (2021)

Table 4. Examples of OT use in the literature.

5.2.1.3.1. Linear TFA

Linear TFA produces a TFR by correlating the signal with one or more basis waveforms localized in time and frequency.

The most obvious basis decomposition technique for TFA, a direct extension of the Fourier transform to the time-frequency domain is the Short-Time Fourier Transform (STFT) or Windowed Fourier Transform, given by Eq. 1, which computes the inner product of the signal $x(t)$ with time and frequency sinusoidal functions localized by a window function $w(t)$:

$$STFT(\tau, f) = \int_{-\infty}^{\infty} s(t) w(t-\tau) e^{-i2\pi f t} dt \tag{1}$$

The common use of the STFT can be explained by its ease of implementation and low computational cost. However its fixed window size imposes a large time-frequency resolution trade-off. This tradeoff would be acceptable if the components of interest in the vibration signals had the same time-frequency resolution, however it is not often the case. An example of the use of the STFT is given in Figure 9, where the TFR of a vibration signal collected during a machine run-up is presented.

The Wavelet Transform (WT), given by Eq. 2 in its continuous version, is another linear TFA technique which uses wavelets as its elementary function. A wavelet is a zero-mean finite-energy oscillation, dilated and translated (b and a coefficients) in order to obtain a multi-resolution TFR of the input signal.

$$CWT(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} s(t) \psi^* \left(\frac{t-b}{a} \right) dt \tag{2}$$

Choosing the mother wavelet $\psi^*(\cdot)$ is often difficult as a wide variety of mother wavelets have been proposed over the years each having a specific set of features. However the multi-resolution capabilities of the WT alleviate the limitations of the STFT as shown in Figure 9, making the WT a useful tool to analyze non-stationary vibration signals. The WT has been further improved by the Wavelet Packet Transform (WPT), which offers better high frequency resolution, and the Second Generation Wavelet Transform (SGWT) which uses a lifting scheme instead of the WT scaling. A detailed review of their application for rotating machines fault diagnosis is given in (Yan et al. (2014)).

There are several examples of the WT used to diagnose fault on rotating machines running under VWC. For instance, in (Meltzer & Dien (2004)), the authors used the wavelet amplitude in polar coordinates to diagnose faults in gearboxes operating under varying speed. The authors in (Al-Badour et al. (2011)) used the WPT to detect rubbing faults on a rotor under start-up and coast-down. The WT is often used as a denoising tool. For instance, in (Mishra et al. (2016)), the DWT was used to enhance the fault signature in rolling element bearings operating under time-varying speed and load.

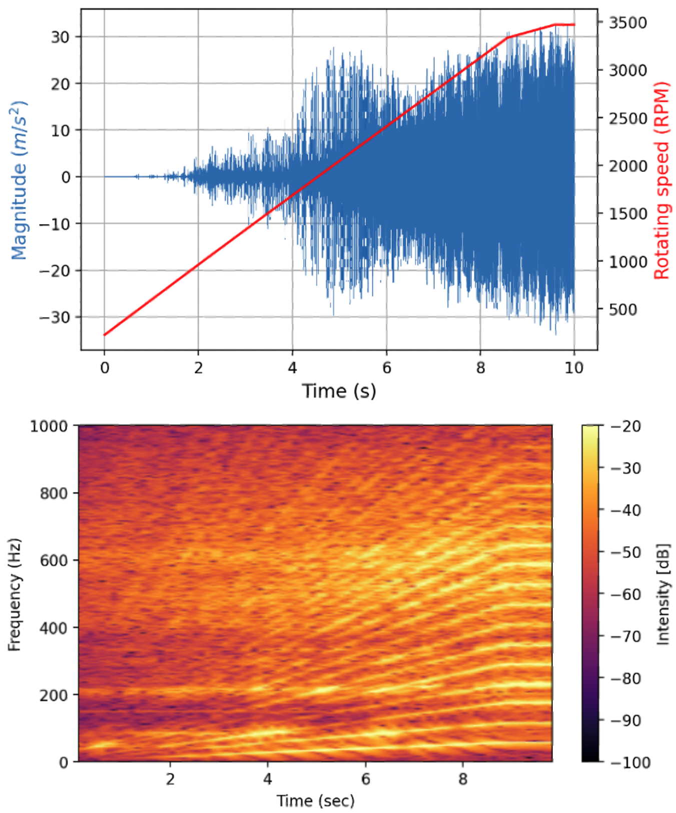

Figure 9. **Top**: Time-domain signal of a rotating machine during run-up. **Bottom**: Corresponding spectrogram.

