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Review

Vibration based condition monitoring and fault diagnosis of wind turbine planetary gearbox: A review

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ABSTRACT

As one of the most immensely growing renewable energies, the wind power industry also experiences a high failure rate and operation & maintenance cost. Therefore, the condition monitoring and fault diagnosis of a wind turbine (WT) generator set are highly needed. Among different components of a WT generator set, WT planetary gearbox plays a crucial role in transmission and leads to relatively higher failure rate and longer downtime. Towards this, a number of studies have been reported in both the academic journals and conference proceedings. This paper provides a systemic and pertinent state-of-art review on WT planetary gearbox condition monitoring techniques on the topics of fundamental analysis, signal processing, feature extraction, and fault detection. Moreover, a few valuable open issues are pointed out and potential research directions are suggested.

Contents

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1. Introduction

Facing the severe energy shortage and air pollution, the development of renewable energy is urgently needed. A statistic from the Organization for Economic Co-operation and Development shows that the annual capacity addition of renewable energy is much higher than traditional energy sources, such as coal and gas since 2000 [1]. Among current renewable energies, wind power is the fastest growing and reliable type [2] whose annual and cumulative installed capacity has experienced immense growth based on the statistic of the Global Wind Energy Council (GWEC) [3]. Not merely the absolute amount, but also the percentage of wind-generated electricity worldwide has continuous grew recently. Table 1 shows the statistics of the wind-generated electricity as percentage of national electric demand of international energy agency (IEA) wind member countries from 2010 to 2016 made by the IEA Wind Technology Collaboration Programme, from which we can see that the percentage of wind generation in the whole electric demand has increased from 2.3% to 5.2% in the past 7 years [4–10]. Another report made by the GWEC shows that the increment in wind generation was equal to almost half of global electricity growth in 2015, and the market forecasts that the wind energy cumulative gigawatts (GW) will be 82.9% higher than the one of 2015's GW by 2020 [3].

With the rapid development of wind power and the increase of WT unit number, the industry will also experience a high failure rate due to the corresponding harsh operational environment. Fig. 1 presents the statistics of WTs accidents which could be found and confirmed through press reports or official information from 1990 to 2016 obtained from some wind power farms [11].

It can be seen that there exist nearly 21 accidents per year from 1997 to 2001, and this number increased to 70 from 2002 to 2006, 135 from 2007 to 2011, and 164 from 2012 to 2016. A clear increasing trend can be revealed that the more turbines are built, the more incidents occur. In the meantime, the operation and maintenance (O&M) costs have become one of the most significant proportions of the wind farm investment based on various published sources [12–14]. It was reported that the O&M costs account for 10–15% of the total expenses of the generated electricity, and this number grew to 20–35% for the offshore WTs. Taking a 750 KW WT as an example, the O&M costs of might take up 25–30% of the overall energy generation cost [15] and 75–90% of the investment costs [15,16]. Therefore, it is necessary to perform condition monitoring and fault diagnosis of the WT.

Table 1
Statistics of IEA Wind Member Countries from 2010 to 2016.

Year	2010	2011	2012	2013	2014	2015	2016
Wind-generated electricity as percentage of national electric demand	2.3%	2.8%	3.3%	3.86%	4.1%	4.8%	5.2%

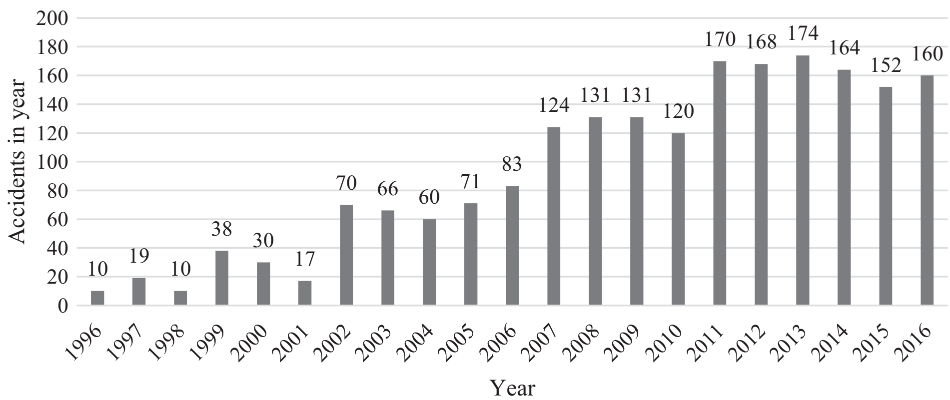

Fig. 1. Number of WT accidents from 1996 to 2016 [11].

A WT is a device which can convert the wind kinetic energy into electrical power. It generally contains complex components, including, blade, pitch system, hub, main shaft bearings, main shaft, gearbox, mechanical brake, generator, control and power electronics systems, hydraulic and cooling systems, yaw system and tower. Just because the WTs always operate under tough circumstances, a large number of techniques have been proposed to fulfill the condition monitoring and fault diagnosis of these WT components. To summarize these studies, reviews [17–22] surveyed the existing fault diagnosis techniques proposed for different kinds of WT components according to their analyzing objects, and review papers [23–25] grouped them concerning various measured signals, such as vibration, Acoustic Emission (AE), temperature and electricity. Recently, Elasha compared the effectiveness of vibration and AE signals in bearing fault detection in a planetary gearbox. It is proved that AE can lead to an earlier indication of fault [26]. Besides the reviews towards the different components with various signals, some articles also reviewed fault diagnosis techniques proposed for a single WT component, such as rolling bearing [27], blades [28–30], power plant [31] and gearbox [32].

Among the aforementioned different WT components, the gearbox is one of the most vulnerable parts. The WT gearbox condition monitoring and fault diagnosis is a significant problem in real application because both the WT gearbox induced failure rate and downtime are relatively higher. A survey indicated that the gearbox failures account for 12% of all failures reported (the second highest rate) in a study of Danish turbines in 2001 [33]. The corresponding percentage of the gearbox failures in another survey mentioned in [34] is 25%. Besides the higher failure rate, the WT gearbox faults will also lead to considerable downtime. Two statistical reports of land-based European WTs, the Wissenschaftliches Mess- und Evaluierungsprogramm (WMEP) database and failure statistics published by Landwirtschaftskammer Schleswig-Holstein (LMK), indicate that the WT gearbox induced downtime is the longer than the one caused by other components over 13 years [35,36].

Furthermore, the WT gearbox condition monitoring and fault detection are also challenging to proceed for its complex structure and the harsh operating environment. *For the structure*, a WT gearbox system always contains planetary gearboxes and fixed-axis gearboxes. Although the planetary gearbox component has the advantages of the large transmission ratio, strong load-bearing capacity, and lightweight, it will also make the corresponding fault diagnosis more challenging due to the complicated vibration response caused by multiple planet gears meshing simultaneously, complicated modulation effect, and the multiple vibration transmission paths. Meanwhile, the WT gearbox system is a speed-up gearbox which makes the rotational speed of the fixed gearbox larger than the one of the planetary gearbox and consequently the fixed gearbox stage induced vibration acting as a strong noise in the WT planetary gearbox fault diagnosis. *For the operating mode*, the corresponding rotational speed and load condition are both time-varying due to the uncertain wind speed and wind intensity in the real application. The factors mentioned above will increase the difficulty of the corresponding fault diagnosis.

In conclusion, the WT planetary gearbox is one of the most important and vulnerable components. It is quite challenging to perform corresponding condition monitoring and fault diagnosis in the meantime. Hence, it is necessary to perform a specific review of the existing techniques in the WT planetary gearbox fault diagnosis. However, there exist few publications which specially reviewed the corresponding fault diagnosis algorithms designed for WT planetary gearbox. Although some articles have summarized planetary gearbox fault diagnosis techniques, such as, Lei et al. have proposed a general review of planetary gearbox condition monitoring and fault diagnosis [37], and Samuel and Pines have summarized vibration-based diagnostic methods for helicopter transmission with a planetary gearbox [38], they are not specific for the WT planetary gearbox fault diagnosis. Recently, Salameh et al. have reviewed the WT planetary gearbox condition monitoring approaches based on lubrication analysis, AE condition monitoring, vibration analysis, machine current signature analysis and SCADA [32].

In this paper, the advanced research and developments on vibration-based fault diagnostic techniques of the WT planetary gearboxes are summarized. Compared with the existed review articles mentioned above, the current paper has a narrower scope of diagnosis media and object, which are the vibration signal and the WT planetary gearbox. For one thing, the vibration signal is one of the most accessible tools, for another, the WT planetary gearbox is a vulnerable component with longer maintenance time. Furthermore, this paper attempts to introduce the exist researches according to their usage in WT planetary gearbox fault diagnosis and provide a comprehensive reference for related researchers. The rest of the paper is structured as follows: Section 2 presents the fundamental analysis of the planetary gearbox vibration response, including the spectral complexity and transfer path effect, and the deduction of fault characteristic frequencies of different components. Section 3 provides a review of publications on signal processing for the fault information enhancement and operating mode effects elimination. Section 4 gives a summary of the feature extraction and fault diagnosis strategies. Section 5 forecasts the latest potential research directions in this area, and Section 6 draws the concluded remarks.

2. Fundamental analysis of the planetary gearbox vibration response

As described in the introduction, it is quite challenging to fulfill the WT planetary gearbox fault diagnosis due to the corresponding complex structure and harsh operating environment. Between these two factors, the former one plays a fundamental role, which makes the corresponding vibration response extremely complicated in both the time and frequency domains. From the early stage, researchers have done many studies on the basic characteristics of the vibration response of the gearboxes, which have laid a solid foundation for different kinds of signal processing algorithms and the final fault diagnostics strategy on the WT planetary gearbox. In this section, brief summaries of the studies on the planetary gearbox vibration response recognition, containing the complexity analysis of the spectrum and how the time-varying vibration transfer path affect vibrational response, are separately given, and the researches of fault characteristic frequency deduction are then reviewed.

2.1. Basic analysis of the spectral complexity and transfer path effect

The complex structure of the WT planetary gearbox can be directly reflected on the complexity of the spectrum. Understanding the spectrum, especially the sideband pattern around the harmonics of the meshing frequency is of great importance for the WT planetary gearbox fault diagnostics. For this, several researchers have made a large amount of contribution on this sub-topic with the signal simulation and dynamic model.

The signal simulation model is a kind of mathematical models which can simulate the main characteristic features directly. Researchers can deduce the theoretical spectrum construction based on this kind of models. In early times, several researchers noticed that the spectrum of the planetary gearbox vibration response is different from the one of fixed – axis gearbox with asymmetric sidebands around the meshing frequency. This abnormal phenomenon has attracted much attention. At very first, McFadden and Smith [39] observed that the sidebands around the tooth meshing frequency are not symmetrical and the prominent spectral peak is generally the sideband rather than the meshing frequency and gave the explanation based on a model of the vibration transmission It is stated that the asymmetry is caused by the fixed sensor and rotating carrier, not a substantive feature. Based on the same model, McNames [40] analyzed and explained the asymmetrical phenomenon through the continuous-time Fourier transform, which can forecast the relative amplitudes of the dominant peaks around the meshing frequency and its harmonics.

