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Adaptive Estimation of Instantaneous Angular Speed for Wind Turbine Planetary Gearbox Fault Detection

YI WANG[1,2,3], BAOPING TANG[1,3], LIHUA MENG[4], AND BINGCHANG HOU[1]
[1]College of Mechanical Engineering, Chongqing University, Chongqing 400044, China
[2]Industrial IOT and Networked Control Key Laboratory, Ministry of Education, Chongqing University of Posts and Telecommunications, Chongqing 400065, China
[3]The State Key Laboratory of Mechanical Transmission, Chongqing University, Chongqing 400044, China
[4]AVIC, China Aero-Polytechnology Establishment, Beijing 100000, China

Corresponding author: Yi Wang (wycqdx@cqu.edu.cn)

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ABSTRACT Planetary gearbox faults are the leading causes of downtime in wind turbines (WTs). In recent years, numerous and various vibration-based approaches have been put forward for WT gearbox fault detection. In the vibration-based techniques, order tracking-based methods, which by identifying fault orders in gearbox drivetrains, are regarded as very promising and powerful techniques. In the currently available order tracking methods, auxiliary devices are required to accurately obtain the instantaneous angular speed (IAS) of drivetrain. To tackle this problem, instantaneous angular speed estimation from vibration signals has been studied and some tacho-less order tracking (TLOT) approaches have been developed. However, many vital parameters for IAS estimation in the currently available TLOT algorithms need to be manually selected, which raise the question of user-friendliness, even result in a false diagnosis. As mentioned earlier, aiming at the shortcomings, a novel TLOT method based on adaptive IAS estimation is proposed for WT planetary gearbox fault diagnosis. In the proposed method, the nonlinear mode decomposition (NMD) method is improved, and its computational burden is reduced. And, the tachometer information of the drivetrain is adaptively extracted by the improved NMD method from generator vibration signal for gearbox vibration signal resampling. A field test is conducted, and the vibration signal of WT planetary gearbox with the compound fault is used for further investigation. The experimental validation results demonstrate that the planetary gearbox compound fault can be successfully detected, and the proposed method outperforms the traditional method based on generalized demodulation.

INDEX TERMS Nonlinear mode decomposition, instantaneous angular speed, tacho-less order tracking, wind turbines, fault diagnosis.

I. INTRODUCTION

Wind turbines are usually operating under harsh environments [1]–[4]. The gearboxes of wind turbines used for power transmission, are often encounter gear tooth pitting or root cracking [5]. If a defect in gearboxes is not identified and repairs are not performed in time, some defects may result in consequent failures of other components and the entire wind turbine system, even causes human injures and significant economic losses. Therefore, an efficient planetary gearbox condition monitoring and fault diagnosis tool, which provides health condition information of wind turbine, is very essential for scheduled maintenance performed ahead of severe failure or critical malfunction occurs.

Up to now, there are two major categories of approaches for gearboxes diagnosis, i.e. data-driven methods and vibration analysis respectively [6]–[8]. Data-driven methods identify the faults types and evaluate remaining useful life by using feature extraction and machine learning [9]–[12]. In the data-driven based methods, train dataset characterize different

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failure modes and various operating conditions should be available ahead of fault identification, and the behaviors of the systems should be repeatable. However, it is very challenging in practical applications to obtain sufficient training samples corresponding to various operating conditions to achieve high diagnostic accuracy.

Aiming at the above-mentioned flaws encountered by the data-driven methods, an alternative way is using vibration analysis to detect wind turbine fault. Faults occur in the transmission chain of wind turbines will induce abnormal vibrations of the corresponding subsystems, and the fault symptoms can be detected by vibration analysis from vibration signals. In contrast to the data-driven based methods, vibration analysis detects fault characteristic frequencies or orders by using various signal processing techniques, such as spectral analysis, envelope analysis, etc. [12]–[19]. In recent years, many powerful vibration-based methods have been developed and used for WT gearbox fault detection [20]–[22]. However, most of the current available vibration-based methods for WTs fault detection are on the basis of stationary assumption. For wind turbines operating under non-stationary conditions, the transient vibration response of the wind turbine system will change with speed fluctuates, and the collected vibration signal will be with strong non-stationarity intrinsically [23]. As a result, fault signatures detected by the conventional vibration analysis approaches, which based on the assumption of stationary conditions, will be contaminated by the non-stationary operating condition information. Therefore, it is very challenging to obtain a high diagnostic accuracy in this circumstance.

Recently, WT planetary gearbox fault diagnosis under non-stationary conditions has attracted considerable attention [24]–[32]. Among the recently developed fault diagnosis approaches, order tracking [24]–[27] has been considered as a powerful and effective technique for fault diagnosis of rotary machineries. Compared with the conventional methods based on spectral analysis, the original signal is resampled at a constant angular increment in the order tracking procedure. Therefore, the original time domain non-stationary signal is transformed to angular domain with stationary waveform. On this basis, the spectral smearing phenomenon which introduced by speed variation condition can be eliminated, and the traditional frequency analysis techniques are applicable for further signal processing. However, most of the traditional orders tracking approaches require the installation of tachometers or encoders, which increases the equipment cost and brings inconvenient in auxiliary sensor installation [32].

In the aim of tackling the challenges encountered by the traditional order tracking methods, researchers turned their attention towards tacho-less order tracking (TLOT) methods [24]–[30]. The essence of TLOT is using advanced signal processing techniques to accurately estimate IAS from the vibration signal, other than using an auxiliary sensor to tracking the instantaneous shaft phase. Since the mono-component decomposition of signals is required to obtain instantaneous phase with physical meaning, therefore, one certain harmonic of the rotating harmonics should be accurately separated from the raw vibration signal in advance. For this reason, mono-component decomposition based IAS estimation methods have been developed [29]–[33]. Inspired by the idea of generalized demodulation [33], some mono-component decomposition approaches are studied in [29]–[31], in which the generalized Fourier transform (GFT) combined with band-pass filtering are used to separate the interested component with arbitrary curved instantaneous frequency trajectory from the raw vibration signal. However, expertise knowledge about one certain harmonic (e.g. the beginning point of the ridge of the harmonic, the actual order, the bandwidth of the harmonic, etc.) is required in the GFT based IAS estimation procedures for mono-components identification and separation. As an adaptive method, Empirical Mode Decomposition (EMD) [34] and its improved versions, such asEnsemble Empirical Mode Decomposition (EEMD) [35], which can be applied to mono-components extraction by numerical approximation, are used for fault detection of WTs [36], [37]. However, the spectral overlaps between different components and the phenomenon of intermittences in decomposed signals may cause spectral mixing among different modes, the finally obtained pseudo mono-component may cause seriously biased instantaneous shaft phase and mislead further WT signal analysis.