5.2.1.3.2. Atomic decomposition and sparse representation

Given the very heterogeneous nature of the frequency content of vibration signals of rotating machines, a single basis function might not be able to accurately describe all frequency components embedded in the signal. Atomic decomposition aims to alleviate this limitation by sparsely characterizing a signal using a set of multiple basis. It can be considered as an extension of the classical basis expansion techniques discussed previously.

Given a redundant and over-complete waveform dictionary Φ, the vibration signal $x(t)$ can be linearly approximated by a sum of decomposition coefficients α weighting atoms ϕ from the collection $\Gamma \subset \Phi$ (and a residual signal in real-world scenarios).

Atomic decomposition and sparse representation have received a significant amount of interest recently and have been used in several contexts. In (F. Peng et al. (2011)), a multi-scale chirplets dictionary was used to diagnose a cracked tooth in a gearbox operating under time-varying rotational speed. In (Cui et al. (2014)), an impulse dictionary was designed to diagnose faults in rolling element bearings operating under time-varying speed. Authors in (H. Wang et al. (2020)) used the K-SVD algorithm to adaptively learn a fault dictionary in order to diagnose bearing faults. A comprehensive survey can be found in (Z. Feng, Zhou, et al. (2017)).

Linear TFA also sometimes serves as a support for very popular fault diagnosis techniques. For instance, the widely used Spectral Kurtosis (Antoni & Randall (2006)) exploits the STFT to aid the design of an optimal filter for detecting transients. Moreover, linear TFA has been successfully used to analyze vibration signals of machines operating under variable working conditions, however the choice of a basis function inevitably introduces a bias in the resulting TFR.

5.2.1.3.3. Quadratic time-frequency analysis

Quadratic or bilinear TFA doesn't use analyzing functions like linear TFA, but correlates the signal with a time and frequency translation of itself, resulting in the finest time-frequency resolution possible within the uncertainty principle limit as it is not bounded by the time-frequency resolution of any basis function. The basis of most quadratic TFA techniques is the Wigner-Ville Distribution (WVD), given by Eq. 3 where τ is the time lag.

$$WVD(t,f) = \int_{-\infty}^{+\infty} s\left(t+\frac{\tau}{2}\right) s^{*}\left(t-\frac{\tau}{2}\right) e^{-i2\pi f\tau} d\tau \tag{3}$$

The main deficiency of the WVD is the cross-term interference, which is especially problematic for its application to vibration signals that are the result of multiple source components. Several techniques have been proposed to alleviate the cross-term interference problem using a carefully chosen kernel function, such as the Choi-Williams distribution (Choi & Williams (1989)) and more generally the Cohen Class distribution (Cohen (1989)), but they fail to conserve the full time-frequency resolution of the WVD.

Some applications of quadratic TFA can be found as in (Climente-Alarcon et al. (2015)) for instance where the WVD is used to diagnose a broken bar and a short circuit in an induction motor under varying load. In (Guan et al. (2019)), Cohen's class distribution was used with the generalized demodulation to diagnose gear wear in a planetary gearbox operating under time-varying speed and load.

5.2.1.3.4. Adaptive mode decomposition

Adaptive mode decomposition techniques aim to decompose the input signal into a set of natural oscillatory modes imbedded in the signal and called Intrinsic Mode Functions (IMFs).

As such, mode decomposition is fully adaptive and doesn't rely on any basis function.

The Empirical Mode Decomposition (N. E. Huang et al. (1998)) algorithm is the earliest example of a mode decomposition method. It successively extracts the IMFs by using the local extrema of the signal to fit a cubic spline and subtracting it from the signal until a monotonic residual is obtained. The Hilbert transform is then used on each of the IMFs to compute the instantaneous frequency and obtain a TFR. The original EMD has shown promising performances, but the method lacks rigorous mathematical formulation, is sensitive to noise and suffers from the mode mixing problem where, in the presence of closely spaced spectral components or intermittence in the signal, different components can be grouped into a single IMF.

