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# Mean Shift Clustering-Based Analysis of Non-Stationary Vibration Signals for Machinery Diagnostics

Stanley Fong, Jinane Harmouche, Sriram Narasimhan and Jerome Antoni

**Abstract**—Vibration analysis is a powerful tool for condition monitoring of rotating machinery. In the non-stationary case, this analysis often involves de-noising and extraction of the time-varying harmonic components buried within the vibration signal. However, the complexity of many contemporary techniques—especially in relation to non-stationary signals—and their dependence on prior knowledge of the system kinematics in order to be effective is an inhibitor to autonomous fault detection and monitoring of non-stationary systems. In this paper, a non-parametric, blind spectral pre-processing approach to simultaneously de-noise and extract harmonic content from non-stationary vibration signals is presented. The proposed approach utilizes Mean Shift Clustering in conjunction with the Short-Time Fourier Transform to separate time-varying harmonics from background noise within the frequency spectrum, without the need for a priori knowledge of the system. The technique is fully invertible, allowing the time signals corresponding to the separated time-varying harmonic and residual components to be reconstructed. The performance of the proposed technique is compared against existing pre-processing methods, and validated using several industrial datasets: first, using vibration data obtained from a low-speed, non-stationary industrial automated people mover gearbox, next using vibration data from an aircraft engine containing outer race faults, and finally, using non-stationary vibration data from a wind turbine containing frequent speed fluctuations.

**Index Terms**—Mean Shift Clustering, non-stationary signals, signal decomposition, gearbox systems, fault diagnosis

## I. INTRODUCTION

IN the realm of machinery maintenance, vibration analysis has been demonstrated to be a powerful tool for fault detection and condition monitoring [1]. If a fault is present within a component, information pertaining to the fault can often be found within the vibration signal. This information can be extracted using a wide variety of diagnostic signal processing techniques, of which the nature and complexity varies widely depending on the application, ranging from statistical approaches and frequency domain-based methods to angular, cepstral and time-frequency-based methods [2]. The tradeoff found in many current techniques is that increased diagnostic capabilities or robustness comes at the cost of increased computational effort, or some requirement for more information regarding the system's characteristics or kinematics to be known a priori. This is especially true for the case of non-stationary signals, in which sophisticated pre-processing is often required in order to extract the diagnostic information from the signal. The combination of these factors inhibits the dissemination of the most powerful contemporary

vibration analysis techniques into large scale, autonomous or semi-autonomous online monitoring frameworks, especially for non-stationary machinery.

The main purpose of pre-processing in machinery diagnostics is to either directly enhance the presence of diagnostic information buried within the signal, or to convert the signal into a form that is more suitable for extracting diagnostic information. Depending on the type of fault, the critical diagnostic information can be found within different components of the signal: gear faults typically manifest themselves within the harmonic components, while bearing faults can manifest themselves within the harmonic or stochastic components of a signal [3]. Hence, the separation of the deterministic and stochastic components of a signal is a fundamental pre-processing phase to many diagnostic approaches.

Current state-of-the-art pre-processing methods for fault detection in non-stationary signals typically approach the problem using a time-frequency approach, or through resampling the signal in the angular domain using Synchronous Averaging (SA) prior to pre-processing [4, 5]. Time-frequency based approaches such as the Synchro Squeezing Transform (SST) [6] and Sliding Singular Spectrum Analysis [7] have seen extensive applications in spectral analysis of non-stationary signals; however, these methods require significant computational resources or parameter tuning, and hence are not conducive for online applications. Similarly, SA based approaches also add an additional layer of computational complexity and constraints to the problem, requiring the instantaneous shaft speed to either be known or estimated [4]. Additionally, the current state-of-the-art pre-processing methods which follow SA are also not conducive to online monitoring. Techniques such as Automated Cepstral Editing [8], Stochastic Resonance Method [9], and Minimum Entropy Deconvolution [10] have been applied as post-processing techniques to enhance the diagnostic information in the signal. These techniques, while powerful, require user expertise, iterative parameter tuning, filter design and prior knowledge in order to be effective. Coupled with the pre-requisite of angular resampling, such techniques are non-conducive to online monitoring applications. Hence, there is a pressing need for computationally efficient, blind pre-processing techniques that are conducive for online monitoring while providing comparable performance to existing state-of-the-art techniques.

In the context of autonomous spectral analysis techniques, literature is relatively sparse and generally inapplicable to non-stationary signals containing time-varying harmonic compo-

nents. Schoukens et al. proposed a method for autonomous spectral analysis [11]. However, the proposed method was limited to analysis of periodic signals, and cannot be applied to highly non-stationary signals. Barbe and Van Moer presented another autonomous approach for the detection of peaks buried within noise using discriminant analysis in conjunction with thresholds [12]. However, this method yields optimal results only under a Gaussian distribution assumption. Nadine et al. proposed an automatic spectral analysis technique using a multi-estimator approach that can be used to autonomously extract and classify spectral peaks in a stationary vibration signal [13]. The proposed method is parametric and the thresholds pertaining to the spectral estimators are user-defined and dependent on the probability distribution of the data, which may vary significantly in non-stationary signals. To the best of the authors' knowledge, there currently does not exist a non-parametric and model-free spectral analysis technique for extraction of time-varying harmonic components in non-stationary signals that is conducive to online monitoring.