Despite many breakthroughs have been offered by the tacho-less order tracking methods, the accurately and adaptively extraction of IAS is remaining to be solved before possible industrial applications. The main challenges encountered by the current available TLOT methods for WTs fault diagnosis can be summarized as follows. First of all, most of the conventional TLOT method need expertise knowledge to tracking one certain harmonic, this introduces a major obstacle in non-stationary signal processing, especially in the cases when expertise knowledge on signal structures is not available. Secondly, mono-components with physically meaningful returned by the methods cannot always be guaranteed. Thirdly, most of the current reported methods are not noise robust. Since the WT vibration signals are always with strong noise intensity, the methods may extract the noise component or the adjacent harmonics rather than the interested harmonic. Finally, for WTs gearbox fault diagnosis under non-stationary operating conditions, it is very important to accurately estimate the instantaneous phase of one certain shaft in the drivetrain. However, in the WTs gearbox vibration signal, the rotating harmonics are always seriously interfered by gear meshing harmonics. As a result, most of the current TLOT methods are invalid for WTs order tracking in this circumstance. Therefore, it is of significant importance to develop a more effective and adaptive tool for instantaneous shaft phase estimation for WTs planetary gearbox fault detection.

The shortcomings mentioned above encountered by the current available mono-component decomposition methods are comprehensively addressed, and a new adaptive and flexible signal decomposition technique namely Nonlinear Mode

Decomposition (NMD) was reported in [38]. In the NMD method, the time-frequency analysis approaches [39], surrogate data tests [40], [41] and the idea of harmonic identification [42] are integrated for mono-component decomposition. In NMD, surrogate tests are used to identify the prominent component and its relevant harmonics or sub-harmonics of a non-stationary signal, and thereby the original signal is decomposed into a set of physically meaningful mono-components, simultaneously suppress the background noise.

To tackle the flaws encountered by the current available techniques, the merits of NMD technique for signal decomposition is inherited in this paper, and a novel TLOT method is proposed for fault detection of WTs operating under non-stationary conditions. In the proposed method, based on the powerful ability of mono-component decomposition, the NMD tool is introduced and further improved to adaptively extract mono-component of rotating harmonics from WT vibration signal. The main innovative ideas of the proposed TLOT method are summarized as follows. Firstly, the calculation efficiency of NMD is improved to make it applicable for WT vibration signals with relative high sampling frequency. Secondly, based on the improved NMD method, the phase reference signal is adaptively extracted without the prior knowledge about the analyzed signal. Thirdly, the vibration signal collected from the generator, rather than the vibration signal obtained from planetary gearbox, is used for reference phase estimation. In this sense, the prior knowledge about the signal characteristics are not required in this method, therefore, the difficulties of IAS acquisition encountered in the conventional TLOT methods can be solved. This research provide adaptive and effective technique for fault detection of WT planetary gearbox under speed variation operating conditions, and thereby, scheduled maintenance can be performed ahead of severe failure or critical malfunction occurs.

The rest of the paper is organized as follows. In Section 2, the theoretical background of surrogate test is introduced, the NMD technique for mono-components decomposition is illustrated and the proposed method is demonstrated. In Section 3, the performance of the proposed method is investigated by a field test. Finally, this paper is summarized and conclusions are drawn in Section 4.

II. THEORIES

In WT system, the measured vibration signals are composed of different nonlinear modes due to the non-stationary operating conditions, which with time-varying amplitudes and frequencies. Valuable rotating speed information, i.e. instantaneous shaft phase about the investigated WT system are embedded in the nonlinear modes. Therefore, in order to conduct tacho-less order tracking on WTs operating under non-stationary conditions, it is of significant importance to adaptively and accurately decompose the original signal into individual oscillations for rotating harmonic extraction. On this basis, a certain mode can be obtained for further analysis. However, it is critical to effectively decompose the signal into different oscillations, and reconstruct the physically meaningful mono-components in the inevitable circumstance of background noise.

A. THE THEORETICAL BACKGROUND OF THE NMD TECHNIQUE FOR MONO-COMPONENT EXTRACTION

Aiming at the shortcomings encountered by the current available mono-components decomposition methods, a new adaptive non-stationary signal decomposition technique was presented in [38]. The target of NMD is to adaptively decompose a non-stationary signal into a set of physically meaningful oscillations and surrogate test [40], [41] is use to identify its true constituent component against noise. For a collected WTs vibration signal $x(t)$, the main procedures of NMD for mono-components decomposition are briefly described as follows.

(1) Obtain the time-frequency representation (TFR) of the original WT vibration signal by Short-Time Fourier Transform (STFT), and denoted as $TF(t, w)$. Each component in the TFR is indicated by a unique ridge in the TFR plane. The WT rotating speed signal which with a non-sinusoidal waveform will appear as several signal components in TFR plane, consisted by fundamental component and its harmonics. The dominant component with a much higher energy in TFR is extracted and considered as a reference harmonic by a ridge detection approach, the corresponding instantaneous frequency and amplitude values are obtained as

$$w_r(t) = w_p(t) + \delta\left[w_d(t)\right] \tag{1}$$

$$A(t)e^{i\phi(t)} = \frac{2TF(t, w_p(t))}{\hat{g}\left[w_p(t) - w_r(t)\right]} \tag{2}$$

where $w_p(t)$ depicts the energy dominant ridge in the TFR plane, denoted as $w_p(t) = \arg\max_w |TF(t, w)|$, the correction of discretization effect based on parabolic interpolation is represented by $\delta\left[w_d(t)\right]$, the Gaussian window function in the Fourier transform is represented as $\hat{g}(w) = \exp[-\frac{1}{2}(f_0 w)^2]$. Accordingly, the reference harmonic can be separated and obtained as