Consequently, many methods have been proposed to iterate on the promises of EMD and alleviate its shortcomings. The Ensemble Empirical Mode Decomposition (EEMD) (Wu & Huang (2009)) and the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) (Torres et al. (2011)) use noise to facilitate the IMF separation, the Local Mean Decomposition (LMD) (Smith (2005)) obtains IMF using data smoothing rather than cubic spline fitting, the Intrinsic Time-scale Decomposition (ITD) (Frei & Osorio (2007)) produces proper rotation component (PRC), the Empirical Wavelet Transform (EWT) fills EMD's need for a rigorous mathematical formulation by adaptively building wavelets, the Variational Mode Decomposition (VMD).(Dragomiretskiy & Zosso (2014)) received a lot of attention recently due to its high noise resistance. The Synchrosqueezing Transform (Daubechies et al. (2009)) is also based on the idea of EMD coupled with wavelet analysis. A detailed review of the mode decomposition methods can be found in (Z. Feng, Zhang, & Zuo (2017)).

Despite the wide use of decomposition methods for fault diagnosis of rotating machines operating under VWC, most of these techniques are ill-suited for this task as they perform poorly if the working conditions experience harsh variability (Z. Feng, Zhang, & Zuo (2017)). On top of that, there's no guarantee that the extracted IMFs contain any relevant diagnosis information, especially if an energy metric is used as an objective function as most mechanical faults have weak signatures. The last issue common to any adaptive method lies in its sensitivity to modifications in the signal which can result in widely different decompositions and is thus very unstable for comparison.

A summary of the aforementioned TFA techniques, along with their strengths, limitations and application examples can be found in Table 5.

5.2.2. Varying load case

In some cases, the loading condition of a machine directly affects its rotating speed, which is the reason both effects are often considered simultaneously. Load variations cause amplitude modulations which also complicate the diagnosis process as they can be mistaken for a fault (Stander et al. (2002)). Despite the fact that very few papers consider the effects of varying load independently compared with the variable speed case, some notable proposals can be noted. Since the main challenge in case of varying load is still the accompanying non-stationarity of the signal, we find the use of TFA to handle these signals. For instance, in (X. Wang et al. (2010)) the authors used the CWT and the Time-synchronous average to attenuate the effects of varying load and compute load-independent health indicators to diagnose fault in a gearbox.

Several normalization methods aiming at removing amplitude modulation effects have been proposed. For instance, in (Schmidt & Heyns (2020)), a method to normalize the amplitude modulation caused by varying working conditions based on the analytic signal is proposed.

5.2.3. Varying environmental noise case

Apart from the variations in speed and load, changes in the background noise characteristics of the acquired vibration signal can also cause significant hurdles. The presence of impulsive noise can be directly linked to the process, as is often the case in the mining industry for instance in milling or crushing operations. Most traditional fault diagnosis techniques assume that impulsive behavior is linked to a fault. For instance, a classical REB fault diagnosis technique consists in identifying the frequency band exhibiting high kurtosis, which is high impulsiveness. Hence, the presence of non-gaussian noise might break this diagnosis scheme (Antoni (2007)).

Several methods have been proposed to eliminate the impulsive noise in the signal. Some examples include the use of different impulsivity indexes such as the Gini index (Miao et al. (2022)). The use of the Infogram (Antoni (2016)) can also be considered to be less sensitive to impulsive noise.

5.2.4. Learning-based feature extraction in VWC

In the previous sections, ad hoc methods to overcome the challenges of specific types of working condition variations were presented. Recently, a lot of interest has been directed towards Deep Learning (DL) methods for their ability to automate the feature extraction step. Deep autoencoders (Z. Yang et al. (2022)), Deep belief networks and Convolutional Neural Networks (Jiao et al. (2020)) are the DL architectures most often used for their ability to extract features from the raw signals directly, but other architectures such as Recurrent Neural Networks (RNN) are also often encountered (Z. An et al. (2020)).

