A review of vibration-based gear wear monitoring and prediction techniques

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Abstract

Gearbox plays a vital role in a wide range of mechanical power transmission systems in many industrial applications, including wind turbines, vehicles, mining and material handling equipment, oil and gas processing equipment, offshore vessels, and aircraft. As an inevitable phenomenon during gear service life, gear wear affects the durability of gear tooth and reduces the remaining useful life of the gear transmission system. The propagation of gear wear can lead to severe gear failures such as gear root crack, tooth spall, and tooth breakage, which can further cause unexpected equipment shutdown or hazardous incidents. Therefore, it is necessary to monitor gear wear propagation progression in order to perform predictive maintenance. Vibration analysis is a widely used and effective technique to monitor the operating condition of rotating machinery, especially for the diagnosis of localized failures such as gear root crack and tooth surface spalling. However, vibration-based techniques for gear wear analysis and monitoring are very limited, mainly due to the difficulties in identifying the complex vibration characteristics induced by gear wear propagation. Understanding the effect of gear wear on vibration characteristics is essential to develop vibration-based techniques for monitoring and tracking gear wear evolution. However, no research work has been previously published to summarize the research progress in vibration-based gear wear monitoring and prediction. To fill the research gap, this review paper aims to conduct a state-of-the-art comprehensive review on vibration-based gear wear monitoring, including studying the gear surface features caused by different gear wear mechanisms, investigating the relationships between gear surface features and vibration characteristics, and summarizing the current research progress of vibration-based gear wear monitoring. This review also makes some recommendations for future research work in this area. It is expected that this review will provide useful information for further development of vibration-based techniques for gear wear monitoring and remaining useful life predictions.

Keywords: vibration analysis, gear wear, wear monitoring, wear mechanism identification, wear prediction, remaining useful life prediction, comprehensive review

Contents

1. Introduction

Gearbox has many advantages, including compact structures, stable transmission capability, and low noise, and thus the gearboxes have been extensively applied in a wide range of industries, such as renewable energy, advanced manufacturing, vehicle, mining, aerospace, material handling, oil and gas, and power industry [1-6], as shown in Figure 1. Gear wear is a progressive material loss due to the relative motion of the meshing tooth surface [7, 8]. It is a common and inevitable phenomenon during gear service life [9-11], and Figure 2 shows some typical gear wear patterns. The propagation of gear wear reduces the durability of the gear surface, deteriorates the contact lubrications of engaging gears, increases the friction/noise, and leads to the formation of stress concentrations [12-14]. These consequences can further induce other failure modes, such as gear cracks [15] and gear tooth breakage, which would result in the sudden shutdown of the gear transmission system and unexpected economic loss or even cause serious accidents [16-18]. For example, in wind turbines, gear wear would contaminate the lubrication oil and increase the friction between the engaging gears, which could increase the risk of gear breakage and cause the unexpected shutdown of the transmission system of the wind turbines. Wind turbines are generally built in deserted areas, on hilltops, or near the ocean. Thus, it may take a couple of weeks or even months to conduct the maintenance for the gearbox. Consequently, the electricity production of wind turbines would be suspended, leading to both electricity loss and economic loss. The gearbox is also a critical component of the vehicle transmission system. Gear wear would degrade the transmission performances. Severe gear wear would damage the whole transmission system, potentially causing serious accidents. Therefore, it is vital to monitor and predict the gear wear propagation, in order to improve the health management of transmission systems.

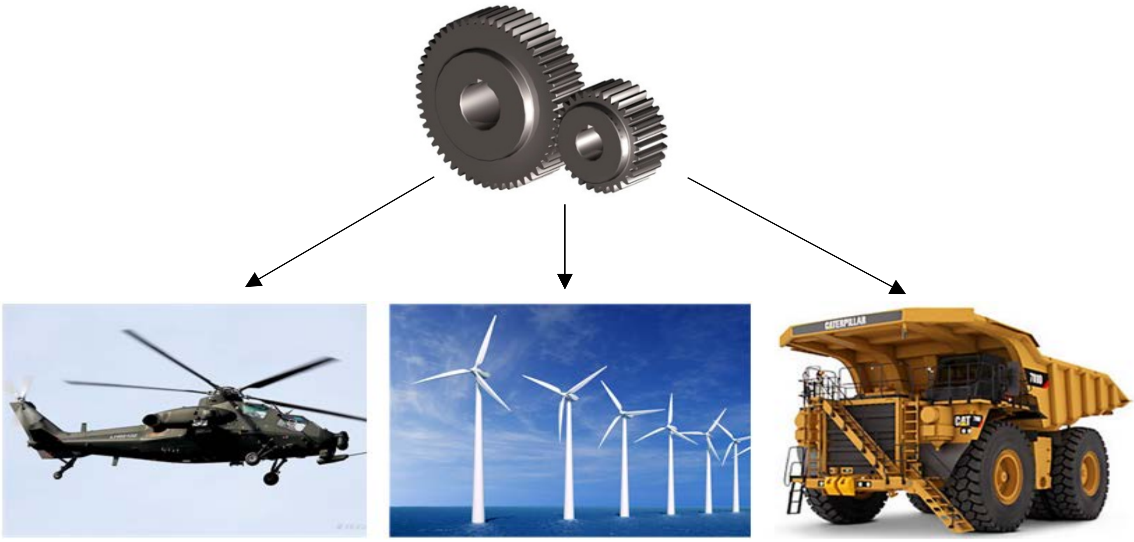

Figure 1 Applications of the gearbox transmission: some examples [19]

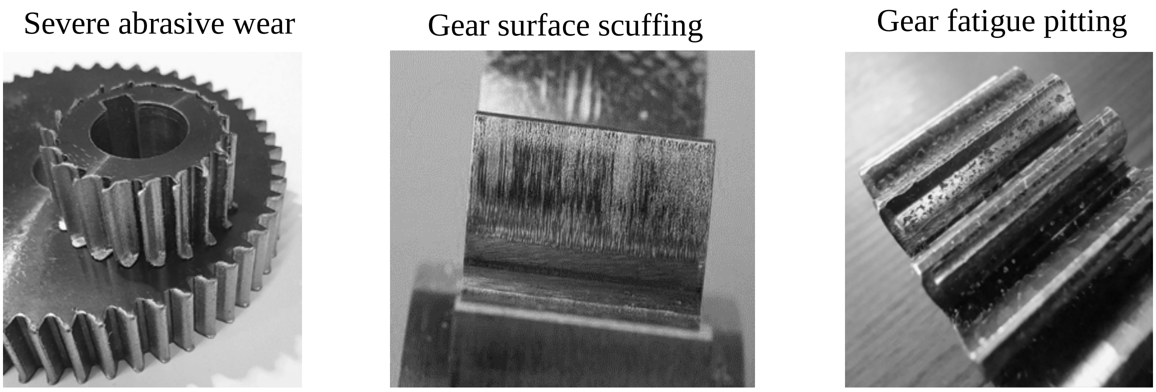

Figure 2 Some typical gear wear patterns [20]

To date, wear particle analysis still plays a vital role in gear wear monitoring and has been widely used in industrial practice [21-26]. The gear wear propagation status can be indicated by analyzing particle number, size, shape, and concentration [27-32]. However, wear particle analysis is usually conducted offline and is often accomplished in an oil analysis laboratory [11, 33, 34]. It would result in a delay in analyzing wear debris, and during this period of wear particle analysis, the operating condition of the gear transmission system might have experienced significant changes. Therefore, the development of online gear wear monitoring techniques is essential to obtain real-time information on gear wear for industrial applications.

Vibration analysis, as an online technique, has been widely used to conduct condition monitoring for rotating machinery [35-42]. A rotating machine under normal operating conditions has the corresponding vibration signature/feature to reflect its running status. The presence of a fault changes the vibration signature to some degree that can be relevant to the fault [35, 43-48]; therefore, vibration analysis has become a practical and popular tool to monitor the operating conditions of machines [49-55]. Compared with the technique of wear particle analysis, vibration-based analysis has some advantages. For example, vibration analysis responds immediately to dynamic change in a mechanical system (e.g., a gearbox) and can thus be used as a permanent tool for intermittent monitoring of its health condition. Also, vibration analysis, together with some advanced signal processing methods and diagnostics techniques, is able to identify the actual faulty component and quantify its severity [56-62]. Thanks to the advantages mentioned above, vibration analysis has become to be an efficient and prevalent method for monitoring machine operating conditions.

Vibration analysis has been well developed and widely applied for the diagnostics of common gear failures such as tooth surface spalling [63-65], gear crack [66-70], and gear breakage [71-75]. Several review papers were published to summarize the vibration-based analysis approaches for monitoring common gear failures, from dynamic modeling to gear prognostics, such as [2, 76-82]. On the contrary, research on vibration-based gear wear monitoring is limited but is receiving increasing attention from the research community and industry practice. However, there is no a systematic review to summarize the progress of vibration-based gear wear monitoring development. Such a review can help researchers and engineers have a better understanding of gear wear degradation behaviors and characteristics, so that predictive maintenance-based decisions can be made to ensure the safe operation of the gearbox transmission system. This paper is intended to bridge this research gap.

There is a complex interaction between gear surface wear and gear dynamics [10, 83-85], and this interaction brings difficulties for vibration-based analysis. It has been recognized that the dynamic load and its distribution would be altered during the gear wear propagation progression [83, 86]. As a result of the wear-induced change to the tooth surface, the transmission ratio of the gear system would no longer be stationary [11, 86], especially for spur gearbox systems, whose transmission errors and dynamic responses through vibration signals are highly sensitive to wear [87], and the gear system vibration characteristics would change considerably. In turn, because of the change in dynamic contact load and its distribution, the gear wear propagation progression changes. Due to there being an interactive process between gear wear and gear dynamics; thus, the effects of gear wear would manifest themselves as changes in vibration features, and a vibration-based tool can be used for gear wear monitoring. However, the complex interactions between gear wear and gear dynamics lead to the generation of vibration characteristics with high complexity, which makes it challenging to extract the vibration features related to wear and develop effective vibration-based technique(s) or indicator(s) for wear monitoring. Therefore, it is necessary to investigate and fully understand the physical relationship between gear wear and vibration characteristics, which can significantly benefit the development of vibration-based techniques for gear wear monitoring. With the effective vibration-based gear wear monitoring techniques, the gear system operation condition can be reflected and monitored in real-time so that proper maintenance strategies can be scheduled in advance to avoid unexpected shutdowns and even serious accidents.

This review paper aims to comprehensively investigate and summarize the effects of gear wear on vibration characteristics under different wear mechanisms. Firstly, the gear wear mode and its consequences on the gear tooth profile alteration are introduced. Then through investigating the internal relations between gear surface features and vibration characteristics, the existing works on gear wear monitoring are reviewed and summarized, from the aspects of signal processing and modeling techniques. After that, the wear prediction techniques for the common wear phenomena are discussed and reviewed. This review paper provides a comprehensive overview of vibration-based gear wear monitoring and prediction technique developments, from the root cause of gear wear to the wear propagation prediction techniques.

This paper is organized as follows: Section 2 introduces the typical gear wear modes and their corresponding consequences on the gear tooth surface. The gear wear effects on vibration characteristics are investigated and summarized in Section 3. Existing works on vibration-based gear wear monitoring are discussed and summarized in Sections 4 and 5. Specifically, the existing signal processing algorithms for gear wear identification and monitoring are reviewed in Section 4, while the development of gear wear monitoring using modeling techniques is presented in Section 5. Section 6 gives an overview of the development of gear wear prediction. A conclusion and some research prospects are presented in Section 7.

2. Gear wear

Common causes for gear failure include bending fatigue, root crack, breakage, scuffing, spalling, and wear. Different categorizations have been used for classifying gear failure modes [17, 88-95]. In this section, some typical gear wear modes will be introduced, as described in Refs. [88, 90-93]. For the purpose of supplementing, the wear types from some international standards will also be listed to show different classifications. Then, the effects of gear wear on gear tooth surface will be investigated and summarized. It should be noted that the introduction of several typical gear wear modes is not intended to give a new gear wear mode classification; instead, it only helps readers better understand the common wear mechanisms in industrial applications.

2.1 Typical gear wear modes

Surface wear is a common and inevitable phenomenon during the gear service life [13, 96]. When gear pairs mesh with each other, the tooth flanks maintain contact under an applied load. The motion of the tooth surfaces is a combination of sliding motion and rolling motion [97, 98]. The sliding component appears where the surface velocities of the two contacting teeth are different [99]. The sliding motion can cause material removal from the gear teeth, which results in gear mass reduction, that is, gear wear.

It should be noted that currently there is no unified framework to classify the wear modes. Even some existing standards give different classifications, as shown in Table 1. In this situation, the readers can refer to the relevant standards for wear mode classification based on the requirements of different industrial scenarios.

