Rotating Machinery Fault Diagnosis Under Time-Varying Speeds: A Review

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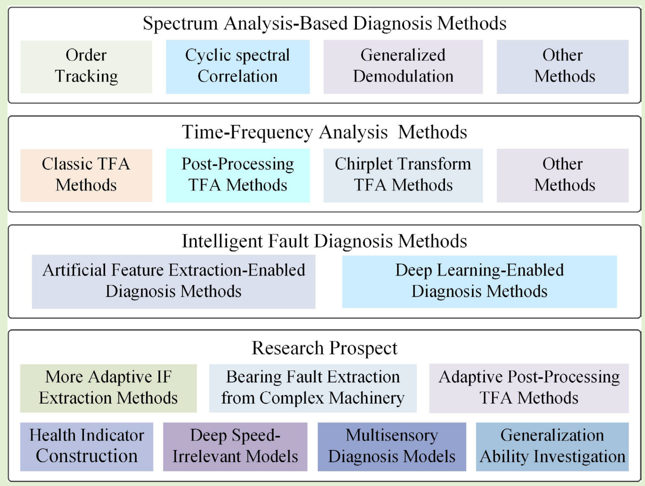
***Abstract*—Rotating machinery often works under time-varying speeds, and nonstationary conditions and harsh environments make its key parts, such as rolling bearings and gears, prone to faults. Therefore, a number of fault diagnosis methods, including nonstationary signal processing methods and data-driven methods, have been developed. This article presents a comprehensive review of the fault diagnosis of rotating machinery under time-varying speeds proposed mainly during the last five years. First, spectrum analysis-based methods, including order tracking, cyclic spectrum correlation, and generalized demodulation, are reviewed. Second, the time–frequency analysis (TFA) methods in machinery fault diagnosis are divided into post-processing methods and chirplet transform-based methods and are reviewed. Then, the artificial feature extraction- and deep learning-enabled intelligent diagnosis methods proposed specifically for time-varying speed conditions are reviewed. Finally, the research prospects are discussed. We not only review the relevant state-of-the-art methods and analyze how they overcome the problems caused by speed fluctuations but also discuss their advantages and disadvantages and the challenges that will be encountered when applying them to industrial applications. This article is expected to provide new graduate students, institutions, and companies with a preliminary understanding of the methods on this topic.**

***Index Terms*—Fault diagnosis, intelligence, order tracking (OT), rotating machinery, time–frequency analysis (TFA), time-varying speed.**



I. Introduction

ROTATING machinery, such as wind turbines, engines, and electric motors, has been widely used in industrial applications. However, due to harsh environments and variable operation conditions, key parts such as rolling bearings and gears are prone to faults [1], [2]. Effective fault diagnosis can reduce unexploited downtime, save maintenance costs, and ensure safe operation [3], [4], [5]. Therefore, fault diagnosis of rotating machinery is vital and has received much attention.

Time-varying speeds are common in various industrial fields, such as wind turbines, mining industry, and petrochemical engineering [6], [7]. According to statistics, about 20%∼25% of the total cost of offshore wind turbines is used for operation and maintenance [8], [9]. However, the rotating speeds of offshore wind turbines fluctuate violently following variations in wind power and directions due to the harsh marine environment, which makes their fault diagnosis very difficult [10], [11]. The time-varying operation mode is also common in the mining industry. For example, the electric shovels, as illustrated in Fig. 1, operate under intermittent mode, and a whole operation cycle includes filling up, moving to the unloading location, unloading, and turning back to the initial location. Although some common machines do not work under variable speeds, the startup and shut-down processes also cause nonstationary signals [12], [13], and these processes contain much running information and some fault symptoms that cannot be revealed under constant speed conditions [12]. Therefore, it is crucial for the fault diagnosis of rotating machinery under time-varying speeds.

To date, fruitful methods have been investigated on the topic of machinery fault diagnosis under variable speeds. These methods can be divided into two categories. The first group focuses on the circumstance where the machine operates under

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(a) (b)

Fig. 1. Examples operated under time-varying speeds. (a) Offshore wind turbines. (b) Mining shovel.

several different speeds, so the signals correspond to variable speeds, but, for a certain operation condition, the speed is constant [14], [15]. Machine learning-based intelligent methods are popular in this circumstance, and they aim at improving the model generalization of speed conditions. The second group focuses on revealing the fault symptoms or realizing the pattern recognition of the machines whose corresponding speeds vary continuously, which conforms to the industrial applications, such as wind turbines and mining equipment mentioned before. In this article, we focus on the second circumstance, and the time-varying speed refers to the speed that changes continuously.

The time-varying speeds bring huge difficulties for machinery fault diagnosis. For a time-domain signal, the intervals of shocks caused by a fault will change if the speed varies, i.e., the periodic pattern of waveform no longer exists, which makes it hard to identify the fault by analyzing the intervals and decreases the recognition accuracy of machine learning methods based on the time-domain signal. In addition, the amplitudes of these fault shocks also change due to the variation in speeds, which also adds difficulty for fault diagnosis. For a frequency spectrum of a signal or a demodulation signal, the fault-related frequency components will be blurred because the fault shocks lose periodicity, the various frequency analysis methods for the fault diagnosis under constant speeds are no longer applicable, and the performance of machine learning methods based on frequency-domain signals also inevitably decreases. Therefore, the fault diagnosis of rotating machinery under time-varying speeds is challenging and is a hot topic.

Converting the time-varying fault-related frequencies into constant frequencies is an effective solution to restoring the effectiveness of spectrum analysis. Order tracking (OT) is a commonly used tool to realize this task and is implemented by resampling the time-domain data with constant angular increments [16]. According to the implementation, OT is divided into hardware OT (HOT, a full hardware technique), computed OT (COT, implemented by an encoder signal), and tacholess OT (TOT, obtained by the instantaneous frequency (IF) detected from the signal itself) [17], [18]. Recently, cyclic spectrum correlation (CSC) theory [19] and generalized demodulation [20] have also been utilized in spectrum analysis. According to those basic approaches, many advanced methods have been further developed to better reveal interest frequency components.

Time–frequency analysis (TFA) is also an effective method for machinery fault diagnosis under time-varying speeds, and it can pinpoint the frequency components of a signal and track their variations. Due to the limited time–frequency resolution of traditional TFA methods, e.g., the short-time Fourier transform (STFT) [21], wavelet transform (WT) [22], and Wigner–Ville distribution (WVD) [23], advanced methods have been developed for fault diagnoses, such as postprocessing methods [24] and chirplet transform (CT)-based methods [25]. These methods have high resolution and have been utilized in fault diagnosis.

In addition to the spectrum analysis- and TFA-based methods, with the rapid development of machine learning methods, intelligent fault diagnosis has attracted much attention [26], [27], [28], [29]. Recently, some advanced methods have been proposed for intelligent fault diagnosis under time-varying speeds. Those methods aim to adopt signal processing methods to remove the effect of speed fluctuations and extract speed-irrelevant features [30] or design deeper models to directly learn the features from raw signals [31]. Therefore, those methods highly decrease the human labor necessary for analyzing nonstationary signals.

Recently, several papers have been published to summarize the research on rotating machinery fault diagnosis, such as the publications on resonance demodulation methods [32], modulation feature extraction methods [33], machine learning in machinery fault diagnosis [26], [34], deep learning in planetary gearbox fault recognition [35], data-driven methods in machinery fault diagnosis [36], transfer learning in machinery fault diagnosis [37], and health indicator construction of rotating machinery [38], [39]. However, these review papers mainly focus on constant speeds. To the best of our knowledge, the review papers on time-varying speed are very limited. In 2014, Lin and Zhao [40] briefly reviewed OT and TFA methods, and in 2019, Lu et al. [17] reviewed TOT methods. Since then, many new methods and meaningful OT and TFA methods have been proposed. With the emerging of deep learning methods, intelligent methods for time-varying speeds have gradually attracted more attention and have achieved great success. In this article, we conduct a systematic and comprehensive review of the state-of-the-art fault diagnosis methods for rotating machinery under time-varying speeds published during the last five years, including spectrum analysis methods, TFA methods, and intelligent fault diagnosis methods. This article aims at helping readers understand the newly published methods, the limitations of some advanced methods in real applications, and the advantages and disadvantages of similar methods. In addition, several research prospects are suggested, potentially providing relevant researchers with valuable insights for their future works.

It should be noted that the relevant papers are retrieved from two databases, i.e., Web of Science and Google Scholar. Most papers have been published in the last five years, and a few classic and representative papers beyond this range are also involved. The search keywords relevant to algorithms such as "OT," "generalized demodulation," "CSC," and "TFA" are combined, respectively, with the diagnosis objects such as "rotating machinery," "bearing," "gearbox," "shaft," and "planetary gear" using the Boolean operator AND. In terms of the intelligent diagnosis methods in Section IV, the keywords such as “intelligent,” “machine learning,” “deep learning,” and “convolutional neural network (CNN)” and the descriptions of operation conditions such as “time-varying,” “variable,” and “nonstationary” are combined with the diagnosis objects mentioned above, respectively. To make the papers more relevant to the topic, and as the papers have more reference values for us, we refined these papers according to the quality of the journals and the relevance of contents. It can be seen that the review is systematic and comprehensive, and we hope that this will provide graduate students, institutions, and companies with a preliminary understanding of rotating machinery fault diagnosis under time-varying speeds.

The rest of this review is organized as follows. In Section II, we focus on spectrum analysis-based diagnosis methods. In Section III, TFA methods are reviewed. In Section IV, intelligent diagnosis methods are reviewed. In Section V, research prospects are provided. The conclusions are provided in Section VI.