$$x_r(t) = Re\left[A(t)e^{i\phi(t)}\right] \tag{3}$$

(2) Fourier transform (FT) surrogates test method is used to distinguish the extracted reference component from noise. In the NMD algorithm, the FT surrogates is constructed through calculating the randomized phase of the extracted reference component. The component's FT which obtained by randomizing the phases of the Fourier coefficients is inverse Fourier transformed by

$$s(t) = \frac{1}{2\pi} \int \left[x_r(t)e^{-i\varphi_s(\xi)}\right] e^{-\xi t} d\xi \tag{4}$$

where $\varphi_s(\xi)$ denotes the random phases with uniform taken on $[0, 2\pi]$ for each frequency $\xi > 0$. If the extracted signal component is true, i.e. not just noise peaks, then both of its amplitude and frequency will be more deterministic than the surrogate components, which should be more random with no apparent difference between each surrogate components. The degree of determinacy between the amplitude $A(\xi)$ and frequency $f(\xi) = w_r(\xi)/2\pi$ of the extracted signal components and surrogate components, can be characterized by combining their spectral entropies for surrogate test

$$D(\alpha_A, \alpha_f) = \alpha_A Q\left[\hat{A}(\xi)\right] + \alpha_f Q\left[f(\xi)\right] \tag{5}$$

in which, the spectral entropies can be calculated as

$$Q\left[v(x)\right] = -\int \frac{|v(x)|^2}{\int |v(x)|^2\,\mathrm{d}x} \log \frac{|v(x)|^2}{\int |v(x)|^2\,\mathrm{d}x}\mathrm{d}x \tag{6}$$

Three tests are performed by the spectral entropies of $D(1, 1)$, $D(0, 1)$ and $D(1, 0)$, the maximum value among them is selected as the significance D_s. In this step, N_s FT surrogates of the signal is created, for each of them the corresponding significance is calculated as $D_s(\alpha_A, \alpha_f)$, $s = 1, 2, \ldots, N_s$, D_0 denotes the significance of the original signal. If the number of surrogates with $D_s > D_0$ is equal or greater than λN_s ($\lambda = 0.95$ is set in this algorithm), then reject the null hypothesis of noise, and the reference signal is regarded as a true component.

(3) Find the subharmonic of the reference component, and check whether it is true one, by time-shifted surrogate test. For the reference signal, extracted as $x_r(t)$, it is assumed to be the fundamental harmonic $x_1(t)$ of the original signal, its instantaneous frequency $f_1(t)$, phase $\phi_1(t)$ and amplitude $A_1(t)$ dynamics will consistent with its ith subharmonics or harmonics $x_i(t)$. For $i = 1/2, 1/3, \ldots$, the subharmonics $x_i(t)$ of the reference signal are found and extracted from the TFR plane, with instantaneous frequency $f_i(t)$, phase $\phi_i(t)$ and amplitude $A_i(t)$. Since the previous procedures yields what is not necessarily a true subharmonic, a surrogate test which is against the independence null hypothesis between the obtained subharmonic candidate and the reference signal can be performed to find the real subharmonic.

Since noise components with temporal correlations will introduce consistency errors, the idea of time-shifted surrogate method is used. In this way, the temporal correlations of candidate components is eliminated but all other features is retained, thereby the time-shift creates new surrogate data which also accords with the independence null hypothesis. For the ith candidate harmonic $x_i(t)$, time-shifted surrogate shifted its instantaneous frequency, phase and amplitude about $\Delta T_d/2$ rearward as

$$A_i^d(t_n) = A_i(t_n - \Delta T_d/2) \tag{7a}$$
$$\phi_i^d(t_n) = \phi_i(t_n - \Delta T_d/2) \tag{7b}$$
$$f_i^d(t_n) = f_i(t_n - \Delta T_d/2) \tag{7c}$$
$$\Delta T_d = M(1 - 2d/N_d)/(2F_s) \tag{7d}$$

in which the index of the signal data points is represented by $n = 1 + M/2, \ldots, N - M/2$, N depicts the total length of the signal to be analyzed, the index of surrogates is denoted by $d = 1, 2, \ldots, N_d$, the number of time-shifted surrogates is indicated by N_d, F_s is the signal sampling frequency and M represents the maximal time-shift in samples.

A measure $q^i_{A,\phi,f} \in [0, 1]$ is introduced to quantitatively characterize the degree of consistency between the dependence of the reference signal $x_1(t)$ and the ith harmonic. It is formulated as

$$q_i^A = \exp\left\{-\frac{\sqrt{A_i(t)\left\langle A_1(t)\right\rangle - \left[A_i(t)A_1(t)\right]^2}}{\left\langle A_1(t)A_i(t)\right\rangle}\right\} \tag{8a}$$
$$q_i^\phi = \left|\left\langle \exp\left[\mathrm{j}\phi_i(t) - i\phi_1(t)\right]\right\rangle\right| \tag{8b}$$
$$q_i^f = \exp\left[-\frac{\sqrt{\left\langle\left[f_i(t) - if_1(t)\right]^2\right\rangle}}{\left\langle f_i(t)\right\rangle}\right] \tag{8c}$$

where the symbol $\langle\cdot\rangle$ is inner product operation. An integrated measure of the consistency among the harmonics can be formulated as

$$\rho_i = (q_i^A)^{\beta_A}(q_i^\phi)^{\beta_\phi}(q_i^f)^{\beta_f} \tag{9}$$

in which the parameters $\beta_{A,\phi,f}$ are the weights of the consistence $q_i^{A,\phi,f}$. In the algorithm, the weight parameters are initially set $\rho_i \equiv \rho_i(1, 1, 0)$.