Table 1 Wear mode classification based on existing standards

References	Wear mode classification
DIN 50320 [100]	Abrasion, adhesion, surface fatigue, and tribochemical reaction
ISO 15243 [101]	Abrasive wear and adhesive wear
ISO 10825 [102]	Sliding wear, corrosion, overheating, erosion, and electric erosion
ANSI/AGMA 9005-E2 [103]	Abrasive wear, adhesive wear, corrosive wear, erosive wear, fatigue wear, and fretting wear
ANSI/AGMA 1010-F14 [89]	Abrasion, adhesion, polishing, corrosion, fretting, scaling, white layer flaking, cavitation, cavitation, erosion, and electric discharge

In the following, some typical wear mechanisms of the gear system in industrial applications are summarized and presented in Figure 3, based on the definitions and discussions in Refs.[88, 90-93]. It should be mentioned that the classification of gear wear modes shown in Figure 3 is slightly different from some research papers, standards, and industry technical reports, as presented in Table 1. The reason is that Figure 3 does not aim to introduce a new wear classification standard; instead, it is used to demonstrate some typical gear wear mechanisms found in the majority of industrial applications.

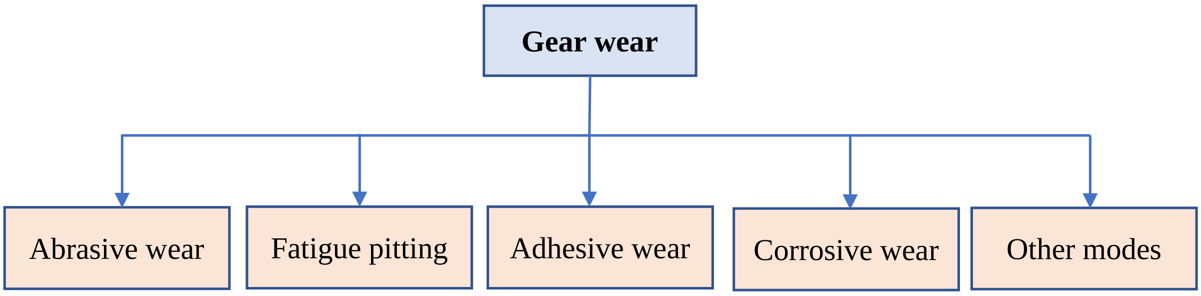

Figure 3 Typical gear wear modes

The typical gear wear modes shown in Figure 3 will be introduced in detail as follows:

- Abrasive wear: Particle contamination or a lack of lubrication could lead to sliding contact, resulting in abrasive wear. Abrasive wear leaves radial scratches on the gear surface and results in gear tooth geometry profile change [104], as shown in Figure 4. Abrasive wear can be categorized as two-body abrasive wear and three-body abrasive wear. Two-body abrasive wear is generated from the rubbing of a softer surface by a hard rough surface, while three-body abrasive wear is caused by hard particles entrapped between two sliding surfaces. In gear transmission system, the engaging gears are usually made from the same materials; therefore, the three-body abrasive wear is one research aspect of this review paper, which will be discussed in the following sections.

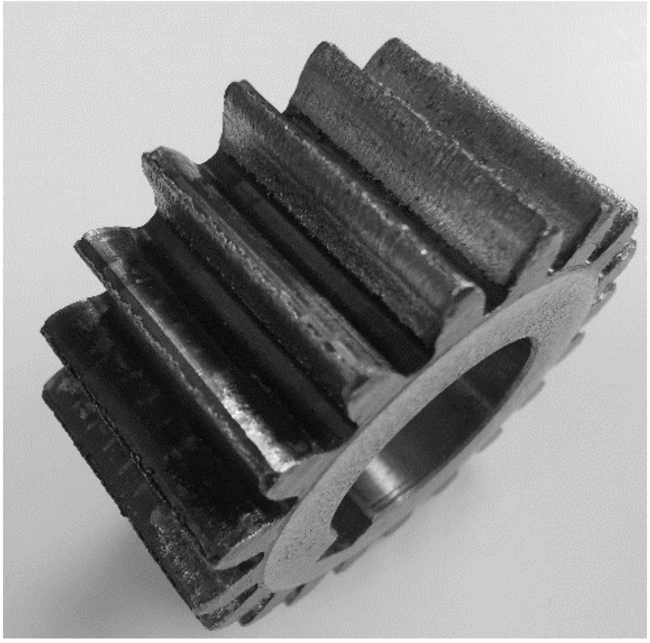

Figure 4 Extremely worn gear due to abrasive particles [13]

- Fatigue pitting: As a common surface fatigue phenomenon, fatigue pitting is caused by cyclic loading conditions, resulting in fatigue cracks either on the gear tooth surface or subsurface (shallow depth below the surface). The initial crack usually propagates roughly parallel to the tooth surface for a short distance, before turning or branching to the gear tooth surface. When the fatigue crack grows long enough to separate a piece of the surface material from the gear tooth, fatigue pitting is formally formed [89], as shown in Figure 5. In this paper, fatigue pitting is the product of fatigue crack propagation and refers in particular to mechanical pitting. Therefore, fatigue pitting in this paper is different from electrical pitting (which belongs to electrical erosion) and pitting corrosion (which belongs to corrosion).

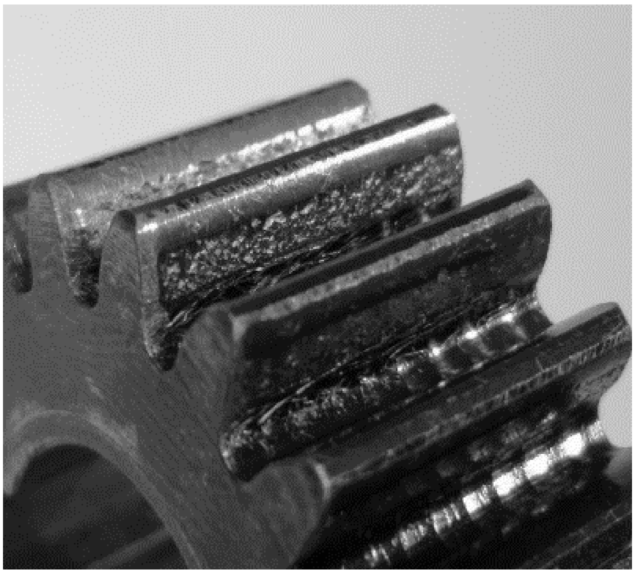

Figure 5 Gear fatigue pitting [13]

Fatigue pitting will be referred to in this paper as micro-pitting, and the macro-pitting will be called spalling in this paper to avoid potential confusion. Mirco-pitting has negligible impacts on the gear tooth geometry profile, unless it is significantly severe and already developed to be macro-pitting (that is, spalling).

- Adhesive wear: Adhesion of gear tooth is caused by the transfer of material from one gear tooth surface to another one due to tearing and microwelding [89].

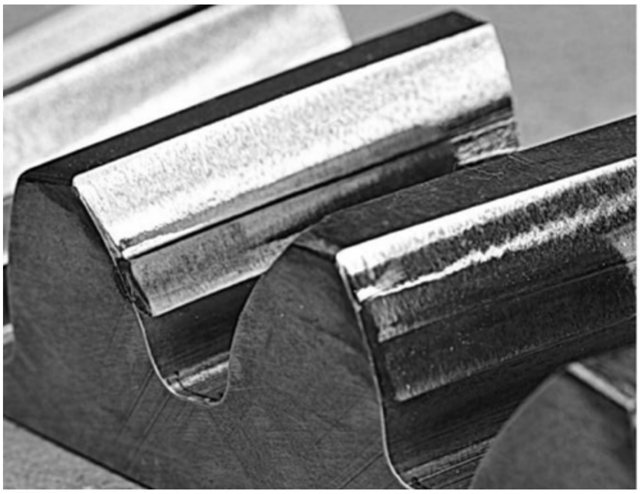

Figure 6 Typical adhesion in gears [89]

- Corrosive wear: Corrosive wear is a visible wear type as a gear tooth surface deterioration, as shown in Figure 7. It is mainly caused by chemical or electrochemical reactions with active ingredients in the lubricant [89, 104]. Mild corrosive wear in gear pairs is usually induced by lubricant additives that are intended for preventing scuffing failure, such as the extreme contact pressure additives [92].

Figure 7 Corrosion damage [89]

The above-discussed wear phenomena cover the main modes of wear in machinery, which probably account either individually or collectively for over 95% of the wear experienced in present-day machinery [90]. However, there are many other wear types that exist during the service life of the gearbox transmission system, such as erosion, impact chipping, polishing, fretting, scaling, cavitation, and electric discharge. These wear modes are distinct from the above-discussed major wear types. Since this paper focuses on reviewing the development of vibration-based gear wear monitoring techniques, these wear modes will not be discussed in detail.

In practical applications, abrasive wear and fatigue pitting are the two most common wear phenomena in gear transmission systems [17, 58, 105]. Therefore, considerable research has been focused on these two wear mechanisms, such as [58, 105-108]. Based on the above descriptions, the wear mechanisms of abrasive wear and fatigue pitting and their impacts on gear surface are summarized and highlighted here. Abrasive wear is the material removal induced by gear sliding contact, and it often acrosses the entire face width; generally, every piece of material that removes from the gear tooth contributes to a change in its geometry profile. In general, abrasive wear is caused by a lack of lubrication or particle contamination. In contrast, fatigue pitting is one kind of material loss included by fatigue behaviors. Even though the gear tooth has fatigue pitting, the effective working profile of engaging gears (across the entire tooth face width) often remains unchanged (unless fatigue pitting of gears is extremely severe). Fatigue pitting usually originates from a subsurface crack. In general, fatigue pitting occurs initially at the gear tooth dedendum or near the gear pitch line, caused by the high contact stress and repetitive rolling-sliding contact [13]. In this review paper, these two are chosen as the subjects for investigation and reviewing.

There are some research works that are focused on gear adhesive wear modeling and mechanism investigation [109-111]. For example, an adhesive wear model of rough gear surface was built in Ref. [109], and the influences of surface roughness, major geometrical parameters, and operational conditions on the wear depth were investigated. Also, the mechanism of adhesive wear was investigated and discussed in [110], and the influences of surface roughness, major geometrical parameters, and operational conditions on the wear depth were investigated. Besides, the mechanism of adhesive wear was investigated and discussed in [111]. However, research on vibration-based adhesive wear monitoring is much less in comparison with abrasive wear and fatigue pitting. The underlining reason might be that two bodies would adhere to one another locally, resulting in a much more complex surface morphology change and then generating a vibration signal with higher complexity compared with abrasive wear. Accordingly, vibration-based adhesive wear propagation becomes to be very challenging, and thus rare research has been found on this topic. This paper mainly focuses on reviewing vibration-based techniques for gear wear monitoring instead of wear modeling techniques and wear mechanism investigations; therefore, adhesive wear will not be defined as the primary research objective of this review paper, like other wear mechanisms. However, vibration-based adhesive wear progression monitoring should deserve more attention from the research community and industry practices.

2.2 Differences between abrasive wear and fatigue pitting

Based on the comparison of abrasive wear and fatigue pitting shown in Figure 4 and Figure 5, there are two major differences between these two surface degradation mechanisms. First, abrasive wear often has a high wear rate and can result in noticeable accumulated material removal in the gear tooth thickness, i.e., changing the gear tooth profile over a certain period. Typically, tooth profile change is in millimeters and can be regarded as macro-level wear, illustrated in Figure 8. In contrast, fatigue pitting has a low wear rate in the tooth thickness direction, and thus it has negligible effects on the geometry profile of gear tooth unless it is extremely severe. Therefore, these two wear mechanisms can often be differentiated in macro-scale for abrasive wear vs. micro-scale for fatigue pitting.

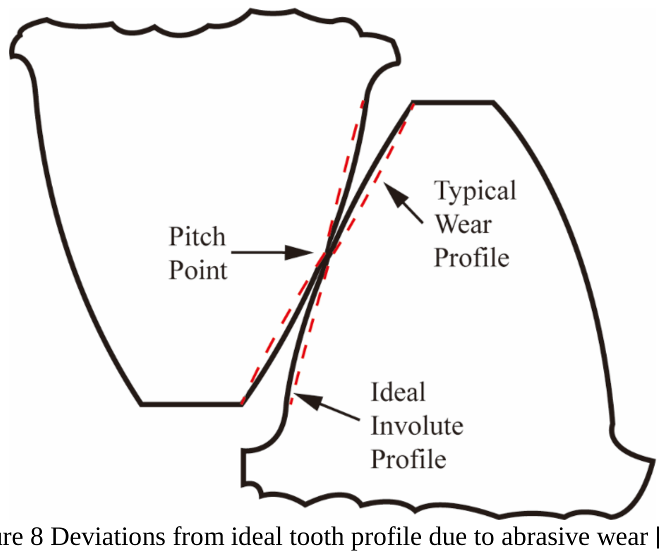

Figure 8 Deviations from ideal tooth profile due to abrasive wear [112]

Second, in view of surface morphology, compared with fatigue pitting, abrasive wear tends to produce a surface with a relatively short wavelength in the direction of sliding, which results in a high spatial frequency [113], as demonstrated in Figure 9. As for fatigue pitting, the material fragments detachment from the gear tooth surface results in valleys with long-wavelength, which corresponds to the low spatial frequency, as demonstrated in Figure 10.