The approach presented in this paper is a spectral pre-processing method for machinery diagnostics, which can be used to separate time-varying harmonics from noise or stochastic components in non-stationary vibration signals. The proposed approach aims to circumvent the aforementioned disadvantages commonly found within current state-of-the-art pre-processing techniques with respect to online monitoring frameworks, by adopting a computationally efficient, fully blind and model free approach. The proposed approach uses Mean Shift Clustering (MSC) in conjunction with a sliding Short Time Fourier Transform window to separate the noise and time-varying harmonic components within each spectrum. One key property of the proposed approach is that the properties of the extracted components of the signal (harmonics and noise), including phase and magnitude, are preserved after performing separation using MSC. The process is invertible, meaning that the time signals corresponding to each separated component can be reconstructed by applying the inverse Fourier Transform. Hence, the proposed approach can be used as a pre-processing technique for many existing fault detection methods. Several applications of the proposed approach and comparisons against existing pre-processing techniques are shown using the following datasets:

- 1) a non-stationary vibration dataset collected from an industrial gearbox, which is used to demonstrate the application of the proposed approach in separation of harmonic content and transformation of non-stationary time-frequency information into an equivalent, stationary, time-invariant representation; the result is compared against those obtained using Synchronous Averaging.
- 2) a non-stationary vibration dataset for an aircraft engine containing faulty bearings, which is used to demonstrate the application of the proposed approach when used as a de-noising tool prior to performing envelope analysis for bearing diagnostics.
- 3) a non-stationary vibration dataset for a wind turbine, containing frequent speed fluctuations, which is used to demonstrate the effectiveness of the proposed approach

in the presence of speed fluctuations; the result is compared against those obtained using sliding Sliding Singular Spectrum Analysis (SSA) [7].

## II. METHODOLOGY

### A. Motivation for Mean Shift Clustering

MSC is a clustering technique which utilizes a density-mode detection algorithm based on the Kernel Density Estimate (KDE) of the data [14], and offers several unique benefits for blind spectral analysis. MSC is a model-free technique, meaning that it does not require any prior knowledge of the number or shape of the clusters present within the data [15]. The lack of restrictions on the number and shape of clusters implies that the probability of convergence in MSC is not dependent on the initialization, which is a common pitfall of other based clustering techniques such as Gaussian mixtures or k-means [16]. Initialization-independence is advantageous for autonomous frameworks as it circumvents the need for iterative user intervention in the clustering process.

The application of MSC as a spectral analysis technique for machinery diagnostics has not yet been studied. In this paper, MSC is shown to be a highly effective technique for performing frequency spectrum decomposition of Short-Time Fourier spectra to separate time-varying harmonic and noise components in non-stationary signals. The proposed approach separates a vibration signal into two components: a de-noised signal containing only the time-varying harmonics, and a residual component containing the noise. Gearbox vibration spectra are typically composed of families of non-stationary discrete frequencies smeared in dense, broadband noise. The distinct contrast between the density of the gearbox-related spectral content and background noise means that separation of these two components can be achieved by isolating the densest cluster, which corresponds to the noise, from the signal. A major advantage to this approach is that the technique is not dependent upon an angular reference signal or kinematics of the gearbox. Spectral decomposition using MSC can be performed directly on the Fourier Transform of the raw time signal, without the need for resampling in the angular domain, which is often required in many current state of the art pre-processing techniques for non-stationary vibration analysis. The ability to directly and simultaneously extract both the time-varying harmonic components and the noise from non-stationary signals significantly reduces the computational complexity, which is important for online monitoring applications.

### B. Bandwidth Parameter Estimation

The performance of MSC for frequency spectrum decomposition depends upon the proper selection of the kernel bandwidth. The bandwidth parameter controls the size of the kernel, which influences the smoothness of estimated probability function over the data set and number of resulting clusters in MSC [14]. The topic of bandwidth estimation has been extensively studied, resulting in a number of data-driven estimators associated with different optimization criteria to confirm the estimated kernel bandwidth [14]. If specific *a priori* information is known, such as the real density function

of the data, the kernel bandwidth estimation can be verified using a metric such as the mean integrated square error. Conversely, if *a priori* information is not available, numerical approaches such as cross validation, or application-specific criterion can be used to select the kernel bandwidth.

In the present context, MSC is used as a pre-processing approach to separate time-varying harmonic components from noise in non-stationary machinery vibration signals. KDE is applied to the magnitudes of the positive frequencies from the STFT, and hence, the kernel bandwidth is represented in units of the frequency magnitude. If *a priori* information regarding the signal properties is available, the bandwidth parameter can be tuned to produce the optimal decomposition for the intended post-processing application. However, in the absence of *a priori* information, to the best of the authors' knowledge, there currently does not exist an optimality criterion to select the kernel bandwidth for MSC decomposition of machinery vibration spectra.

An experimental study is conducted in this paper in order to evaluate the influence of the kernel bandwidth on the decomposition of vibration spectra. For the types of signals studied in this paper, it was found that smaller bandwidths increase the sensitivity of the decomposition with respect to the frequency amplitude, which allows for a larger number of clusters and isolation of weak harmonic components. A lower bound exists in which the bandwidth will result in over-decomposition of the noise. On the contrary, larger bandwidths can only capture significant differences in frequency amplitudes, resulting in clusters which contain mixtures of harmonic and noise components. It will be shown (Section III-D) that the skewness of the resulting noise decomposition spectrum is an effective metric to perform kernel bandwidth selection in the absence of *a priori* information.