The amplitude-phase consistences $\rho_d^i(1, 1, 0)$ for the time-shifted surrogates are calculated and compared with the value $\rho_0^i(1, 1, 0)$ with zero-time shift $T_0 = 0$. Then, the possibility measure of whether the ith harmonic is true one, is conducted by quantifying the significance of the surrogate tests, i.e. the ratio of surrogates for which $\rho_d^i > \rho_0^i$. In this sense, a WT rotating harmonic can be taken to be genuine harmonics while the probability is no less than 95%. Besides, a minimum threshold $\rho_{\min} = 0.5^{(\beta_A+\beta_\phi)}$ (initially set $\rho_{\min} = 0.25$) is imposed on the surrogate test process, to eliminate the influence caused by noise components. In this circumstance, the candidate component is taken to be a genuine harmonic, only if it both gets through the surrogate test, and the simultaneously, is featured by $\rho_i \geq \rho_{\min}$.

(4) The real harmonic with minimum index i is taken as the fundamental harmonic and regarded reference component for nonlinear mode extraction a step further.

(5) Repeat step 3 for $i = 2, 3, \ldots$, to extract all of its harmonic signals from the TFR plane.

(6) Iterate the step over the residuals until a preset stopping condition accorded with.

Based on the above-mentioned procedures, the WT vibration signal can be adaptively decomposed into several NMs constituted by mono-components, therefore, the shaft instantaneous phase can be extracted with physical meaning for further signal processing.

B. ILLUSTRATIONS OF SPEED IMPROVEMENT OF THE NMD TECHNIQUE

The NMD is a very powerful decomposition tool. However, the computation speed should be improved to make it applicable for WT vibration signal processing. Since the sampling frequency of WT vibration signal is up to several thousand hertz, it is time-consuming and not necessary to search the entire frequency range [38]. Therefore, the frequency range for harmonic candidate extraction is squeezed to the area in

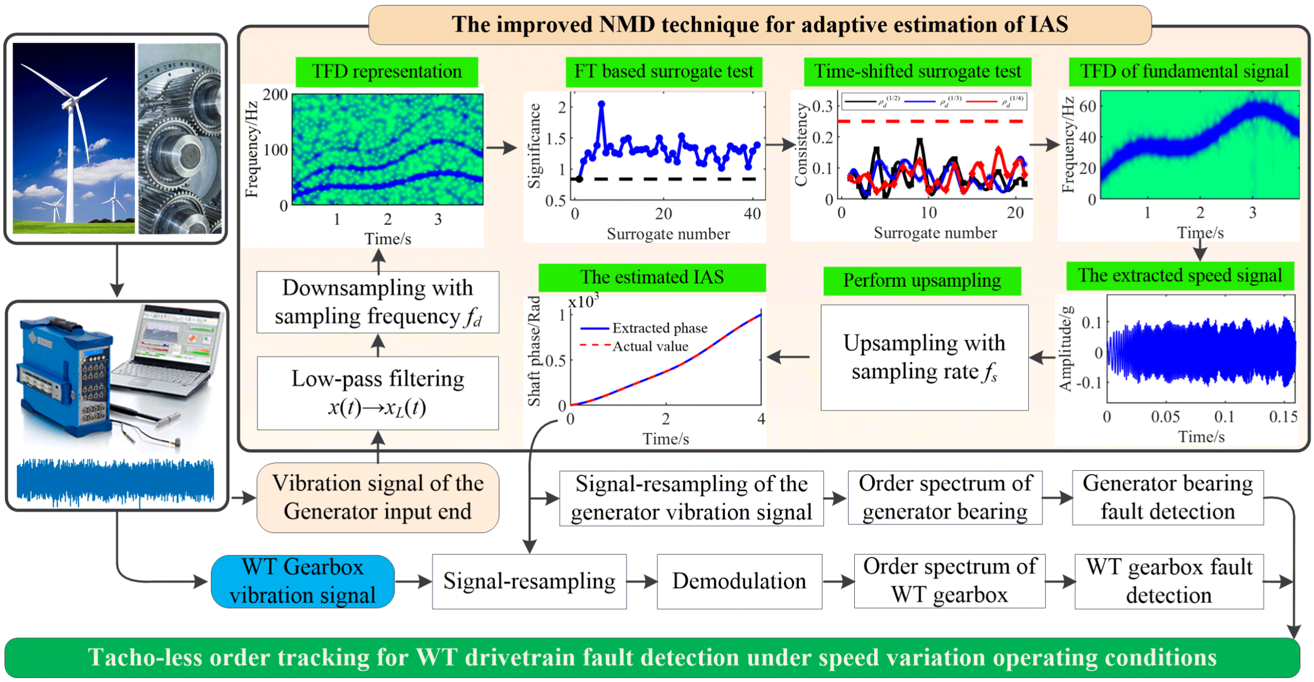

FIGURE 1. The proposed tacho-less order tracking method based on improved NMD.

which the harmonic possibly exists. For the estimated first harmonic with time-frequency range $[f_-(t), f_+(t)]$, its whole frequency bandpass could be expressed as $\{\min[f_-(t)], \max[f_+(t)]\}$. To eliminate the frequency range estimation errors effected by the amplitude of the first harmonic, a narrower frequency range which is used and mathematically defined as

$$\tilde{f}_-(t) : \left|TF(t, f \in [f_-(t), \tilde{f}_-(t)])\right| < \varepsilon \left|TF(t, f_p(t))\right| \quad (10a)$$

$$\tilde{f}_+(t) : \left|TF(t, f \in [f_+(t), \tilde{f}_+(t)])\right| < \varepsilon \left|TF(t, f_p(t))\right| \quad (10b)$$

where $f_p(t) = w_p(t)/2\pi$, and $f_p(t) \in [f_-(t), f_+(t)]$ is the position of the peaks. The parameter ε is set 0.001.

For the ith harmonic, its frequency range estimated by using Eq. (10a) and (10b) can be formulated as

$$f^{(i)}(t) = i\frac{f_{\max}^{(1)} + f_{\min}^{(1)}}{2} \mp \max(1, i)\frac{f_{\max}^{(1)} - f_{\min}^{(1)}}{2} \quad (11)$$

$$f_{\min}^{(1)}(t) = \min\left[\underset{0.05}{\operatorname{perc}}[\tilde{f}_-(t)], \min[f_p(t)]\right] \quad (12)$$

$$f_{\max}^{(1)}(t) = \max\left[\underset{0.95}{\operatorname{perc}}[\tilde{f}_+(t)], \max[f_p(t)]\right] \quad (13)$$

in which perc_p indicates the pth biggest percentage value.