II. Spectrum Analysis-Based Diagnosis Methods

Spectrum analysis-based methods mainly focus on the fault diagnosis of rolling bearings, fixed-shaft gearboxes, and planetary gearboxes. The diagnosis results of these methods rely on matching the prominent peaks with the calculated values of fault-related components [41], [42]. For rolling bearings, when the fault is on different parts, e.g., outer race, inner race, and rollers, the values of fault characteristic frequency (FCF) are different, so the fault types can be identified by analyzing the values of FCFs [43]. For fixed-shaft gearboxes, when a fault occurs, the meshing vibration will be modulated via the shaft frequency, so the fault is usually localized by analyzing the sidebands around GMF or its harmonics [44]. For planetary gearboxes, when the fault is on different parts, such as planet gear, ring gear, and sun gear, different amplitude modulation (AM) characteristics will result, so the fault can be identified by the sidebands around GMF or its harmonics [24], and can also be identified by the FCFs via amplitude demodulation [11].

When the rotating speed varies, the intervals of adjacent shocks caused by the fault will change, so the relevant frequencies, such as FCF, sidebands, and GMF, also change following the variation in speed [45]. The traditional spectrum analysis methods are no longer applicable. Therefore, it is necessary to convert the relevant frequencies into constants by nonstationary signal analysis methods, such as resampling and generalized demodulation. After the transformation, the relevant frequency components could be revealed by spectrum analysis methods. Researchers at various universities, such as the University of New South Wales [46], [47], [48], [49], the University of Lyon [50], [51], [52], Beijing Jiaotong University [53], [54], [55], [56], Xi’an Jiaotong University [57], [58], [59], [60], the Beijing University of Technology [45], [61], [62], and the University of Ottawa [63], [64], [65], have contributed a lot to this topic.

A. OT-Based Methods

1) Hardware Order Tracking: HOT is implemented by analog instrumentation, which adjusts the sampling rate proportional to the rotating speed. In this procedure, two pieces of equipment are necessary, i.e., a ratio synthesizer and an antialiasing tracking filter [16], [66]. Because HOT is implemented by hardware circuits, it is time-saving and can be accomplished online, but it also has inherent drawbacks. First, the sampling rate and the cutoff frequency are adjusted dynamically during data collection so that data acquisition is subject to latency and error, especially when the speed fluctuates rapidly [67]. Second, additional hardware components are needed, which increases the complexity and costs.

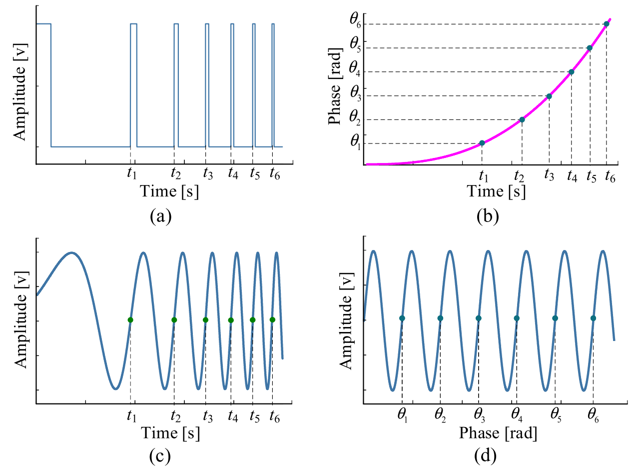

Fig. 2. Illustration of the two COT methods: (a) tachometer pulses, (b) shaft phase, (c) raw signal, and (d) angular-domain signal. (Note that there are two methods to complete COT, i.e., the procedures of the two methods are (a)→(b)→(c)→(d) and (a)→(c)→(d), respectively.)

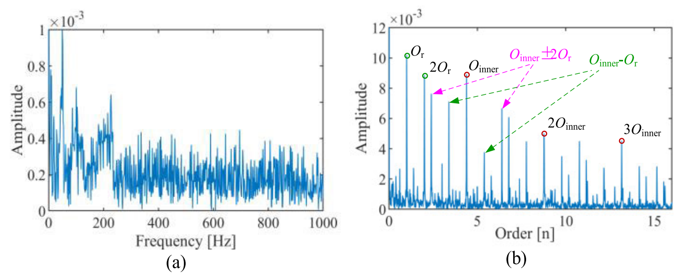

Fig. 3. (a) and (b) Frequency spectrum and the order spectrum of an inner race fault bearing envelope signal.

2) Computed Order Tracking: For COT, the signal and the tachometer pulse are recoded at the same sampling frequency, and then, the vibration signal is resampled at constant angular increments using software [16]. The principle of COT is simple and can be seen in Fig. 2.

One example is conducted to illustrate the effectiveness of COT, as shown in Fig. 3. The vibration signals are collected from the test rig in Fig. 4. Fig. 3(a) shows the envelope spectrum of one inner race fault bearing signal, in which no prominent peaks appear. However, in the order spectrum of the envelope signal, as demonstrated in Fig. 3(b), the modulation rotating frequency (O_r), FCF (O_{inner}), sidebands ($O_{\text{inner}} \pm O_r$), and their corresponding harmonics appear clearly.

To realize compound bearing fault diagnosis, Tang et al. [68] proposed a virtual multichannel signal-based COT method in which the vibration signal was first resampled and then decomposed by variational mode decomposition (VMD) to produce

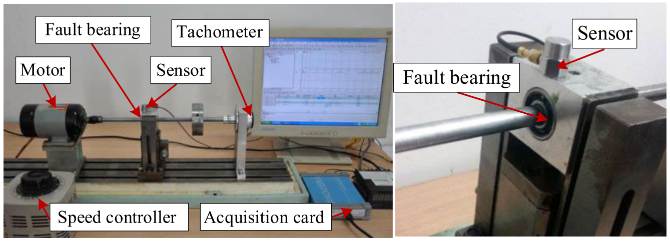

Fig. 4. Rolling bearing fault test rig.

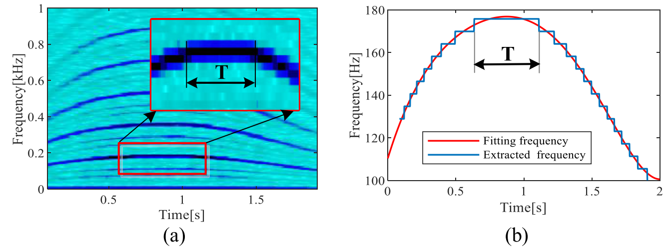

Fig. 5. (a) TFR obtained by STFT and (b) extracted frequency.

virtual multichannel signals. Finally, constrained independent component analysis (ICA) and an fast Fourier transform (FFT) were adopted to generate the order spectra. In addition, Yang et al. [69] utilized COT to obtain the signal in the angular domain and then applied stochastic resonance to enhance the weak bearing vibration. Song et al. [57] used COT to reveal the orders and the resonance frequencies, and then, the Vold–Kalman filter and VMD/variational mode extraction (VME) were adopted to realize the vibration source separation. Wang et al. [70] used COT to obtain the angular bearing signals and then proposed a novel indicator to determine the optimal frequency band. The indicator was constructed by fusing kurtosis, spectral negative entropy, and correlation coefficient via different weights and then combined with a 1/3 binary tree structure to select the frequency band. Zhang et al. [71] proposed an adaptive order-band energy ratio approach for planetary gearbox fault diagnosis, in which the COT was utilized to achieve the order spectrum, and then, the order-band energy ratio was calculated as an indicator. Finally, the obtained indicators were fed into a machine learning classifier to achieve automatic recognition.

Another challenge in COT-based fault diagnosis is to remove the deterministic interference components in weak fault diagnosis. For example, in bearing fault diagnosis, the weak fault vibration is usually overwhelmed by the gear meshing vibration [46], [47], [63]. When the speed is time-varying, the GMF and the sidebands around it cannot be removed, so the common scheme is to separate them in the angular domain. A whole benchmark method was provided in [47] as follows. First, the vibration signal was resampled, and then, time synchronous averaging (TSA) or discrete/random signal separation (DRS) was adopted to remove the deterministic components. Second, minimum entropy deconvolution (MED) was used to improve the impulse of fault shocks, and the bandpass filter was then applied to identify the optimal frequency band. Finally, the angular-domain signal was obtained again through resampling, and then, the order spectrum was calculated to reveal the weak bearing FCF.

Based on the methods summarized above, it can be concluded that COT-based spectrum analysis methods are usually combined with advanced denoising algorithms or signal decomposition methods to realize fault diagnosis. However, it should be noted that the resonance frequency is determined by the whole mechanical system and is independent of the rotating speed [54], but, when the signal is resampled, the resonance frequency is also changed. Therefore, although the characteristic frequencies are converted into constant frequencies in the angular domain, denoising methods whose mechanisms rely on the resonance frequency are not applicable or their performance degrades, such as spectral kurtosis [72] and MED [73], [74]. It should be mentioned that a larger degree of the shaft phase function means higher accuracy, but it will entail massive equations of higher degrees and will result in more computation time. When the speed fluctuates complexly, the small degree will cause higher interpolation errors. Therefore, the degree of the shaft phase function should be designed according to the real speed variation complexity of the monitored equipment.

3) Tacholess Order Tracking: Although COT has been widely used and investigated, its application still requires hardware, e.g., a tachometer/encoder, to collect the speed pulses, which not only brings additional cost but also creates difficulties in installation. Therefore, TOT, which refers to OT implemented by an IF obtained from the signal itself, has attracted much attention recently. The applications of TOT are listed in Table I.

There are several ways to extract the IF, such as TFR-based peak search methods, phase demodulation, and atom matching. Among them, TFR-based methods are the most common, and how to extract an accurate IF from the TFR and implement OT is a hot topic. An example is conducted to illustrate TFR-based frequency estimation. Fig. 5 shows the envelope TFR of an outer race fault bearing signal collected from the test rig in Fig. 4. Researchers have paid much attention to extracting more accurate IFs, and the developed techniques mainly improve accuracy through the following two aspects.