### C. Procedure

The discrete gearbox vibration signal to be analyzed  $x[n]$  by the proposed spectral analysis technique is assumed to be sampled from a continuous time process  $x(t)$  such that:

$$x[n] = x\left(\frac{n}{f_s}\right) \quad (1)$$

where,  $n$  is the sample number, and  $f_s$  is the sampling rate. The continuous process  $x(t)$  is assumed to consist of convolved harmonics  $c(t)$ , and a noise process  $e(t)$ , satisfying the relationship:

$$x(t) = c(t) + e(t). \quad (2)$$

In the above equation, the probability distribution of  $e(t)$  is uniformly bounded and unknown. The proposed technique consists of applying the following steps to the discrete signal  $x[n]$ .

1) *Segmentation*: given a discrete signal of length  $L$  satisfying the given representation, the signal is segmented into  $m$  equally sized, non-overlapping rectangular windows  $w[n]$  of length  $l = \lfloor L/m \rfloor$ . Steps 2) through 4) are performed for each window  $w[n]$ .

2) *Discrete Fourier Transform*: the corresponding frequency spectrum is obtained by computing the  $l$ -point Discrete Fourier Transform (DFT) given by:

$$X(k) = \sum_{n=0}^{l-1} w[n]x[n]e^{-j2\pi kn/l}, \quad k = 0, \dots, l \quad (3)$$

The mean shift clustering procedure described in subsequent steps is to be applied to the set of  $N = l/2$  magnitudes of the DFT coefficients at the positive frequencies within  $X$ , denoted by  $f^+$ .

3) *Mean Shift Clustering*: the general algorithm for Mean Shift Clustering consists in two sequential steps: kernel density estimation followed by mode seeking [14]. The kernel density estimate  $p(f^+)$  using kernel  $K(u)$  and bandwidth  $h > 0$  is defined as,

$$p(f^+) = \frac{1}{N} \sum_{n=1}^N K\left(\frac{f^+ - f_n^+}{h}\right). \quad (4)$$

Given the kernel density estimate  $p$ , the cluster centers, or modes of  $p$  can be found by applying to each point, the iterative transformation  $f_{\tau+1}^+ = g(f_{\tau}^+)$ , where  $\tau = 0, 1, 2, \dots$  denotes the iteration number. The gradient ascent function  $g(f^+)$ , is obtained by setting the gradient of  $p$  equal to zero, resulting in

$$g(f^+) = \frac{\sum_{n=1}^N f_n^+ K'\left(\left\|\frac{f^+ - f_n^+}{h}\right\|^2\right)}{\sum_{n=1}^N K'\left(\left\|\frac{f^+ - f_n^+}{h}\right\|^2\right)} \quad (5)$$

where  $K' = dK/du$ . Using the flat kernel reduces the search for the local maxima of the density function to the computation of the local mean. At each iteration, each peak is shifted and associated to a local mean until the magnitude of the "mean shift" vector  $g(f^+) - f^+$  is less than the standard error. Once this convergence criteria is met, the stationary points at which all surrounding points have been shifted to are considered the modes of  $p$ . The subset of spectral peaks belonging to each mode is defined as an "elementary spectrum" i.e. a spectrum where all frequency components are of similar magnitude.

4) *Separation of harmonic components from noise*: The result of the previous step is a set of clusters that can be sorted in decreasing order of their densities. The first cluster with the highest density corresponds to the background noise of the spectrum. The remaining clusters, when grouped together, are comprised of the harmonic components in the signal. Hence, removal of the densest cluster, and amalgamation of the remaining elementary spectra will result in a de-noised spectrum vector containing only the harmonic components of the original spectrum. Additionally, time signals corresponding to the harmonic and noise component can also be obtained by applying the inverse Fourier Transform to the corresponding spectra.

5) *Post-processing*: The procedure presented in steps 1) - 4) can be applied as a pre-processing technique in any existing fault detection method where extraction of time-varying harmonic components or de-noising is required.

#### D. Summary of procedure

The procedure to implement the proposed pre-processing method is summarized in Fig. 1.

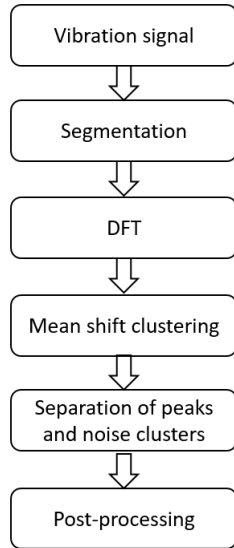


Fig. 1: Flowchart for proposed spectral pre-processing method

### III. VALIDATION AND DISCUSSION

For validation, the proposed spectral analysis approach was applied to following three cases:

- 1) separation of time-varying harmonic content from noise in highly non-stationary vibration data; obtained from the gearbox of the LINK train (LINK) automated people mover (APM) located at Toronto Pearson International Airport; this data was collected by the authors;
- 2) de-noising of non-stationary aircraft engine vibration data prior to performing envelope analysis for bearing fault detection; obtained from exercise 2 of the Surveillance 8 challenge, which features an accelerating Safran aircraft engine containing two outer race bearing faults [5].
- 3) separation of time-varying harmonic content from noise in a non-stationary wind turbine vibration signal containing non-linear speed fluctuations; obtained from the CMMNO 14' challenge [17].