Similarly, Mosher [41] analyzed the corresponding vibration spectra with a kinematic model for fault detection. The frequencies with higher amplitudes around the harmonics of meshing frequency can be predicted. It should be noted that these researches are mainly to explain the underlying reasons for the asymmetric sidebands and the corresponding distribution pattern. The constructed model is relatively simple, which cannot reflect the real situation.

To consider the real situations comprehensively, Inalpolat and Karhraman (2009) built a simplified mathematical model to explain the mechanisms of planetary gear sets modulation sidebands. The proposed model is more general for different planet spacing and meshing phasing conditions. The planetary gear set is classified into five distinct groups based on their sideband patterns [42]. A similar study proposed by Vicuña [43] divided the planetary gearboxes into four types according to the spectral structure. Inalpolat and Karhraman (2010) predicted the modulated sidebands pattern considering the manufacturing errors using a dynamic model [44]. Luo et al. [45] explained the amplitude modulation of sequentially phased WT planetary gears with a mathematical method. Although these models can predict the spectrum more accurately, they do not consider the fault condition.

Different from the signal simulation model, a dynamic model is much more similar to the real vibration response. More accurate features can be obtained from this kind of model. For example, Karray et al. [46] built a torsional model to analyze the modulation sidebands of the planetary gear set. Liu et al. (2016) built a two-dimensional lumped-parameter dynamic model of a planetary gear set considering two transfer paths (inside path and casing path) [47]. Parra and Vicuña (2017) separately built a phenomenological model and lumped-parameter model to study the frequency characteristic of planetary gearbox vibrations under health and fault conditions. Moreover, a particular function is proposed to decompose the lumped-parameter model based simulated signal to the one with fixed reference[48]. Liu et al. (2018) developed a resultant vibration signal model of a single-stage planetary gear train considering the effects of the transmission path and the direction variation of the excitation source [49].

Recently, several researchers have focused their attention on how the time-varying vibration transfer paths affect the corresponding spectrum. Towards this problem, Vicuña (2012) distinguished the external meshing processes from the internal meshing processes. It stated that the former one could influence all the spectral components, the later can only affect the gear meshing frequency and it's harmonic [43]. Lei et al. (2016) built a phenomenological model of planetary gearboxes considering all the six possible transfer paths and the planet gear angular shift [50]. He et al. (2017) developed a mathematical model to analyze the healthy planetary gear train response considering the meshing vibrations of the planet–ring and planet–sun gear pairs, the time-varying transmission path and meshing force direction [51].

2.2. Fault characteristic frequency deduction

Fault characteristic frequency is a widely useful fault characterizing feature in rotating machine fault diagnosis because the fault induced features repeat themselves periodical as the rotational frequency is a constant value. As for the gearbox, the meshing frequency and its harmonic, together with the sideband around them are of great importance in the corresponding fault diagnosis [52]. With the studies on the spectrum complexity of the planetary gearbox summarized in Section 2.1 as the foundation, the corresponding fault characteristic frequencies are deduced in some studies.

Feng and Zuo (2012) constructed the mathematical models for fault diagnosis of planetary gearboxes, considering the amplitude modulation, and frequency modulation (AMFM) effects result from gear fault and different transfer paths. The characteristic frequencies of different faulty gear (planet gear, ring gear, and sun gear) under localized and distributed damage were also deduced for faults detection and location [53].

Liu et al. (2014) analyzed the vibration spectrum of equally spaced planetary gear system under healthy condition obtained from a fixed sensor mounted on the annulus, considering both the gear meshes between planets and the annulus

Table 2
The deduced fault characteristic frequencies of different components of the planetary gearbox and the spectral lines distribution around the meshing frequency or the resonance frequency [53,57].

	FCF value	Sidebands
Sun gear	$\frac{f_m}{Z_s}N_p$	$f_m \pm kf_s^{(r)} \pm lf_s$
Ring gear	$\frac{f_m}{Z_r}N_p$	$f_m \pm kf_r$
Planet gear	$\frac{f_m}{Z_p}$	$f_m \pm kf_c \pm lf_p$
Planet bearing	$f_o = \frac{n}{2}(1 - \frac{d}{D}\cos\lambda)\frac{f_s^{(r)}(Z_r - Z_p)Z_s}{(Z_s + Z_r)Z_p}$ $f_i = \frac{n}{2}(1 + \frac{d}{D}\cos\lambda)\frac{f_s^{(r)}(Z_r - Z_p)Z_s}{(Z_s + Z_r)Z_p}$ $f_b = \frac{D}{d}\left[1 - (\frac{d}{D}\cos\lambda)^2\right]\frac{f_s^{(r)}(Z_r - Z_p)Z_s}{(Z_s + Z_r)Z_p}$	outer race fault : $f_n \pm mf_o, f_n \pm f_o^{(s)} \pm mf_o, f_n \pm f_c \pm mf_o, f_n \pm f_o^{(s)} \pm f_c \pm mf_o$ inner race fault : $f_n \pm mf_i, f_n \pm f_c \pm mf_i$ rolling element fault : $f_n \pm mf_b, f_n \pm f_{cg} \pm mf_o, f_n \pm f_c \pm mf_b, f_n \pm f_{cg} \pm f_c \pm mf_b$

Note: Z_r: ring gear tooth number, Z_p: planet gear tooth number, Z_s: sun gear tooth number, N_p: planet gear number, n: planet bearing rolling element number, d: planet bearing rolling element diameter pitch diameter, D: planet bearing, f_m: meshing frequency, f_s: sun gear fault characteristic frequency, f_r: ring gear fault characteristic frequency, f_c: carrier rotational frequency, f_p: planet gear fault characteristic frequency, f_o: planet bearing outer race fault characteristic frequency, f_i: planet bearing inner race fault characteristic frequency, f_b: planet bearing rolling element fault characteristic frequency, f_{cg}: planet bearing cage spinning frequency, m: integer value, k: integer value, l: integer value, f_n: resonance frequency induced by localized rolling bearing fault.

and the ones between planets and the sun gear. The localized faults induced additional frequency component were predicted at the same time [54].

Gui et al. (2014) found that the sidebands pattern around the meshing frequency will become more complex if the manufacturing error is considered. The corresponding fault characteristic frequencies considering the manufacturing error were also deduced [55].

Planet bearing is also an easily damaged component in a planetary gear set although the related studies are much less than the ones on gear fault case. Several latest studies investigated the corresponding fault characteristic frequencies with theoretical analysis [56], phenomenological [57] and dynamic model [58].

In conclusion, Table 2 summarizes the equations of fault characteristic frequencies of different localized faults, including a sun gear, ring gear, planet gear, and planet gear bearing, and the distribution rules of these fault characteristic frequencies in the corresponding spectrum.

It should be mentioned that this review paper only summarize the fault diagnosis related studies. As for the dynamic modelling related studies, Liang et al. [59,60] have given several comprehensive discussion.

3. Fault information enhancement and operation pattern effect elimination

Considering the intricate structure, complex operating modes, and the harsh working environment of a WT planetary gearbox, it is difficult to realize the final fault diagnosis merely using the raw vibration signal-based features. Signal processing has become an unavoidable step in machinery fault diagnosis, especially for the object with a complex structure like the WT planetary gearbox. It is worth to mention that most of the reviewed studies aim to make the fault-related vibration or feature more clearly by removing the background noise, the unrelated vibration part or eliminating the side effect caused by the time-varying rotational speed or load. Hence, the related studies are summarized according to their function in the planetary gearbox fault detection. In specific, the existing signal processing algorithms for the WT planetary gearbox diagnosis are mainly reviewed in two categories. One is designed for enhancing the fault-related information, and the other is developed to deal with the problems caused by the operating modes, including time-varying rotational speed and load which are typical for the WT planetary gearboxes.

3.1. Algorithms for fault information enhancement

As mentioned above, it is hard to directly measure vibration signal with evident WT planetary gearbox fault features because of the intricate structures. The accelerometer mounted on the outer case generally measures vibration signal containing several different sources, some of which will act as the noise against the fault diagnosis. Therefore, it is necessary to perform fault information enhancement at first for more representative feature extraction and accurate fault diagnostics. In here, the related studies are summarized in three main parts, which are the vibration separation-based algorithms, amplitude, and frequency demodulation-based algorithms, and the advanced signal processing-based algorithms, respectively. It should be mentioned that not all of the reviewed algorithms are used for the real WT planetary gearboxes. The reason for summarizing these studies lies in that these algorithms have the potential to solve the difficult issues in the WT planetary gearbox fault detection.

3.1.1. Vibration separation based algorithm

Vibration separation-based algorithms are proposed to deal with the complex structure of the planetary gearbox by eliminating the unrelated vibration from other components through the time synchronized average (TSA) algorithm and its improved versions. Hence, it is necessary to review the related studies.

The original version was developed from the algorithm of the TSA, which is one of the earliest and most useful signal processing algorithms in periodic components extraction from additive noises, such as isolating the gear fault-related features from the vibration of the gearbox with complex structure [61–66]. As for the planetary gear, however, several planet gears mesh with the sun gear and ring gear simultaneously at different positions, which will make the corresponding signal averaging algorithm difficult. For this, improved TSA algorithms with the help of vibration separation based methods have been proposed to proceed reliable planetary gearbox fault diagnosis since the early 1990s [67].

As the fundamental studies, McFadden [67,68] proposed techniques to proceed the TSA algorithm on the individual planet gear and the sun gear by sampling the vibration signals with a window function as a particular planet passing through the transducer mounted on the case, then storing and mapping the samples to form the vibration signals of the sun gear or the planet gear. In addition, several scholars attempted to improve the performance this windowing and mapping based strategy: some studies [69–71] focus on investigating the techniques to determine the proper windows positions and others [72,73] tried to find the best window type and window length for the sampling. This kind of signal separation based algorithms can enhance the fault features of the gear of interest and reduce the other gears interference.

However, this algorithm still has some limitations such as geometry constraints, computation efficiency, the robustness of the sensor and the noise synchronized with the carrier. As such, Samuel and Pines (2000) expanded the original TSA algorithm with multi-sensors for planet gear faults detection. For the final damage location, the continues wavelet transform was used [74].

Liang et al. (2016) developed a new algorithm consisting of windowing and mapping steps for planet gear tooth crack fault detection. This study can decompose the planetary gearbox vibration signal into the tooth level and extract the symptoms generated by a single cracked tooth. As the key step of the proposed algorithm, the first window position was determined with a newly designed numerical method [75].