The first is to generate a TFR with clearer time–frequency ridges, which is usually implemented by using signal preprocessing methods to deal with the vibration signal or by using more advanced TFA methods. Vibration signals are usually multicomponent and usually contain heavy noise, so some researchers have focused on signal preprocessing methods to separate the interest component. In [75], the raw signals were decomposed by correlated ensemble empirical mode decomposition (CEEMD), and then, from one component, the instantaneous rotating frequency (IRF) was detected. Finally, time-spectral kurtosis (TSK) was used to select one component, and the component was resampled. Jiang et al. [61] utilized spectrum AM (SAM) to separate the frequency components, and entropy was used to evaluate the TFRs of different weights to identify the optimal weight. Finally, the IF was detected from the TFR of the modified signal, and the raw signal was resampled by the IF for bearing fault diagnosis.

The time–frequency ridges in the TFRs obtained by the traditional TFA methods are always affected or even overwhelmed by noise, so highlighting these ridges using advanced

TABLE I
LIST OF REFERENCES ON IF ESTIMATION METHODS FOR TOT

Reference	Preprocessing method	IF extraction method	Target IF/IFs	Fault location
Chen et al. [75]	CEEMD	STFT+ Peak search method	IRF	Bearing
Jiang et al. [61]		SAM+ STFT+ Peak search method	IRF	Bearing
Kumar et al. [76]	VMD	FSST+ Penalized forward-backward greedy method	IRF	Bearing
Zhao et al. [77]		IACMD+ An improved ridge detector	IRF	Planetary gearbox
Zhang et al. [58]		TVSME+ Generalized demodulation	IRF	Bearing
Yang et al. [78]		GPEFT+ Ridge detection	IRF	Bearing
Wu et al. [59]	Regression filter	STFF+ NCDT	One harmonic of IRF	Bearing
Duan et al. [60]	Morphological filtering	GLCT+ Peak search method	IRF	Bearing
Wu et al. [79]		STFT+ Dynamic programming algorithm	IRF	Bearing
Ding et al. [80]		STFT+ Regional peak search and probability density function	IRF, IFCF and their harmonics	Bearing
Wang et al. [81]	Adaptive chirp mode decomposition	STFT+ Synchroextracting transform	IRF, IFCF and their harmonics	Bearing
Hu et al. [82]		STFT+ Dynamic path optimization	IRF	Bearing
Jiang et al. [83]	STFT-based IF search	Optimization tendency guiding mode decomposition (OPGMD)+ Peak search method	IRF, IFCF and their harmonics	Bearing
Tu et al. [84]		Polynomial chirplet transform (PCT)+ Fast path optimization	IRF	Bearing
Wang et al. [85]	Bandpass filter	STFT+ CWT+ Amplitude-sum-based peak search	IFCF	Bearing
Wang et al. [55]	Kurtogram	STFT+ Amplitude-sum-based peak search	IFCF	Bearing
Schmidt et al. [86]		STFT+ Improved maxima tracking procedure	IRF	Gearbox
Wang et al. [63]		STFT+ Peak search method	One harmonic of GMF	Bearing
Shi et al. [87]		STFT+ Improved Viterbi algorithm	IRF	Bearing
Huang et al. [64]		STFT+ Fast path optimization	IRF, IFCF and their harmonics	Bearing
Bonnardot et al. [48]	Bandpass filter	Phase demodulation	One harmonic of GMF	Gearbox
Choudhury et al. [88]	VMD	Phase demodulation	One harmonic of GMF	Gearbox
Xu et al. [89]	Inverse STFT+SVD	Phase demodulation	One harmonic of GMF	Gearbox
Urbanek et al. [90]		STFT+ Peak search method+ Phase demodulation	One harmonic of IRF	Not mentioned
Peeters et al. [91]	STFT-based IF search	Phase demodulation+ Maximum likelihood weighting method	One harmonic of IRF; One harmonic of GMF	Bearing; gearbox
Barrios et al. [92]	SSD	Phase demodulation	One harmonic of GMF	Gearbox
Zhang et al. [93]	ESGMD	Surrogate data test+ Phase demodulation	IRF	Bearing

TFA methods is also an effective way to better estimate the frequency [76]. Wu et al. [59] proposed a nonlinear compensating demodulation transform (NCDT) in which the interest harmonic component was demodulated and filtered so that the weak rotating frequency could be extracted from the result TFR of the rolling bearing vibration signal more accurately. In [60], the generalized linear CT (GLCT) was adopted to obtain a fine TFR, and the parameters of GLCT were analyzed. Kumar et al. [76] extracted the IF from the Fourier synchrosqueezed transform (FSST)-based TFR in which the IF was sharpened, and then, an improved VMD approach was applied to deal with the angular-domain signal. Zhao and Niu [77] proposed an iterative adaptive crucial mode decomposition (IACMD) to estimate the IF, and then, an enhanced order spectrum analysis method was proposed for planetary gearbox fault diagnosis, in which the weighted kurtosis index was designed to determine the intrinsic mode functions (IMFs). Zhang et al. [58] proposed a time-varying sinusoidal mode extraction (TVSME) method for the current signal analysis of the induction motor by using generalized demodulation for accurate IF extraction, and then, the current signals were resampled by the IF. Yang et al. [78] utilized the general parameterized time–frequency transform (GPTFT) and peak search method to detect the IF, and then, the vibration data were resampled by IF. Then, an autogram was utilized to select the resonance frequency band based on angular-domain data, and the square envelope spectrum was obtained to identify the fault locations of bearings. Finally, the energy ratio of FCF to its neighborhood was calculated via the square envelope spectrum, termed the neighborhood power density ratio (NPDR) index to quantify the fault degree.

The second technique is to first apply common TFA techniques to the collected signal, and then, postprocessing methods are developed to estimate the IF [79], [80], [82], [83], [85], [94]. In [86], a TFR was first obtained by STFT, and then, a maximum tracking procedure was proposed for frequency estimation in which a probabilistic approach was developed to infer the actual frequency. In [87], an energy centrobaric correction method-based frequency search method and an improved Viterbi algorithm were proposed, which can adaptively optimize the IF profile and improve the accuracy. In [64], fast path optimization was used to optimize the profile of the IF, by which the IFCF, the IRF, and their harmonic components can be extracted from the TFR achieved via applying STFT to bearing signals.

In addition to TFR-based methods, phase demodulation is also effective in IF estimation [48], [88], [89], [95]. This method was first proposed in [48], in which a harmonic component of GMF was extracted based on phase demodulation, and the time-domain data were resampled by the IRF calculated by the extracted IF. It is obvious that it cannot be used in applications with wide speed variations because the target harmonic component cannot be effectively separated from the multicomponent signal by a bandpass filter. Urbanek et al. [90] proposed a two-step operation for frequency detection, in which one rough IF was first extracted from the TFR and used to resample the signal. Then, this component was separated, and the accuracy IF was obtained by phase demodulation. Through the two steps, the IF can be extracted from the signal under large speed fluctuation conditions. Peeters et al. [91] extended the phase demodulation to the frequency estimation of multiple components, which was implemented by weighting the harmonic phases in time so that the effect of the low signal-to-noise ratio (SNR) harmonics was prevented. The IRF was finally calculated via the extracted frequency to resample the vibration signal. Zhang et al. [93] utilized enhanced symplectic geometry mode decomposition (ESGMD) to decompose the signal, and the interference components were filtered out with the help of a surrogate data test. The IRF was extracted and used to resample the bearing signal for fault identification.

The comparisons of TFR- and phase demodulation-based methods are listed in Table II. No matter for TFR-based methods or phase demodulation-based methods, with the help of advanced signal processing methods and postprocessing methods, one IF can be easily extracted from the TFRs. However, for most of those methods, one target time-varying time–frequency ridge must be selected manually before extraction. The order spectra will be different when the resampling operation is implemented by referring to different IFs, which means that those methods cannot be extended to online fault detection. It is expected that more adaptive IF estimation methods will be investigated to meet the requirements of online fault diagnosis.

The comparisons of HOT, COT, and TOT are listed in Table III. It is found that, for real applications, the methods should be selected based on the actual requirements and conditions. For example, if real-time condition monitoring is required, HOT and COT are two good choices, but one appropriate installation location should be prepared. For the condition that there are not available locations to install the hardware, TOT methods are the best choice, but more adaptive methods should be further investigated for online fault diagnosis.

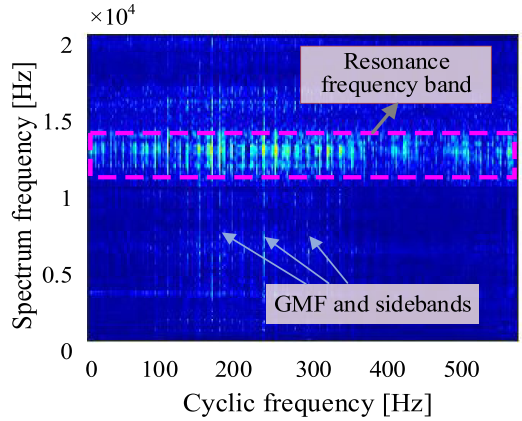

Fig. 6. Spectral correlation map of a planetary gearbox signal.

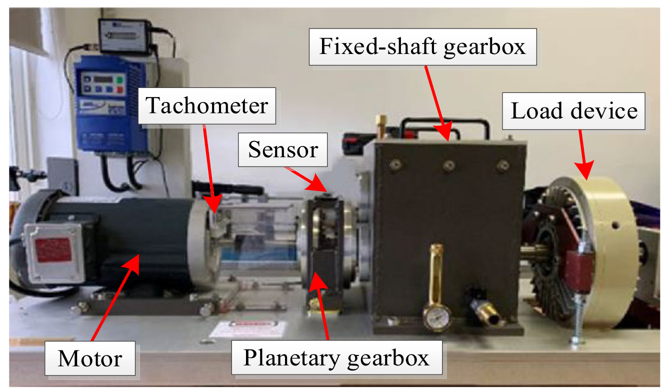

Fig. 7. Wind turbine drive train test rig.