While the main objective of the proposed approach is the extraction of time-varying harmonic components in non-stationary vibration signals, the extracted harmonic components are inherently de-noised as a part of the process. For each of the above cases, this level of inherent de-noising achieved by the proposed approach is estimated. Often in practice, the signal-to-noise ratio is unknown and varying in the case of non-stationary and time-varying signals. In order to estimate the inherent de-noising performance of the proposed method, all non-harmonic signal components are assumed to be part of the noise process. Hence, at each position of the time window, the energy of the non-harmonic signal components isolated by MSC is assumed to be equivalent to the local noise level. The

global level of noise extracted from the entire signal can then be represented in terms of the average and standard deviation ( $\sigma$ ) of the the local noise values obtained at each position of the time-window.

#### A. LINK APM gearbox

1) *Experimental Setup*: LINK provides an around-the-clock transportation service for the airports' passengers and employees between the airport's two terminals (terminal 1 and 3) and parking facilities. The trains themselves are computer-controlled, cable-driven carriages that are devoid of any drive assemblies. Rather, power is generated from a central station that houses all of the drive train machinery. Tractive forces are then transferred to the train through a cable that is fixed to the underside of the carriage. Hence, the critical component to be monitored is the APM gearbox.

The LINK gearbox is a three-stage gearbox with a maximum input shaft speed of 1340 rpm and corresponding maximum output shaft speed of 54 rpm. The fundamental gear mesh frequencies ( $h_1$ ) and corresponding harmonics for the gearbox are shown in Table I for each gearbox stage. Each shaft of the gearbox was instrumented with a uniaxial PCB model: 352C68 accelerometer (A1, A2, A3, A4 in Fig. 2), measuring tangential acceleration. In addition, the input shaft of the gearbox was instrumented with reflective taping to accommodate order tracking using an optimal tachometer. The gearbox and accelerometer mounting positions are illustrated in Fig 2. Vibration data was sampled at two rates: 20 kHz as a base line sampling rate and 200 kHz to provide adequate frequency resolution when applying SA.

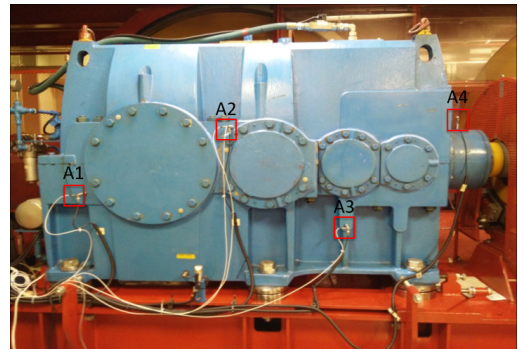


Fig. 2: LINK APM gearbox and accelerometer mounting locations

TABLE I: LINK APM gearbox stages: gearmesh frequencies and harmonics (Hz)

Gearbox Stage	$h_1$	$h_2$	$h_3$	$h_4$
a (Input)	624	1248	1872	2496
b (Intermediate)	221.8	443.6	665.4	887.2
c (Output)	47.23	94.5	141.7	189

2) *LINK APM gearbox vibration signals*: Order-tracked vibration data was sampled from the LINK APM gearbox to perform validation of the proposed spectral analysis technique. The discussion presented hereafter focuses on the vibration data obtained from the input shaft accelerometer (A4 in Fig. 2). The sampling period for each signal corresponded to one round-trip of the train. A typical LINK APM gearbox time signal acquired from a complete round trip of the train's travel, including the stop phases at the serviced terminals, is shown in Fig. 3. The vibration amplitude increases gradually when the train is leaving a station, reaches a certain level as the train is traveling between stations, and decreases to a stop as the train approaches the next station. This behavior occurs 4 times in a round-trip, which corresponds to the 4 segments shown in Fig. 3. The time-frequency analysis of this vibration signal

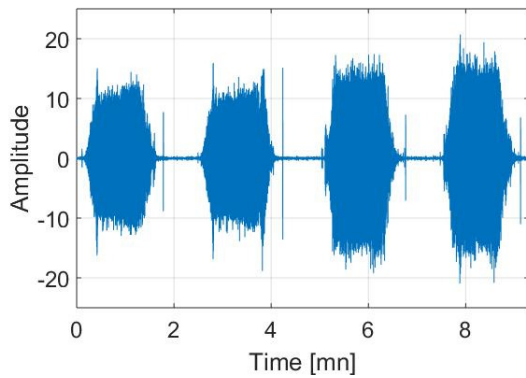


Fig. 3: Vibration signal for LINK APM gearbox - round trip

yields the spectrogram shown in Fig. 4. The spectrogram shows that the vibration behavior of the gearbox is highly non-stationary and noisy throughout the train's travel. The spectral content of the signal varies between different segments of the train's route. Apart from amplitude and frequency modulation during operation, the APM signals exhibit many instances where harmonics may appear and disappear from the signal entirely, depending on the position of the train. This behaviour is illustrated in the zoomed time-frequency representation in Fig. 5 and the Fourier transform spectra shown in Fig. 6. Fig. 6 illustrates the STFT spectra obtained from different time windows of the APM signal, in which several harmonics are present at one point of the signal, but missing from another. The non-stationarities can be attributed to operational factors, such as the stop and start phases and fluctuating passenger loads; as well as to mechanical factors such as the bi-directionality of the gearbox and gradient of the guideway.

3) *Performance of proposed approach*: The proposed spectral analysis approach is applied to the collected round-trip vibration signals, using a frequency resolution of 1 Hz. Fig. 7 illustrates the original frequency spectrum and resulting spectral components obtained when the mean shift procedure is applied to the frequency spectrum of a single time window. Through the clustering and grouping steps, the original spectrum is decomposed into noise and peak components without any loss of information.