Ha et al. (2016) presented autocorrelation-based time synchronous averaging for a long period of stationary operation and with window modification [76].

In [77], Jae et al. (2016) summarized the main drawbacks of the vibration separation based TSA algorithms and employed the spectral averaging algorithm to analysis the vibration signals measured from the WT planetary gearbox. The proposed algorithm can separate the fault on sun gear, planetary gear and ring gear from each other.

D'Elia et al. (2017) proposed two alternative methods based on power flow and statistical parameter to identify the precise angular positions of all the planet gears regarding the transducer [78].

Recently, Wang et al. (2017) expanded the windowed synchronous averaging algorithm into speed fluctuation condition with the help of the computed order tracking [79]. Ha et al. (2018) expanded the windowed TSA method and proposed a health data map based algorithm which can isolate the fault visually without discarding any information and requiring preliminary knowledge [80].

In this subsection, we have reviewed the studies on a vibration separation based algorithm based WT planetary gearbox fault diagnosis. It can be seen that this type of algorithms has developed a lot comparing with the original version. However, accurate speed information and meshing details will determine the corresponding effectiveness to a great extent, which makes this kind of algorithms hard to apply in real engineering. Therefore, the vibration separation based algorithms are not recommended for the WT planetary gearbox fault diagnosis if the sensors which can acquire the details of meshing and speed information are not available. It is worth to mention that, the vibration separation based algorithms are not suitable for the planet bearing fault detection.

3.1.2. Amplitude and frequency demodulation-based algorithm

Identifying the increment in the magnitude and number of the fault characteristic sidebands around the meshing frequency and its harmonics in the corresponding spectrum is another strategy which will help to realize gearbox fault diagnosis [52]. For the planetary gearbox, however, the spectral components around the meshing frequency and its harmonics are quite complex due to the AMFM caused by multiple reasons, including local damages, planet gear passing effect, and time-varying vibration transfer path. Therefore, it is not easy to directly identifying the fault characteristic sidebands just by the raw spectrum.

Towards this issue, the demodulation based fault diagnosis strategy provided an alternative way because the fault characteristic frequency can be highlighted in the envelope spectrum with fewer spectral interruption. To realize this strategy, a signal decomposition step is always proceeded at first, which can decompose the raw vibration signal containing multi-sources into the mono-component sub-signals with fault information. Then, the demodulation algorithms can be then applied to highlight the fault characteristics. This subsection summarizes the related studies according to the decomposition algorithms.

Antoniadou et al. (2015) used the Empirical Mode Decomposition (EMD) to decompose the vibration signal of a WT gearbox under varying load condition, and the Hilbert transform (HT) and the Teager–Kaiser energy operator (TKEO), combined with an energy separation algorithm were separated used to realize the demodulation. It is proved that the TKEO approach can result in better instantaneous spectral characteristics. The proposed algorithms have been used to analyze three different datasets from the real WT gearbox data with damaged gear [81].

Feng et al. (2012) used Ensemble empirical mode decomposition (EEMD) to decompose the raw signal into several Intrinsic Mode Functions (IMFs) which satisfy the mono-component requirement. And the energy separation algorithm with the Teager energy operator was employed to estimate the amplitude and frequency demodulation. Vibration signals measured from the planetary gearbox test rig with worn gear and chipped tooth faults under two-speed conditions are used to testify the effectiveness of the proposed algorithm [82].

The local mean decomposition (LMD) algorithm [83,84] (2012, 2013) was used in decomposing the raw planetary gearbox vibration into a set of product functions (PFs). Comparing with the EMD based decomposition, the corresponding PFs retain more of the frequency and amplitude variations. This characteristic can result in better-demodulated results. As for the demodulation step, [83] used the amplitude and frequency demodulation together to detect the seeded planet pitting faults with three different levels and wear gear fault developed naturally, and [84] detected the seeded gear local crack fault form a real WT planetary gearbox using the first PF and its spectrum.

Wang et al. (2014) decomposed the measures one channel WT signal into several IMFs with the EEMD algorithm, and the independent component analysis algorithm was then employed to separate fault bearing signal from the gear meshing signals. A real WT planetary gearbox signal with a localized bearing fault from the National Renewable Energy Laboratory (NREL) is used to testify the effectiveness of the algorithm [85].

Recently, Feng et al. [86] introduced the intrinsic time-scale decomposition (ITD) algorithm to WT planetary gearbox signal analysis, because it has the advantages of better computation efficiency, suitable for both time-varying and multi-component signals, and good capability of suppressing mode mixing. Seeded local faults on different components of the planetary gearbox test rig under different load conditions are used to test the accuracy of the ITD based algorithm.

In 2017, Feng et al. exploited the variational mode decomposition (VMD) for the following amplitude and frequency demodulation analysis since its robustness against the noise interferences with the planetary gearbox test rig containing localized faults on the different position as the test objects [87].

Literatures summarized in this subsection seek several feasible strategies to highlight the planet gear related vibration from the multi-components vibration employing different kinds of decomposition algorithms. It can be concluded that the decomposition based algorithms summarized above are proposed by adaptive decomposition algorithms, such as EMD, EEMD, and VMD. The decomposed components are generated adaptively, and there exist no quantitative criteria to determine which component are the best one containing most of the fault information. In addition, researchers also sought other techniques to highlight the planetary signal from the multi-component signal. Wang et al. (2017) proposed a meshing resonance based filtering algorithm for the WT ring gear fault diagnosis. In specific, the meshing index and MRgram were developed to highlight the planetary gearbox vibration from the strong background. Then the ring gear fault characteristic frequency and its harmonics could be recognized from the envelope spectrum with less interruption [88].

In conclusion, the amplitude and frequency demodulation-based algorithms are listed in Table 3 with their respective decomposition algorithms, demodulation algorithms and the fault types being detected. A common disadvantage of the decomposition based algorithms is that they are not suitable for analyzing the signal under the time-varying rotational speed.

3.1.3. Advanced signal processing based algorithm

Applying advanced signal processing methods is a popular strategy in performing machinery fault diagnosis. Towards the WT planetary gearbox fault detection, following five type algorithms are summarized in this section, which are, spectral kurtosis, wavelet, stochastic resonance, sparse representation, and other signal processing algorithm, respectively.

Table 3
List of the references on the amplitude and frequency demodulation-based algorithms with specific decomposition algorithms, demodulation algorithms and the fault types being detected.

Ref	Decomposition algorithm	Demodulation algorithm	Fault types
Antoniadou [81]	EMD	HT & TKEO	Real gear tooth fault on WT
Feng [82]	EEMD	Teager energy operator	Seeded gear worn and chipped tooth fault on test rig
Feng [83]	LMD	HT and energy separation	Seeded gear pitting faults with different levels & real gear wear fault on test rig
Liu [84]	LMD	Envelope analysis	Real gear crack fault on WT
Wang [85]	EEMD	HT	Real bearing localized fault on WT
Feng [86]	ITD	Single wave based method	Seeded gear localized faults on different components of test rig
Feng [87]	VMD	Amplitude envelope and instantaneous frequency	Seeded gear localized faults on different components of test rig
Wang [88]	Meshing index based multirate filter-bank	HT	Seeded ring gear localized faults on different components of test rig

(1) *Kurtosis based algorithm*

Spectral Kurtosis (SK) based algorithm [89] is one of the popular techniques for vibration signal analysis and has been proved to be able to highlight local fault induced impulses from the noise background [90] by identifying the corresponding resonance frequency band. For example, Barszcz et al. (2009) employed the SK algorithm to highlight the WT planetary gear fault induced impulses from the noisy background. The algorithm can detect the gear fault in a relatively early stage [66]. Considering the complexity of the vibration signal measured from the WT planetary gearbox, several studies combined the SK based algorithm with other methods. For example, Fan and Li (2015) utilized the internal vibration sensor mounted on the planetary carrier to measure the weak signal generated by planetary bearings. The traditional rolling bearing fault diagnosis methods, including Cepstrum whitening, minimum entropy deconvolution (MED), SK and envelope analysis, were employed to analyze the measured signals [91]. However, it is inconvenient to mount the internal sensor in the real WT planetary gearbox. Wang et al. (2016) proposed an SK-based algorithm to detect the planet bearing fault under strong background noise. In particular, the ratio between the kurtograms of the vibration signals under faulty and healthy conditions called SKRgram was constructed to locate the planet bearing fault induced resonance frequency band [56]. The corresponding shortage is the need of health baseline which is not always available. Recently, Wang et al. (2018) combined the kurtosis and meshing modulation phenomenon to construct a meshing frequency modulation (MFM) index-based kurtogram which can determine the planet bearing fault induced resonance frequency band without the help of health baseline [92].

The kurtosis based algorithms are recommended to be used for planet bearing fault detection because of its advantage of analyzing fault induced impulsive components. Comparing with the gear fault diagnosis, the bearing fault, especially the planet bearing fault in a WT planetary gearbox is more difficult to detect.

(2) *Wavelet-based filtering algorithm*

Wavelet-based algorithms are usually employed for noise elimination as a preprocessing step before realizing the final fault diagnosis [93], which is also applied to WT fault diagnosis.

In 2010, Tang [94] made use of the continuous wavelet transformation (CWT) to filter noise in WT fault diagnosis.

To extract the faults induced impulses, Jiang et al. (2011) proposed a de-noising algorithm based on an adaptive Morlet wavelet and singular value decomposition (SVD). It was proved that the impulsive feature extracted by the proposed algorithm is better than the ones obtained by traditional wavelet based de-noising methods, such as Donoho's and Morlet wavelet based de-noising methods [95].

Sun et al. (2014) proposed the GHM multi-wavelet transform as the de-noising algorithm, with which the WT bearing fault induced impulses can be highlighted from the noise back ground [96].

Hu et al. (2015) used the wavelet package transform (WPT) and the ensemble intrinsic time-scale decomposition (EITD) algorithm together to extract the fault feature. It was proved that the proposed algorithm could identify the working conditions and fault types of WT gearbox [97].

Ma et al. (2017) noticed a particular characteristic of the wide frequency range which happens on the gearboxes installed in industrial WTs and made use of the advantage of the multi-scale enveloping spectrogram to realize the multiple faults diagnosis in a WT gearbox [98].

Based on the Wavelet transform based algorithms summarized above, the Wavelet transform can be considered as an effective de-noising method, which can make the weak fault-related features more evident in the filtered results. It should be mentioned that the Wavelet transform based methods can only be considered as the pre-processing tool. Other algorithms are expected to fulfill the fault detection based on the filtered results.