Category	**Method**	**Pros**	**Cons**	**Application examples**
Linear methods	Short-Term Fourier Transform (STFT)	Widely used, Easy to implement, Computationally efficient	Fixed window size, large time-frequency tradeoff	Z. Feng et al. (2019) D. Liu et al. (2018) T. Wang et al. (2014) S. Wei et al. (2021) J. Shi et al. (2019)
	Wavelet Transform (WT)	Multi-resolution analysis, Effective for transient detection	Mother wavelet selection, limited time-frequency resolution	Heidari Bafroui & Ohadi (2014) Mishra et al. (2016) Al-Badour et al. (2011) Gangsar & Tiwari (2018)
	Atomic decomposition	Use of multiple time-frequency atoms	Difficult dictionary design High computational cost	J. Wang et al. (2019) Cui et al. (2014) F. Jiang et al. (2021) G. He et al. (2016) Cui et al. (2016)
Quadratic methods	Wigner-Ville Distribution (WVD)	Highest possible time-frequency resolution	Cross-terms interference	K. Li et al. (2013) Climente-Alarcon et al. (2015) Baydar & Ball (2000)
	Cohen class Distribution	Partly suppresses the cross-terms of the WVD	Decreased time-frequency resolution compared with WVD	Guan et al. (2019)
Adaptive mode decomposition	Empirical Mode Decomposition (EMD)	Adaptive approach	Mode mixing Lack of rigorous theoretical basis	Ziani et al. (2019) Saidi et al. (2014) Sharma & Parey (2017) H. Liu et al. (2016)
	Ensemble Empirical Mode Decomposition (EEMD)	Reduced mode mixing Resistance to noise	Computational complexity Noise level choice	J. Chen et al. (2018) H. Chen et al. (2017) Bouhalais et al. (2018) B. Chen et al. (2018)
	Local Mean Decomposition (LMD)	Better time-frequency resolution than EMD	Computational complexity Mode mixing	Y. Yang et al. (2013) Hou & Lee (2019) W. Liu et al. (2012)
	Intrinsic time-scale decomposition (ITD)	Low computation complexity Guarantee of physically meaningful PRCs	Low time resolution	A. Hu et al. (2017) Yu et al. (2021) X. An et al. (2012)
	Empirical Wavelet Transform (EWT)	Rigorous theoretical basis	Lower performance on highly varying signals	Y. Hu et al. (2018) Pan et al. (2016)
	Variational mode decomposition (VMD)	Rigorous theoretical basis Robust to noise	Lower performance on highly varying signals	Sharma & Parey (2020) Xu et al. (2020) S. Chen et al. (2019) H. Ren et al. (2019) J. Zhang et al. (2020)

Table 5. Summary of the TFA techniques with their strengths and limitations along with some application examples.

Despite the state-of-the-art performance of DL methods, they tend to encounter a decrease in accuracy when confronted with VWC. Consequently, improved architectures of traditional DL methods have been proposed. For instance, a CNN with wide convolution kernels was shown to have better robustness to varying loads in (W. Zhang et al. (2018)). Similarly, in (D. Peng et al. (2020)) a Multibranch and Multiscale CNN was shown to have better resistance to noise and load variations.

Some DL architectures have also been modified to better handle speed variations. For instance, the authors of (Rao et al. (2023)) proposed an autoencoder architecture which includes speed normalization to achieve fault detection in a gearbox. A similar idea has been utilized in (Z. Yuan et al. (2023)), where a speed-adaptive graph convolutional network is proposed for the fault diagnosis of a wheelset-bearing system. In (Xie et al. (2025)), a pyramid attention residual network is proposed to handle the diagnosis of various rotating machines operating under sharp speed variations.

Other approaches still rely on a preprocessing step using classical signal processing tools in order to learn a meaningful feature set. A very common practice is to produce a two dimensional Time-Frequency Representation (TFR) using Time-frequency Analysis (TFA) and feed it into a DL model as a 2D image. For instance, the authors of (L.-H. Wang et al. (2017)) used the STFT to create a spectrogram and feed it into a CNN achieving up to 100% diagnosis accuracy on a motor. In (M. Zhao, Kang, et al. (2018)), Wavelet Packet Transform coefficients were used as input of a Deep Residual Network to diagnose faults in a planetary gearbox.