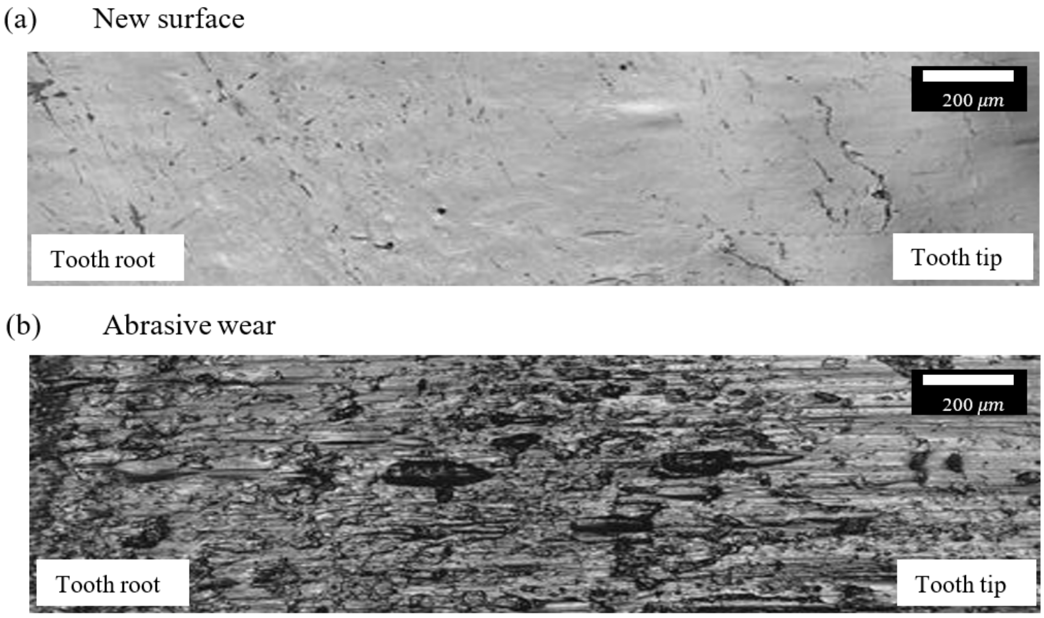

Figure 9 The gear tooth morphology changes caused by the abrasive wear (micro-level): (a) a new gear tooth surface morphology; (b) a worn gear surface caused by abrasive wear [13]

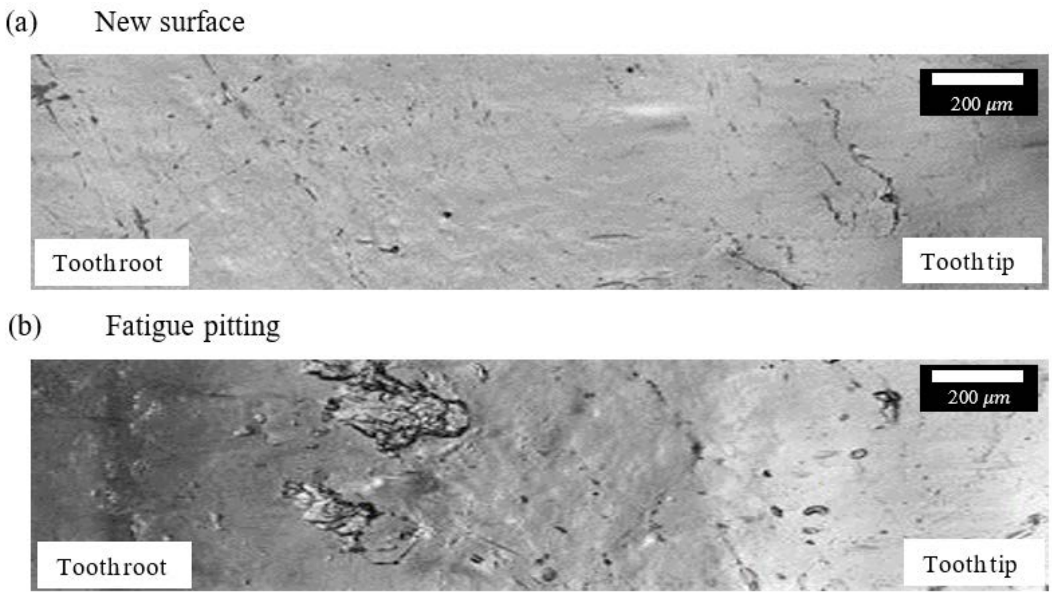

Figure 10 The gear tooth morphology changes caused by the fatigue pitting (micro-level): (a) a new gear tooth surface morphology; (b) a mild pitted gear surface [13]

The differences in the features/characteristics of abrasive wear and fatigue pitting are summarized in Table 2.

Table 2 Differences between abrasive wear and fatigue pitting in surface features

Wear types	Wear rate	Morphology (spatial frequency)	Final form
Abrasive wear	High	High	Tooth profile change (together with a rough gear surface)
Fatigue pitting	Low	Low	Valleys on the certain region of gear tooth (between gear root and pitch line)

3. Effects of gear wear on vibrations of gear systems

There is a complex interaction between the gear wear process and gear system dynamic response. In general, gear wear can result in the alteration of gear tooth profile geometry or a reduction of the contact area. This changes the geometric transmission error (GTE) and meshing stiffness of the gear system, and then the dynamic characteristics of the gear system will be affected, including the dynamic contact force and its distribution. As a consequence, the vibration level and noise increase [114]. In turn, the change of dynamic contact force could alter and accelerate the gear wear process. The dynamic interaction between gear surface wear and gear dynamics produces extremely complex gear dynamic response and vibration feature (as shown in Figure 11), which brings significant challenges in condition monitoring of gear wear compared with other failures, such as gear root crack, tooth surface spalling, and tooth breakage.

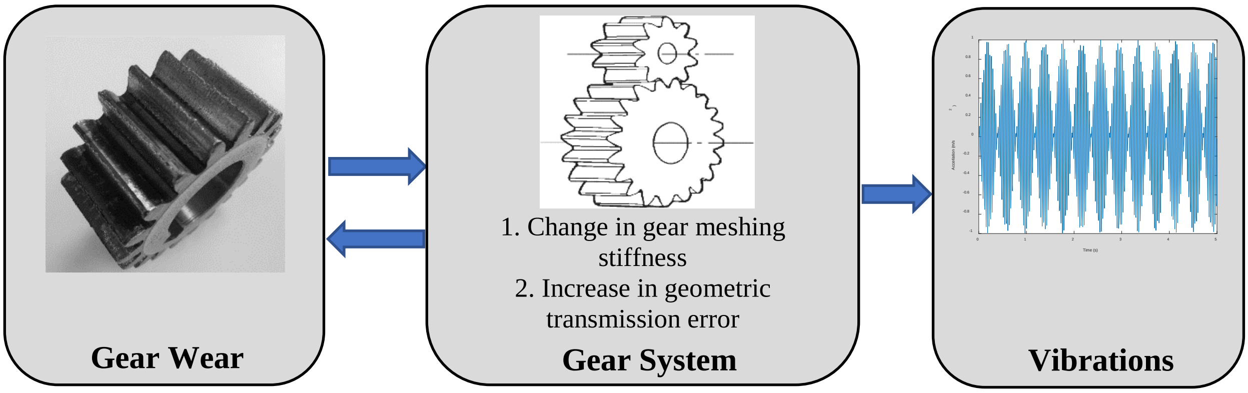

Figure 11 The interaction between gear wear and gear dynamics, and its induced vibrations [115]

With consideration of the contact patterns, abrasive wear and fatigue pitting have different impacts on the vibrations of the gear system on two different scales: macro-level and micro-level. Therefore, an understanding of gear wear effects on vibrations will be discussed in terms of these two scales below.

Macro-level wear (usually as tooth profile change) is a kind of geometric deviation of gear tooth from the ideal one, and it is serviced as geometric transmission error to the gear system. The macro-level wear can lead to an increase in the magnitudes of gear meshing harmonics [116]. Meanwhile, due to the wear-induced tooth profile change, the load distribution on the tooth surface is also altered, and thus the dynamic characteristics of mating gears will change. The effect of macro-level wear on vibrations is illustrated in Figure 12.

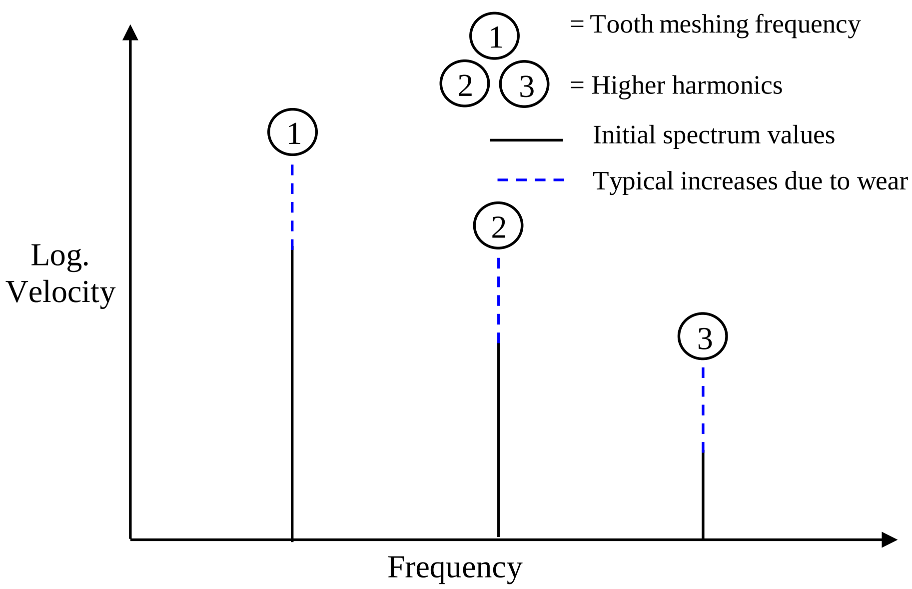

Figure 12 Typical vibration spectrum due to wear [112]

As explained in Section 2.1, abrasive wear can easily result in the gear tooth profile change, while fatigue pitting usually does not modify the gear tooth profile if gears are lubricated with a relatively low wear rate. However, both gear abrasive wear and gear fatigue pitting have significant impacts on the micro-geometry of the gear surface. Abrasive wear and fatigue pitting can induce different surface morphologies, which are at the micro-level. Abrasive wear can lead to a creation of protrusions (i.e., lumps) distributed from gear root to tip uniformly, while fatigue pitting induces the occurrences of valleys on the gear surface, normally distributed from gear root to pitch line, as shown in Figure 9 and Figure 10 respectively.

The micro-level wear generates a rough gear surface, which increases the friction force between the meshing gears, increasing the overall vibration level and changing its frequency characteristics [117]. The energy induced by micro-level wear might be low in comparison with the macro-geometry of the gear surface. The micro-level wear would induce a random vibration, namely sliding vibrations [118], so it could not be represented in gear meshing harmonics (deterministic signals). Thus, it is difficult to distinguish and extract micro-level wear information from other effects in originally measured vibration and its deterministic components [119].

Based on the above discussions, the effects of abrasive wear and fatigue pitting, in both macro-level and micro-scale, on vibrations are summarized in Table 3.

Table 3 Effects of wear on vibrations [112, 118, 120, 121]

Wear type	Macro-level	Micro-level
	Change in gear meshing harmonics (deterministic components)	Change in sliding induced vibration (random components)
		Magnitude
Abrasive wear	Significant	Increase
Fatigue pitting	Slight	Increase

As noticed from Table 3, these two wear mechanisms have distinct impacts on different vibration features. In practice, when fatigue pitting propagates, abrasive wear may co-exist due to oil contamination [17]. The abrasive wear could help remove high asperities, then lead to a smooth gear surface and good lubrication, which can help prevent the occurrence of fatigue pitting. In contrast, the occurrence of fatigue pitting can break the oil film and lead to a contact pressure concentration, which could advance the abrasive wear process [105]. There is a coupling effect between abrasive wear and fatigue pitting. This coupling effect results in complex nonlinear vibration characteristics and makes it challenging to extract gear wear-related vibration features/characteristics and develop specific vibration-based technique(s) or indicator(s) for gear wear mechanism identification and evolution tracking. In the following, the existing vibration-based gear surface wear monitoring methodology, using vibration features and models, will be reviewed, discussed, and summarized.