Based on the above improvement, the frequency range to search for one certain harmonic is squeezed and the computational burden is decreased. For the signals, such as electroencephalogram (EEG) signal, sampled at hundreds of hertz, the length of the analyzed signal signals are relatively short, and the NMD method is very rapid to complete the calculation in several seconds. However, for WT vibration signal with a very high sampling frequency, the length of the signal should be long enough to capture the non-stationary information for further signal analysis, the resultant computation burden is very huge in this situation. To address this issue, down-sampling and up-sampling are combined and performed on the signal for speed improvement in our research.

III. THE PROPOSED METHOD

The main procedures of the proposed method are demonstrated in Fig.1. The main idea of the proposed method is summarized and illustrated as follows.

(1) The vibration signal collected from the generator input end, other than the gearbox vibration signal, is utilized to obtain the reference phase of the WT's drivetrain. Therefore, the difficulties in phase reference signal acquisition in the conventional tacho-less order tracking can be solved by the designed method.

(2) Based on the merits for mono-component decomposition, the NMD tool is introduced and further improved to adaptively extract mono-component of rotating harmonics from generator vibration signal.

(3) After that, the IAS of the WT's drivetrain is obtained for signal resampling and the gearbox vibration signals are transformed into angular domain.

(4) The fault orders of the WT gearbox are calculated according to a reference shaft.

(5) Fault detection of gearbox is conducted according to the fault orders of the drivetrain, without auxiliary devices, such as tachometer or encoder.

TABLE 1. Sensor installation locations.

Sensor Number	Sensor location
1	X orientation of drivetrain's input end
2	X orientation of stage I
3	X orientation of stage II
4	X orientation of stage III
5	Y orientation of stage III
6	Y orientation of generator
7	Z orientation of stage III
8	X orientation of generator
9	X orientation of generator

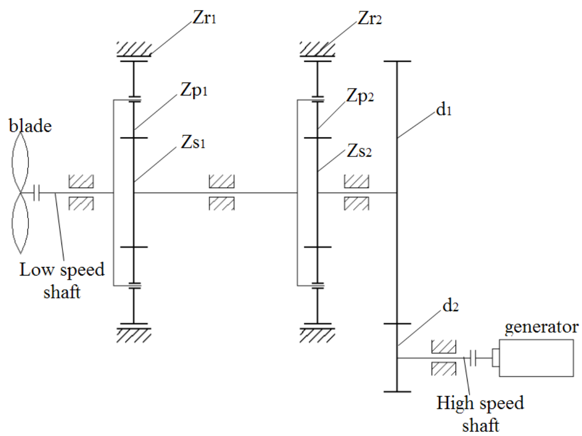

FIGURE 2. Drivetrain configuration of the WT and gearbox transmission layout.

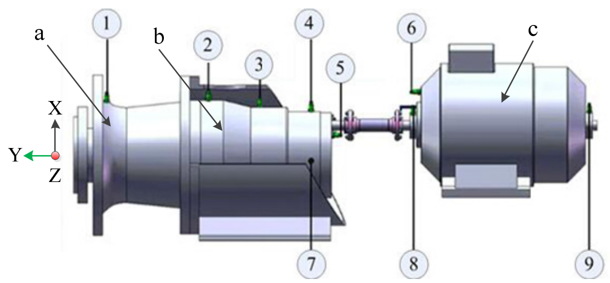

FIGURE 3. Sensor installation locations. (a) depicts the main bearing, the planetary gearbox is indicated by (b), and (c) illustrates the generator.

IV. EXPERIMENTAL VERIFICATION

To improve the now available TLOT methods, an innovative TLOT method is proposed in our research. In this section, based on the improved NMD technique, the proposed TLOT method for WT gearbox compound fault diagnosis is illustrated and a field experiment is also accomplished and shows the validity of the proposed method.

A. AN OVERVIEW OF THE INVESTIGATED WTS

The drivetrain configuration and the sensor installation locations of the investigated WTs are depicted in Fig.2 and Fig.3. In this proposed method, the fault characteristic orders of the WT gearbox are calculated and demonstrated in Table 2 and all the fault orders in Table 2 are obtained by using the planet carrier shaft of the first stage planetary gear as reference. The rotational order f_r of the reference shaft was normalized to 1. The corresponding gear mesh orders of stages I, II and III (denoted as f_1, f_2 and f_3, respectively) were accordingly computed and represented in Table 3. However, when the high-speed shaft in stage III is taken as the reference shaft, the difference between f_r and f_1 is only about 0.02, difficulties will be introduced in the fault feature identification process. Therefore, the planet carrier shaft of the first stage planetary gear is used as the reference shaft in this study.

B. THE EXPERIMENTAL RESULTS OBTAINED BY THE PROPOSED METHOD

The vibration signal, collected from sensor 8 which using for generator shaft bearing condition monitoring, is employed for instantaneous phase estimation of the drivetrain. Fig.4 shows the raw vibration signal collected from the vertical direction of generator. Since the rotating speed of the generator shaft varies with the wind changes, therefore, the traditional mono-component extraction method, based on manually selecting the beginning point of the target ridge, cannot adaptively obtain the fundamental harmonic of the speed signal.

Then the improved NMD method is applied for mono-component separation. First of all, the energy dominant component in the TFD plane is extracted and then tested against noise based on the surrogate test of Fourier transform. The Fourier transform surrogate test result of the energy dominant harmonic is presented in Fig.5. All of surrogates with $D_s > D_0$, it indicates that the extracted component is true, and the null hypothesis of noise is false, decomposition can be continued.