B. CSC-Based Methods

CSC has been proven to be effective in revealing the periotic pattern of a signal, and it is implemented by calculating the double Fourier transform of the covariance function [49], [96]. Compared with envelope analysis, CSC can reveal the periodicities of second-order cyclostationarity, such as bearing signals with stronger noise.

Through CSC, the periodic patterns are presented in the bivariable map of spectrum frequency and cyclic frequency, as shown in Fig. 6. The signal is measured from the planetary gearbox, including a fault sun gear, as demonstrated in Figs. 7 and 8. The former could pinpoint the carrier frequency, while the periodic characteristic frequency harmonics are revealed from the cyclic frequency direction. The spectral axis can be integrated to form an improved envelope spectrum (IES) or enhanced envelope spectrum (EES) [97].

However, the above methods can only be applied to signals under constant speed conditions. Abboud et al. [50], [51] further extended the CSC to cyclononstationary signals, which was implemented by applying spectrum correlation or spectrum coherence to the angular-domain signal. By this theory,

TABLE II
LIST OF COMPARISONS OF DIFFERENT IF DETECTION METHODS

Methods	Advantages	Disadvantages
TFR-based IF estimation	The principle is simpler and more intuitive, so it is easier to understand and implement. Because there are many TFA methods, such as STFT, WT and various newly developed methods, the application of TFR-based IF estimation methods can be implemented according to the characteristic of monitored components.	The application of TFR-based methods is subject to time-frequency resolution, so not appropriate TFA methods will result in large errors. It is challenging to generate a proper TFR via common TFA methods for the signals with low frequency, and the advanced TFA methods, such as synchrosqueezing transform, will greatly increase the computation burden. TFR-based methods are not applicable to strong speed fluctuation due to the fixed window length.
Phase demodulation-based IF estimation	The IF extracted by phase demodulation-based methods is usually more accurate. Phase demodulation-based IF estimation methods are not subject to the time-frequency resolution.	One target IF component needs to select before extraction, and the preprocessing procedures, such as analyzing the TFR to determine the component and designing a band-pass filter to separate it, so the operation is more complex. When the IF changes largely, the bandwidth will be large, so multiple harmonics will be encompassed in the filtered signal, which results in larger errors. The prior knowledge and preprocessing methods make this kind of methods heavily rely on manually operations.

TABLE III
LIST OF COMPARISONS OF HOT, COT, AND TOT

Methods	Advantages	Disadvantages
HOT	The application of HOT is very simple, and importantly, does not rely on expert knowledge, so it is very suitable for common users. HOT is time-saving and the application is automatic, so it can be used in online fault diagnosis.	The data acquisition is subject to latency and error, especially when the speed fluctuates rapidly. Additional hardware components are needed, which increases the complexity and costs.
COT	The hardware, such as ratio synthesizer and an anti-aliasing tracking filter, are not needed, so the cost and complexity are reduced compared to HOT. Similar to HOT, the application of COT is automatic, and it can be used in online fault diagnosis.	A tachometer/encoder is still needed, so a proper location on the monitored equipment is needed to install it. There are inevitable interpolation errors in the resampling process, and if the errors are too large, the order spectrum will be blurred.
TOT	No hardware is required, so it is suitable for the machine with no available location to install additional equipment.	The calculation accuracy depends on the quality of extracted IF. The implementation is complex and time-consuming. In some cases, such as early fault and strong noise, the IF is difficult to extract. Prior knowledge and manual operations are usually needed, so it is hard to apply to online fault diagnosis and more adaptive methods should be further improved for performing online.

Mauricio et al. [6] developed a novel tool for band selection called the IES via feature optimization-gram (IESFOgram), which was applied to the bearing fault diagnosis under variable speeds. Schmidt et al. [98] utilized the order-frequency spectrum and angle-frequency spectrum to construct several band selection methods for the fault diagnosis of bearings and gears under time-varying speeds.

Compared with envelope/order spectrum analysis, spectrum/order analysis based on CSC can better reveal periotic patterns from cyclostationary/cyclononstationary signals, but the computation is more complex, which leads to much computation time, especially when analyzing signals collected at high sampling rates, such as Safran engine data [52]. Therefore, the investigation of faster methods may promote their applications.

C. Generalized Demodulation-Based Methods

Generalized demodulation is also an effective technique to deal with nonstationary signals, by which the time-variant trajectory of an IF can be converted into a linear path in TFR [20]. Different from the resampling technique, an interest time-varying IF can be selected as a target to be converted into a constant, and the other frequency components are still variable, which means that, for multicomponent signals, the interest fault-related components can be highlighted in the demodulation spectrum. An example in [62] is presented to illustrate the principle of generalized demodulation. The rotating speed $f_r(t)$ of a fault bearing signal is measured from the test rig shown in Fig. 4; a phase function $p_r(t)$ is shown in Fig. 9(a); and the IRF $f_r(t)$, IFCF $f(t)$, and their harmonics are also time-varying, as shown in Fig. 9(b). Guided by

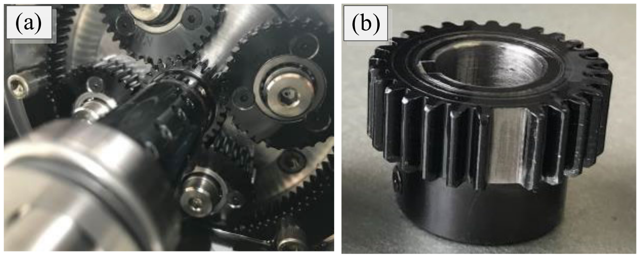

Fig. 8. (a) Planetary gearbox. (b) Fault sun gear.

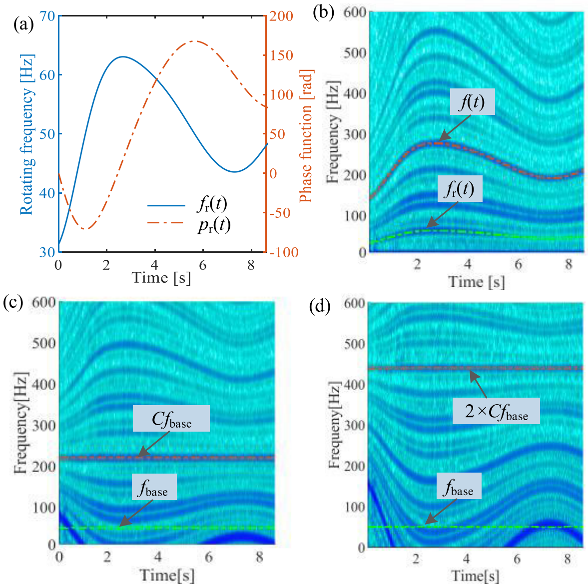

Fig. 9. (a) IRF and its phase function. (b) TFR of the vibration signal. (c) TFR of the demodulation signal [phase function $Cp_r(t)$]. (d) TFR of the demodulation signal [phase function $2Cp_r(t)$].

proper phase functions calculated by $p_r(t)$, the IFCF and its second harmonic are converted into constant ones, as shown in Fig. 9(c) and (d), respectively. It is introduced into the fault diagnosis of rotating machinery under time-varying speeds for TFA [99]. Feng et al. [100] and Feng and Chen [101] further extended it to the TFA of multicomponent planetary gearbox signals. The generalized demodulation-related TFA methods are detailed in Section III-B.

Recently, researchers have also investigated generalized demodulation in spectrum analysis for rotating machinery fault diagnosis [56], [102], and most of them focused on how to construct phase functions. In [65], the time-varying bearing IFCF was extracted, and the phase functions of IFs were obtained by multiplying the extracted IFCF with constant increments. The advantage of this method is that only one IF is needed, and the others are estimated by the IF with no prior knowledge. In [103], the phase function was calculated by the rotating speed collected by a tachometer. OT converts the time-varying frequencies into fixed constant values. For example, if the signal is resampled by referring to the IRF, the time-variant rotating frequency will be transformed into the order of 1, and the other components will be transformed into multiples of 1, which are determined by the relationship of the frequencies with the rotating frequency. However, the time-varying frequencies are converted into their starting frequencies by generalized demodulation, which means that, if the rotating speeds of different signals vary with different profiles, and even if the health condition of the monitored part is the same, the demodulation spectrum will be different. Therefore, flexible generalized demodulation was proposed in [62]. By introducing a base frequency, the time-varying rotating frequency was converted into the base frequency, and the other frequencies with the same physical meanings were converted into the same base frequency-related constant values.

Generalized demodulation has its own unique merits in nonstationary signal spectrum analysis, but the limitations cannot be neglected. In the demodulation operation, the interest frequencies can be selected, which is beneficial for the demodulation of those frequencies and prevents the interference of fault-irrelevant frequency components, but the other potential fault characteristic frequencies that are not selected are still time-varying. If a monitored machine has a complex structure and there are many parts to be monitored, the phase functions corresponding to all target frequencies caused by all parts should be calculated in advance, which is unrealistic. Therefore, generalized demodulation-based methods are suitable for machinery with simple structures or machinery with few parts prone to faults.

D. Other Methods

To the best of our knowledge, most spectrum analysis-based diagnosis methods for machinery under time-varying speeds rely on resampling techniques, CSC, or generalized demodulation, and there are only a few other approaches. In [104], one IF was first detected from a signal of a fault gear, and then, the fractional Fourier transform (FrFT) was applied to demodulate the meshing frequency and its sidebands. In [105], the envelope TFR of the rolling bearing signal was first obtained, and then, the TFR was reconstructed based on one extracted IF so that the 1-D demodulation spectrum could be calculated by integrating the TFR over the time axis. However, those methods have inherent drawbacks. For example, FrFT-based methods are only applicable when the rotating frequency varies linearly, and TFR reconstruction-based methods are subject to the time–frequency resolution.