4. Vibration feature-based gear wear monitoring

The existing wear monitoring work (using vibration features) mainly focuses on gear wear evolution tracking. Moreover, most of the studies aim at monitoring gear tooth profile change (at the macro-level). In contrast, only a handful of studies are designed for micro-level wear monitoring, such as detecting surface roughness changes or monitoring fatigue pitting propagation. Compared with wear evolution tracking techniques, the vibration-based techniques for gear wear mechanism identification are less. Therefore, in the following, the existing vibration-based research works for wear evolution tracking are presented first, then the studies for wear mechanism identification will be presented and summarized.

4.1 Vibration feature-based wear evolution tracking

As discussed in Section 2.2, abrasive wear (or extreme severe fatigue pitting) could lead to gear tooth profile change (macro-level wear) with an increase in the overall energy of vibration signal and the magnitude of gear meshing harmonics. Therefore, the relationship between signal energy or gear meshing harmonics and gear wear severity is worth investigating.

Root mean square (RMS) (as given in Eq. (1)) has been widely used for reflecting the vibration amplitude and energy of the signal in the time domain. Considering that the worn gear would bring in geometric deviation from ideal gear tooth involute, resulting in a stronger vibration, some research works [58, 122] use the RMS to monitor the propagation of gear wear. It was found that the RMS value has a positive relationship with the gear wear severity. In addition, to improve the sensibility and reliability of RMS for detecting gear wear change, a sample parameter, namely matched filtered RMS, was proposed in [123]. This developed parameter was set to be the logarithmic value (which is expressed in dB) of the averaged power ratio between components of the current vibration signal and those of the reference vibration signal. Compared with classical parameters such as kurtosis, RMS, and peak values, the matched filtered RMS is easy to trend and performs better in tracking the gear wear process [11].

$$\mathrm{RMS_x} = \sqrt{\frac{1}{\mathrm{N}}\left[\sum_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{x_i})^2\right]} \tag{1}$$

As an extended version of RMS, an indicator named energy ratio (ER) was proposed in Ref. [124]. The ER is calculated using Eq. (2) as the difference signal d divided by the RMS of the signal which contains only the normal meshing components y_d [125].

$$\mathrm{ER} = \frac{\mathrm{RMS_d}}{\mathrm{RMS_{y_d}}} \tag{2}$$

The ER increases with wear severity when it occurs uniformly on the tooth surface since it would be expected that $\mathrm{RMS_d}$ would increase while $\mathrm{RMS_{y_d}}$ would decrease in this case.

However, RMS and its extended versions mainly focus on the signal’s power changes and thus may not have the capability of reflecting the signal spectral distribution changes, which also have a close relationship with gear wear. Therefore, some studies investigated the signal spectral distribution changes due to the gear wear processes.

Taking into consideration of the gear wear pattern, the uniform wear effects on gear mesh harmonics were explored and investigated in Ref. [112], and it was found that systematic wear would tend to generate a kind of tooth profile deviation, which is indicated in an exaggerated form in Figure 8. Consequently, the higher harmonics of the tooth meshing increase. Therefore, the higher-order gear meshing harmonics' amplitudes could be a reliable and effective tool for detecting and diagnosing uniform gear surface wear at its early stage. With this knowledge as a basis, the first three meshing harmonics of the spectrum and quefrencies of cepstrum were investigated and used in study [126] to track the gear surface wear propagation.

However, the average gear tooth working profile geometry steadily deviates from the initially designed ideal involute gear profile in the gear wear propagation progression, but the gear meshing harmonics changes are not stable and determinate. That is, all the gear meshing harmonics could vary in different behaviors, and each harmonic's amplitude may keep increasing in one period but start to decrease in another period. Considering this complex situation, the use of only a specific gear meshing harmonic may not be effective enough or sufficient to track and monitor the propagation of gear wear. Therefore, all the gear meshing harmonics with significant energy were taken into consideration in Ref. [11], then a sideband ratio (SBR) proposed in Ref. [127] was extended and modified into two new indicators: the averaged logarithmic ratio (ALR) and the moving averaged logarithmic ratio (mALR). The ALR can be utilized to reflect the gear wear effects on the gear running status, while the mALR shows the changes in the gear running status within short time intervals. The performance of these two indicators was evaluated and validated by two sets of tests with different initial gear surfaces.

In theory, gear surface wear can cause a gradual change in the mechanical properties and contact characteristics of the engaging gears (most notably in gear tooth profile and gear meshing stiffness); therefore, a gradual change occurs in vibration characteristics of the gear system compared with its initial state. Thus, the difference between vibrations with healthy gears and vibrations with worn gears can be used to represent the gear wear process. For example, an indicator named model prediction error (MPE) was proposed to track the gear wear process (tooth profile change) [128]. In the developed MPE, an auto-regressive (AR) model was used to predict the current state of the vibration signal based on the historical data; then, the prediction error, which is the difference between the predicted signal and the current measured signal, was used to indicate the gear wear process. A comparison with FM0, FM4, NA4, and RMS was made to show that MPE has a better performance than those indicators in gear wear monitoring.

Compared with the above-mentioned research on macro-level wear severity assessment, there is less research on micro-level wear monitoring. The reason is that the micro-level wear induced vibration is a random vibration with low energy, which is not easy to distinguish micro-level wear information from other effects in the originally measured vibration. In the following, the existing research for micro-level wear assessment will be introduced.

Recent developments [13, 118, 120, 129] showed that the surface roughness (induced by abrasive wear or fatigue pitting) information can be detected using a cyclostationary based approach, considering the unique kinematics characteristics of gear systems as demonstrated in Figure 13. An indicator that quantifies the second-order cyclostationarity of vibrations, ICS2 proposed in Ref. [130], was used to monitor the gear surface roughness change in Ref. [120], see Eq. (3):

$$\mathrm{ICS2}^{\mathcal{A}_\mathrm{h},\mathrm{H}} = \frac{\sum_{\mathrm{h}=1:\mathrm{H}} \max\limits_{\mathrm{n}\in\mathcal{A}_\mathrm{h}} (\mathrm{SES}[\mathrm{n}]^2)}{\mathrm{SES}[0]^2} \tag{3}$$

where h denotes the harmonic order of gear meshing frequency, $\mathcal{A}_h$ with $h = 1, 2, \ldots, \mathrm{H}$ is the equivalent sets for the corresponding gear mesh harmonics, and a tolerance band is set in Eq. (3) in the case of the deviations of expected cyclic frequency. For gear case, to monitor gear surface wear progression, $\mathcal{A}_1$ is set to be the gear meshing frequency. The SES is the squared envelope spectrum. In the experimental part, a high correlation coefficient was found between

ICS2 and gear surface roughness. However, the connection between ICS2 and surface roughness was found to be much more complex by a further investigation [118], which involved a wider range of surface roughness values and a longer duration of the experiment. To date, there are insufficient conclusions drawn. With studies [118, 120] as the basis, in Ref. [13], the carrier frequency f, instead of the cyclic frequency α, was further investigated, and an informative band that contains the most informative surface morphology was selected, then in the selected bands, the fatigue pitting propagation and surface roughness change induced by abrasive wear could be well monitored and tracked. Also, an autoregressive conditional heteroskedasticity model was used in [129] to represent the random vibration signals with cyclic amplitude modulation, and the surface roughness change was effectively evaluated. The capability of cyclic correntropy in monitoring gear wear propagation was investigated and proven in [131], and a novel cyclostationary indicator was developed for gear wear monitoring. Recently, based on the dispersion theory, a novel similarity-based status characterization methodology was developed in [14] to monitor the gear surface wear propagation progression, and a series of endurance tests (under different lubrication and operation conditions) were applied to prove the effectiveness of the developed methodology.

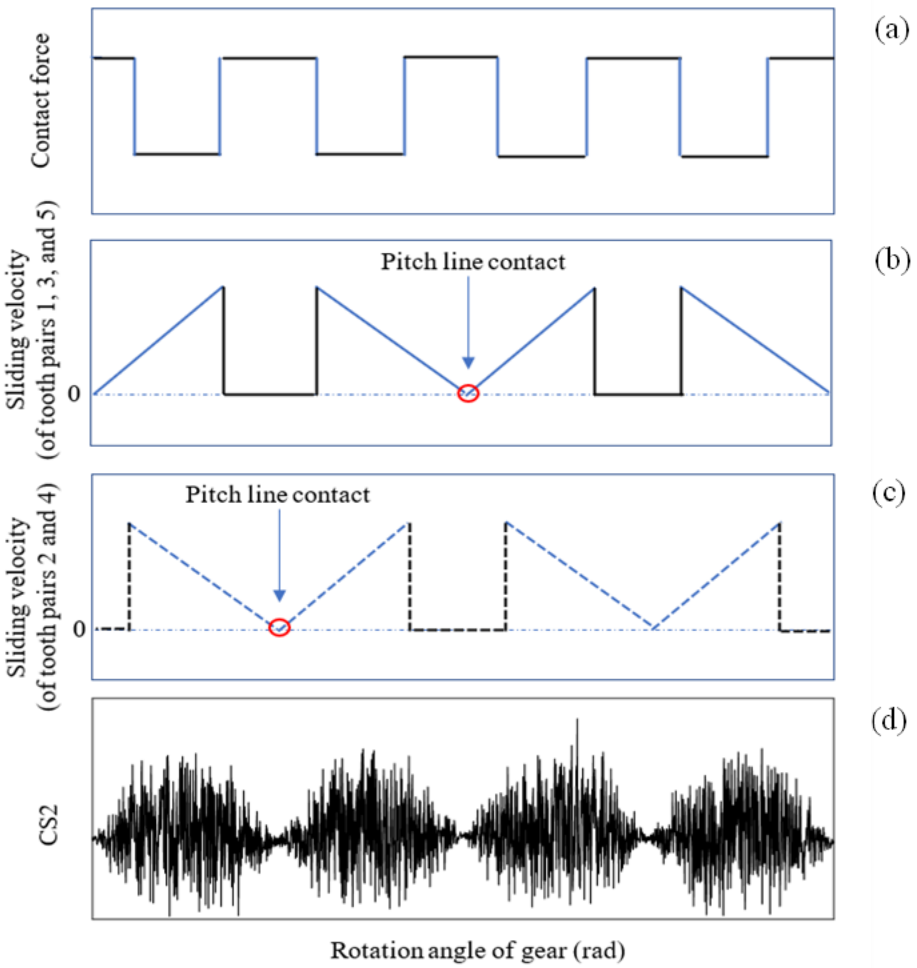

Figure 13 Conceptual link between the gear vibration second-order cyclostationary (CS2) and varying gear contact force and the sliding velocity exiting in engaging gears; (a) gear contact force; (b,c) each tooth pair sliding velocities; (d) CS2 amplitude-modulated gear random vibration signal [13]

In addition, the strength of frequency modulation and amplitude was assumed to be correlated to the gear wear severity in Ref. [132] , and the correlation coefficient was used to quantify the difference between the reference signal (vibrations with healthy gears) and the current measured vibrations, then the correction coefficient was linked to gear wear severity. Five natural pitting propagation tests were conducted to verify the effectiveness of the approach proposed in [132]. It should note that a residual signal, after removing gear meshing and shaft harmonics, was used in Ref. [132] for correlation coefficient calculation. And the difference between Ref. [132] and Ref. [128] is that the correlation coefficient used in Ref. [132] is for monitoring fatigue pitting propagation (micro-level wear), whose information is hard to detect in the deterministic part of the vibration signal.

Based on the above literature review, the existing vibration feature-based technique for gear wear evolution monitoring can be summarised in Table 4. From Table 4, it can be seen that the vibration feature-based techniques for gear monitoring are quite limited and general. Most of the studies focus on tracking macro-level wear progression (tooth profile change), which can be easily detected and monitored in deterministic components of vibrations. In contrast, the studies for micro-level wear, such as fatigue pitting or abrasive wear induced surface roughness change, are rather limited. The reason is that the vibration characteristics of micro-level wear are weak, and most of them are contained in the random components of vibrations, which are easily masked by background noise. This challenge brings huge difficulties in extracting and monitoring micro-level wear evolution. Therefore, research works on investigating the internal relations between micro-level wear and vibration features, which could benefit the development of vibration-based fatigue pitting propagation, are in demand.