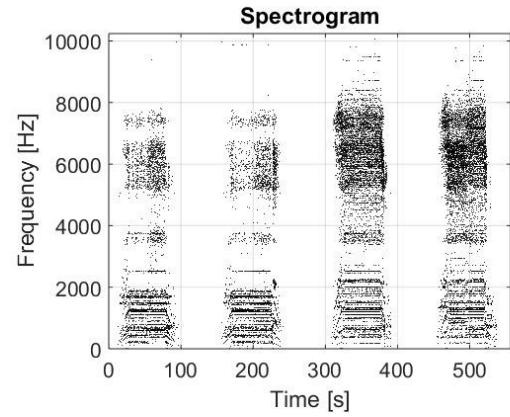


Fig. 4: Spectrogram of LINK APM gearbox round-trip vibration signal

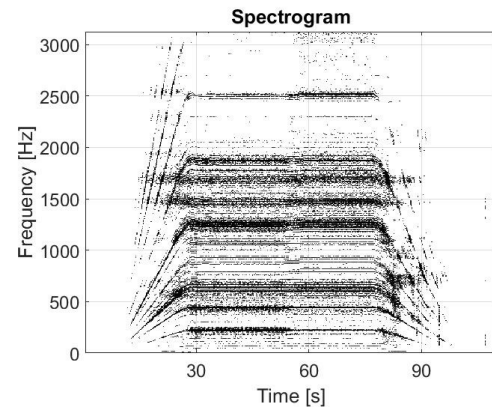


Fig. 5: Spectrogram for a single stop-start-stop phase

By applying the spectrum decomposition approach to all of the time windows for a given round-trip vibration signal, the de-noised time-frequency spectrogram can be obtained, as shown in Fig. 8. The average level of noise removed during the MSC process is estimated to be -0.13 dB with  $\sigma = 7.5$  dB. The spectra of all time windows contained in Fig. 8 can be averaged to obtain a single de-noised, enhanced spectrum, as shown in Fig. 9a. For comparison, Fig. 9b illustrates the marginal spectrum distribution of the entire vibration signal, which is obtained by averaging the spectrogram shown in Fig. 4 across the time axis. Gear mesh frequencies found in both spectra are labeled according to Table I. Direct comparison between the two spectra shows that the spectrum obtained from the proposed technique contains more spectral information than its marginal counterpart. While both spectra contain spectral components related to the gear meshing families from gearbox stage a and b, the averaged spectrum was able to capture more harmonics from these families, as well as a gear mesh harmonic from gearbox stage c. Specifically, the enhanced spectrum in Fig. 9a captures the harmonics  $h_c^3, h_b^3, h_b^4, h_a^6$ , which are missing from the marginal counterpart. Furthermore, the resonant region around 6-8 kHz is captured in the averaged spectra, but are far less obvious in the marginal spectra.

Further comparisons between the enhanced and marginal



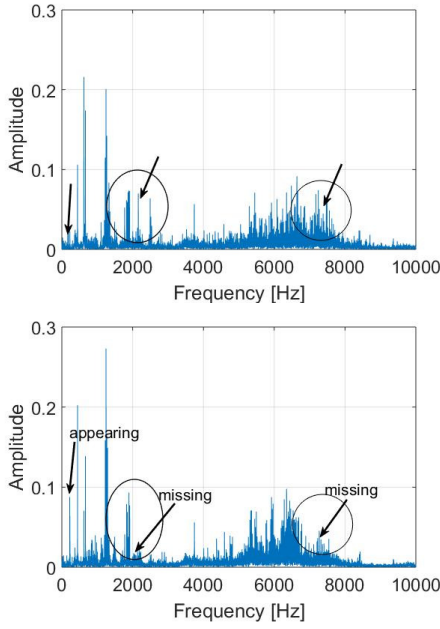


Fig. 6: Fourier spectra from different segments of the raw LINK APM vibration signal, containing different harmonic components

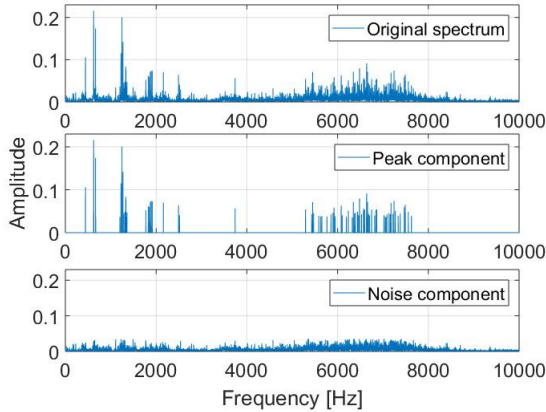


Fig. 7: Typical decomposition of a frequency spectrum into peak and noise components using Mean Shift Clustering

spectra can be made from zoomed in depictions, such as those shown in Fig. 10a and b. Comparison of these spectra again shows that the enhanced spectrum contains more information than its marginal counterpart. Components related to the shaft rotational frequency are present in the enhanced frequency spectrum while missing from the marginal spectrum. Other prominent spectral structures, such as modulation sidebands, were also captured more clearly by the proposed spectral analysis technique. Fig. 11a shows that the modulation sidebands surrounding the second harmonic from gear mesh stage were also captured in the enhanced frequency spectrum. Fig. 11b shows that in the corresponding marginal spectra, the same modulation sidebands are not as pronounced.