(3) *Stochastic resonance based algorithm*

Stochastic resonance (SR) [99] is a widely used weak feature extraction algorithm. It can enhance the weak characteristic from a signal with a low signal-to-noise ratio by utilizing noise components not eliminating them. As for the planetary gear fault-related impulses extraction, several researchers have utilized the SR-based algorithms as follows:

Li et al. (2013) proposed a new noise-controlled second-order enhanced SR method to meet the characteristics of the WT vibration signal. The corresponding innovations were the smoother output waveform and capability of extract periodic signal with both low frequency and high frequency [100]. In 2016, a new adaptive cascaded stochastic resonance method was proposed for the gear fault induced impulses extraction [101].

Lei et al. (2013) proposed an adaptive stochastic resonance (ASR) method with the ant colony algorithm to optimize the SR parameters. The proposed algorithm can overcome the disadvantage of SR subjectively selecting parameters and highlight the weak characteristics. The proposed algorithm was used to analyze planetary gearbox signals with the fault of chipped tooth and missing tooth in sun gear [102].

Hu and Li (2016) introduced the dual-tree complex wavelet transform into the multiscale noise tuning stochastic resonance instead of discrete wavelet transform. The newly proposed algorithm is less time-consuming [103]. With the proposing algorithm, the looseness fault of the shaft coupling connected in WT drivetrains can be detected.

As mentioned above, the SR based algorithms are good at extraction weak impulsive features. It cannot be used for detecting the sidebands features result from the gear fault.

(4) *Sparse representation based algorithm*

Sparse representation gradually begins to be widely used in fault diagnosis area recently. Through carefully selecting the optimal dictionary, the fault features buried under strong noise interruption can be extracted.

As for the WT planetary gearbox fault diagnosis, the gear characteristic frequencies of interest were enhanced from the background noise interferences employing the iterative atomic decomposition thresholding method, in which, the Fourier dictionary is selected to match the harmonic waves in the frequency domain [104]. Both the experimental data with sun gear fault and on-site WT signal with faulty planet gear are used to test the corresponding effectiveness.

Du et al. (2015) utilized the union of the redundant dictionary for the WT gear fault diagnosis. With the redundant dictionary, multiple faults can be detected simultaneously. The superiority of the proposed method towards traditional kurtogram based algorithm has been proved with the field tests of the WT planetary gearbox with spalls fault on the gear wheel [105].

To analyze the complex signal measured on the planetary gearbox, Feng et al. (2016) employed the shift invariant K-means singular value decomposition (SI-K-SVD) dictionary learning method to meet its time shift invariant feature and realized chipping and wear sun gear fault detection using the experimental test [106].

Qin et al. (2018) proposed an automatic sparse representation method to identify the transient features with an improved kurtosis index in determining the sparse parameters and an iterative thresholding algorithm in solving the optimization problem [107]. The WT gearbox with the output sun gear pitting fault can be detected using the proposed algorithm.

Comparing with other advanced signal processing algorithms, the sparse representing algorithm can describe the signal using their intrinsic characteristic, which makes it a useful tool for the fault feature representation in a concise way. However, the adaptive construction of the dictionary for the WT planetary gearbox is still an open issue.

(5) *Other signal processing algorithm*

Except the advanced signal processing algorithms summarized above, several other algorithms, which are difficult to be classified into a specific class, are reviewed in this part.

Tang et al. (2010) proposed a new Wigner-Ville distribution (WVD) based time-frequency analysis technique on realizing the WT fault diagnosis. With the help of auto terms window (ATW) function, it can lead to a high time-frequency resolution without the cross terms interruption [94]. With the WVD based ATW spectrum, the root gear tooth crack fault defect induced fault feature can be clearly detected.

Liu and Dhupia (2014) revised a voice signal processing algorithm called dynamic time warping (DTW) algorithm to analyze the faulty planetary gear vibration. In detail, the revised algorithm called Fast DTW and the Correlated kurtosis were used together to extract the seeded ring gear localized fault-induced periodic impulses with a test rig [108].

Tian and Qian (2015) utilized two kinds of adaptive filter algorithms to enhance the planetary gearbox fault features. In details, the self-adaptive Noise Cancellation algorithm was used to eliminate the white noise. The kernel least mean square (KLMS) algorithm was employed to suppress the nonlinear interference with two accelerometers. The feature of the planetary gear surface wear fault can be enhanced under different load condition [109].

Li et al. (2015) employed adaptive multi-scale morphological gradient filter to enhance planetary gearbox fault features with the help of EMD. Seeded gear faults on different components (Sun, ring, planet gear) of a planetary gearbox test rig are used to testify the effectiveness of the proposed algorithm [110].

Lei et al. (2015) decomposed the planetary gearbox signal using the adaptive Ensemble Empirical Mode Decomposition, and the gear tooth root crack fault induced impulses could be highlighted in one IMF [111].

The survey of the publications, which utilized advanced signal processing algorithms in fault diagnosis of the WT planetary gearbox, has been presented in this subsection. Table 4 presents these advanced signal processing based algorithms with specific purpose and the fault types being detected. By reviewing these publications, we find that most of the fault diagnosis algorithms are proposed by SK, wavelet transform, and SR, which have been proved effective in general rotational machinery fault diagnosis with acceptable performance. However, the algorithms specially designed for the WT planetary gearbox fault detection are the minority, which makes the sparse representation-based algorithms a new development direction. The corresponding dictionaries are always specially designed for the vibration signals themselves.

Furthermore, there is another issue worth discussing is that the difference between the gear fault and bearing fault makes the corresponding diagnostics strategies different too. As for the gear fault, the primary fault information concentrates in the meshing frequency and its sidebands. As for the bearing fault, the primary fault information concentrated in the fault induced resonance frequency bands. Among the algorithms summarized in Section 3.1, the vibration separation based algorithms and the amplitude and frequency demodulation based algorithms are not suitable for the bearing fault detection. In specific, the vibration separation based algorithm is especially proposed for the gear fault detection from the very beginning. Most of the amplitude and frequency demodulation based algorithms focus on the modulation phenomenon around the meshing frequency, which makes this kind more suitable for the gear fault detection methods. As for the advanced signal processing algorithms, most of the other algorithms are proposed for the gear fault detection.

Table 4
List of the references on the advanced signal processing based algorithms with specific purpose and the fault types being detected.

Ref.	Algorithm	Purpose	Fault type
Tomasz and Robert [66]	SK	Detect the peak fault symptom	Real gear crack fault on WT
Fan [91]	Cepstrum whitening & MED & SK	Detect the impulsive component	Seeded bearing localized fault on test rig
Wang [56]	SKRgram based technique	Detect the impulsive component	Seeded bearing localized fault on test rig
Wang [92]	MFM index-based kurtogram	Detect the impulsive component	Seeded bearing localized fault on test rig
Tang [94]	CWT	De-noising	Real gear tooth root crack on WT
Jiang [95]	Adaptive Morlet wavelet and SVD	De-noising	Real gear tooth crack on WT
Sun [96]	GHM multi-wavelet transform	De-noising	Real bearing fault on WT
Hu [97]	WPT	De-noising	Seeded gear crack fault on WT
Ma [98]	Multi-scale enveloping spectrogram using the CWT	Detect weak faults	Real intermediate stage gearbox fault on WT
Li [100]	Noise-controlled second-order enhanced stochastic resonance method	Amplify the weak fault	Real shaft coupling connection looseness fault on WT
Li [101]	Adaptive cascaded stochastic resonance method	Enhance weak impact feature	Real gear crack for on WT
Lei [102]	ASR	Highlight weak fault characteristics	Seeded gear localized faults on test rig
Hu [103]	Multiscale noise tuning stochastic resonance	Extract weak signals under strong noise	Real shaft coupling looseness fault on WT
Feng [104]	Iterative atomic decomposition thresholding	enhance the gear characteristic frequencies of interest	Seeded gear localized faults on test rig & real gear fault on WT
Du [105]	Union redundant dictionary	Identify the sparse feature	Real gear spalls fault on WT
Feng [106]	SI-K-SVD dictionary learning method	Suppress noise and reveal the true vibration patterns	Seeded gear localized faults on test rig
Qin [107]	Automatic sparse representation method	Identify the transient features	Real gear pitting fault on WT
Tang [94]	ATW function based WVD	Obtain clear fault feature in TFR	Real gear tooth root crack on WT
Liu [108]	Fast DWT and the Correlated kurtosis	Extract gear fault induced impulses	Seeded gear localized faults on test rig
Tian [109]	Self-adaptive Noise Cancellation algorithm & KLMS algorithm	Eliminate the noise and enhance gear fault feature	planetary gear surface wear fault
Li [110]	EMD and adaptive multi-scale morphological gradient filter	Eliminate the noise and enhance gear fault feature	Seeded gear localized faults on test rig
Lei [111]	Adaptive Ensemble Empirical Mode Decomposition	Extract the gear fault feature related vibration	Seeded gear tooth root crack fault on test rig

3.2. Algorithms for eliminating the operating mode effects

As described in Section 1, two main obstacles, the complex structure, and harsh operating environment, will affect the WT planetary gearbox condition monitoring and fault diagnosis. Most of the studies reviewed in Section 3.1 are designed to deal with the first problem, and this section presents a brief summarization of the algorithms proposed for neutralizing the side effect caused by the specific operating mode of time-varying rotational speed and load.

3.2.1. Algorithms for the time-varying rotational speed

The WT planetary gearbox always works under time-varying speed because the corresponding wind speed varies a lot with time. As a consequence, the fault characteristic frequencies cannot be found at their theoretical values, which will strongly affect the corresponding fault diagnosis. To deal with this problem, two kinds of strategies, eliminating the corresponding side effect with the order tracking algorithm, or identifying the time-varying spectral components in time-frequency representation (TFR) with high resolution using advanced time-frequency analysis algorithms are commonly used.

Order tracking [112] is a widely used technique under time-varying rotational speed condition by resampling the original vibration signal at a constant angle increment which will convert the non-stationary time-domain signal into the stationary one in angular domain. It is widely used as a preprocessing step in fault diagnosis of rolling bearing and gearbox operating under time-varying rotational speed [113,114]. Followed part is intended to summarize the relevant studies of employing order tracking algorithm in WT planetary gearbox fault diagnosis.

He et al. (2016) proposed a novel order tracking method for the WT planetary gearbox to eliminate the effect result from the time-varying rotational frequency. In this algorithm, the discrete spectrum correction technique was used to reduce the estimation error of the instantaneous frequency trend [115]. The misalignment fault in the shaft of the fixed-shaft gear in a WT gearbox has been identified.

Jiang et al. (2016) proposed a new time-frequency ridge tracking method based on the ridge fusion and logarithm transform. The algorithm was used in planetary gearbox defect identification under large speed oscillation [116]. With the order spectrum, the fault on the inner race of one of the planet bearings can be detected.