Table 4 Studies of vibration feature-based gear wear evolution tracking

References	Main techniques	Purpose
[11, 58, 121-123]	RMS and its extension versions	Accumulated gear wear evolution tracking (at macro-level)
[112, 126]	Gear mesh harmonics or quesfrencies	Accumulated gear wear evolution tracking (at macro-level)
[11, 126]	Sideband energy ratio, sidebands	Accumulated gear wear evolution tracking (at macro-level)
[128]	Auto-regressive model, then prediction error	Accumulated gear wear evolution tracking (at macro-level)
[132]	Correlation coefficient-based approach	Fatigue pitting propagation monitoring (at micro-level)
[118, 120]	ICS2 to monitor roughness change	Gear surface roughness monitoring (at micro-level)
[129]	ARCH model to monitor roughness change	Gear surface roughness monitoring (at micro-level)
[13]	ICS2 to monitor fatigue pitting propagation and surface roughness (induced by abrasion) change	Fatigue pitting propagation and surface roughness (induced by abrasion) monitoring (at micro-level)

[131]	A novel cyclic correntropy based indicator to monitor gear wear progression	Gear surface roughness monitoring (induced by abrasive wear and fatigue pitting)
[14]	A novel similarity-based status characterization methodology to monitor gear wear progression	Gear surface roughness monitoring (induced by abrasive wear and fatigue pitting)

4.2 Vibration feature-based wear mechanism identification

Up to date, there is very limited work on using vibration-based methodologies for identifying wear mechanisms. The existing techniques for identifying wear mechanisms mainly rely on visual examination/inspection of a worn gear surface and/or its wear particles/debris generated from the gear surface. Based on the literature review, the development of gear wear mechanism identification using vibration-based techniques will be presented as follows.

A phenomenon was found in study [133], that is, fatigue pitting information is in the low-carrier frequency range. In study [133], artificial pits were introduced to all the teeth of the pinion with different sizes to simulate different pitting severities, then the mean frequency variation of a scalogram was used to detect the pitting damage. The experiment results showed that the mean frequency decreased when the pitting became severer and severer. This suggested that pitting has effects on the low-frequency part of vibrations.

Even though insufficient conclusions were drawn in studies [118, 120], it was suggested that surface morphology information could be detected in sliding induced vibration. It was also shown that the wavelength of surface asperities might impact the surface roughness monitoring results [118]. This information can be used to identify the gear abrasive wear and fatigue pitting.

Based on the research findings in [118, 120, 133, 134], the carrier frequency information of sliding induced vibrations was explored in [13] for its potential in identifying fatigue pitting and abrasive wear. The relationship between the surface morphology spatial frequency f_v (Hz) and the sliding vibration frequency $f_s(1/\mathrm{m})$ was established [13], see Eq. (4):

$$f_v \propto v_s \cdot f_s \tag{4}$$

where $v_s(\mathrm{m/s})$ is the engaging gear surface sliding velocity. The manners of *excitation* induced by gear wear were described in Figure 14 and Figure 15 [13]. It should be noted that a system transfer function would shape the measured response, and the observed dominant vibration carrier frequencies of the measured vibration signal in the cyclostationarity content would also depend on gear transmission resonances and the applied cyclostationary tool which is used for their detection and diagnostics. To verify the phenomenon shown in Figure 14 and Figure 15, spectral coherence map of vibrations and ICS2-based frequency band selection approaches were used to analyze the measured vibrations from two run-to-failure tests under different lubrication conditions to identify abrasive wear and fatigue pitting. Besides, the wear mechanism identification results were confirmed using power spectral density (PSD) analysis techniques, which were applied to the scanned gear surface images. The definition of spectral coherence is

$$\gamma_x(\alpha, f) = \frac{S_x(\alpha, f)}{\sqrt{S_x(0, f) S_x(0, f-\alpha)}} \tag{5}$$

where $S_x(\alpha, f)$ represents the ordinary power spectral density at frequency f. The CS content at frequency f is normalized by the power at frequencies f and $f-\alpha$ in the stationary part of the signal.

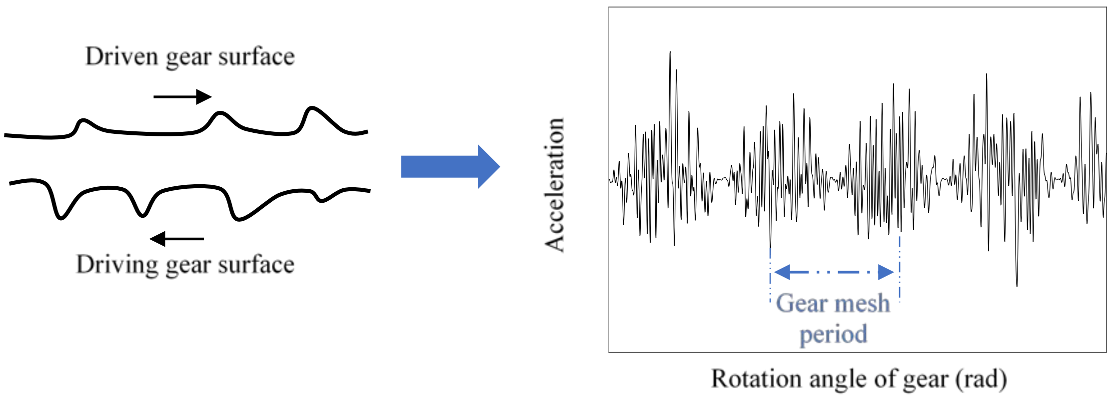

Figure 14 The sliding vibration characteristics induced by fatigue pitting [13]

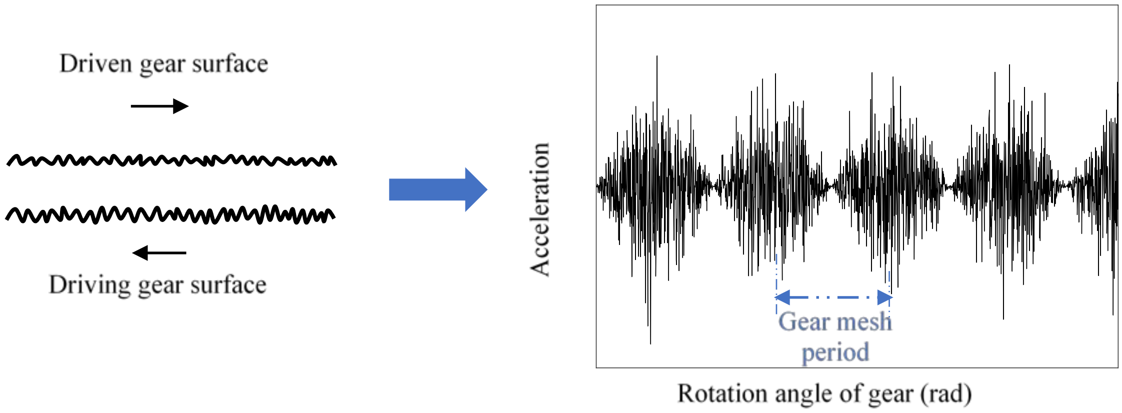

Figure 15 The sliding vibration characteristics induced by abrasive wear [13]

Table 5 summarizes the current development in vibration-based wear mechanism identification and the relevant works. Based on Table 5 and the above literature review, it can be seen that the investigation of unique surface morphology features induced by different gear wear mechanisms is at the outset, and vibration analysis has shown its significant benefits to wear mechanism identification. The sliding vibration characteristics can help reveal the gear tooth contact mechanisms with details. Therefore, more vibration feature-based techniques for gear wear monitoring with consideration of unique vibration characteristics induced by different gear wear mechanisms are needed.

Table 5 Developments of vibration-based gear wear mechanism identification and the relevant work

References	Main observation or contribution	Wear mechanism identification
[133]	The mean frequency of the scalogram will decrease when the pit size increases	×
[118, 120]	Surface morphology information could be detected in sliding induced vibration	×
[13]	The relationship between surface morphology and sliding vibration is built; the abrasion and fatigue pitting are identified.	√

5. Model-based gear wear monitoring techniques

Gear wear simulation has significant benefits to gear wear monitoring and prediction. The gear wear simulation mainly uses the gear meshing mechanism, wear mechanism, and vibration characteristics to establish dynamic models, tribological (wear) models, and their interactions. Then, with the help of the established models, dynamic responses (such as vibrations and contact force) in different health conditions can be evaluated and simulated, and fault symptoms of the gear system can be disclosed and concluded for fault diagnostics and prognostics [135-137]. In the gear wear simulation, gear dynamic models are concerned with the relationship between dynamic properties (stiffness, transmission error, friction, etc.) and system responses such as vibration responses (dynamic forces and vibration signals) [138-141]. Tribological models rely on wear mechanism theory or experimental data to establish a damage propagation model, in which pressure distribution, oil film thickness and/or wear rate are studied based on certain inputs, including the load, lubricant viscosity, sliding velocity, and surface roughness [142-144]. In the following sections, the research progress on gear wear model developments will be discussed.

5.1 Dynamic models of spur gearboxes

The gearbox is usually modeled by the techniques of lumped parameter modeling (LPM) and finite element modeling (FEM) [2]. As for the lumped parameter model techniques, the modeling components are considered to be rigid, and the masses are concentrated at a set of points [145]. In contrast, in the finite element modeling techniques, the physical model is discretized into disjoint components of simple geometry called finite elements, and its system response is obtained by connecting or assembling all elements [145]. Each modeling technique has its unique advantages; thus, it is hard to simply justify which method is better. As introduced in Ref. [146], the two methods could be equally accurate, if the corresponding degree of discretization and boundary conditions are well defined; Also, the solution costs of these two methods are different, which depend on the discretization characteristics of the LPM and various FEM derivations as well as the efficiency of the programmer. LPM, FEM, and their combinations have been applied for gear wear monitoring to achieve a reliable and efficient wear analysis, which will be introduced together with the existing gear wear monitoring methodologies in this section. Since the focus of this review paper is on gear wear monitoring, thus, the developments of gearbox dynamic modeling techniques will not be introduced and reviewed. Instead, some critical parameters of the dynamic model closely related to the gear wear progression will be introduced and reviewed in the following.

Contact force is an essential input of the tribological models. Based on the contact force, the contact pressure of engaging gear pairs can be calculated based on Hertzian contact theory [147, 148], then the wear propagation behaviors can be simulated using tribological (wear) models. There are lots of research works using empirical equations or finite element models to evaluate contact force and its distribution between meshing gear pairs, such as references [149-154]; however, most of them are effective under quasi-static conditions. Without considering the inertia effects due to gear dynamics, the gear contact force under quasi-static conditions can be easily simulated using finite element models and empirical equations. However, in industrial practices, the gear system is usually operated under dynamic operating conditions, and the corresponding system responses are very different from those under quasi-static operating conditions [83]. Usually, owing to the inertia effects, the dynamic gear meshing forces are usually larger than the corresponding contact forces under quasi-static conditions, and their waveforms and magnitudes are significantly different [83]. Therefore, the dynamic contact force and its distribution should be properly evaluated to guarantee that wear propagation behaviors can be simulated and wear-induced dynamic responses can be exhibited.

To obtain proper/accurate dynamic contact force during gear wear progress, a dynamic model of the gear transmission system, which can also generate wear-induced dynamic responses (such as vibrations) for wear analysis, is required. In general, the dynamic model includes many parameters. Figure 16 shows a typical gear dynamic model, reproduced from references [155, 156], and the equations of motion of the gear system can be written as

$$\mathbf{M}\ddot{\mathbf{x}} + \mathbf{C}\dot{\mathbf{x}} + \mathbf{K}\mathbf{x} = \mathbf{F} \tag{6}$$

where

$$\mathbf{x} = \left[x_p, y_p, \theta_p, x_g, y_g, \theta_g\right]^T \tag{7}$$

represents the translational and angular displacements of the modeled gear system. **C**, **K**, and **F** are the corresponding damping, stiffness, and force matrices. In the dynamic model, the vibrations of the gear systems are caused by two kinds of sources of excitations: one is the external excitations coming from the fluctuation of the applied load and input operating rotating speed, and the other is the internal excitations related to meshing stiffness-$k(t)$ and GTE- $e(t)$.