Then, the extracted energy dominant mono-component is assumed to be the fundamental one. And subsequently, time-shifted surrogate test against null hypothesis is performed to confirm the assumption, and the consistence between the extracted mono-component and its subharmonic candidates are investigated. The consistence $\rho_d^i(1, 1, 0)$ of the time-shifted surrogates and $\rho_0^i(1, 1, 0)$ of the candidate subharmonic with zero time shift $\Delta T_0 = 0$, are calculated according to Eq. (8) and (9), as shown in Fig.6. For each subharmonic, all of its time-shifted surrogates' consistency values are lower than the threshold indicated by red dashed line, i.e. $\rho_d^{1/2} < \rho_{\min}$. Therefore, all of the candidate components are identified as false subharmonics. Besides, the consistency of the higher order harmonics are calculated as shown in Fig.7, and the second order harmonic is identified as true component while the third order harmonic is identified as false. Therefore, the original extracted energy dominant harmonic is considered as the fundamental one for the drivetrain phase calculation.

The extracted mono-component of the generator shaft signal is shown in Fig.8(a). The matching speed curve in the

TABLE 2. The system parameters and fault orders.

Transmission chain	Component	Teeth number	Fault order	Transmission ratio
First stage of the planetary gear (Stage I)	Ring gear-Zr1	102	-	5.25
	Planet gear-Zp1	39	1.615	
	Sun gear-Zs1	24	5.25	
	Planet carrier	-	1	
Second stage of the planetary gear (Stage II)	Ring gear-Zr2	102	-	5.25
	Planet gear-Zp2	39	8.48	
	Sun gear-Zs2	24	27.56	
	Planet carrier	-	5.25	
Parallel-gear (Stage III)	Big gear-d1	102	27.56	3.78
	Small gear-d2	27	104.125	
The transmission ratio	-	-	-	104.125

TABLE 3. The calculated orders with different shaft as reference.

Shaft taken as reference	f_r	f_1	f_2	f_3
Shaft of drivetrain's input end	1	102	535.50	2811.38
Shaft of parallel-gear	1	0.98	5.03	27.00

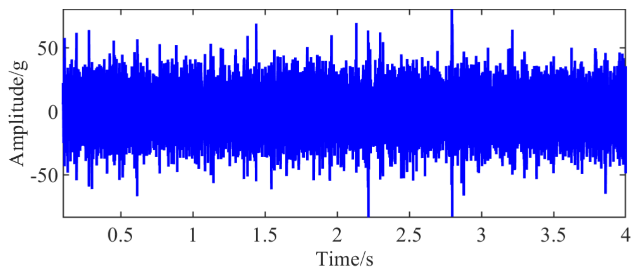

FIGURE 4. The raw vibration signal collected from the vertical direction of the generator.

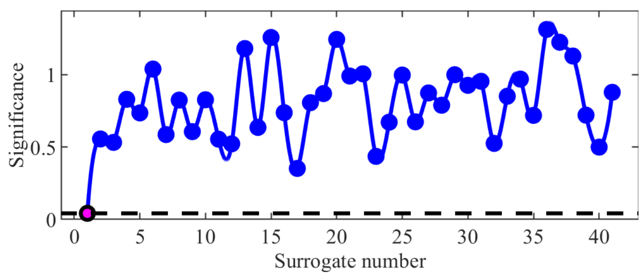

FIGURE 5. Fourier transform surrogate test of the energy dominant harmonic.

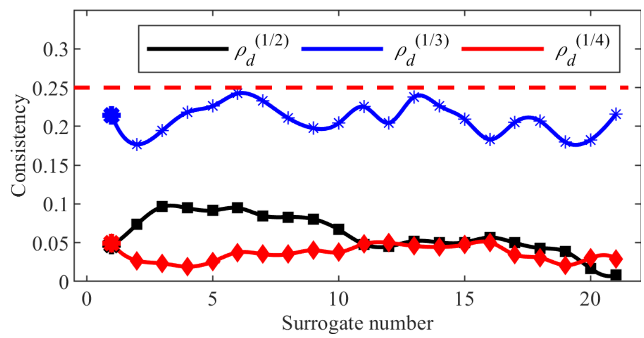

FIGURE 6. The consistency of the candidate sub-harmonics obtained by time-shifted surrogate test.

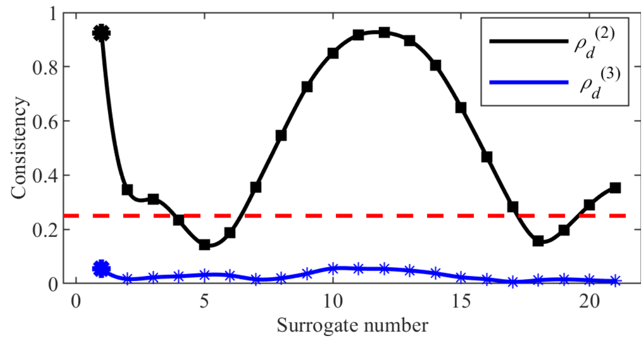

FIGURE 7. The calculated consistency of the higher order harmonics obtained by time-shifted surrogate test.

period of signal Fig.8(a) is depicted in Fig.8(b), though its frequency fluctuation range is only about 0.5 Hz, the variation range of the gear meshing frequency will be enlarged and up to about 13 Hz. In this circumstance, effective diagnosis of the WT planetary gearbox fault will be challenged. And then, the instantaneous phase belonging to the extracted generator shaft speed signal that is plotted in Fig.8(a) is calculated. The phase information owning to the reference shaft, i.e. the planet carrier shaft of the first stage planetary gear, is correspondingly obtained.

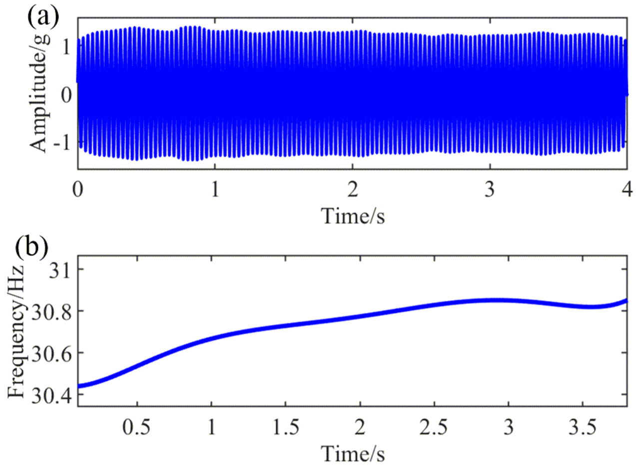

FIGURE 8. **(a) The extracted fundamental harmonic of the generator shaft speed signal and (b) the fluctuation trend of the generator shaft instantaneous frequency.**