Feng et al. (2016) used iterative generalized demodulation to analysis the WT planetary gearbox signal under non-stationary condition. It can lead to the order spectrum without a tachometer and the interpolation error caused by traditional order tracking [117]. With the envelope order spectrum, the sun gear wear and chipping fault can be detected by recognizing the fault characteristic orders.

Feng et al. (2017) combined two kinds of order tracking algorithm, namely the computed order tracking and the Vold-Kalman filter order tracking to extract the order(s) of interest and obtain a selected vibration, from which the time-domain statistics can indicate the gear localized faults [118].

Liu et al. (2017) proposed a dynamic time-warping algorithm based resampling algorithm to eliminate the side effect of the speed fluctuation by projecting the original time-scale to a new warped one without using a tachometer [119]. The localized gear fault can be detected through the order spectrum around the meshing order.

Wang et al. (2018) resolved the problem of WT planetary gearbox diagnosis under time-varying rotational frequency and shaft rotational frequency-unrelated interferences using a multiscale filtering reconstruction with the shaft rotating frequency estimated from the generator rotor current signals [120]. The artificially added gear crack fault and naturally generated bearing fault in a test rig are used to test the proposed algorithm.

It should be mentioned that the order tracking based algorithms cannot completely solve the problems introduced by the time-varying rotational speed. If the rotational speed varies in a broad range, the corresponding vibration magnitude will change significantly as a consequence. This kind of magnitude modulation effects cannot be removed using the order tracking based algorithm. Hence, it is recommended that the order tracking based algorithm should be used to analyze the data when the WT rotational speed does not change too much.

Another strategy is extracting the time-varying fault characteristic frequency from the fine TFR. Regarding this issue, researchers have provided the following investigation.

Feng et al. (2014) exploited the adaptive optimal kernel (AOK) time-frequency analysis to extract a time-varying characteristic of WT planetary gearbox under non-stationary condition because of its fine time-frequency resolution and cross-term free nature [121].

Feng et al. (2015) proposed a new method called iterative generalized synchrosqueezing transform which can lead to a fine time-frequency representation. It was used to detect the WT planetary gearbox faults under nonstationary condition [122].

Feng et al. (2016) combined the Vold-Kalman filter and higher order energy separation to fulfill the fault diagnosis of WT planetary gearbox under time-varying rotational frequency. In this study, the Vold-Kalman filter and the TFR based instantaneous frequency trajectories were used together to decompose the signal to mono-components, and the higher order energy separation was employed to estimate the accurate instantaneous frequency and the TFR with a fine resolution [123].

Chen et al. (2016) used iterative generalized time-frequency reassignment algorithm to enhance the time-frequency representation which can help to realize the WT planetary gearbox fault detection under nonstationary condition [124].

Chen et al. (2016) applied the Reassigned Wavelet Scalogram to analyze the vibration signal measured from WT planetary gearbox under nonstationary condition. Based on the corresponding scalogram, the local and distributed features can both be identified [125].

Guan et al. (2017) proposed a velocity synchrosqueezing transform (VST) to solve the planetary gearbox fault diagnosis under the time-varying speed with higher time-frequency resolution. The VST method is consists of three steps of angular resampling, synchrosqueezed transform and the time-frequency representation restoring [126].

Guo et al. (2017) employed the LMD and synchrosqueezing transform together to analyze non-stationary signals of WT gearbox under high noise [127].

Hu et al. (2018) extracted the instantaneous frequency from the TFR from the high-order synchrosqueezing transform based time-frequency representation [128].

Based on the TFR based algorithms summarized above, it can be concluded that the synchrosqueezing transform is widely employed for its advantage of improving the TFR resolution. However, this kind of algorithm is quite time-consuming, which makes it an off-line analysis tool. Besides this shortage, the effectiveness of the TFR based algorithm under the time-varying rotational speed is based on the appearance of the continuous sidebands ridge around the meshing frequency ridge in the TFR. However, the background noise always makes the sideband ridges difficult to extract even using the advanced TFR analysis tools. Recently, Feng [129] proposed an adaptive iterative generalized demodulation which can separate the background noise from the useful sideband ridges adaptive using the surrogate test technique.

Besides the above studies which attempt to solve the variable speed problems using the order tracking and the TFR-based algorithms, another important issue worth discussing is that the effect of speed variation on gear and bearing signal are different from each other [130].

At first, the speed variation condition will affect the vibration signals of the faulty gear and bearing in different frequency areas. As for the gear, which is usually considered as the deterministic component, the change of the rotational speed will affect the meshing harmonics components significantly but the local gear fault induced resonance frequency areas. The bearing fault induced vibration can be seen as a cyclostationary component. The increase of the rotational speed will make the energy of the localized bearing fault induced resonance components higher.

Then, the appearance of the gear and bearing faults under time-varying rotational speed are also different from each other. As for the gear, the corresponding fault feature usually acts as multi-spectrum containing not only the meshing frequency harmonics but also the sidebands around them. As for the bearing fault feature, it is always the single-spectrum containing the fault characteristic frequency and its harmonics. Hence, the gear fault feature acts as multiple time-frequency ridges which are very close to each other under the time-varying rotational speed. In comparison, the bearing fault related fault feature is relatively more straightforward.

According to these two differences, the TFR-based algorithm is more suitable for solving the gear fault detection under the time-varying condition, because the bearing fault induced resonance frequency band does not change with the rotational speed.

Aforementioned summary in this subsection describes two different strategies in dealing with time-varying rotational speed condition. The effectiveness of these two strategies highly relies on the measurement of accurate instantaneous rotational speed or the TFR with high resolution. However, the auxiliary speed sensor is not always available, and the high-resolution TFR-based algorithms are always time-consuming. Hence, the combination of these two strategies perhaps can provide a more efficient solution.

3.2.2. Algorithms for the complex load condition

Load fluctuation is another problem in the real application. However, there exists no efficient algorithm in eliminating the corresponding side effect as the order tracking algorithm does towards the time-varying rotational speed. To deal with this problem, algorithms proposed for the excavator planetary gearbox fault diagnosis [131] can give a reference.

Bartelmus et al. (2009) did fundamental research of analyzing the vibration signal of planetary gearbox under varying external load with the procedures of band-pass filtering, enveloping and envelope frequency analysis. Results showed that a planetary gearbox in fault condition is more susceptible to load than in normal condition [132].

To realize the fault diagnosis, Bartelmus et al. (2009) proposed a new feature which is suitable for varying load condition. In specific, the distribution of features as a function of instantaneous speed was employed to distinguish between the good and bad condition [133]. Also, two dynamic models of gearboxes operating under varying load condition were constructed [134].

Recently, Zimroz et al. (2014) proposed a load-susceptibility characteristic to realize condition monitoring of the WT bearing. In particular, the distributions of peak-to-peak and RMS values as a function of the generator power were used [135].

To extract features suitable for the non-stationary condition, Jacek (2013) extracted features from every range of operating conditions separately [136].

Yang et al. (2014) made use of the S-transform to track the vibrational energy, in which an amplitude normalization equation was employed to mitigate the influence of varying load [137].

Urbanek et al. (2014) used the changing mode of the peak to peak values under different rotational speeds and generator output powers as the features for detection of mechanical fault occurrence [138].

Antoniadou et al. (2015) used the EMD to analysis the vibration signal of a WT gearbox under varying load condition. As the conclusion, the load related part can be separated from the original signal, and the hypothesis of the relationship between numbers of IMFs and damage and different load condition is not testified [81].

Feng et al. (2017) utilized the phase angle data for the planetary gear fault detection under a nonstationary operational condition with the sample entropy as the indicator by taking advantage of two characteristics, which are the external loads have little influence on the frequency modulation part, and the fault modulation contains the characteristic fault information [139].

Comparing with the studies proposed to deal with time-varying rotational speed, the corresponding researches on time-varying load condition is relatively less. Moreover, the underlying principle of the proposed algorithms is not clear. What's more, the majority of currently exist algorithms are designed for other equipment with planetary gearbox such as excavator, rather than the WT.

4. Feature extraction and fault diagnostics strategy

After summarizing the basis analysis studies of the planetary gearbox vibration response in frequency domain as the foundation, and the corresponding signal processing algorithms used in analyzing WT planetary gearbox vibration signals which can remove the background noise, extract the fault-related and eliminate the side effect caused by the harsh operating condition in some level, the corresponding feature extraction and fault diagnosis strategy for the WT planetary gearbox are reviewed in this section.

As for the fault diagnostics strategy, there are mainly two kinds, which are (1) extracting features which can describe the operating states of the monitored WT planetary gearbox, and detecting the fault types according to the classifier with the extracted features as the input, and (2) identifying the fault characterizing features directly from vibration signals or the analyzed resulting using the signal processing algorithms summarized in Section 2. Considering the related studies of the second strategy has been reviewed in Section 3, this section only reviews the studies on the first strategy. In specific, the structure of this section is organized as follows: the studies on the feature extraction are summarized in Section 4.1, and the corresponding fault diagnosis strategies are revised in Section 4.2,

4.1. Feature construction and extraction

Extracting features which can reflect the monitored object is crucial for the final fault detection. In this section, the existing feature extraction strategies for the WT planetary gearbox are summarized in the following two parts; dimension reduction-based feature set generation and specifically designed features, separately.

4.1.1. Dimension reduction-based feature set generation

The feature-based method is one of the oldest and most widely used ones in machinery condition monitoring and fault diagnosis [37]. However, the complex structure and multi-component characteristics of WT planetary gearboxes will result in an extraordinary complex vibration signal and spectrum. Hence, it is difficult to realize fault diagnosis just based on traditional statistical features. To solve this problem, a widely-used strategy was proposed with following 3 steps: at first, a multi-dimensional feature set is constructed by extracting different types of features from the raw vibration signal, or the signal processing results, such as the signal envelopes, raw spectra or filtered signals, then, the dimension reduction algorithm is employed to select or generate more suitable features with less dimension, and the final fault diagnosis is realized through the classifier. In this subsection, the studies on the former two topics are separately reviewed.

(1) **Multi-dimensional features set construction**

Extracting features which can reflect the monitored object as comprehensive information as possible is the major goal of the multi-dimensional features set construction. Following this thinking, researchers have extracted different kinds features according to two main strategies: extracting all kinds of traditional statistical indicators from the different reexpressions and transform results of the raw signals, such as the raw signal itself, spectrum [140–146], envelope spectrum [61,141], residual signal [141,147,148], filtering results with specific band-pass filters [143,148]; extracting specific feature from decomposed results of the raw signal, such as entropy-based features from the PFs generated by the EEMD [149] and LMD [150]. Frequently used statistical features including time domain feature, frequency domain feature and the statistical feature designed for the gears and the entropy-based features are introduced in Table 5 with the corresponding feature name, definition and physical meaning. The specific definitions can be found in [148].