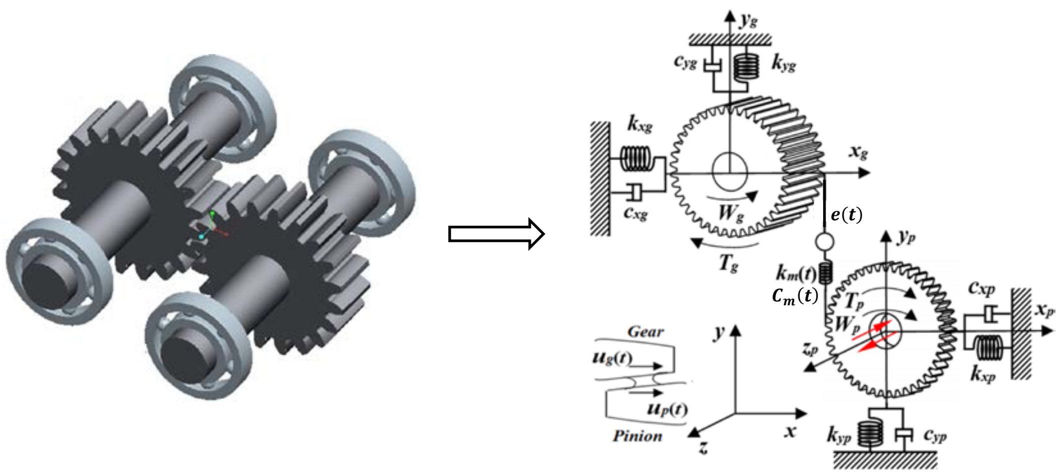

Figure 16 Dynamic model of a spur gearbox [155, 156]

The gear wear directly impacts the internal excitations of the dynamic model. The contact force of meshing gears can be calculated as

$$\begin{cases} F_k = k_m(t)\left(r_{bp}\theta_p(t) - r_{bg}\theta_g(t) + y_p(t) - y_g(t) + e(t)\right) \\ F_c = C_m(t)\left(r_{bp}\dot{\theta_p}(t) - r_{bg}\dot{\theta_g}(t) + \dot{y_p}(t) - \dot{y_g}(t) + \dot{e}(t)\right) \end{cases} \tag{8}$$

It should be noted that the gear meshing stiffness is usually estimated by the FEM model or the potential energy method as follows [157]:

$$k_m(t) = \sum_{j=1}^{m} \frac{1}{1/k_{h,i} + 1/k_{b1,i} + 1/k_{s1,i} + 1/k_{a1,i} + 1/k_{b2,i} + 1/k_{s2,i} + 1/k_{a1,i}} \quad (9)$$

where k_h, k_b, k_s and k_a are Hertzian contact stiffness, bending stiffness, shear stiffness, and axial compressive stiffness, respectively. j denotes the jth pair of the meshing teeth. The driving gear and driven gear are indicated by subscripts 1 and 2, respectively. The $C_m(t)$ is a major unknown factor, which is difficult to be determined in industrial practice. The $C_m(t)$ can be evaluated based on the $k_m(t)$ (as shown in Eq. (10)) [158], nevertheless, its accuracy still needs to be further checked.

$$C_m = 2\zeta \sqrt{k_m \frac{m_1 m_2}{m_1 + m_2}} \quad (10)$$

where ζ is the damping ratio, m_1 and m_2 are the masses of driving and driven gears, respectively.

Generally, when gear wear occurs, the contact patterns between engaging gear pairs can be substantially modified, that is, tooth profile change (e.g., from abrasive wear) and contact area reduction (e.g., from fatigue pitting). Tooth profile change is one kind of GTE. Both tooth profile change and contact area reduction can alter the gear meshing stiffness $k_m(t)$. Consequently, the gear wear will affect the dynamic contact force of the meshing gears and change the responses of the gear system. There are some research works that investigate the relationship of gear wear with meshing stiffness and GTE. In the following, research on meshing stiffness and GTE with gear wear will be reviewed and discussed.

5.1.1 Effects of gear wear on meshing stiffness

The meshing stiffness of the planetary gearbox was evaluated in [159], with consideration of wear-induced tooth profile change. The numerical results indicated that the gear wear could decrease meshing stiffness, and the reduction depends on the severity of gear wear. In [160], the gear meshing stiffness of gears in the shearer cutting section under different degrees of wear was analyzed, and it was found that the gear wear could cause a decrease in meshing stiffness. Besides, the helical gear meshing stiffness change due to wear was investigated in [161]. It should be mentioned that studies [159-161] only consider the wear-induced tooth profile change, which is mainly caused by gear abrasive wear. Unlike abrasive wear, fatigue pitting can bring localized valleys to the gear tooth surface and then reduce the gear meshing stiffness differently. Therefore, some researchers investigated the impacts of surface pitting on meshing stiffness. Initially, a single pit was considered, and its impact on meshing stiffness was investigated (such as [162-164]). Afterwards, the meshing stiffness calculation equation was derivated to study the influence of multiple tooth pits on the meshing stiffness of an external spur gear pair [165]. However, single pits or multiple pits distributed evenly is far different from the pitting propagation in engineering practices. Therefore, with consideration of the appearance and propagation process of gear surface pitting, a new model was established to describe gear pitting based on the probability distribution (see Figure 17), and a finite element model was applied to verify the effectiveness of the proposed analytical model [166].

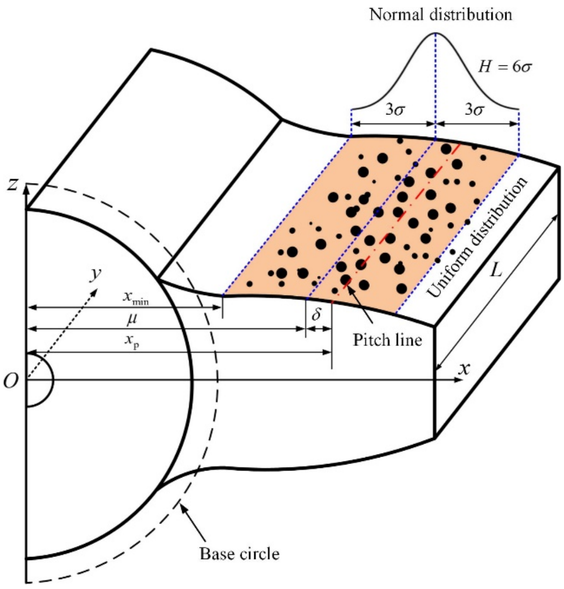

Figure 17 Distribution of pits on the tooth surface [166]

However, it should be noted that no matter whether it is abrasive wear induced gear tooth profile change or surface pitting, the deformation change caused by meshing stiffness reduction is much smaller than wear induced tooth profile change, even at the micro-level. Therefore, considering the scale of gear wear-induced geometric error, the meshing stiffness change induced by gear wear can be neglected since it is significantly less important than the transmission error effect at both micro and macro levels [10, 104, 116, 167]. In the following sections, studies on wear-induced transmission error of the dynamic model will be reviewed.

5.1.2 Effects of gear wear on the geometric transmission error

Owing to the wear-induced GTE, the dynamic load and its distribution between the meshing gear pairs are altered, leading to a dynamic transmission error (DTE) and thus resulting in changes in vibration and noise level. Different from the other parameters in the dynamic model, such as backlash, manufacturing error, and tooth relief, gear wear can cause a tooth profile change with particular distribution, which is almost zero around the pitch line and generally has a maximum value at the root or tip of the gear tooth [168-171], see Figure 18. Different tooth profile changes can cause different dynamic characteristics and responses; therefore, to acquire accurate wear-induced dynamic characteristics and responses, GTE should be properly obtained or simulated according to the characteristics of wear-induced gear tooth profile changes. There are two possible approaches to obtaining wear-induced GTE: simulation-based and experimental methods. In the following, studies relevant to the GTE for gear wear analysis will be introduced.

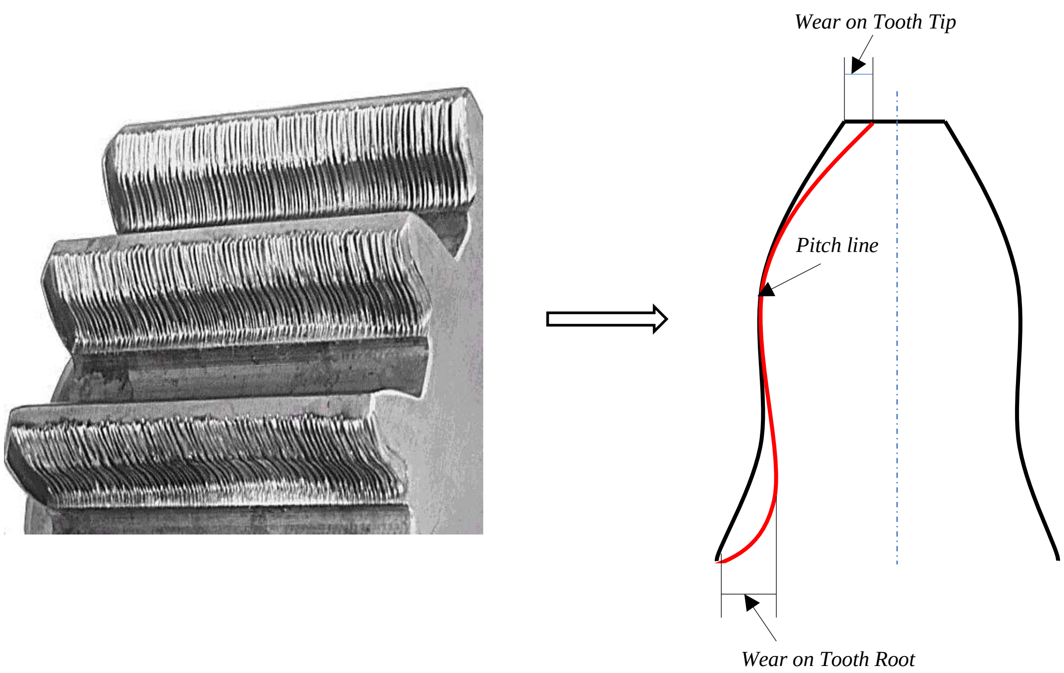

Figure 18 Wear distribution (abrasive wear) [172]

Experimentally, GTE can be measured using a special device. For example, a mass of lead traces was obtained using a gear coordinate measurement machine in [173]; each trace contains around 200 measurement points, which are aligned using a single profile trace to obtain a three-dimensional comprehensive measurement of the actual gear tooth surface. This approach can acquire wear-induced GTE accurately. However, when measuring and evaluating the tooth surface changes, the gearbox needs to be dismantled, which may bring other failure modes into the gearbox, such as shaft misalignment. Therefore, many researchers choose the simulation-based approach. For example, a finite element model was applied to simulate the wear-induced tooth profile change in [174].

Since wear-induced tooth profile change is complex, therefore, it is not easy to use simple equations such as sine/cosine functions to represent it accurately. Considering that, some researchers use the tribological (wear) models to obtain the wear-induced tooth profile changes (such as [83, 84, 175, 176]). This approach can be regarded as an integration of dynamic and tribological models, and it will be introduced in Section 5.3. In the following, tribological models to simulate and represent wear propagation behaviors will be presented first, followed by a review of the integration of the dynamic model and the tribological model.

5.2 Tribological (wear) models for monitoring wear depth and pitting density

There are different approaches to establishing tribological models with consideration of wear modes (abrasive wear, scoring, corrosive wear, etc.). The tribological can help reveal the contact status of the engaging gears, which is beneficial to the gear design. For example, with the help of tribological models, the impact of gear meshing behaviors on the lubrication status (such as the minimum film thickness) was investigated in [177]; the results can provide useful guidance for gear design and then improving its lubricating performance. Since abrasive wear and fatigue pitting are common wear mechanisms during gear service life and also the objectives of this review, tribological models of these two wear mechanisms will be reviewed in this sub-section.

As for abrasive wear, even though researchers proposed a large number of advanced wear models using different methodologies and parameter sets [178-182], the Archard wear model [183] is the most widely used one for various materials, such as plastic [184] and steel [98]. The theoretical basis of the Archard wear model is the Archard wear equation:

$$h = \int K_{wear} P v dt \tag{11}$$

where h denotes the wear depth, ν is the sliding velocity at time t, P represents the contact pressure and K_{wear} is a dimensional wear coefficient. The ν and P can be determined by the parameters of the gearbox and dynamic model; in contrast, K_{wear} will be different in different lubrication conditions; therefore, the wear coefficient K_{wear} is a major unknown factor and it is usually determined/obtained from experiments or by an approximate wear coefficient model [87, 185-187]. The wear coefficient model is established based on the effect of surface roughness and oil film thickness [187]. It is challenging to measure the wear coefficient directly from experiments [188]. Therefore, the widely used approach is to evaluate and determine the wear coefficient using empirical models/equations.