In addition to comparison against the marginal spectrum, the performance of the proposed spectral analysis technique

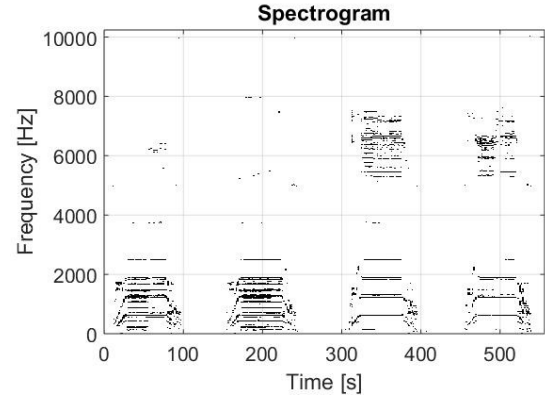


Fig. 8: De-noised spectrogram of LINK APM gearbox round-trip signal after mean shift clustering

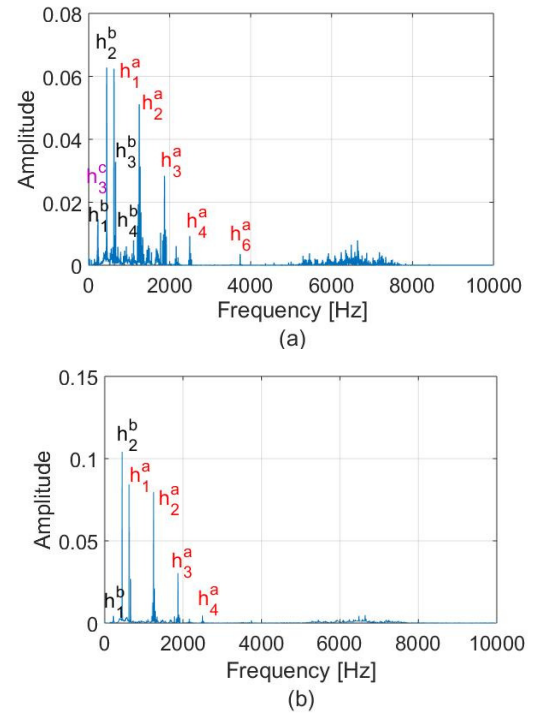


Fig. 9: (a) Enhanced frequency spectrum obtained using the proposed approach in conjunction with time averaging (b) Marginal frequency spectrum obtained from the signal spectrogram - the extracted gearmesh components labeled

is also assessed against the SA spectrum. The SA spectrum for the APM signal was computed using the frequency domain SA algorithm presented in [4], which applies re-sampling of the time domain data in order to account for non-stationary shaft speed. The SA spectrum corresponding to the input shaft, is shown in Fig. 12, for data sampled at 200 kHz and 20 kHz. Comparison of the 200 kHz SA spectrum with the enhanced spectrum in Fig 9a shows that both spectra contain the same harmonic content corresponding to the input shaft, with very similar noise levels. However, the proposed spectral analysis technique presented several advantages over SA for the type of vibration data considered. When using

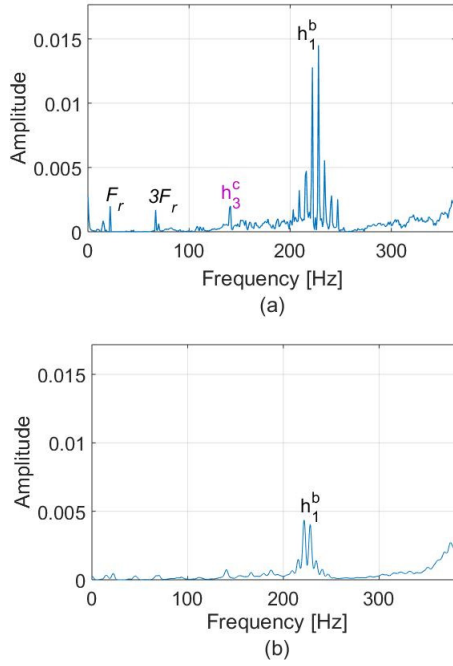


Fig. 10: Rotational frequency, gearmesh components and modulation sidebands extracted using (a) the proposed approach in conjunction with time averaging, (b) the marginal frequency spectrum

SA, the spectrum corresponding to each gearbox stage must be obtained separately, as opposed to the proposed spectral analysis technique, where all of this information is obtained simultaneously. In addition, the kinematic information (i.e. gear ratios) for the gearbox must be known a priori for SA. Furthermore, comparison of the spectra shown in Fig. 12a and b illustrates the importance of sampling rate on the frequency resolution when using SA. Closely spaced harmonics and sidebands, which are visible in the enhanced spectrum shown in Fig. 9a, are not visible in the SA spectrum for data sampled at the same rate. Comparable frequency resolution between the two methods could only be obtained for SA data sampled at 200kHz, which would increase the data rate required for online monitoring by an order of magnitude.

In terms implementation on such systems, the presence of speed fluctuations within the APM gearbox presented a challenge for obtaining suitable data for SA. Without the use of more sophisticated techniques, SA data could only be obtained in regions where the speed fluctuations were nominal, whereas in the proposed technique, this was not an issue.