E. Comparisons

The advantages and disadvantages of OT-, CSC-, and generalized demodulation-based spectrum analysis methods are listed in Table IV. It should be noted that each method has its inherent disadvantages and advantages. Therefore, in real applications, we should select one appropriate method according to specific requirements. For example, if the monitored machine is complex, but only one part is prone to faults, it is better to choose generalized demodulation because the phase functions of fault-related components of the monitored part can be easily calculated. If the machine is complex and all parts are evenly prone to faults, generalized demodulation is not a good choice because it is hard to calculate all phase functions, while OT may be more suitable. CSC is subject to

TABLE IV
LIST OF COMPARISONS OF DIFFERENT SPECTRUM ANALYSIS METHODS

Methods	Advantages	Disadvantages
Order tracking	The principle of order tracking is simple to understand and it is easy to implement compared to the other two methods. Because only the speed pulses or one IF is needed and the operation process does not involve the knowledge on the vibration signal itself, it has strong applicability to various machines, and is one best choice for online fault diagnosis.	The resample process is time-consuming, especially when the rotating frequency or IF is fitted by high-order equation and the targeted fault-related frequencies are high (the largest order will be set to be a large value to capture the high frequency content). The interpolation errors are inevitable in the resample process.
Cyclic spectrum correlation	Cyclic spectrum correlation can reveal the weak periodic pattern of a signal and is more robust to noise, so it can be used for weak fault diagnosis and analyzing the signals with strong noise. Cyclic spectrum correction can reveal the carrier frequency and periodic frequency components simultaneously, and thus provides more fault information, rendering a suitable domain to deep learning-enabled intelligent fault diagnosis.	Cyclic spectrum correlation is subject to high computation burden, so optimization methods are still needed to extent this method to online fault diagnosis. Down-sampling is usually required to ease the computation burden, but for the signals with high interest frequency components, the raw signals can not be down sampled with a high rate to capture these fault-related components, so down-sampling can not solve the problem. Interpolation errors also exist in the application.
Generalized demodulation	Generalized demodulation is free from resample, and it owns high computation efficiency. Generalized demodulation can reveal one target component from a multi-component time-varying signal, which means that for a complex equipment, it can be used to detect whether there are several target frequency components.	All phase functions of target components are needed, and they are usually calculated by extracted IFs or estimated by combining one known IF and the modulation characteristics of the signals, so its application relies on prior knowledge and usually is implemented manually. Because it is difficult to estimate all phase functions of all frequencies for a complex equipment, generalized demodulation is only suitable for simple machine or the machine with a few parts prone to faults, such as the main shaft of a wind turbine. Different from resample, the iterative operation is usually adopted and the target component is usually determined manually, so although the computation efficiency is high, it is still challenging to apply it to online fault diagnosis.

a high computation burden, but it is robust to noise. Therefore, for early fault diagnosis, CSC seems more appropriate.

III. TFA METHODS

TFA is also one popular method for machinery fault diagnosis under time-varying speeds. Recently, various advanced TFA methods have been investigated for the fault diagnosis of machinery under time-varying speeds. The researchers at the universities such as the University of Science and Technology Beijing [106], [107], [108], [109], [110], [111], Shanghai Jiao Tong University [112], [113], [114], [115], [116], Xi'an Jiaotong University [117], [118], [119], [120], the Beijing University of Chemical Technology [121], [122], [123], the University of Jinan [124], [125], [126], [127], Tsinghua University [25], [128], [129], [130], and the Beijing University of Technology [131], [132], [133], [134] have made great contributions to this field.

A. Traditional TFA Methods

Traditional TFA methods include linear methods, such as STFT [21] and continuous WT (CWT) [22], and bilinear/quadradic methods, such as WVD [23]. The applications of linear TFA methods in fault diagnosis are subject to low time–frequency resolution because of the Heisenberg uncertain principle. A vibration signal of the planetary gearbox with a fault sun gear collected from the tested rig in Fig. 7 is analyzed as an example. As shown in Fig. 10(a) and (b), IFCF f_{sun}, IRF f_r, and their harmonics are not clear in the TFRs obtained by STFT and CWT due to the poor time–frequency resolution. Bilinear/quadradic TFA methods have higher resolutions, but, when dealing with multicomponent signals, they are often subject to cross-term interference, so they are rarely used in fault diagnosis.

Nevertheless, they still play an irreplaceable role in fault diagnosis under time-varying speeds. On the one hand, they are regarded as the most common tool to generate TFRs used for IF extraction, which can be found in Table I. On the other

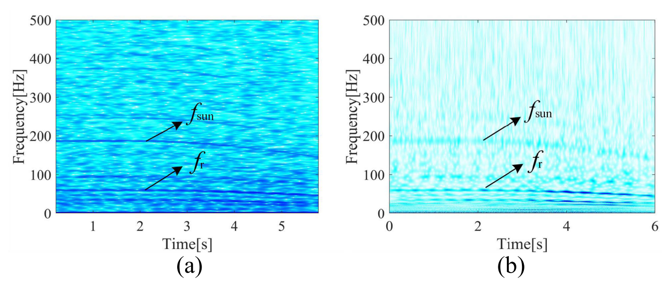

Fig. 10. (a) and (b) Envelope TFRs of the vibration signal collected from a planetary gearbox with a fault sun gear obtained by STFT and CWT, respectively.

TABLE V
LIST OF REFERENCES ON THE PPTFA-BASED FAULT DIAGNOSIS METHODS

Reference		Method	Key assist techniques	Target IFs	Fault location
Feng et al. [106]	Common SST-based PPTFA	ConceFT	Kurtogram	IRF, IFCF and their harmonics	Bearing
Hu et al. [112]		HSWT	High order group delay, and chirp rate operator	IRF and its harmonics	Planetary gearbox
Yu et al. [124]		MSST	STFT	IRF and its harmonics Resonance frequency	Rub-impact of rotor; Bearing
Yuan et al. [146]		MLST	STFT	IRF, IFCF and sidebands; IRF and its harmonics	Bearing; Shaft misalignment
Yang et al. [117]		AICIM	Matching time-frequency theory	IRF and its harmonics	Shaft crack
Li et al. [147]		OTFC	TQWT, and MMSST	IFCF and its harmonics	Bearing
Li et al. [148]	Generalized demodulation-based PPTFA	GST	Generalized demodulation, and WT	GMF and sidebands	Gearbox
Feng et al. [107]		Iterative generalized demodulation-based TFA	Iterative generalized demodulation, and STFT	GMF and sidebands	Planetary gearbox
Chen et al. [149]		IMSST	Generalized demodulation, and EFT	IRF, IFCF, and harmonics	Bearing
Chen et al. [108]		IGDTFR	Iterative generalized demodulation, and reassignment transform	GMF and sidebands	Planetary gearbox
Feng et al. [100]		IGDSST	Iterative generalized demodulation, and SST	GMF and sidebands	Planetary gearbox
Shi et al. [150]		GSDT-based SST	Generalized stepwise demodulation transform, and SST	IRF, IFCF and their harmonics	Bearing
Tu et al. [113]		DHST	Generalized demodulation, and SST	IRF and its harmonics	Planetary gearbox
Feng et al. [101]		Adaptive iterative generalized demodulation-based TFA	Adaptive iterative generalized demodulation	GMF and sidebands; IRF, IFCF and their harmonics	Planetary gearbox; Bearing
Feng et al. [109]	Signal decomposition-based TFA methods		Vold-Kalman filter, and higher order energy separation	GMF and sidebands	Planetary gearbox
Feng et al. [110]			Vold-Kalman filter, and Hilbert transform	GMF and sidebands	Planetary gearbox
Chen et al. [114]			VNCMD, and a spectrum concentration index-based optimization method	GMF and sidebands	Planetary gearbox
Zhang et al. [24]			Vold-Kalman filter, and various TFA methods	GMF and sidebands; IRF and its harmonics; IFCF and sidebands	Planetary gearbox; Shaft misalignment; Bearing
Zhang et al. [111]			Adaptive mode decomposition, and resampling method	GMF and sidebands; IFCF and sidebands	Planetary gearbox; Bearing
Chen et al. [151]			Adaptive chirp mode decomposition, and Gini-index	Wheel flat characteristic frequency and its harmonics	Wheel flat

hand, they are the basis of postprocessing TFA (PPTFA) methods, i.e., various advanced TFA methods have been developed based on those traditional TFA methods.

B. PPTFA Methods

To enhance the time–frequency resolution, various PPTFA techniques have been investigated and widely utilized in the fault diagnosis of rotating machinery under time-varying speeds [135], [136], [137]. They enhance the quality of TFRs by suppressing the interference terms and improving the time–frequency energy concentration. The signals of rotating machinery are usually multicomponent, and some components are very close to each other, such as the GMF and the various sidebands around it in planetary gearbox vibration signals [25], [138]. It is difficult to reveal those components clearly and then realize fault diagnosis. Therefore, some PPTFA methods specifically suitable for AM and frequency modulation (AM–FM) signal analysis have been investigated. In this section, we mainly review the traditional PPTFA methods and the PPTFA methods proposed specifically for the TFA of rotating machinery. The relevant publications on PPTFA methods are listed in Table V, where "target IFs" refers to the frequency components on which the diagnosis decision is based, i.e., the frequency components that are expected to be revealed.