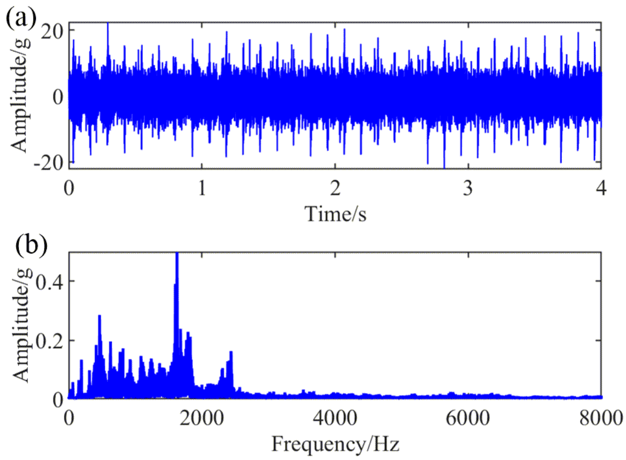

FIGURE 9. **(a) The raw gear vibration signal of the vertical direction in the parallel gears and its corresponding spectrum is shown in (b).**

Subsequently, based on the obtained instantaneous phase, the WT planetary gearbox vibration signals are resampled, and thereby, fault characteristic orders can be detected. The noise contaminated gear vibration signal belonging to the vertical direction of the parallel gears by sensor 4 is shown in Fig.9(a), in which the transient impulse can be observed and a preliminary judgement can be made that a fault may be occurred in the WT gearbox. Fig.9(b) demonstrate the spectrum of raw vibration signal. Because of the nonstationary nature of the gearbox vibration signal, the fault features are hardly obtained. Besides, when the auxiliary tachometer signal is not available, it is very difficult for fault characteristic frequency identification, because the fault characteristic frequencies are multiples of the instantaneous frequency. Therefore, the original raw signal should be resampled, the tacho-less order tracking method is very necessary on such a situation.

Finally, based on the adaptively estimated reference phase, the planetary gearbox vibration signal plotted in Fig.9(a) is

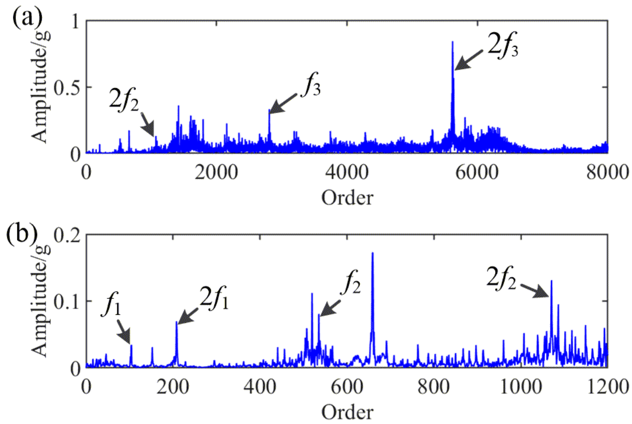

FIGURE 10. **(a) The order spectrum of the resampled signal and (b) its partially zoomed picture.**

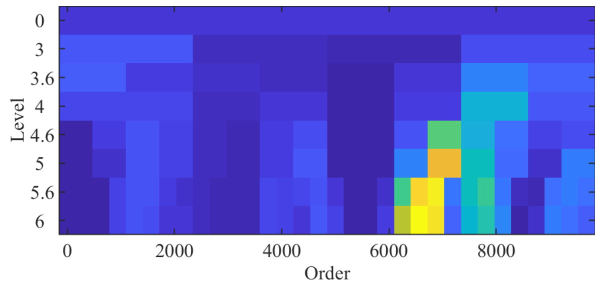

FIGURE 11. **The kurtogram belonging to the resampled signal.**

resampled with equal angular incensement. Fig.10(a) shows the order spectrum of the resampled signal. From the order spectrum, it can be observed that the second harmonic of the meshing order of the second stage f_2 (theoretically equal to 535.5) and the meshing order of the third stage f_3 (theoretically equal to 2811.38) and its second harmonic $2f_3$ are apparently uncovered. For convenience, the local room of the order spectrum is obtained and given in Fig.10(b), it is obvious that the meshing order of the first stage f_1 (theoretical value 102) and its second harmonic $2f_1$, the meshing order of the second stage f_2 and its second harmonic $2f_2$, are clearly demonstrated. Besides, a modulation phenomenon can be found in Fig.10(a) and ranged approximately in 6100 and 6400 order which is indicated by red dashed rectangle. On this basis, with fast kurtogram method performed, the resampled signal is demodulated and the kurtogram belonging to the resampled signal could be plotted in Figure.11, thereby the band of order with maximum kurtosis value is automatically obtained for demodulation analysis in further.

The envelope order spectrum of the demodulated signal is depicted in Fig.12, in which the rotating order of the big gear in the parallel stage f_{d1} (theoretically equal to 27.56) and its harmonics, such as $2f_{d1}$, $3f_{d1}$, $4f_{d1}$, etc. Furthermore, it can be observed from Fig.12 that the rotating order of planet gear in the second stage can be identified, besides, a modulation phenomenon around f_{p2} and its harmonics are apparent, such as $f_{d1} \pm f_{p2}$, $2f_{d1} \pm f_{p2}$, $3f_{d1} \pm f_{p2}$, etc. To demonstrate

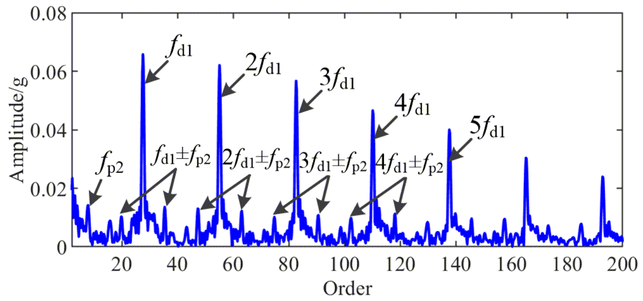

FIGURE 12. The envelope order spectrum acquired by demodulation with kurtogram.