#### B. Bearing fault detection - Surveillance 8 Safran aircraft engine

The proposed spectral analysis technique was also applied as a pre-processing technique to de-noise a high-speed gearbox signal prior to using envelope analysis to detect bearing faults. The data used was obtained from exercise 2 of the Surveillance 8 challenge, which was sampled from an accelerating Safran aircraft engine at a rate of 50 kHz for 200 s. The engine contained two faulty bearings (L1 and L5) with outer race

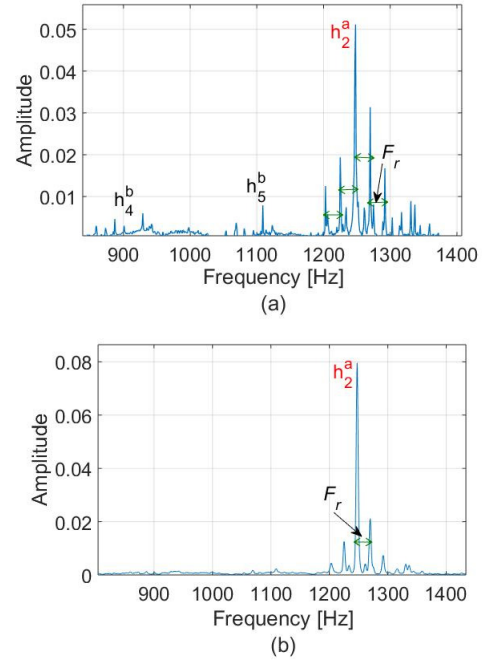


Fig. 11: Gearmesh harmonics and modulation sidebands extracted using (a) the proposed approach in conjunction with time averaging, (b) the marginal frequency spectrum

faults. Fig. 13 illustrates the speed of the shaft containing the damaged bearing (L5), and shows non-stationarity due to the acceleration of the engine over the sampling interval. A full description of the engine, gearbox kinematics and data acquisition process can be found in [5].

1) *Performance of proposed technique:* To perform bearing fault detection, the given signal was segmented into 2s windows and MSC was applied in conjunction with envelope analysis to identify and track the bearing fault frequencies as the speed of the shaft changes over the sampling interval. A frequency resolution of 1 Hz was used for all analyses. The procedure consists in the following steps:

- 1) For each segment, the DFT is calculated and MSC is applied to the signal to separate the gearbox harmonics from the noise as per steps 2) 3) and 4) described in section II-C ; the resulting de-noised spectrum is subsequently band-pass filtered at a resonant band of 21.5 - 24.8 kHz.
- 2) The band-pass filtered signal is demodulated using the Hilbert Transform to produce the envelope signal and the corresponding envelope spectrum.
- 3) After all segments have been processed according to steps 1 and 2, the resultant envelope spectra are aggregated into a single time-frequency representation or spectrogram.

The performance of the proposed technique was determined by comparing the envelope spectrograms obtained with and without the application of mean shift clustering. Fig. 14a illustrates the envelope spectrogram without the pre-processing technique applied, while Fig. 14b illustrates the spectrogram with the proposed pre-processing approach used for de-



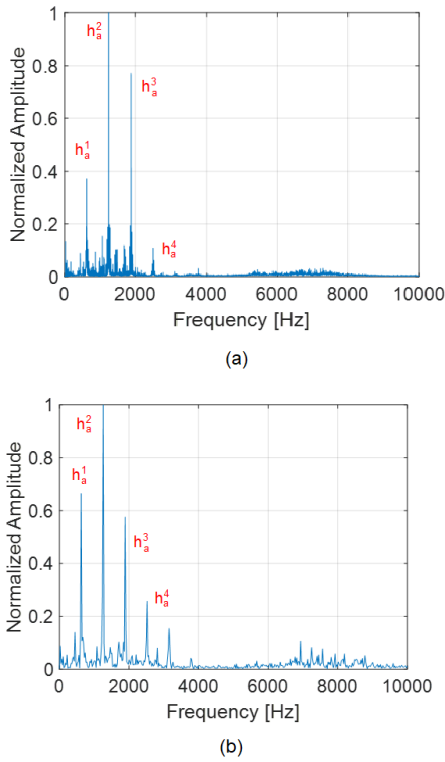


Fig. 12: Frequency spectrum obtained using time synchronous averaging where the sampling frequency is (a) 200 kHz, (b) 20 kHz

noising. Comparison of the two spectrograms shows that the unprocessed envelope spectrogram contains a high level of background noise, resulting in only faint traces of the outer race bearing fault frequency and its second harmonic (BPFO 1 and 2) appearing in the spectrogram. However, the de-noised envelope spectrogram shows relatively sharp traces of the outer race fault frequency along with two harmonics (BPFO 1, 2 and 3) and their corresponding modulation sidebands. Furthermore, the cage frequency (CF), and its corresponding sidebands are also visible in the pre-processed spectrogram. Comparing the noise level of the two resulting spectrograms, it was found that the MSC spectrogram contained 18 dB less noise than the non-processed counterpart, indicating a significant improvement to the SNR after the application of the proposed approach. These results demonstrate that the proposed spectral analysis technique can be used as an efficient, non-parametric and blind de-noising tool to pre-processing signals in bearing fault detection.