The idea of reassignment was first proposed by Kodera et al. [139], and then, Anger and Flandrin [140] proposed time–frequency reassignment, which was implemented by reallocating the time–frequency energy of the TFR obtained via common TFA algorithms to the center of gravity. Daubechies et al. [141] and Oberlin et al. [142] further developed the synchrosqueezing transform (SST) based on the WT and the STFT, respectively, which reassign the TFR in the frequency domain. These methods lie the foundation of PPTFA methods, and researchers have introduced them to machinery fault diagnosis. In addition, some PPTFA methods that are more suitable for vibration signal analysis have been proposed according to the modulation characteristics of vibration signals [143], [144].

Feng et al. [106] applied ConceFT [145] to bearing envelope signals, and the IFCF and its harmonics were pinpointed clearly in the TFRs. They further validated that the TFA method had higher resolution compared with the WT, SST, and MMSST in analyzing bearing signals. Hu et al. [112] proposed a high-order synchrosqueezing WT (HSWT) for fault diagnosis of planetary gearboxes, in which the chirp rate operators and the high-order group delay were adopted to estimate the IF. Yu et al. [124] proposed a multisynchrosqueezing transform (MSST) for fault diagnosis of machinery under strongly time-varying speeds, which utilized an iterative procedure to condense the blurry energy based on STFT, and because the STFT was operated only once in the iterative operation, the computation burden was released. Yuan et al. [146] proposed a multilifting SST (MLST) for the fault diagnosis of rotating machinery under fast-varying rotating speeds, in which a multisqueeze second-order lifting operator was designed for estimating the IFs more accurately, and the deviation of time–frequency energy was corrected by a correction operator. Yang et al. [117] proposed an amplitude-independent crack identification method (AICIM) for shaft crack fault diagnosis, in which amplitude-independent IF was first extracted by matching time–frequency theory, and then, the energy of TFR along the trajectory of the IF was concentrated. Li et al. [147] developed an oscillatory time–frequency concentration (OTFC) method, in which a tunable Q factor WT (TQWT) was adopted to decompose the signals into low- and high-oscillatory components. The former was regarded as the target component and then was concentrated by multitaper synchrosqueezing. Liu et al. [121] developed an adaptive time-reassigned SST (ATSST), in which the Renyi entropy was utilized to obtain the variable optimal window width of time-reassigned SST. Tu et al. [115] developed generalized horizontal SST, in which a high-order Taylor expansion-based group delay was proposed as the synchrosqueezing operator. Zhou et al. [118] developed a second-order iterative time-rearrangement SST, in which the approximation order was increased and multiple iterations were conducted to gain better time–frequency readability. These methods have achieved great improvement. However, when dealing with multicomponent signals under time-varying speeds whose IFs are very close to each other or when there exist cross-term interferences, those methods are still subject to some degree of time–frequency blurs.

The vibration signals of rotating machinery are usually composed of rotating frequency harmonics, which makes it possible to improve the time–frequency resolution by using this characteristic. For example, in terms of bearing vibration signals, the useful frequencies are the FCF, the rotating frequency, and their harmonics; for planetary gearbox signals, the GMF and the sidebands around it are essential for fault detection. According to the characteristic, the IFs can be extracted first from the TFRs obtained by the common TFA techniques, or the target IFs can be estimated by the rotating frequency obtained by the tachometer; then, they are utilized to enhance the resolution.

Based on the IF, in [148], generalized demodulation was used to convert the target GMF into a constant, and then, the WT was utilized on the demodulation signal. Because the target frequency was converted into a constant, the resolution was improved. Finally, the TFR was restored by a time-scale domain restoration process. In [107], the IFs were estimated, and then, iterative generalized demodulation was applied to convert the time-varying harmonic components around the GMF of the planetary gearbox into constant components. Those constant ones were separated by proper bandpass filters, and the traditional TFA methods were applied to them. Finally, the TFRs were reconstructed so that the time-varying profiles of those IFs could be restored. In [149], an improved MSST (IMSST) was used to detect the IF of bearing signals, and then, the phase functions of generalized demodulation were calculated by the IF and fault characteristic coefficient. Then, the empirical Fourier transform (ETF) was used to separate the demodulated components, and the final high-quality TFR was obtained by an adaptive time–frequency method. According to this principle, the iterative generalized time–frequency reassignment [108], the iterative generalized SST [100], the generalized stepwise demodulation transform and synchrosqueezing [150], the adaptive demodulation synchroextracting transform [131], the demodulated high-order SST [113], and the adaptive iterative generalized demodulation-based time–frequency transform [101] were proposed, and their purpose was to further enhance the time–frequency resolution or make the procedure more adaptive. This kind of TFA method highly improves the resolution, and most of them are validated to reveal the time-varying close-spaced sidebands around the GMF of the planetary gearbox.

Improving the time–frequency resolution by signal processing methods is also common and effective in fault diagnosis. The signals of rotating machinery are usually multicomponent and contaminated by noise and interference components. If the multicomponent signals are decomposed into monocomponents by signal decomposition methods, e.g., the Vold–Kalman filter [109], local mean decomposition (LMD) [152], and single-mode function decomposition (SMFD) [153], the background noise and the interference components are filtered before the TFA, and it is easier to identify the frequency components. Recently, signal decomposition-based TFA methods have been widely investigated and have contributed greatly to the machinery fault diagnosis.

In [110], the Vold–Kalman filter was used to separate multicomponent signals into monocomponents, and the TFRs of those components were obtained. Finally, the TFR of a raw signal was obtained by reconstructing the TFRs of monocomponents. In [114], the variational nonlinear chirp mode decomposition (VNCMD) method was proposed, which was utilized as a filter bank to separate the multicomponent signal to remove the background noise and interference components. Furthermore, in [116], variational nonlinear component decomposition was proposed for planetary gearbox

TABLE VI
LIST OF COMPARISONS OF DIFFERENT PPTFA METHODS

Methods	Advantages	Disadvantages
Common SST-based PPTFA	They have higher time-frequency readability, i.e., the time-frequency ridges are more condensed and are more robust to background noise compared to traditional TFA methods. No prior knowledge on the signal itself is needed, so their applications are more adaptive and automatic.	These methods suffer from high Computation burden. Their performance decreases when the close-spaced frequency components of a multi-component signal, such as the sidebands of GMF of a planetary gearbox signal collected under low rotating speeds.
Generalized demodulation-based PPTFA	Compared to these common SST-based PPTFA methods, generalized demodulation-based methods perform well when dealing with the close-spaced frequency components, so they are very suitable to analyze the signals with complex frequency components such as the signals of the planetary gearbox operated under low speeds. These methods are more robust to noise because band-pass filters with narrow bandwidths are usually utilized for all components. They can separate several target frequency components from a complex multicomponent signal.	Various generalized demodulation-based methods involve SST, so the iterative operation further adds the computation burden. The phase functions of target components need to be estimated or calculated based on traditional TFA methods, which adds the complexity and relies on prior knowledge.
Signal decomposition-based PPTFA	These methods also perform well for close-spaced frequency components, and have good readability. Because signal decomposition methods are involved in this kind of method, they are robust to noises, and the decomposition methods can be selected according to the modulation characteristics of signals, they are suitable for the fault diagnosis of machinery with multiple vibration sources.	The final TFRs obtained by this kind of methods are usually obtained by reconstructing each TFR of the decomposed components, which increases the complexity. These methods inherent the drawbacks of the corresponding decomposition methods, and the prior knowledge such as the values and number of IFs of the signal to be analyzed.

fault diagnosis, which was more adaptive owing to a novel frequency estimation method. In [111], angular resampling and adaptive mode decomposition were combined to decompose the signal into monocomponents, and then, reverse resampling and the TFR reconstruction methods were adopted to recover the initial IFs. In [151], a two-level adaptive chirp mode decomposition (ACMD) was developed for wheel flat fault diagnosis. For the method, ACMD was first utilized to decompose the raw signals, and then, the Gini index was used to select a component containing fault information. Finally, ACMD was applied to the selected component to reveal the wheel flat FCF.

The comparisons of different PPTFA methods are listed in Table VI. The PPTFA methods have improved the time–frequency resolution to a great extent, and especially for generalized demodulation- and signal decomposition-based methods, they have been validated to be effective in analyzing signals whose frequencies are very close and vary fast, but the limitations are also obvious. First, the application of those methods is time-consuming. Usually, downsampling is applied to save time, but, for signals with high resonance frequency or with fault characteristic frequencies that are high due to the mechanical structure and the high rotating frequency, the data must be measured at a higher sampling rate to capture the resonance frequency and the characteristic frequencies. Second, most PPTFA methods rely on IFs extracted from TFRs, which are usually obtained manually. Therefore, reducing the complexity and improving the adaptability may make it possible to extend these methods to online fault diagnosis of rotating machinery.

C. CT-Based TFA Methods

CT-based TFA methods are also effective in the fault diagnosis of rotating machinery under time-varying speeds [128], [154], [155]. The basic principle of a CT is to match the analyzed signal with a designed special basis. When the chirp kernel is the same as the IF of the signal, a TFR with a better energy concentration is obtained. However, the traditional CT only performs better for signals with a linear IF, which does not meet the requirements of real mechanical applications. To avoid this limitation, Peng et al. [156] developed a polynomial CT (PCT) method, which used a polynomial function instead of the traditional linear chirp kernel and can better approximate nonlinear IFs.

To improve the performance in multicomponent signal analysis, Yu and Zhou [125] proposed a general linear CT (GLCT) method, which generated the final TFR by fusing a series of TFRs obtained by the linear CT with a set of different chirp rates. Guan et al. [157] developed a velocity synchronous linear CT (VSLCT), which correlated the chirplet with the velocity of the rotating shaft and exhibited high time–frequency resolution. Researchers have also combined CT-based TFA methods with postprocessing methods to further improve readability [122], [123]. For example, Zhu et al. [119] proposed a multisynchrosqueezing CT (MSSCT), which combined the MSST with a CT and can produce a more accurate IF estimator to correct the time–frequency energy deviation. Owing to the merits of the synchroextracting transform (SET) [126], a few improved versions of the CT have been proposed, such as the synchroextracting CT (SECT) [120], general SECT (GSECT) [158], velocity synchronous chirplet extracting transform (VSCET) [159], the combination of the PCT and SET [160], synchroextracting frequency synchronous CT (SEFSCT) [161], and multiple squeezing based on velocity synchronous CT (MSVSCT) [162]. The main idea of these methods is that the time–frequency information around the IFs is retained, and the smeared time–frequency energy is removed to enhance the energy concentration and readability.