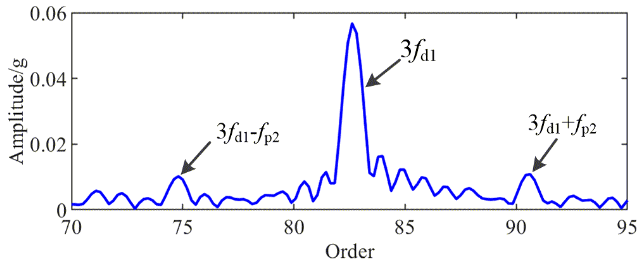

FIGURE 13. A local room of the envelope order spectrum.

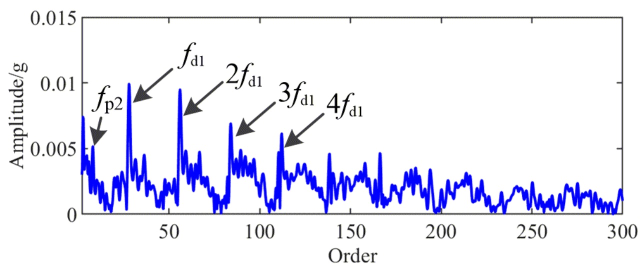

FIGURE 14. The order spectrum acquired by the GFT based tacho-less order tracking method.

the modulation phenomenon more clearly, an enlarged drawing of the envelope order spectrum around $3f_{d1}$ is obtained and given in Fig.13, in which the modulating components $3f_{d1}+f_{p2}$ and $3f_{d1}-f_{p2}$ are apparently displayed. The aforementioned descriptions indicate that there is a fault formed in the big gear of the fixed-shaft stage, besides, a defect was induced in one of the planet gears in the second stage.

C. PERFORMANCE COMPARISON

In order to further illustrate the improved characteristics of the proposed method, the traditional GFT based tacho-less order tracking method is also employed to analyses the raw signal, the corresponding order spectrum is acquired as given in Fig.14. It can be concluded from Fig.14 that the fault characteristic order f_{d1} of the big gear in the fixed-shaft stage and its harmonics are successfully uncovered. However, when compared with that shown in Fig.12, the rotating order f_{p2} of planet gear in the second stage can only be found and there is no apparent modulation phenomenon around f_{d1}. It is because the GFT method relies on the integration of the estimated instantaneous frequency to obtain the phase demodulation function, which will introduce errors in IAS extraction. Besides, the GFT based tacho-less order tracking methods need expertise knowledge to manually determine the interested harmonic for IAS extraction, errors may introduce to the estimated IAS due to the inappropriately selected parameters. Therefore, the experimental validation results indicate that the proposed tacho-less order tracking method based on improved NMD method is effective and applicable for planetary gearbox fault detection under speed variation operating conditions.

V. CONCLUSIONS

Aiming at the shortcomings of the traditional IAS estimation techniques for WT gearbox fault detection under non-stationary operating conditions, a novel tacho-less order tracking method based on improved NMD is proposed in this paper. The merit of NMD, which can adaptively separate mono-component from non-stationary signals and determine the fundamental harmonic, is inherited in our proposed method. The original NMD method is improved and the computational burden is reduced to make it applicable for gearbox vibration signal processing. The IAS is adaptively estimated by improved NMD method, from the vibration signal collected from generator rather than gearbox vibration signal. On this basis, the reference phase of the entire drivetrain is obtained. The improved characteristics of the proposed method are verified by a field test. The validation results show that the proposed method is more flexible and reliable for WT gearbox fault detection, when compared with the conventional GFT based IAS estimation method for tacho-less order tracking. It can be concluded that this study provide an effective tool for WT gearbox fault detection, and have a promising industrial application prospect.

VI. ACKNOWLEDGMENT

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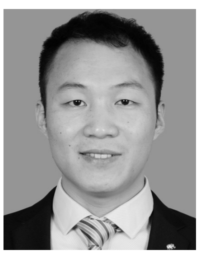
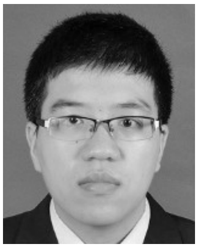


YI WANG received the B.Eng. degree from Southwest Jiaotong University, Chengdu, China, in 2011, and the Ph.D. degree from Xi'an Jiaotong University, Xi'an, China, in 2017. From 2016 to 2017, he was a Visiting Scholar with the City University of Hong Kong, Hong Kong. He is currently a Lecturer with Chongqing University, China. His current research interests include mechanical signal processing, weak signal detection, rotating machinery fault diagnosis under non-stationary conditions, manifold learning, and deep learning.

BAOPING TANG received the M.Sc. and Ph.D. degrees in mechanical engineering from Chongqing University, Chongqing, China, in 1996 and 2003, respectively.

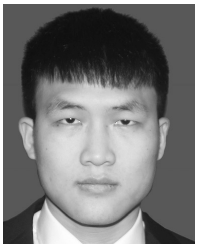
He is currently a Professor and a Ph.D. Supervisor with the College of Mechanical Engineering, Chongqing University. He has published more than 150 papers in his research career. His main research interests include wireless sensor networks, mechanical and electrical equipment security service and life prediction, and measurement technology and instruments.

Dr. Tang was a recipient of the National Scientific and Technological Progress Second Prize of China, in 2004, and the National Invention Second Prize of China, in 2015.



LIHUA MENG received the B.Eng. and Ph.D. degrees in mechanical engineering from Xi'an Jiaotong University, Xi'an, China, in 2008 and 2012, respectively.

Since 2016, he has been a Senior Engineer in the reliability analysis of mechanical products with AVIC, China Aero-Polytechnology Establishment. His current research interests include the reliability evaluation of mechanical products and the health management of airborne equipments.



BINGCHANG HOU was born in Sichuan, China, in 1998. He was with Chongqing University, Chongqing, China, in 2016. He is currently pursuing the Students Research Training Program with Chongqing University, under the supervision of Dr. Y. Wang. His research interests include mechanical fault diagnosis, signal processing, and machine learning.