Table 5
List of the references on the statistical features and the corresponding definitions.

Feature type	Feature name	Definition	Feature name	Definition	Feature name	Feature name	Definition
General Time domain feature	Maximum value	max $x(n)$	Minimum value	min $x(n)$	Frequency domain feature	Mean frequency	$\frac{1}{K}\sum_{k=1}^{K}X(k)$
	Average absolute value	$\frac{1}{N}\sum_{n=1}^{N}\lvert x(n)\rvert$	Peak to Peak	max $x(n)$- min $x(n)$		Frequency center	$\frac{\sum_{k=1}^{K}f(k)\times X(k)}{\frac{1}{K}\sum_{k=1}^{K}X(k)}$
	Variance	$\frac{1}{N}\sum_{n=1}^{N}\left(x(n)-\bar{x}\right)^2$	Standard Deviation	$\sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(x(n)-\bar{x}\right)^2}$			
	Kurtosis	$\frac{\frac{1}{N}\sum_{n=1}^{N}\left(x(n)-\bar{x}\right)^4}{\left(\frac{1}{N}\sum_{n=1}^{N}\left(x(n)-\bar{x}\right)^2\right)^2}$	Root mean square (RMS)	$\sqrt{\frac{1}{N}\sum_{n=1}^{N}x(n)^2}$		Root mean square frequency	$\sqrt{\frac{\sum_{k=1}^{K}\left(f(k)^2\times X(k)\right)}{\frac{1}{K}\sum_{k=1}^{K}X(k)}}$
	Skewness	$\frac{\frac{1}{N}\sum_{n=1}^{N}\left(x(n)-\bar{x}\right)^3}{\left(\frac{1}{N}\sum_{n=1}^{N}\left(x(n)-\bar{x}\right)^2\right)^{\frac{2}{3}}}$	Clearance factor	$\frac{\max x(n)}{\frac{1}{N}\sum_{n=1}^{N}x(n)^2}$		Standard deviation frequency	$\sqrt{\frac{\sum_{k=1}^{K}\left(\left(f(k)-\frac{1}{K}\sum_{k=1}^{K}X(k)\right)^2\times X(k)\right)}{\frac{1}{K}\sum_{k=1}^{K}X(k)}}$
	Kurtosis	$\frac{\frac{1}{N}\sum_{n=1}^{N}\left(x(n)-\bar{x}\right)^4}{\left(\frac{1}{N}\sum_{n=1}^{N}\left(x(n)-\bar{x}\right)^2\right)^2}$	Impulse factor	$\frac{\max x(n)}{\frac{1}{N}\sum_{n=1}^{N}\lvert x(n)\rvert}$	Statistical feature designed for gearboxes	NA4	$\frac{\frac{1}{N}\sum_{k=1}^{K}(r(n)-\bar{r})^4}{\left(\frac{1}{M}\sum_{m=1}^{M}\left(\frac{1}{N}\sum_{n=1}^{N}(r_m(n)-\bar{r}_m)^2\right)\right)^2}$
	Shape factor	$\frac{\sqrt{\frac{1}{N}\sum_{n=1}^{N}x(n)^2}}{\frac{1}{N}\sum_{n=1}^{N}\lvert x(n)\rvert}$	Energy operator	$\frac{\frac{1}{N}\sum_{n-1}^{N}\left(\Delta x(n)-\Delta\bar{x}\right)^4}{\left(\frac{1}{N}\sum_{n=1}^{N}\left(\Delta x(n)-\Delta\bar{x}\right)^2\right)^2}$		NA4*	$\frac{\frac{1}{N}\sum_{k=1}^{K}(r(n)-\bar{r})^4}{\left(\frac{1}{M'}\sum_{m=1}^{M'}\left(\frac{1}{N}\sum_{n=1}^{N}(r_m(n)-\bar{r}_m)^2\right)\right)^2}$
Statistical feature designed for gears	FM4	$\frac{\frac{1}{N}\sum_{n=1}^{N}(d(n)-\bar{d})^4}{\left(\frac{1}{N}\sum_{n=1}^{N}(d(n)-\bar{d})^2\right)^2}$		M8A*	$\frac{\frac{1}{N}\sum_{n=1}^{N}(d(n)-\bar{d})^8}{\left(\frac{1}{M'}\sum_{m=1}^{M'}\left(\frac{1}{N}\sum_{n=1}^{N}(d_m(n)-\bar{d}_m)^2\right)\right)^4}$		
	FM4*	$\frac{\frac{1}{N}\sum_{n=1}^{N}(d(n)-\bar{d})^4}{\left(\frac{1}{M'}\sum_{m=1}^{M'}\left(\frac{1}{N}\sum_{n=1}^{N}(d_m(n)-\bar{d}_m)^2\right)\right)^2}$		NB4	$\frac{\frac{1}{N}\sum_{n=1}^{N}(e(n)-e)^4}{\left(\frac{1}{M}\sum_{m=1}^{M}\left(\frac{1}{N}\sum_{n=1}^{N}(e_m(n)-\bar{e}_m)^2\right)\right)^2}$		
	M6A	$\frac{\frac{1}{N}\sum_{n=1}^{N}(d(n)-\bar{d})^6}{\left(\frac{1}{N}\sum_{n=1}^{N}(d(n)-\bar{d})^2\right)^3}$		NB4*	$\frac{\frac{1}{N}\sum_{n=1}^{N}(e(n)-e)^4}{\left(\frac{1}{M'}\sum_{m=1}^{M'}\left(\frac{1}{N}\sum_{n=1}^{N}\left(e_m(n)-\bar{e}_m\right)^2\right)\right)^2}$		
	M6A*	$\frac{\frac{1}{N}\sum_{n=1}^{N}(d(n)-\bar{d})^6}{\left(\frac{1}{M'}\sum_{m=1}^{M'}\left(\frac{1}{N}\sum_{n=1}^{N}(d_m(n)-\bar{d}_m)^2\right)\right)^3}$		FM0	$\frac{\max x(n)-\min x(n)}{\sum X(k^*)}$		
				Largest sideband amplitude	$\max(X(k^*))$		
	M8A	$\frac{\frac{1}{N}\sum_{n=1}^{N}(d(n)-\bar{d})^8}{\left(\frac{1}{N}\sum_{n=1}^{N}(d(n)-\bar{d})^2\right)^4}$		Sideband index	$x_{SI}=\frac{\sum X(k^*)}{2}$		
				Sideband level factor	$x_{SI}=\frac{\sum X(k^*)}{\sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(x(n)-\bar{x}\right)^2}}$		

(2) **Feature dimension reduction**

The above studies on the multi-dimensional statistics set construction attempted to describe the measured vibration signal as comprehensive as possible. However, it not easy to fulfill the final classifier-based fault detection with too many features. Because some of them may contain irrelevant information that may lead to the decrease the corresponding classification accuracy. Hence, several feature dimension reduction algorithms are employed to generate a feature set with higher representativeness but less dimension. In this part, the relative studies are summarized according to the corresponding two main dimension reduction strategies, which are feature selection and feature extraction.

Feature selection based dimension reduction strategy aims to generate a set of promising new features with low dimension from original multi-dimensional feature space, which can retain the intuitive interpretation of the original feature. A feature selection algorithm includes a search technique and evaluation metrics, which can propose new feature subsets and evaluate them, respectively. Several researchers employed this strategy for the PG feature selection, which are reviewed according to three different main categories, filters, wrappers, and embedded methods.

Filter type methods perform feature selection only based on the intrinsic information content of the feature subset with the particularly effective in computation time and robust to overfitting. Several studies have employed this type of feature selection strategy for the purpose of dimension reduction. Zhao et al. (2013) used the correlation coefficient, include the Polyserial and Pearson correlation coefficients, as the evaluation metrics to search optimal feature subset which is suitable for the ordinal ranking algorithm for planetary gearbox fault level diagnosis [141]. Liu et al. (2014) proposed a new feature selection algorithm for the planetary gearbox fault level diagnosis with cosine similarity in the Gaussian radial basis kernel space as a criterion and with the sequential backward algorithm as the feature selection method [143]. Cheng et al. (2012) [151,152] (2015) used the two-sample Z-test as the evaluation metrics to select feature with the characteristics of sensitivity and relational for planetary gearbox crack level estimation and residual useful life estimation. Wang and Shao (2018) proposed an improved hybrid feature selection technique (IHFST) to remove the irrelevant or redundant features using the distance evaluation technique (DET) & Pearson's correlation analysis as the evaluation metrics [146]. Li et al. (2018) combined multi-scale morphological filter (AMMF) and Laplacian score (LS) approach to remove the fault-unrelated interruption and refine the fault features extracted using the modified hierarchical permutation entropy (MHPE) [153]. Li et al. (2017) select optimal features from the modified multi-scale symbolic dynamic entropy (MMSDE) features from different scales with max-relevance and min-redundancy (mRMR) method which contains two criterions, Max-relevance and Min-relevance [154].

Wrapper methods realize the feature selection by scoring the feature subsets with the help of a predictive model. The advantages lie in the high classification accuracy mainly because they are designed for specific classifiers. Dybała (2013) proposed a novel Noise-Assisted Feature Subset Evaluation (NAFSE) method to select better feature subset with lower dimension using the NBV-based classifier which is also the technique for the final classification [136]. Barkowiak and Zimroz (2014) used multivariate linear regression (MLR) for the optimal subset features selection with the evaluation metrics of minimal squared prediction error and a greedy forward selection search strategy [144].

Embedded methods select the feature as part of the model construction process. Barkowiak and Zimroz employed a widely used strategy of the least absolute selection and shrinkage operator (Lasso) in feature selection for the planetary gearbox condition monitoring [144].

To survey the former feature selection algorithm used in dimension reduction for the PG fault diagnosis, Table 6 lists the details of these feature selection algorithm, including the corresponding selection function type, searching technique, evaluation metrics, and classifier.

Table 6
List of the references on the feature selection algorithm with specific search technique, evaluation metrics, classifier and selection function.

Ref. No.	Search technique	Evaluation metrics	Classifier	Selection function
Zhao [141]	Forward selection	Correlation coefficient	Ordinal ranking	Filter
Liu [143]	Backward selection	Within-class & the between-class separability in the kernel space	SVM	
Wang [146]	Backward selection	Distance evaluation & Pearson's correlation	k-means clustering	
Cheng [151]	Forward selection	Z-test	Grey relational analysis	
Li [153]	Forward selection	Laplacian score	SVM	
Li [154]	Forward selection	Minimum redundancy maximum relevance (mRMR)	least square support vector machine (LSSVM)	
Barkowiak [144]	Forward selection	Minimal squared prediction error	Multivariate linear regression	Wrapper
Dybała [136]	Forward selection	FSUI&BDI	NBV-based classifier	
Barkowiak [144]	FORWARD Selection	Lasso	Multivariate linear regression	Embedded

Different from the feature selection algorithms, the **feature extraction algorithms** generate a set of features with less dimension which are different from any of the multi-dimensional features using existed statistical dimensionality reduction strategies. Traditional dimensionality reduction methods can be divided into two types, which are linear and non-linear.