In the determination of wear coefficient using empirical models/equations, lubrication plays an important role, and its effect is considered based on the oil film thickness-to-surface roughness amplitude ratio defined as $\lambda = h_{min}/R$. The minimum film thickness h_{min} can be determined by empirical equations [189]. And, $R = (R_1 + R_2)/2$, where R_1 and R_2 are root mean square values of surface roughness on the pinion and gear [189]. Based on the value of the calculated λ, three lubrication regions are considered in the simulations to represent the level of interaction between the mating surfaces, and the wear coefficient K_{wear} is calculated as follows:

a) if $\lambda > 4$, it means the film thickness is sufficient to separate the engaging surface and avoid direct engaging surface contact, gear wear is neglected and K_{wear} is set to be zero.

b) if $\lambda \leq 0.5$, it indicates a strong interaction, wear is maximum and K_{wear} is usually determined and evaluated based on the experiment results and measurements.

c) in the intermediate zone, in theory, K_{wear} is supposed to be calculated by linear interpolations based on λ.

The relationship between λ and K_{wear} can be summarized in Eq. (12) [83]:

$$K_{wear} = \begin{cases} k_{0,} & \lambda < \dfrac{1}{2} \\ \dfrac{2}{7} k_0 (4 - \lambda), & \dfrac{1}{2} < \lambda < 4 \\ 0, & \lambda > 4 \end{cases} \tag{12}$$

It can be seen that the values of K_{wear} depend on the oil film thickness and gear surface roughness, which are used to determine λ. Note that k_0 is an initial value of wear coefficient.

In a gearbox, the engaging gear teeth are always in sliding and rolling motion against each other and under high contact pressure, which means that the lubrication state/condition is most likely in the boundary or mixed lubrication regime [190]. Therefore, tribological models to simulate abrasive wear behaviors are almost always under boundary lubrication or mixed elastohydrodynamic lubrication (EHL). In the following paragraph, research on abrasive wear models under boundary lubrication or mixed EHL will be briefly introduced.

As introduced in Eq. (12), surface roughness is an important factor in determining the empirical wear coefficient K_{wear}. However, initially, tribological models for abrasive wear were built without considerating the surface roughness update; in other words, wear coefficient K_{wear} is a constant value during the abrasive wear propagation process [173, 175, 191-195]. In these research works, to achieve a gear wear profile that is close to actual worn gear, [173, 175] used a comprehensive finite element model to calculate the meshing gear pairs' contact pressure. However, the wear coefficient K_{wear} has not been updated based on Eq. (12), which means surface roughness remains to be a fixed value without updating, which is not true during the actual gear wear process. The surface roughness update issue was addressed in studies [196-198]. Time-varying gear contact parameters (the radii of curvature, normal load, surface velocities, and slide-to-roll ratio) and wear coefficient K_{wear} updating based on surface roughness were considered in a proposed transient mixed EHL model [196], then the transient behaviour of this model was studied. The model proposed in Ref. [196] was employed in studies [197, 198] to establish a gear fatigue model, and a relatively more accurate wear assessment result can be achieved by considering surface roughness updating during the wear process.

From the above literature review, it can be found that the wear coefficient K_{wear} in most existing tribological models is an empirical value, even considering surface roughness updating during the gear wear process. However, in actual practice, in addition to the surface roughness, lots of other factors can also affect the wear coefficient K_{wear}, such as contamination of the lubricant, operation condition change, etc. Therefore, to accurately simulate wear propagation behaviors, it is necessary to obtain the actual accurate wear coefficient K_{wear} based on actual measurements using efficient and reliable tools.

Compared with abrasive wear, studies on simulating gear surface pitting progression behaviors are sparser, although there are plenty of publications focusing on explaining the process of surface pitting initiation [197, 199-201]. In study [202], a multi-axial fatigue criterion and an EHL model [196] were combined to develop a fatigue pitting model; with the developed model, the progression of pits in the micro-level on the tooth surface is simulated. Similarly, based on the fatigue formula and EHL model, simulation of fatigue pitting propagation behaviors under mixed elastohydrodynamic lubrication conditions was achieved in [105]. Different from [202], the competition behaviors between fatigue pitting and abrasive wear induced mild wear were also investigated. Research works [105] and [202] involve the EHL model, which is time-consuming due to its high complexity, and high-level expert knowledge is required for model establishment. It brings huge challenges to application in industrial practices. Therefore, it is vital to develop more efficient models/tools to simulate fatigue pitting behaviors. To address this issue, based on the Lundberg-Palmgren model [203], a modified fatigue model with high computational efficiency was proposed in research [204], and the results from spur gearbox test rig trials and material analyses were presented to demonstrate the effectiveness of the proposed fatigue pitting model. Also, considering the time-varying surface morphology, lubrication conditions, and operational conditions, a novel fatigue pitting model was developed in [17], and its capability of simuating the surface degradation hebiavors caused by fatigue pitting was verified by the moprhohlogy of real worn gear surface.

5.3 Integration of dynamic and tribological models for gear wear monitoring

As mentioned in Section 5.1, GTE is a crucial parameter of the gear dynamic model for gear wear analysis, but it is challenging to acquire an accurate tooth wear profile solely relying on experimental or simple analytical approaches (e.g., sine or cosine curve). The tribological (wear) model can be used to generate the wear curve on the tooth flank, then the generated wear curve can be incorporated into the gear dynamic model to generate vibrations induced by gear wear. This integration of dynamic and tribological models can reveal the relationship between gear wear and vibration characteristics, which significantly benefits gear wear monitoring and gear design. For example, the dynamic model was integrated with the Archard wear model in [205], and the impacts of tip relief modifications on the gear wear propagation were investigated.

However, there are only limited research works [83-85, 168, 176] using the integration of tribological and dynamic models for gear wear monitoring. Among them, Refs. [83, 84, 168] combined the tribological model and dynamic model to study the dynamic interaction between gear surface wear and gear dynamics (such as meshing stiffness, contact force, and vibrations). This approach was extended to the planetary gearbox in references [85, 176]. A single-degree-of-freedom torsional dynamic model was employed in [83], and it was then integrated with a wear prediction model [173] to investigate the dynamic interactions between the gear surface wear and the gear system's dynamic characteristics. However, an accurate and reliable prediction for gear dynamic characteristics relies on a comprehensive dynamic model that can simulate the behaviors of the actual running rig. Only the torsional deflections and responses were considered in gear-shaft systems [83], and the impacts of translational responses coming from the bearing radial deflections and shaft bending were not considered, which could significantly degenerate the wear analysis accuracy. To solve this problem, a 4-degree-of-freedom model, including translational motions of gears, was introduced in [84], and a new dynamic wear analysis method was proposed to study the interactions between tooth surface wear and gear dynamics. However, simple sine/cosine functions were used to represent the meshing stiffness and GTE [84], while the meshing stiffness and GTE are much more complex in real applications. An improper evaluation of meshing stiffness and GTE of the gear dynamic model could cause degeneration of the accuracy of the wear analysis. This issue was addressed by using the FEM model to simulate the gear contact mechanism with gear wear [168]. It should be mentioned that only numerical results were demonstrated in references [83-85, 168, 176], and there is no model validation involved with the association of actual measurements, which is a crucial procedure for industry practice.

5.4 Summary

Table 6 summarizes the key developments of the model-based gear wear monitoring. Based on the discussion of the publications in Sections 5.1-5.3 and Table 6, it can be seen that research on fatigue pitting simulation is far less than abrasive wear. Nevertheless, fatigue pitting is a common degradation phenomenon in the lubricating system. Thus, more attention should be paid on developing gear fatigue pitting to better understand its propagation behaviors. In addition, studies on the interaction of tribological and dynamic models for assessing gear wear processes are still needed with consideration of a comprehensive dynamic model together with proper parameters (stiffness and GTE) evaluation and necessary model validation. Therefore, it is necessary to establish a comprehensive dynamic model with proper meshing stiffness and

GTE, then validate it with the association of actual measurements, which could simulate realistic wear-induced vibrations (compared with the actual running rig) for wear analysis.

Table 6 Developments of model-based gear wear monitoring

References	Research objectives
[173, 175, 191-196]	Tribological model for abrasive wear
[17, 105, 197, 198, 202, 204]	Tribological model for fatigue pitting
[10, 17, 83-85, 98, 168, 176]	Integration of dynamic and tribological models

6. Wear prediction techniques

Having the capability of predicting the gear wear process would bring enormous and significant benefits in cost and safety to various industries. In the following, the existing studies of vibration-based gear wear prediction techniques will be reviewed and discussed.

6.1 Prediction of tooth profile change from abrasive wear

With the help of the Archrad wear model, the wear distribution on gear tooth was predicted in research [206] under dry conditions, and experimental observations validated the prediction results, that is, the maximum wear occurs in the dedendum and addendum regions of gears. However, the gear system usually operates under lubrication conditions instead of dry conditions [207-209], and good lubrication can reduce wear on the gear tooth, reduce noise and vibration, and improve the power conversion efficiency as less energy irrecoverably. To address this issue, an EHL model was applied to simulate the wear propagation behaviors and predict the accumulated wear depth under lubrication conditions [210]. However, the applied EHL model in study [210] is time-consuming and requires a high level of expert knowledge for establishment. To reduce the computation cost of the EHL model, a simplified EHL model was developed in [211]; also, temperature factors were considered, and the wear predicted results were validated by isothermal formulas defined in [212]. However, in studies [206, 210, 211], the contact force was calculated using empirical equations without considering the actual worn tooth profile geometry, which could degrade the accuracy of prediction results.

To obtain a relatively reliable contact force, the finite element model was used in several studies by considering the worn tooth profile instead of using the empirical formula. A gear surface wear prediction methodology for helical gears was proposed in [173]. In the proposed methodology, in conjunction with Archard's wear model, a finite elements-based gear model was developed to predict gear wear propagation. To guarantee the accuracy of prediction results, a special measurement machine was used to acquire the real worn tooth profile during the gear wear process as an input of the finite element model, and the prediction results were validated through comparison with experimental results. However, in the approach proposed in [173], when measuring the tooth profile, the gearbox should be dismantled, which could bring in other failure modes into the gearbox. Similarly, a finite element model was applied in [213, 214] to provide contact force for the Archard wear model; then, with the Archard wear model, the wear depth of spur and planetary gears could be monitored and predicted. The finite element model was improved in [215, 216] to provide more accurate contact pressure with less computation cost, so that the wear prediction results can be improved. However, there is a drawback of using a simple finite element model (without well-defined boundary conditions and mesh generations), that is, the dynamic characteristics induced by inertia could not be properly represented. With the finite element model, the simulated contact force is usually under quasi-static conditions. However, in actual practice, the gearbox is running under dynamic operation conditions, and the dynamic contact force is different from the quasi-static contact force in both magnitude and waveform [83, 217]. Therefore, the use of a simple finite element model could bring noticeable errors to wear prediction, unless the worn tooth profile can be timely corrected using gear tooth profile geometry measurement devices as demonstrated in [218, 219] and the finite element model is improved significantly to include the dynamic system characteristics. Thus, a dynamic model, after necessary validations, is required to provide the dynamic contact force, whose response is close enough to the actual running test rig.

Besides physical model-based gear wear prediction, some other approaches were also proposed to monitor and predict wear-induced tooth profile change. For example, an integrated prognostics method was proposed for wear prediction in terms of wear depth change [114]. In this hybrid approach, the Archrad wear model was used to simulate wear behaviors, and the Bayesian update process was implemented to determine the wear coefficient during the wear process. The prediction results were validated using a run-to-failure test on the planetary gearbox. Also, a novel updating methodology was developed in [10, 17, 98]. The novel updating methodology was implemented on the Arachard wear models to update the wear coefficients if necessary, by regularly comparing with measured vibrations. The run-to-failure tests under different lubrication conditions were used to demonstrate and validate the effectiveness of the vibration-based updating methodologies [10, 17, 98] in wear monitoring and predictions; compared with the wear prediction purely relying on physics models or experiments, the results suggested that the integration of the wear model and actual measurements could achieve a more reliable and accurate wear prediction. The relationship between gear hobbing processing technique and gear geometric deviation was modeled by applying the improved particle swarm optimization (PSO) and back propagation algorithm (BP) in [220]. The accuracy of both algorithms was evaluated by the root mean square error between the predicted and experimental values. In [221], the artificial neural network was applied to predict the film thickness and lubrication conditions during the gear wear progression so that the severity of wear can be indicated. An approach for slow-speed gear wear monitoring was developed in [222], and this approach consists of an automated feature selection process, random forest regression, and gradient boosted regression tree. The effectiveness of this gear wear monitoring approach was validated using actual wear mass loss [222]. A statistical model with statistical parameters was proposed to monitor and predict the gear behaviors with extreme tooth profile alteration induced by abrasive wear [223], and the effects of applied load and sliding distance of mating teeth were statistically and physically analyzed. Furthermore, a fusion of ultra-complete independent component analysis and parameter estimation was developed in [224] to monitor and predict the severity of gear wear. Even though promising prediction results were achieved in [220, 223, 224], these statistical model-based approaches could not reveal the wear behaviors and gear dynamic responses change during the wear process. Also, most of the statistical model-based or artificial-intelligence-based approach heavily relies on a large amount of experimental data, which limits its capability to apply in industrial practice. Therefore, a vibration-based tool, which can reveal the gear wear and dynamic behaviors and also requires a small amount of experimental data for model parameter updating/calibration, is urgently needed for gear wear monitoring and prediction in industrial applications.