However, these applications of DL-based feature extraction do not derogate from the overarching critique of DL in fault diagnosis, namely:

- Interpretability: there's no guarantee that the features learned by the DL models carry any physically meaningful information.
- Generalization capabilities: as a consequence of the first item, the overall poor generalization capabilities of traditional shallow learning algorithms are further hindered by the eventual overfitting of DL architectures.
- Need for large amounts of varied quality training data: the success of deep architectures in computer vision and natural language processing is inextricably linked to the availability of large amounts of quality, varied training data. As stated before, quality vibration datasets are scarce.
- Uncertain ground truth: the partitioning in classes of most available datasets can be uncertain, more generally framing the diagnosis task as a one-class classification problem is a simplistic approach considering the complex failure modes often encountered in industrial applications.

5.2.5. Statistical Time Series Models

Beyond direct signal processing, advanced statistical time series models with varying parameters can explicitly capture the non-stationary nature of vibration signals under VWC. Key approaches include Linear Parameter Varying (LPV) models, and Random Coefficient (RC) models, addressing unmeasurable uncertainties.

To address significant uncertainty and time-dependent dynamics, Gaussian Mixture Random Coefficient (GMM-RC) models have been proposed in (Avendaño-Valencia & Fassois (2017)), in the context of Structural Health Monitoring. This framework represents the system's dynamics for each health state using elementary time-dependent parametric models (such as a Linear Parameter-Varying Model (LPV) model). The core idea is that the coefficients of these underlying models are not fixed but are treated as random variables following a multivariate Gaussian Mixture Model (GMM). This GMM structure for the parameters provides considerable flexibility in representing complex parameter variability due to VWC.

In this context, a LPV-AutoRegressive (LPV-AR) model tailored for gear tooth crack detection under random speed variations was proposed in (Y. Chen et al. (2021)). In an LPV-AR model, the autoregressive (AR) coefficients, which describe how the current signal value depends on its past values, are not constant but expressed as functions of time-varying operating conditions. For gearbox diagnosis, the instantaneous rotating speed and the rotating phase of the gear were used as covariates. This allows the model to adapt to changes in vibration characteristics caused by speed fluctuations and overcome their effects.

More recently, a more advanced Sparse LPV-ARMA model was proposed in (Y. Chen et al. (2025)), which built upon (Y. Chen et al. (2021)) to include a moving average component to the model, and a sparsity penalty to avoid overfitting.

These statistical time series models, by allowing parameters to vary with conditions or by probabilistically modeling parameter distributions, offer a powerful way to integrate time-dependencies and uncertainty directly into diagnostic models, enhancing the accuracy and reliability of fault diagnosis under VWC.

5.3. Fault Detection and Diagnosis

Variations in working conditions, depending on their nature, can have a variety of impacts on the vibration signals. Several methods to mitigate said impacts have been presented in the preceding sections, however all effects can often not be completely alleviated.

Most data-driven learning algorithms, whether it be traditional ML or state-of-the-art DL models, rely on a fundamental assumption that the training data is sampled from the same underlying distribution as the test data. If the effects of VWC subsist, this inevitably causes discrepancies between the distributions of the working conditions, breaking this fundamental assumption.

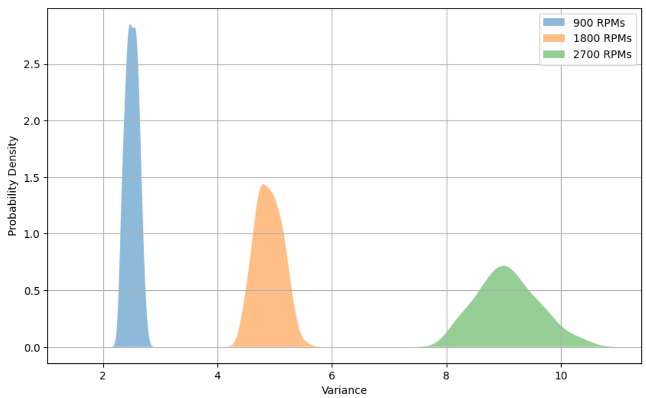

Figure 10. Probability density function of healthy vibration signals sampled at three different rotating speeds.

The distribution discrepancy between working condition is exemplified in Figure 10, where the probability density function of the variance of healthy signals from the University of Ottawa dataset (Sehri & Dumond (2024)) are plotted at three different rotating speeds. The obvious variance differences highlight the distribution shifts caused by varying rotating speed (Qian et al. (2024)).