Researchers have paid much attention to CT-based TFA methods for fault diagnosis. Most of them focused on constructing a chirplet basis to better approximate nonlinear IFs, designing an IF estimator to more accurately estimate IFs and utilizing postprocessing methods to improve the time–frequency energy concentration. Compared with PPTFA methods, CT-based TFA methods are more adaptive, but it is still challenging to achieve an ideal TFR for vibration signals with cross-interference components and with IFs whose trajectories are very close, such as the vibration signals of planetary gearboxes under low-speed conditions.

D. Other Methods

To the best of our knowledge, some other TFA methods, such as improved WTs, sparse time–frequency representations [163], [164], [165], and time–frequency manifolds [166], [167], have also been investigated recently, and they have made great contributions to fault detection. However, they are mainly proposed for transient fault feature extraction. For example, the impulses caused by bearing faults are usually overwhelmed by noise, but they can be revealed by these TFA methods. In the time–frequency plane, the impulses exhibit higher magnitudes, so their appearance indicates the existence of a fault, and the intervals of those impulses can be used to infer the fault location. They are usually not used in revealing time-varying characteristic frequencies for fault diagnosis under time-varying speeds.

IV. Intelligent Fault Diagnosis Methods

Intelligent fault diagnosis aims to automatically recognize health conditions through an appropriate model. Recently, machine learning methods have attracted much more attention, and some advanced methods for the fault recognition of rotating machinery under variable speed conditions have been investigated. According to their realizations, they are divided into artificial feature extraction- and deep learning-enabled techniques. In terms of the research teams, unlike the spectrum analysis- and TFA-based methods, the publications on this topic are not concentrated. In this review paper, Xi’an Jiaotong University has published several papers [168], [169], [170], [171], [172], [173], [174], and the others such as Chongqing University [175], Beihang University [176], [177], and Yanshan University [178], [179] published less than three papers. However, most of the papers on this topic have been published in the past three years. It is predicted that the number of intelligent fault diagnosis methods for time-varying speeds will grow rapidly considering the wide range of researchers, the popularity of intelligent methods, and the significance of fault diagnosis under time-varying speeds.

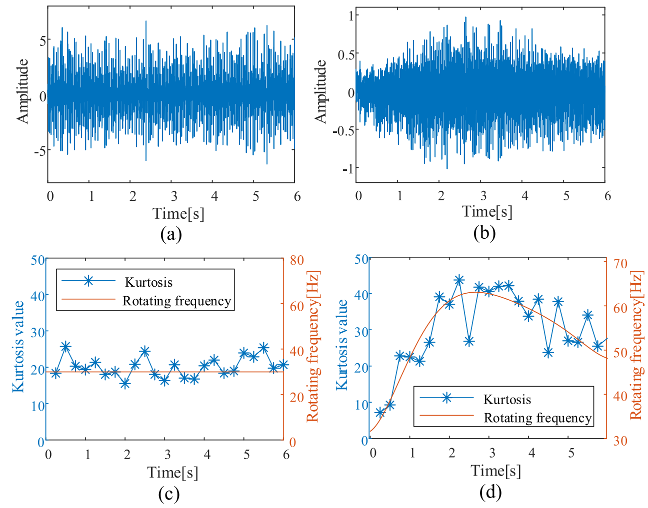

Fig. 11. (a) and (b) Waveforms of the fault bearing signals under constant and time-varying speeds, respectively. (c) and (d) Kurtosis values corresponding to (a) and (b), respectively.

A. Artificial Feature Extraction-Enabled Methods

Artificial feature extraction-enabled methods refer to the joint application of signal processing methods and classifiers to implement automatic fault recognition. For fault diagnosis under constant speeds, the common time-domain [180], frequency-domain [181], and time–frequency-domain [182], [183] features are usually effective and can be easily extracted. However, when the speed varies, the corresponding features also change with the speed variations. The signals of a fault bearing under constant speed and variable speed are demonstrated to illustrate this effect, and the waveforms are displayed in Fig. 11(a) and (b), respectively. The amplitude of the waveform changes with the speed variation. The most common feature kurtosis values combined with the speeds of the two signals are also presented in Fig. 11(c) and (d), which confirms the effect of speed variation on the features.

To implement intelligent fault diagnosis under variable speeds, researchers have proposed more effective features through signal processing methods. Zhou et al. [184] calculated the time- and frequency-domain features of angular-domain data and then fed them into a modified self-organizing map (SOM). To eliminate the interference of speed fluctuations, the resampling technique was adopted. However, only the periodicity of the impulses was recovered, and the magnitudes of the amplitudes were still affected by the speed. In [185], EMD was utilized to decompose the angular-domain signal, and then, the multiscale entropy features of the selected IMFs were fed into a decision tree (DT) classifier for fault classification. Furthermore, in [30], the Vold–Kalman filter was used to remove the fault-unrelated components, and the refined composite multiscale fuzzy entropy (RCMFE) features were selected and fed into logistic regression for fault recognition. Those methods mainly rely on resampling to remove the effect of speed variation. In [62], flexible generalized demodulation was proposed to produce a demodulation frequency domain, and the features related to characteristic frequency harmonics were extracted for fault recognition. In [186], the persistence spectra of the vibration signals were calculated, which were claimed to be more independent of the rotating speed, and then, a multiscale structural similarity index was applied to differentiate the health conditions.

The above review shows that feature extraction via signal processing methods combined with appropriate classifiers can effectively decrease the need for human labor. However, limitations and challenges still exist. Most feature extraction methods rely on resampling techniques, but they can only restore the periodicity of fault-related impulses, and the effect of rotating speeds on the amplitude of a waveform cannot be removed. In addition, the artificial feature extraction operation still relies on expert knowledge and does not totally eliminate the need for human labor.

B. Deep Learning-Enabled Methods

Deep learning-enabled diagnosis means that the effective features are learned from the raw signals or the signals through simple preprocessing, such as transforming 1-D data to a 2-D TFR, automatically by deep neural networks, such as deep autoencoders [187], deep belief networks [188], and CNNs [189], [190], [191]. Recently, some researchers have attempted to construct deep diagnosis models to implement fault recognition under time-varying speeds. According to the implementation of those methods, they are divided into signal preprocessing-based methods, improved CNN-based methods, and other methods.

1) Signal Preprocessing-Based Methods: Signal preprocessing-based methods refer to signals that are processed in advance to remove/weaken the effect of speed variation, and then, the processed signals are analyzed by common deep learning methods. In [192], the vibration data of bearings were resampled, and then, a 1-D CNN was utilized to learn the features from the angular-domain signals. In [193], the vibration signals were demodulated by generalized demodulation, and then, the features were learned by a CNN. In [194], the order spectra of the collected signals were obtained, and an adaptive normalized CNN was adopted to mine the features via the order spectra for planetary gearbox fault recognition. In [195], the signals of the planetary gearbox were resampled, and then, the angular-domain signals were mapped into 2-D images by recurrence plot (RP) analysis. Finally, the features were learned from the images and classified by a CNN. In [196], the Fourier SST (FSST) and OT were applied to achieve the angular-domain data, and then, a CNN was applied to the WT-based TFR for bearing fault recognition.

The above methods aim to utilize signal processing methods to weaken the interference of speed variation, and then, deep learning methods are adopted to realize fault recognition. However, as mentioned before, most methods can only restore the periodicity of fault shocks, and the effect on the amplitude of the waveform is not removed. Even in commonly used TFRs, the amplitudes of the resonance frequency band or characteristic frequency harmonics are different under time-varying speeds. Therefore, although the signal processing methods have improved the performance, the performance of this scheme cannot totally recover the effectiveness of deep learning methods.

2) Improved CNN-Based Methods: A typical CNN consists of convolutional layers, pooling layers, and fully connected layers [190]. Because of their excellent feature extraction ability, CNNs have been widely applied in machinery fault recognition [197], [198]. To extend a CNN to time-varying speed conditions, some improved versions of CNNs have been investigated.

In [199], a novel intraclass and interclass constraint (IIC) integrated with an adaptive activation function was combined with a CNN, which can adapt the data with class fluctuation owing to the feature mapping constraint ability of IIC and the good nonlinear mapping ability of the adaptive activation function, and the improved CNN was validated to be effective in gearbox fault diagnosis under variable speeds. In [200], a nuisance attribute projection (NAP) was performed on the loss function of a CNN, which was used to project the feature to another space to weaken the interference attribute and, thus, remove the effect of the speed condition. In [201], the CWT was utilized to the vibration data of bearings to achieve 2-D TFRs, and because the distributions of frequency components in the TFRs changed following the variation in speeds, a Pythagorean spatial pyramid pooling (PSPP) layer was added to a CNN, which was validated to be able to analyze TFRs with scalograms of different sizes. In [31], a multiscale kernel algorithm and a residual learning method were introduced into a CNN, which was proven to be able to capture the features from raw signals and be more robust to condition variation. In [168], a cascade CNN with progressive optimization was proposed. For the method, a dilated convolution operation that can capture different sizes of respective fields was conducted to extract the features of different scales caused by speed variation, and the cascade structure and progressive optimization were performed to improve the feature mining ability.

In the literature review, it is concluded that researchers mainly focused on two aspects to extend common CNNs to time-varying speed conditions. First, new methods are introduced to CNN to address the scale variation caused by speed fluctuations. Second, new modules are added to the CNN to make the models more effective in mining the condition-irrelevant features.