As for the linear method, Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are two representative methods that can realize the dimensionality reduction with different underlying physics of extracting similarity of the analyzed data and pursuing maximum class variance and minimum class variance, respectively. Zimroz et al. (2013) employed the PCA and Canonical Discriminant Analysis (CDA) to reduce the feature dimension from multi-dimension features of the spectral amplitudes of the meshing frequency and its harmonics to realize distributed fault detection of planetary gearbox under non-stationary operating conditions [142].

As for the non-linear method, there exist two main sub-types named kernel function-based and eigenvalue-based dimensionality reduction methods. With the kernel function-based dimensionality reduction methods, Cheng et al. [149] (2012) used kernel principal component analysis (KPCA) to obtain lower dimension feature set from four kinds of entropy features with multi-dimension to detect different types of localized fault on the sun gears under different load and speed conditions. With the eigenvalue-based dimensionality reduction methods, Tang et al. (2014) compressed the mixed domain high-dimensional feature vector into low-dimensional eigenvectors with a manifold learning algorithm, called the orthogonal neighborhood preserving embedding (ONPE) for the WT transmission system fault diagnosis [155]. Chen et al. (2017) used Laplacian eigenmaps (LE) algorithm to select sensitive features with lower dimension from 12 traditional features with four types of the time domain feature, frequency domain feature, entropy feature and fractal dimension feature to fulfill the planetary gear fault identification of different fault states and degradations [156].

In conclusion, the strategies of feature selection and extraction are separately used dimension reduction for the multi-dimensional features for the planetary gearbox fault detection. These two strategies both have their own advantages and disadvantages. As for the feature selection, the non-selected features are not considered after the feature selection process. In this level, the selected features have less information than the ones obtained using the feature extraction because it concentrates all the feature information into extracted features. On the other hand, the corresponding disadvantage of the feature extraction based dimension reduction algorithm lies in that the currently used feature selection methods are mostly proposed based on the statistical theory not the specific characteristic of the monitored object. Hence, the selected features with low dimension usually only have statistical meanings but the original physical meanings. Therefore, if one wants to keep most of the information from the original features, the feature extraction-based algorithm is recommended. And if one wants the employed low dimension feature set with physical meanings, the feature selection method should be used.

To combine the advantages of these two strategies, Liu et al. (2013) propose a hybrid method containing feature selection and extraction step. In specific, the kernel feature selection method and kernel Fisher discriminant analysis were used sequentially for removing irrelevant features and establishing more compact features vector with Gaussian radial basis function as the kernel function [140].

Except for the traditional statistical dimensionality reduction strategies, Zhao and Feng (2017) employed the sparse filtering to select outperforming features from multi-domain features extracted from the time-domain, frequency domain and instantaneous amplitude energy analysis with the help of VMD for fault identification of planetary gearbox [145]. Compared with the traditional statistical algorithms, the sparse filter has the advantage of hyper-parameter-free.

4.1.2. Specially designed features

Except for the statistical feature selection and fault characteristics frequency, researchers have also created several specially designed features to indicate the operating condition of the WT planetary gearbox.

Zimroz and Bartkowiak (2011) considered the internal spectral structure as the feature and used correlation coefficients between different features and the corresponding distribution as the diagnostic feature to distinguish the good and bad conditions [157].

Lei et al. (2012, 2015) specially developed four statistical features, Root mean square of the filtered signal (FRMS), Normalized summation of positive amplitudes of the difference spectrum(NSDS), Accumulative amplitudes of carrier orders (AACO) and Energy ratio based on difference spectra (ERDS), to realize planetary gearbox fault detection. Compared with the traditional features, the newly proposed features perform better at recognizing different fault types of planetary gearbox [158,159].

Hu et al. (2015) employed the correlation dimension (CD) of the refactoring proper rotation component which is obtained based on the EITD and Wavelet packet transform as the feature to distinguish the normal condition, tooth pitting fault and the worn, and broken tooth fault in the real WT planetary gearbox [97].

Liang et al. (2016) employed the energy (RMS) of the vibration signal generated by each tooth as the symptoms to locate a cracked tooth [75].

Skrimpas et al. (2017) test the effectiveness of traditional five statistical features from the residual signal using two fields cases with a planet carrier bearing defect and planet wheel spalling. It is shown that the features measuring the Gaussianity are suitable for the localized fault, and the ones measuring the RMS value are good at recognizing distributed faults [147].

Except for proposing new features, some studies also attempted combining the vibration signals with other information together for the final fault detection. For example, Lei et al. [160] took advantage of the information from multi-sensors using adaptive neuro-fuzzy inference system (ANFIS). M. Khazaee et al. [161] used information from different types of sensors (vibration and acoustic) based on the Dempster–Shafer (D-S) evidence theory.

Recently, self-adaptive features extraction method based on deep learning theory has become a new hot topic because the selected features are suitable for the measured signal. For example, Zhao et al. (2018) developed the deep residual networks to learn a set of new features which can recognize eight faulty planetary gear states from the health one using the wavelet packet coefficients as the network input [162]. Jing et al. (2017) used the deep convolutional neural networks to extract features from various types of sensory data and select suitable fusion level in planetary gearbox fault diagnosis via multi-sensor data. A high recognition rate of 99.28% is obtained [163].

As summarized above, the specially designed features are more targeted comparing with the dimension reduction based features and can result in a higher recognition rate compared with the traditional statistical features with the same dimension. However, the customized features are not suitable for all the operational modes such as different speeds or load conditions.

4.1.3. Discussion

In this section, all the feature extraction based studies summarized in Section 4.1 are listed in Table 7 with the corresponding four main characteristics, feature extraction method, fault type and location, operation mode, generalization level.

Based on the main characteristics of the reviewed studies listed in Table 7, the following discussions are given

(1) It can be easily concluded that most of the extracted features are designed for gear but bearing. Among the studies which can be used to realize bearing fault detection, most of them are the specially designed fault, which indicates that the traditional statistical features are not suitable for diagnosing the bearing fault.

(2) Non-stationary conditions, including the time-varying rotational speed and load are common for the WT planetary gearbox. However, most of the existed researchers failed to consider these two conditions. Refs. [136,142,144,157] paid much attention to the time-varying load condition by extracting features for the planetary gearbox of the excavator, which provided a good reference of the WT planetary gearbox fault detection under time-varying load. It should be mentioned that most of these studies can only tell fault condition from the health one. As for the time-varying rotational speed, [61] extracted the features from the angular resampled result, [136] decomposed the signal in several segments under the time-varying condition assuming the rotational speed keep constant in each segment.

(3) As for the classification-based algorithms, the effectiveness of the extracted features is always tested by the data which measured under the same measuring point and operating conditions, which makes the corresponding studies less convincing, especially in real application. In here, we define the ability to test the algorithm with the testing data in other machine or operating mode as the generalization. The generalization of all the reviewed studies in Section 4.1 are listed in Table 7, with three levels, high, medium and No. In specific, "High" means that the trained system is finally tested with real data under different operating conditions. "Medium" means that the training set contains data measured under different operating speed or load, which makes the trained system has generalization in some level. "Low" indicates that the trained system is just tested by the testing data whose operating condition is just as the same as the training data.

4.2. Fault diagnosis strategy

As summarized in the above two sections, there exist a great many valuable studies in the steps of feature extraction and signal processing. For the final fault diagnosis, related studies can be divided into two classes and separately reviewed in this section. Some of them realize the fault diagnosis based on the classifier, and the others detect the fault condition based on the feature comparison.

4.2.1. Classifier-based fault diagnosis strategy

Classifier-based fault diagnosis strategy is suitable for multi-dimensional features. As for the specific designed or selected features, some researchers just displayed them in Euclidean Space (two directions or three directions). Following studies are some representative examples.

Liu et al. (2013) identified different fault levels with the top two features selected by the KFDA shown in a 2D Euclidean Space [140].

Radoslaw and Bartkowiak 2013 employed top two features selected by the PCA and CDA in the 2D Euclidean spaces to identify fault condition from the healthy one [142].

Lei et al. (2012) constructed statistical features of FRMS and NSDS to identify different fault locations in a 2D Euclidean space [159], and in 2015, the AACO and ERDS were constructed to detect different fault types in different locations [158].

Ha et al. (2016) detected the fault condition with traditional statistical features extracted from ATSA based averaged result in the 2D or 3D Euclidean Space [76].

Artificial intelligent techniques are also widely used in fault types identification. The representative studies are reviewed as follows.

Yang et al. (2008) used the Backpropagation (BP) network to realize the WT gearbox fault diagnosis with nine inputs extracted from the decomposed results of the raw vibration signal using the Wavelet-based algorithm [164].

Table 7
List of the references on the fault feature extraction based studies with specific feature extraction method, fault type and location, operation mode and generalization level.

Ref. No.	Feature extraction method	Fault type and location	Operation mode	Generalization level
Liang [75]	Specially designed feature	Seeded gear crack fault in test rig	Constant speed	N/A
Hu [97]	Specially designed feature	Seeded gear crack fault in WT	Constant speed	N/A
Dybała [136]	FS of DR	Real bearing and gear fault in bucket wheel excavator	Nonstationary operating condition	High
Zimroz [135]	Specially designed feature	Real bearing and gear fault in bucket wheel excavator	Nonstationary operating condition	N/A
Liu [140]	FE&FS of DR	Seeded gear fault level in test rig	Stationary operating condition	Low
Zhao [141]	FS of DR	Seeded gear fault level in test rig	Stationary operating condition	Low
Zimroz [142]	FE of DR	Real gear fault in bucket wheel excavator	Nonstationary operating condition	N/A
Liu [143]	FS of DR	Seeded gear fault level in test rig	Different operate condition	Medium
Bartkowiak [144]	FS of DR	Real gear fault in bucket wheel excavator	Nonstationary operating condition	Low
Zhao [145]	FE of DR	Seeded gear fault in test rig & real fault	Stationary operating condition	Yes
Wang [146]	FS of DR	Seeded gear crack fault in test rig	Different operate condition	Medium
Li [154]	FS of DR	Seeded gear fault in test rig	Stationary operating condition	Low
Skrimpas [147]	Statistical features from the residual signal	Real gear and bearing fault in WT	Nonstationary operating condition	N/A
Cheng [149]	FE of DR	Seeded gear fault in test rig	Different operate condition	Medium
Chen [150]	Statistical features from the residual signal	Seeded gear fault in test rig	Stationary operating condition	Low
Cheng [151]	FE of DR	Simulated signals of gear crack fault	Stationary operating condition	Low
Cheng [152]	FS of DR	Simulated signals of gear crack fault	Stationary operating condition	Low
Li [153]	FS of DR	Different seeded gear fault in different location in test rig	Stationary operating condition	Low
Tang [155]	FE of DR	Seeded gear crack fault in real WT	Nonstationary operating condition	High
Chen [156]	FE of DR	Different seeded gear fault in different levels in test rig	Stationary operating condition	Low
Zimroz [157]	Specially designed feature	Real gear fault in bucket wheel excavator	Nonstationary operating condition	N/A
Lei [158]	Specially designed feature	Seeded gear and bearing fault in test rig	Different operate condition	N/A
Lei [159]	Specially designed feature	Seeded gear and bearing fault in test rig	Different operate condition	N/A
Lei [160]	Specially designed feature	Seeded gear and bearing fault in test rig	Different operate condition	N/A
Khazaee [161]	Statistical features from different types of signals	Seeded gear fault in test rig	Nonstationary operating condition	Low
Zhao [162]	Deep learning based features	Seeded gear and bearing fault in test rig	Different operate condition	Medium
Jing [163]	Deep learning based features	Seeded gear fault in test rig	Different speed conditions	Medium