Consequently, a model trained on a given working condition, say at a given rotating speed, sees its performance significantly degrade when departing from said rotating speed. This problem is known as a distribution shift, and is widely studied across many fields, not limited to the fault diagnosis of rotating machines. Examples of distribution shifts include models in medical imaging failing across hospitals due to variations in equipment, species recognition models underperforming in new wildlife locations due to environmental differences, and molecular property prediction models struggling with new chemical structures they weren't trained on (Koh et al. (2021)).

This problem could be alleviated by using training data representative of all working conditions. However collecting sufficient data is tremendously difficult, especially samples depicting mechanical faults.

In light of this, several approaches to this problem have been proposed based on the data availability scenario considered. We find two main learning paradigms in the literature: Domain Adaptation (DA) and Domain Generalization (DG). The difference between DA and DG is illustrated in Figure 11. In both these approaches, a domain refers to a set of data characterized by a specific working condition. The domain shift is characterized by the difference in conditional and marginal distributions between domains. The goal is then to use the source domain, which is available and fully labeled, to train a model which generalizes well to an unlabeled or scarcely labeled target domain. Both learning paradigms are discussed in the following sections.

5.3.1. Domain Adaptation

In DA, it is assumed that a fully labeled source domain is available, and that the target domain is also available during training, but is unlabeled or scarcely labeled. The learning process is then modified to take into account the target domain, and align the target distribution with the source distribution. We generally find two main ways of achieving this: feature alignment and adversarial training.

Feature alignment methods aim to reduce domain shifts by incorporating a discrepancy measure in the learning objective. Typical discrepancy measure include the Maximum Mean Discrepancy (MMD), the Multiple Kernel Variance MMD (MK-MMD), the Wasserstein distance, and the Deep Correlation Alignment (CORAL). Early examples of this approach can be found in (W. Lu et al. (2017)), where a Deep Autoencoder is trained with a MMD term to align the marginal distributions between domains in order to diagnose gearbox faults at different running speeds. A similar approach in (Wen et al. (2019)) is adopted to diagnose bearing faults across different loads. More recent methods propose to also consider the alignment of the conditional distribution, as only aligning the marginal distributions can be insufficient. Examples of joint distribution adaptation can be found in (Han et al. (2020)) where pseudo-labels were used to align the conditional distributions, or in (Zhong et al. (2024)) where the the MK-MMD is used to align the marginal distributions, and the Wasserstein distance is used to align the conditional distributions for the diagnosis of bearing across loading and rotating speed conditions.

Adversarial methods were first introduced in (Ganin et al. (2016)) with the Domain Adversarial Neural Network (DANN). This adaptation mechanism inspired by Generative Adversarial Networks aims at matching the source and target distributions by encouraging the feature extractor to generate domain-invariant representations. It achieves this by training a domain classifier to distinguish between the source and target domains, while simultaneously training the feature extractor to confuse the domain classifier, leading to aligned feature spaces across domains. A typical example of this approach can be found in (Han et al. (2019)), where adversarial training is used to build a CNN which generalizes well across speed and load conditions. A more recent study (Y. An et al. (2023)) employs adversarial training as part of the Domain Adaptation Network based on Contrastive Learning (DACL) for bearing fault diagnosis under variable working conditions.

Although effective, DA still assumes that a unlabeled target domain is available during training, which can be unrealistic in real-world scenarios. Indeed, the acquisition of fault data, even unlabeled, is very difficult. Consequently, a more