6.2 Prediction of surface pitting propagation

The focus of the research described in Section 6.1 was on the prediction of the change in the gear profile caused by abrasive wear. There are some research works involving fatigue pitting propagation prediction [105, 204]. In [105], an EHL model and fatigue equation were combined to simulate fatigue pitting propagation and mild tooth profile change (caused by abrasive wear) under mixed elastohydrodynamic lubrication conditions, even though the competition behaviors between abrasive wear and fatigue pitting were exhibited during the gear wear process, this approach is time-consuming and high level of expert knowledge is required to realize the EHL model. Compared with the research in [105], a more efficient approach was proposed in [204], Archard wear model and empirical fatigue pitting formula were used to predict both the abrasive wear (in terms of wear depth) and fatigue pitting (in terms of surface pitting) propagation. Inspired by the fatigue model in [204], a novel efficient fatigue pitting propagation model was developed in [17] to predict the pitting severity and distribution. The co-existing abrasive wear propagation was taken into consideration in [17]. In addition, a statistical formulation was proposed in Ref. [225] to depict the asperity shape evolution induced by plastic deformations and wear under mixed lubrication, and an asperity strain-hardening model was developed to predict the surface roughness change and fatigue pitting propagation. Although there is an almost perfect agreement between the model predictions and the experimental reference measurements in [225], the model predictions must rely on a huge amount of experimental evaluations for a more decisive validation and a final judgment on their precision, which brings great challenges to the application in industrial practices. The wear propagation processes were not timely examined nor calibrated by actual measurements to accommodate changes in operating and lubrication conditions as well as wear conditions and rates [105, 204, 225].

In practice, the abrasive wear and fatigue pitting propagation rate would be influenced by the lubrication contamination, roughness change, operation condition change, etc. Therefore, without real-time examination and updating, the accuracy of prediction results is uncertain and may decrease significantly during the wear propagation. Therefore, reliable, effective, and efficient vibration tools are needed to predict gear wear propagation progress, with consideration of actual measurements.

In addition to the above-mentioned physical model-based approaches, other techniques were also developed for fatigue pitting prediction. For example, the artificial neural network (ANN) was used in [226] to predict the severity of gear fatigue pitting. American Gear Manufacturing

Association (AGMA) design standard was employed in Ref. [227] to predict fatigue pitting and fatigue crack initiation caused by bending behaviors along the gear tooth profile. Based on the ISO standard of gear micropitting (ISO/TR 15144-1:2020) and taking into consideration of the operating conditions (load and speed), a theoretical study was conducted in [228] to assess and quantify the risk of gear micropitting by determining the local contact temperature, contact pressure, sliding parameter and thickness of lubricant oil film along the action line of gear tooth contact. Generally, a large set of experimental data is required to train the ANN or determine/optimize the parameters in the AGMA and ISO standards. In real applications and industry practice, it is hard to obtain sufficient historical data for training or parameter optimization. Also, having the ability to demonstrate the fatigue pitting propagation behaviors can help understand the fatigue mechanisms. However, ANN, AGMA or ISO standards can not reveal the fatigue pitting propagation behaviors with details.

6.3 Prospects of the digital twin technologies in gear wear prediction

The digital twin (DT) is a virtual representation (mirror) of a physical structure or a system in real space along its lifecycle [229]. Through real-time interaction between the virtual model and physical structure, the degradation status of the system and its RUL can be reflected and evaluated effectively. Thanks to its unique feature, DT has received considerable attention from the research community over the last decades [230]. However, due to the complex structures and harsh operation conditions, research on DT-based gearbox transmission system RUL prediction is rather rare. And existing conceptual approaches [229, 231, 232] have limitations in indicating the specific contact status and providing insights on degradation stages of gearbox transmission systems, all of which are of high value to RUL prediction. Therefore, the development of a systematic and practical digital twin technology for gear wear monitoring and RUL prediction will provide significant benefits to industrial applications.

The rudiment of digital twin techniques in gear wear monitoring can be found in several studies. For example, an integrated prognostics method was proposed for gear wear prediction [114]. In this integrated method, the Archard wear model could be recognized as the virtual model, and the connection between the virtual model and the physical structure was the collected wear particle mass. The experimental results proved the effectiveness of the proposed integrated prognostics. Also, comprehensive dynamic wear models were established as virtual models [10, 17, 98], and a novel updating procedure was proposed to help the virtual (wear) model communicate with physical measurement, that is, vibration signal. The endurance tests under different lubrication conditions demonstrated and validated the proposed vibration-based gear wear prediction methodology. The flexible and evolving nature of the prediction approaches shown in Refs. [10, 17, 98, 114] means that they could be easily executed and deployed within existing digital twin frameworks, which can bring enormous potential benefits to gear system prognostics in practice.

6.4 Summary

Table 7 summarizes the developments of wear prediction techniques. From Table 7 and the above review on wear (abrasive wear and fatigue pitting) prediction techniques, it can be seen that most of the existing wear prediction techniques are designed for predicting abrasive wear induced tooth profile change, while the fatigue pitting prediction techniques have not yet been fully developed. The main reason might be that i) there are few effective and efficient models/tools for simulating fatigue pitting propagation behaviors, ii) abrasive wear usually co-exists with the fatigue pitting propagation, which leads to a complex surface degradation process; and iii) the fatigue pitting induced vibration feature is weak and difficult to be extracted. These challenges restrict the development of vibration-based fatigue pitting propagation monitoring and prediction. Nevertheless, a reliable, effective, and efficient fatigue pitting model/tool is required to uncover fatigue pitting propagation behaviors.

Table 7 Gear wear prediction techniques

References	Main methodoligies/techniques	Research objective
[173, 206, 210, 211, 213-216]	Tribological model-based techniques	Tooth profile change prediction (mainly caused by abrasive wear)
[220-224]	Data-driven based techniques	Tooth profile change prediction (mainly caused by abrasive wear)
[105, 204]	Tribological model-based tecniques	Fatigue pitting propagation prediction
[225-228]	Data-driven based techniques	Fatigue pitting propagation prediction
[10, 17, 98, 114]	Digital twin techniques	Gear wear predictions (abrasive wear or fatigue pitting)

From the review of the existing research on gear wear prediction, it is noted that the physical-based approach has been widely used. Compared with the statistical model-based approach, artificial intelligence-based approach, and standard-based approach, the physical (wear) model has its unique advantage in that the surface degradation behaviors can be directly determined for understanding the wear mechanism and its consequences to the gear system. However, the existing model-based wear prediction methodology has not been fully calibrated using actual measurements, which could degrade the wear prediction accuracy. Thereby, it is necessary to develop a vibration-based tool for gear wear prediction, in which the wear model can be established following a complete understanding of the wear mechanism, and the model parameters can be timely calibrated and updated with a reasonable amount of experimental data available.

7. Conclusion and recommendation for future work

Research progress on vibration-based gear wear monitoring developments has been reviewed and summarized in the preceding sections. This section presents the conclusion and recommendations for future research in this area.

7.1 Conclusion

From the literature review of vibration feature-based gear wear monitoring, it was noticed that most of the existing research works are focused on tracking the abrasive wear-induced tooth profile change, which is usually at millimeter level (macro-level wear). On the contrary, fatigue pitting monitoring (usually at micro-level wear) and wear mechanism identification have received less attention mainly due to weak vibration characteristics related to fatigue pitting, which are easily submerged and masked by background noise. In reviewing the progress of vibration model-based gear wear monitoring, it was observed that the Archard wear equation still plays an important role in modeling the abrasive wear behaviors. In contrast, analytical models for fatigue pitting are limited, and the combination of the EHL model and fatigue criterion is currently the primary approach to theoretically investigate fatigue pitting propagation behaviors, which is a time-consuming process and requires a high level of expert knowledge for establishing the model. More effective and efficient models/tools for simulating fatigue pitting propagation behaviors would be highly desired to further understand fatigue pitting propagation.

Moreover, in industrial practices, abrasive wear and fatigue pitting can both arise in the gear surface degradation progression, either simultaneously or individually appearing at different times on the same gear. Therefore, it would be better if both the gear tooth profile change and surface pitting density could be simultaneously monitored and predicted. To do so, it would require to quantify the wear-induced tooth profile change/alteration (in terms of wear depth) and the surface pitting density in situations when these two wear events take place separately or simultaneously.

From the perspective of industrial applications, the cyclostationary analysis approach could bring significant benefits to various industrial scenarios. The cyclostaionary analysis is a real-time nondestructive monitoring method. Performing the cyclostationary analysis can identify the wear mechanisms and assess the wear severity. The information obtained from the cyclostationary enables engineers to have a deep insight into the current degradation status of the gearbox, analyze the possible cause of the degradations, and then make reliable predictive maintenance-based decisions.

The digital twin techniques discussed in Section 6.3 also have enormous potential benefits to industry practice. The virtual models (such as the dynamic and tribological models) can help reveal the actual running status of the gearbox without disrupting its operations. Also, the real-time communication of virtual models and actual measurements from the gearbox can guarantee accurate gear operating status representations and remaining useful life predictions, which are of great interest to analysts and engineers. Moreover, with some transfer learning techniques or adaptive model updating techniques, the virtual models can be applied to various applications, thereby significantly reducing labor costs and bringing substantial economic benefits.

7.2 Recommendations for future work

From the above discussions, there are some potential topics for future research in this area, which are listed as follows:

1) Vibration-based adhesive wear progression monitoring

As discussed in Section 2.1, the studies on adhesive wear are much less than those on abrasive wear and fatigue pitting, especially for the vibration-based wear progression monitoring. The adhesive wear is caused by the shear of adhesive bonding and is a common form of dry wear in industrial practices. Severe adhesive wear would induce noticeable changes in vibration features. Therefore, the investigations of the relationship between adhesive wear and vibration characteristics could benefit the development of vibration-based adhesive wear progression monitoring techniques, which are of great significance for the health management of gear transmission systems.

2) Vibration-based fatigue pitting evolution tracking

As reviewed in Section 4.1, many studies were focused on tracking the tooth profile change, which is mainly caused by abrasive wear, while fatigue pitting propagation tracking has been less considered in the literature. Analytical techniques that can extract or enhance the weak features induced by fatigue pitting are needed to be developed for tacking fatigue pitting propagation. On the other hand, sliding vibration contains rich information of gear surface morphology [233]. More studies on extracting the useful information existing in sliding vibrations are deserved.

3) Vibration-based wear mechanism identification

As stated in Section 4.2, the online wear mechanism identification techniques via vibrations have not been well developed. Investigating the micro-level surface morphology difference could facilitate the development of vibration-based gear wear mechanism identification. For example, the different wear mechanisms have different spatial frequencies, resulting in different vibration frequencies. Also, the surface roughness levels of different wear mechanisms are different, which might lead to vibrations with different magnitudes.

4) Development of fatigue pitting model

Unlike abrasive wear, there are no simple and widely used models to simulate fatigue pitting propagation. Most of the existing research used the EHL model and combined it with fatigue criteria. However, establishing the EHL model requires a high level of expert knowledge and is time-consuming. An efficient, effective, and reliable fatigue pitting model is highly anticipated for practical utilization in industrial applications.

5) Vibration-based techniques to understand multiple wear mechanisms and predict their propagation

Even though there are several approaches to predict the wear propagation as introduced in Section 6, most of them were focused on a single wear mechanism/event, either abrasive wear or fatigue pitting. In practical engineering, multiple wear phenomena co-exist in the wear process during the gear service life. Vibration-based techniques, which can accurately predict these wear events separately or simultaneously, would offer significant benefits to industrial applications.

6) Digital twin based model for gear system monitoring during the gear wear propagation progression

Digital twin-based model can help reveal the gear wear propagation behaviors by using numerical simulations and limited measured data. This model would virtually provide deep insights into the wear mechanisms and contribute to a deep understanding of the degradation of the gear transmission system. Valuable information from the digital twin-based model can help create smart maintenance scheduling and gear design.

7) RUL prediction of the gearbox transmission system

Gearbox transmission system is widely used in many industrial areas, and its reliable operation is a key for mechanical power transmission in rotating machinery. Gear wear is an inevitable phenomenon during gear service life. It is beneficial to predict the RUL of the gear system so that predictive maintenance can be scheduled in advance. The artificial intelligence approaches and digital twin methodologies can help predict the RUL of the gear transmission system.

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