Note: FE represents feature extraction, FS represents feature selection, DR represents the dimension reduction. As for the generalization column, "High" means that the trained system is finally tested with real data under different operating conditions. "Medium" means that the training data contain data measured under different operating speed or load, which makes the trained system has generalization in some level. "Low" indicates that the trained system is just tested by the testing data whose operating condition is just as the same as the training data. "N/A" indicates that the corresponding study does not contain the classification step.

Tomasz et al. (2011) employed the fuzzy-ART neural network to realize WTs states classification based on a normalized signal with the stereographic projection algorithm [165]. And in [166] (2016), the ART-2 Neural network was used. Both of these two studies can identify different operating states of the monitored WT.

Cheng et al. (2012) chose the grey relational analysis (GRA) algorithm for planetary gearbox damage level estimation with simulated signals [151].

Chen et al. (2016) employed the fuzzy entropies of the LMD based decomposed results as the features and realized the planetary gearbox fault diagnosis using the ANFIS [150].

Cheng et al. (2016) applied the extracted kernel principal components and learning vector quantization (LVQ) neural network to realize the fault diagnosis of the planetary gear [149].

Lei et al. [167] (2015) utilized a multiclass relevance vector machine (mRVM) as the classifier for the multi-stage planetary gearbox health condition identification with the features proposed in [158].

Marcin and Tomasz [168] (2016) made use of the Backpropagation Artificial Neural Network (ANN) to train the healthy WT at first and then employed the taught net to recognized fault condition based on the error in assessment.

Chen et al. (2017) employed the deep belief networks (DBNs) classifier to identify planetary gearbox faults in different types using the particle swarm optimization algorithm (PSO) in parameters selection [169].

Wang and Shao (2018) used the K-means Clustering Method to separate crack faults on different positions, sun gear, planet gear and ring gear with selected features [146].

Several other classifiers were used to realize the final fault diagnosis, such as the ordinal ranking algorithm [141], NBV-based classifier [136], and Lasso technique [144].

To sum up, the fault diagnosis strategies mentioned above, all of the reviewed studies are listed in Table 8. Both the used classifier and the classification result are listed.

4.2.2. Feature comparison based fault diagnosis strategy

Expect the classifier based strategy, the corresponding operating condition can also be identified by feature comparison between healthy and fault conditions. With this strategy, the corresponding feature can usually directly indicate a fault condition. Just because most of the specific algorithms have been reviewed above, the corresponding studies are just concluded and listed in Table 9 in following four groups: specially designed feature, vibration signal, spectrum and envelope spectrum, and time-frequency representation.

Table 8
List of the references on classifier based fault diagnosis strategy.

Ref. No.	Author(s), Year	Classifier	Classification result
[165]	Tomasz et al., 2011	Fuzzy-ART neural network	Operating state
[151]	Cheng et al., 2012	Grey relational analysis	Fault level
[159]	Lei et al., 2012	2D Euclidean Space with FRMS and NSDS	Fault type
[140]	Liu et al., 2013	2D Euclidean Space with top two features selected by the KFDA	Fault level
[141]	Zhao et al., 2013	Ordinal ranking	Fault level
[136]	Jacek, 2013	NBV-based classifier	Health/Fault
[142]	Radoslaw and Bartkowiak, 2013	2D Euclidean spaces with top two features selected by the PCA and CDA	Health/Fault
[158]	Lei et al., 2013	2D Euclidean Space with AACO and ERDS	Fault location & type
[155]	Tang et al., 2014	Shannon wavelet support vector machine	Fault level
[143]	Liu et al., 2014	“one-against-all” approach for SVM	Fault level
[144]	Bartkowiak et al., 2014	Lasso technique	Health/Fault
[167]	Lei et al., 2015	Multiclass relevance vector machine (mRVM)	Fault location & type
[168]	Strdczkiewicz and Barszcz, 2015	BP Network	Health/Fault
[77]	Jae et al., 2016	K-nearest neighbor, BP, LAMSTAR	Fault location
[150]	Chen et al., 2016	ANFIS	Fault type
[149]	Cheng et al., 2016	Learning vector quantization	Fault type
[76]	Ha et al., 2016	2D or 3D Euclidean Space with traditional statistical features extracted from ATSA based averaged result	Health/Fault
[173]	Tomasz et al., 2016	ART-2 Neural network	Operating state
[146]	Wang and Shao, 2018	K-means Clustering Method	Fault location

Table 9
List of the references on feature comparison based fault diagnosis strategy.

Compared object	Refs.
Specially designed feature	Bartelmus and Zimroz [133]. William et al. [174]. Radoslaw and Anna [157]. Jacek et al. [138]. Radoslaw et al. [135]. Assaad et al. [61]. Hu et al. [97]. Liang et al. [75].
Vibrational signal	Tomasz and Robert [66]. Jiang et al. [95]. Sun et al. [96]. D’Elia et al. [78]
Spectrum and Envelope spectrum	Feng et al. [82,83,104,86,106]. Li et al. [100,101]. Li et al. [110]. Tian and Qian [109]. Fan and Li [91]. Wang et al. [88]. Wen et al. [175]. Hu and Li [103].
Time-frequency representation (TFR)	Tang et al [94], Feng et al. [121,122,117]. Chen et al. [124,125].

5. Discussions and prospect

Above three sections have summarized various studies concerning the WT planetary gearbox condition monitoring and fault diagnosis on feature extraction, signal processing, and fault condition determination. Most of these reported algorithms are proposed to deal with complex structure and harsh operating environment of the WT gearboxes, and remarkable progress has been made. However, there still exist several un-addressed problems in current studies. Meanwhile, the authors will provide some potential prospects for future research in the WT planetary gearbox condition monitoring and fault diagnosis.

(1) As mentioned in Section 3.2, the operating modes of time-varying rotational speed and load condition always affect the planetary gearbox fault diagnosis, and several researchers have proposed some useful algorithms. Moreover, there still exists another problem of the low-speed condition. Although the low-speed working condition is common in WT, it does not attract plenty of attention. Especially for the planet gear and the planet bearing, the corresponding fault signatures are always difficult to identify because of the low speed. However, the studies specifically involving the condition monitoring and fault diagnosis of WT planetary gearbox under low speed are very limited. Therefore, mastering the weak fault signature under low-speed and developing techniques to enhance the features out of the strong interruption are both important potential issues in WT planetary gearboxes fault diagnosis.
(2) As mentioned in Section 4.2, there are two main WT planetary fault detection strategies based on the classifier and fault feature comparison. As for the first type, the majority of the existed studies test the trained classifier with the test set whose measuring point and operating conditions are as same as the ones of the training set. This makes the effectiveness of the trained classifiers less convincing. Hence, the trained classifiers with higher generalization are exceedingly expected. As for the second type, the majority of the fault feature comparison based methods require a health baseline, which is sometimes unavailable under the real applications. Therefore, the fault features which only appear under fault condition are highly needed.
(3) Different from the ordinary planetary gearboxes operating on the ground, the WT planetary gearbox commonly installed in the nacelle locating at high altitude. In real applications, the WT tower always acts as a moving base which will lead to translational and pitching motions towards the monitoring of the WT planetary gearboxes. These additional motions will make the corresponding vibration and frequency response more complex and the condition monitoring and fault diagnosis even more challenging. Although several studies have discussed this issue carefully in dynamic aspect [170,171], few related research has been reported on the WT planetary gearbox fault detection considering this specific characteristic. Hence, careful studies are needed to reveal how the moving base affects the corresponding vibration and the spectrum and how to realize corresponding condition monitoring and fault diagnosis.
(4) It can be concluded that most of the current studies on WT fault diagnosis can identify the fault locations, such as planet gear, sun gear or ring gear, and some of them can only identify fault condition from the normal one. However, it is still quite challenging to determine the fault types, such as tooth root crack and tooth surface pitting. Hence, the authors suggest paying more attention to more precise fault diagnosis, including the following aspects: building accurate dynamic models for different fault types, designing more specifically representative features, and developing more powerful classifier.
(5) Most of the studies reviewed above only focus on the detection of the one fault type on certain components, such as gear and bearing. Only a few scholars do researches on the degradation and root cause analysis of these faults [172]. Hence, it is significant to pay more attention to the factors influencing vibration, such as design, production technology and condition change, and the degradation process of certain faults. As for WT planetary gearbox, it is recommended to measure the degree of misalignment to avoid further gearbox degradation.
(6) Most of the developed WT planetary fault diagnosis techniques were proposed to analyze the signal measured by a single sensor within a relatively short period. However, recent condition monitoring systems always collect real-time data from machines for such a long time and lead to massive data, which will make most of the traditional fault diagnosis techniques disable. Hence, there is an urgent need for diagnostic methods that can effectively analyze massive data and automatically provide accurate diagnosis results.

6. Concluding remark

In this paper, the literature summarization is conducted on condition monitoring and fault diagnosis of WT planetary gearboxes in three parts. Section 2 introduces the spectral complexity of the planetary gearboxes and summaries the fault characteristic frequency deduction studies, which can be seen as the fundamental analysis of the planetary gearbox vibration response. As for the signal processing algorithms reviewed in Section 3, the literature reports on fault information enhancement from complexity interruption and operating mode effects elimination are respectively summarized. Section 4 summarizes the studies on the feature extraction and the fault diagnosis strategy. Finally, several open topics of future research are put forward and discussed. This review paper attempts to survey the existent techniques according to their usage in WT planetary gearbox fault diagnosis by explaining which problem they solved and how to solve. We believe that this review can provide a comprehensive reference for related researchers.

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