3) Other Methods: In addition to the signal preprocessing-based methods and the improved CNN-based methods, there are some other deep learning-enabled methods to be reviewed in this part.

In [169], a subspace network with shared representation learning (SNSR) method was proposed, in which shared representation learning was designed to promote the learning ability of domain irrelevant features. In [177], the samples were segmented, and the time-domain feature dimensions of those segments were calculated as the input. Then, a deep bidirectional long short-term memory (DB-LSTM) was applied to implement fault recognition. In [170], a multibranch redundant adversarial network (RedundantNet) was developed for bearing fault recognition under variable speeds, in which a generator was designed to obtain various signals with different speeds and the training data were expanded. In [202], a parallel adversarial learning inference (PALI) model was proposed, in which the encoder and the decoder were trained by a parallel adversarial game to enhance the feature learning ability. Liang et al. [179] developed a deep residual deformable subdomain adaptation framework for wind turbine fault recognition under variable speeds. The deformable convolution module was used to enhance the traditional residual network, and the local maximum mean discrepancy (LMMD) was used to remove the feature distribution discrepancy of samples under different speed conditions. Yuan et al. [203] proposed a speed-adaptive graph convolutional network (SAGCN) for wheelset bearing fault diagnosis, in which the vibration data and encoder data were fed into convolutional layers, respectively, the global average pooling was used to fuse the two channel features, and the graph neural network was finally utilized to further learn the features for fault recognition of the bearings under time-varying speeds. Shi et al. [171] developed a reliable feature-assisted contrastive generalization net (RFACGN), in which a contrastive framework was used to remove domain distribution discrepancy, and more importantly, a feature-assisted multibranch module was developed to guide the model to extract more fault information. Zhao and Shen [204] proposed a mutual-assistance network for semisupervised domain generalization fault diagnosis (SemiDGFD), in which labeled and unlabeled source domain data were used to release the burden of labeling source domain data, pseudolabels were assigned to unlabeled data, and the entropy-based module was applied to enhance the quality of pseudolabeled data. Lei et al. [173] proposed a prior knowledge-embedded metatransfer learning (PKEMTL) model for few-shot fault diagnosis of machinery under time-varying speeds. This method employed a metric-based metalearning framework to implement cross-domain learning, and COT was used to provide the prior knowledge for data augmentation.

The comparisons of artificial feature extraction-enabled and deep learning-enabled methods are listed in Table VII. Deep learning-enabled methods can learn the features directly from the collected signals or preprocessing signals and, thus, decrease the need for human labor and expert knowledge. However, compared with the research on fault recognition under constant speeds, there are far fewer investigations on time-varying speeds, and the recognition rates need further improvement. In addition, signals under time-varying speeds exhibit strong nonstationary characteristics and variabilities, which adds the difficulties in capturing useful features for fault recognition. Therefore, how to construct a diagnosis model with limited data and improve model generalization should be given more attention.

V. Research Prospect

Although much progress has been made in the fault diagnosis of rotating machinery under time-varying speeds, there is still a large potential for improvement and optimization, especially for actual applications. Accordingly, some research prospects are suggested in the following.

A. More Adaptive IF Estimation Method

Much attention has been given to IF estimation for TOT and generalized demodulation, but the target IF usually needs to be selected manually before extraction. After obtaining the IF, the IRF is calculated according to the known proportional relationship. Although spectrum smearing can be avoided according to one arbitrary IF proportional to the rotating frequency, different IFs will result in different spectra. As a result, it is necessary to pay more attention to adaptive IF extraction to facilitate actual applications. Incorporating the prior knowledge on the physical systems and probability knowledge into the TFR- and phase demodulation-based IF estimation may provide us with a solution to realizing adaptive IF extraction so that the TOT and tacholess generalized demodulation can be extended to online fault recognition.

B. Bearing Fault Extraction of Complex Machinery

Most spectrum analysis methods for bearing fault diagnosis focus on machinery with a simple structure. In real applications, bearings are usually mounted in more complex machinery, such as planetary gearboxes. The weak bearing fault feature is usually overwhelmed by interference components. In addition, time-varying speeds will cause more complex modulation characteristics and further add difficulties for fault detection. Therefore, weak bearing fault feature extraction from complex machinery under time-varying speeds is highly needed.

C. Adaptive PPTFA Methods

PPTFA methods have many advantages, such as high resolution, and are even free from interference components, but good TFRs are always generated by various postprocessing methods combined with manual visual observation of the traditional TFRs, which means that, for common engineers, it is difficult to implement. As such, research on more automatic multicomponent IF extraction methods may help to improve the adaptability of PPTFA methods. Rather than improving the time–frequency resolution by the algorithm itself, the unique modulation characteristics of rotating machinery, such as the proportional relationship of different frequency components, may be helpful. For example, if the information of IRF is embedded into the TFA algorithms, some parameters of bases can be determined with the IRF as prior knowledge.

D. Health Indicator Construction for Time-Varying Speed Condition

Health indicator plays a vital role in fault detection, degradation assessment, and prognosis. Various health indicators, such as root mean square (rms) and kurtosis, have been constructed and proved to be effective for the stationary conditions, as reviewed in [38] and [39], but they are not applicable for time-varying conditions, as shown in Fig. 11. To the best of our knowledge, few publications focus on the time-varying

TABLE VII
LIST OF COMPARISONS OF DIFFERENT INTELLIGENT METHODS

Methods		Advantages	Disadvantages
Artificial feature extraction-enabled methods		The methods are simple and own high computation efficiency. The extracted features have clear physical meanings.	Prior knowledge is needed, which makes them rely on expert knowledge. These methods can not mine deeper distinguishing features, especially from the strong nonstationary signals under time-varying speeds, so the recognition rates are usually lower than deep learning methods.
Deep learning-enabled methods	Signal preprocessing-based methods	These methods usually include signal processing methods and common deep learning models, so they are relatively simple, and are easily implemented. Only simple signal processing methods are utilized and the results are fed into deep learning models, which reduces the dependence on expert knowledge and enables these methods to learn deeper features.	Although signal processing methods can reduce the effect of time-varying speeds on the signals, the effect can not be removed completely (e.g., the most common method order tracking only recovers the periodicity, and the effect of speed on the amplitude still exists). For some methods, such as order tracking or generalized demodulation, the rotating frequency is often obtained by tachometer/encoder because it is difficult to extract one IF from a large number of samples to train the models, so the additional hardware is needed.
	End-to-end deep learning methods	These methods do not rely on prior knowledge and expert experience. These methods can mine deeper features adaptively, and a higher accuracy can usually be obtained.	The models are usually complex and their applications need high time cost. The features extracted by such deep models lack interpretability, so their generalization to the interference factors such as installation, should be further tested.

speeds. Although the most popular resample operation can restore the periodicity of signals, the effect on amplitudes of fault shocks is not removed. In addition, the resample operation will cause a variance in resonance frequency. It is suggested that more attention should be paid to constructing health indicators that are insensitive to speed variations to achieve health condition monitoring based on a simple index more effectively in real-time-varying speed conditions.

E. Deep Speed-Irrelevant Diagnosis Models

Compared with artificial feature extraction-enabled methods, deep learning-enabled methods can better take advantage of massive historical data and apply it to machinery health conditions, which is vital for the implementation of smart manufacturing. However, there are still few relevant studies on time-varying speeds, and the recognition accuracy needs further improvement to meet the requirements of actual industrial applications. Therefore, deep speed-irrelevant diagnosis models may be a very interesting and meaningful research direction. CNN is one popular method in deep learning-based fault diagnosis methods under time-varying methods. Nowadays, the transformer has gradually received more attention and has become popular [205], [206]. It has demonstrated great potential in global information mining. The amplitudes of fault shocks are affected greatly by rotating speeds, but the AM characteristics of vibration signals caused by different faults that exhibit for a long time will be quite different. Theoretically, the transformer may be suitable for the fault diagnosis of machinery under time-varying rotating speeds.

F. Multisensory Models

The collected signals under time-varying speeds exhibit strong nonstationary characteristics and variability; compared with those under constant speeds, much more data are required to optimize the diagnosis models. However, a large volume of effective data is not always available in practical applications. Therefore, it is necessary and effective to develop multisensory diagnosis models for fault diagnosis under time-varying speeds. As a new emerging powerful network, graph neural network performs well in capturing the relationships among data by the nodes and edge weights [207], [208], so it could capture the interaction among sensors and, by combining domain adaptation technique, may provide good results in multisensory recognition models.

G. Model Generalization Ability

The diagnosis models proposed for both constant speeds and time-varying speeds are only tested in this way, in which the data used for training and testing are from the same dataset, i.e., for a health condition, the data used for training and testing are from the same mechanical part and the same installation. In real applications, the faulty mechanical parts are used to train the model, but the monitored part is typically newly installed. As Liu et al. [53] reported, the average accuracy of CNN in dealing with the bearing data under the joint effect of rotating speeds and installation factors is only about 50%. It is necessary to pay more attention to the investigation of model generalization to narrow the gap between theoretical research and real applications. Model interpretation helps us understand how the models make decisions [209], [210] and provides us with the potential to identify whether the decisions are made based on fault information or other interference factors.

VI. CONCLUSION

In this article, a comprehensive review of rotating machinery fault diagnosis under time-varying speeds is conducted. The relevant studies are divided into three categories, i.e., spectrum analysis-based methods, TFA methods, and intelligent fault diagnosis methods. The advantages and challenges of these three types of methods in actual applications are also discussed. Finally, we provided several open topics for future research. Despite the promising results reported thus far, there are still some limitations to extending those methods to some challenging applications. Accordingly, we will pay more attention to solving these challenges. We hope that this review can provide relevant researchers with a preliminary understanding of recently published works.

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