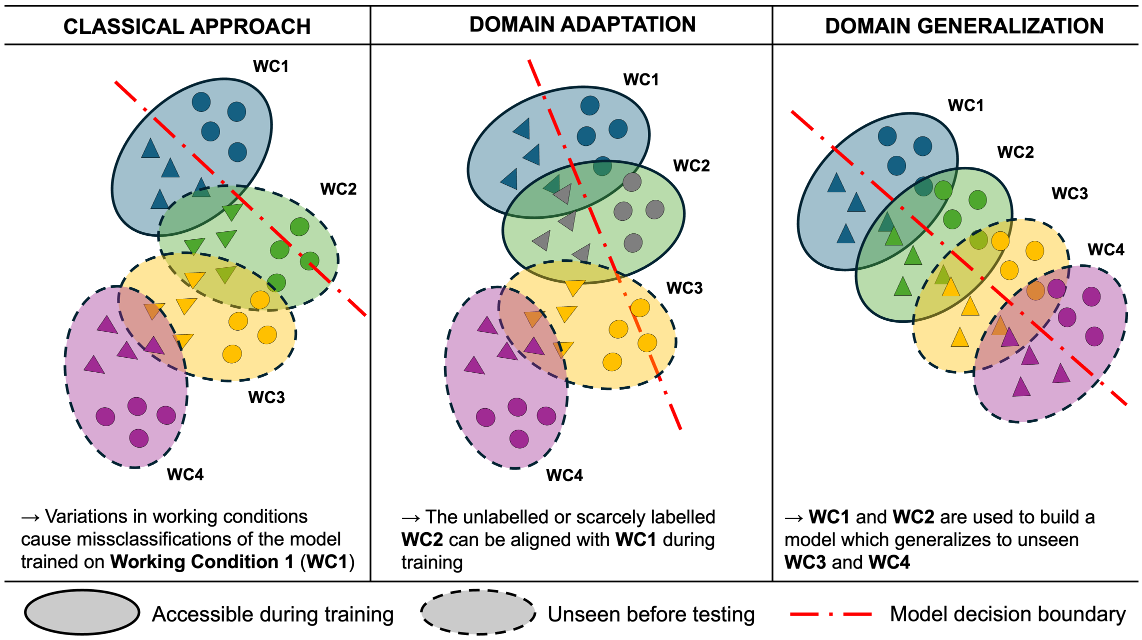

Figure 11. The differences between the classical approach, Domain Adaptation and Domain Generalization.

challenging but realistic scenario consists in considering that the target domain is unseen before testing. This is the Domain Generalization problem statement, it is discussed in the following section.

5.3.2. Domain Generalization

In Domain Generalization, multiple source domains are used to extract domain-invariant knowledge, able to generalize to domains unseen during training. Various ways of addressing DG can be found in the literature.

Some propose to use data augmentation techniques to expand the training data with transformations similar to the ones susceptible of being provoked by varying working conditions. In (X. Li et al. (2020)) for instance, signals from the source domains were augmented via time-stretching, and a significant increase in performance was achieved in diagnosing shaft cracks across different rotating speeds. In (Y. Shi et al. (2023)), an improved version of the popular data augmentation technique Mixup (H. Zhang et al. (2018)) was used to build a model able to generalize across different speed and load conditions. While these methods have been proven to be useful in some situations, their performance greatly depends on the credibility of the augmented samples. However, as mentioned previously, the effects of varying working conditions can be very complex depending on the structure of the machine, and it is then difficult to build realistic augmentations.

Others try to learn domain-invariant representations. Current approaches often rely on adversarial training to mitigate discrepancies between multiple source domains. Typical examples can be found in (L. Chen et al. (2022)) where multiple source domains are used to learn domain-invariant representation through adversarial learning between a feature extractor and a domain classifier, or in approaches like the relationship transfer domain generalization network (RTDGN), which employs an adversarial network with several domain discriminators to enhance domain confusion and reduce distribution discrepancies between source and target domains without requiring target domain samples during training (Qian et al. (2023)).

Other notable examples of DG include (H. Ren et al. (2023)) where a domain-invariant feature fusion networks (DIFFN) is proposed, fusing intra-domain and inter-domain invariant features to improve the model generalization across varying speed, load torque and radial force. In (R. Wang et al. (2023)), a domain generalization network with multiple domain-specific auxiliary classifiers is proposed, which removes domain-specific features through a convolutional autoencoder and aligns feature distributions across source domains to enhance diagnosis generalization to unseen working conditions.

An even more challenging problem than DG considers the case where a single source domain is available during training. Several single-source methods have been proposed, for instance in (C. Zhao & Shen (2023)), an adversarial mutual information guided single domain generalization network (AMINet) is introduced for intelligent fault diagnosis. The AMINet framework generates fake target domains through a domain generation module and uses mutual information minimization to handle significant distribution discrepancies, enhancing generalization to unseen rotating speeds. Other methods include, (Pu et al. (2024)) introduced a single-domain incremental generation network (SDIGN) for machinery fault diagnosis, which incrementally generates augmented domains from a single source domain to simulate various working conditions. The model combines adversarial and contrastive learning strategies to extract domain-invariant features and enhance generalization to unseen target domains. Furthermore, (J. Wang et al. (2024)) proposed the multi-scale style generative and adversarial contrastive networks (MSG-ACN), which employs multi-scale style learning and adversarial contrastive learning to generate diverse samples from a single domain, enhancing the model's ability to generalize across unseen conditions.

Despite the aforementioned proposals, the DG problem in cross-working condition scenarios is still a very difficult problem. A recent benchmark study on domain generalization showed that state-of-the-art methods still struggle to generalize across significant changes in working conditions (C. Zhao et al. (2024)).

5.3.3. Self-Supervised learning

Beyond Domain Adaptation and Generalization, Self-Supervised Learning (SSL) offers a compelling alternative strategy to the challenges of VWC. Self-Supervised Learning (SSL) leverages abundant unlabeled data to learn meaningful representations, reducing reliance on scarce labeled datasets. This typically involves a pre-training stage where a model learns from the data itself followed by fine-tuning on a small labeled dataset for the specific diagnostic task. Notable works in the context of VWC include (L. Yang et al. (2023)), where a signal masking and reconstruction strategy is used. Their self-supervised training enables an autoencoder to learn effective representations from unlabeled data under VWC by understanding signal context to restore masked segments, which then aids fault diagnosis with limited labeled samples. A more recent study (Song et al. (2025)) uses the same masking principle within a teacher-student architecture where reconstruction tasks grow in difficulty.

SSL's main advantage for VWC is its ability to utilize extensive unlabeled data. Pre-training on diverse signals across various working conditions allows the model to learn features inherently robust to these variations.

6. FUTURE RESEARCH PROSPECTS

The domain of vibration-based data-driven fault diagnosis for rotating machinery operating under varying working conditions (VWC) has seen significant advancements. Several critical challenges remain for future investigation to enhance the robustness and practical applicability of diagnostic systems. This section outlines key directions for future research.

- **Development of Comprehensive and Realistic VWC Datasets:** A persistent challenge in the field is the scarcity of large-scale, publicly available, and diverse datasets that represent real-world VWC. Future efforts should prioritize the creation of benchmark labeled datasets. These datasets need to encompass a wider variety of rotating machinery types beyond common examples like bearings and simple gearboxes. They must also include a comprehensive range of fault types, such as incipient and compound faults, to test the sensitivity and specificity of diagnostic methods.
- **Enhancing Generalization and Interpretability of Deep Learning Models:** While Deep Learning (DL) models have shown considerable promise, their generalization capabilities across unseen VWC and their inherent "black-box" nature remain significant concerns. Future research should focus on developing novel DL architectures that are inherently more robust to significant domain shifts induced by VWC. Methods for improving the interpretability and explainability of features learned by DL models in the context of VWC are already a rapidly evolving field of research and are indispensable for real-world adoption of data-driven diagnosis systems.
- **Real-World Validation, Deployment Challenges, and Scalability:** Bridging the gap between laboratory research and real-world industrial applications is a critical step. Future work must emphasize the rigorous validation of proposed methods on data from actual industrial machinery operating under genuine VWC, moving beyond reliance on laboratory test rigs or limited public datasets. This is easier said than done, since industrial environments are notoriously hard to operate in, however this step is critical to build and deploy data-driven diagnosis systems in the future.
- **Beyond diagnosis:** Beyond detecting and diagnosing faults, the ultimate goal in many industrial settings is to predict the Remaining Useful Life (RUL) of components and optimize maintenance decisions. Future work should focus on integrating VWC-robust diagnostic features into prognostic models to improve the accuracy of RUL estimations, especially under variable operating profiles that can significantly impact degradation rates.

7. CONCLUSION

The fault diagnosis of rotating machines operating under varying working conditions (VWC) is a challenging topic. The presence of non-stationary signals and distribution shifts induced by changes in operating speed, load, and environmental noise necessitates the development of robust diagnostic techniques. This paper provided a comprehensive review of various signal processing and data-driven methods that have been developed to address these challenges. Despite recent advancements, especially with the integration of machine learning and deep learning, significant hurdles remain. These include the need for large, representative datasets and improved generalization capabilities of models. Future research should focus on creating more generalized and adaptive methods capable of functioning reliably in real-world industrial environments where working conditions are often unpredictable and constantly changing.

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