### C. Performance of proposed approach in the presence of frequent speed fluctuations

The wind turbine signal to be analyzed consists of multiple families of deterministic frequencies embedded within broadband noise, which are subjected to frequent non-linear speed fluctuations. The raw time-frequency spectrogram of the wind turbine signal is shown in Fig. 15a, which was generated using overlapping 2s windows (75% overlap) and a frequency resolution of 1Hz. Using the same parameters, spectral de-noising

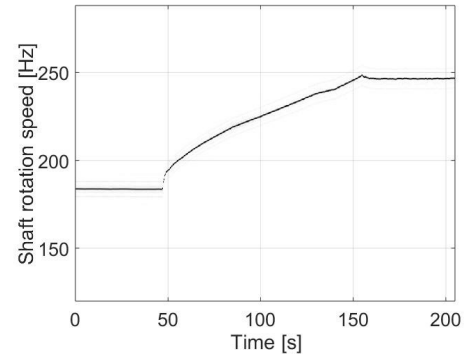


Fig. 13: Rotational speed of shaft containing damaged bearing L5

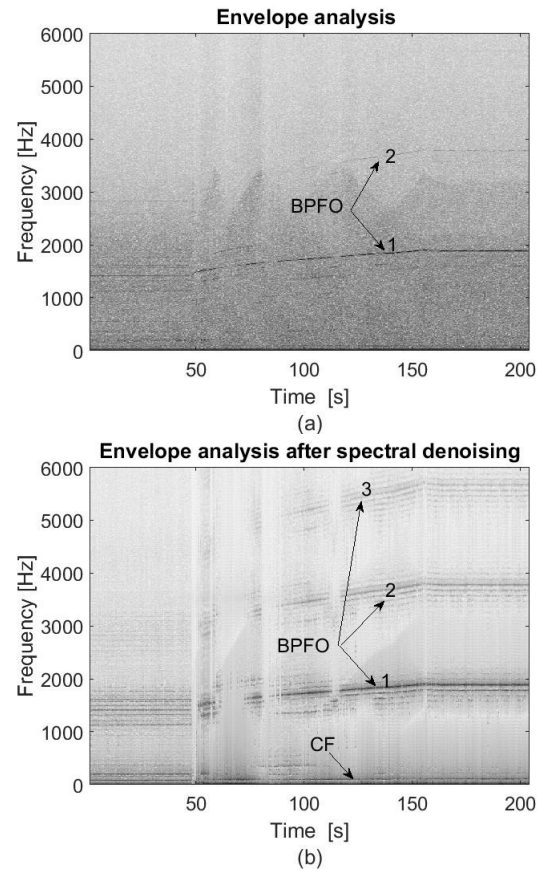


Fig. 14: Envelope spectrogram of vibration signal: (a) without and (b) with spectral de-noising using Mean Shift Clustering

was performed by applying the mean shift clustering technique to each window, resulting in the de-noised spectrogram shown in Fig. 15b. The resulting spectrogram shows that the time-varying harmonic components were successfully separated from the broadband noise, despite the presence of frequent speed fluctuations. The average level of noise removed from the signal using MSC is estimated to be 1.45 dB, with  $\sigma = -11$  dB.

The performance of the MSC approach can be further quantified by comparing the results to those obtained using Sliding SSA. Sliding SSA is a data-driven spectral analysis

tool that utilizes singular value decomposition (SVD) in conjunction with a sliding window to decompose a non-stationary signal into physically interpretable components representing oscillations and noise [7]. According to SSA-based de-noising, the separation of signal harmonics from noise is achieved by selecting the first  $n$  pairs of singular values, which are sorted in decreasing order, and reconstructing the signal using the associated singular vectors, where  $n$  is the number of harmonics perceived to be in the signal. Based on the spectral information shown in Fig. 15a, a value of 20 was chosen for  $n$ . Using the same sliding window parameters (2s, 75% overlap), Sliding SSA was applied to the signal, resulting in the de-noised spectrogram shown in Fig. 16. The level of noise removed using the SSA approach is estimated to be -18 dB, with standard deviation  $\sigma = 1$  dB. Comparison of the SSA spectrogram shown in Fig. 16 to MSC spectrogram in Fig. 15b shows that the results obtained from both methods are comparable and they are equivalently effective at highlighting the signal harmonics buried in noise. However, the MSC spectrogram contains less residual noise and sharper harmonics than the SSA counterpart. Additionally, unlike MSC, Sliding SSA involves SVD, which can be computationally intensive for long signals and challenging for online monitoring applications.

These results illustrate the robustness of the proposed approach, and suggests that the MSC approach is insensitive to the type of speed fluctuations commonly found in non-stationary systems such as wind turbines. For these types of signals, the performance of the proposed approach in both the extraction of time-varying harmonic components and de-noising was found to be comparable to that of Sliding SSA, while requiring significantly less computational resources.

#### D. Evaluation of the kernel bandwidth parameter

The tuning of the kernel bandwidth parameter was investigated in the context of machinery vibration signals. The Safran and wind turbine vibration signals were considered for the study. For each signal, an arbitrary 3s window of the data was selected, and MSC decomposition was performed on each window across a range of bandwidth values. For each value of the bandwidth, the skewness i.e. the asymmetry of the probability distribution of the power spectra amplitudes, and power of the resulting decomposition power spectra was calculated. As shown in Fig. 17, the skewness of a spectrum consisting of purely harmonic components is high compared to the skewness of the spectrum consisting of purely noise.

As discussed in Section II-B, there appears to be an optimal range for the kernel bandwidth parameter for both signals, which is defined by the area surrounding the local minimum of the skewness of the noise spectrum. Fig. 18 shows the decomposition spectra for the wind turbine signal using the bandwidth corresponding to the minimum skewness, illustrating an effective separation of harmonic and noise components. Additionally, the trends described in Section II-B in relation to the extreme values of the bandwidth parameter were observed in both signals, but were significantly more evident in the wind turbine signal, in which the spectrum is primarily comprised of weak harmonic components buried in noise. Fig. 19a-b

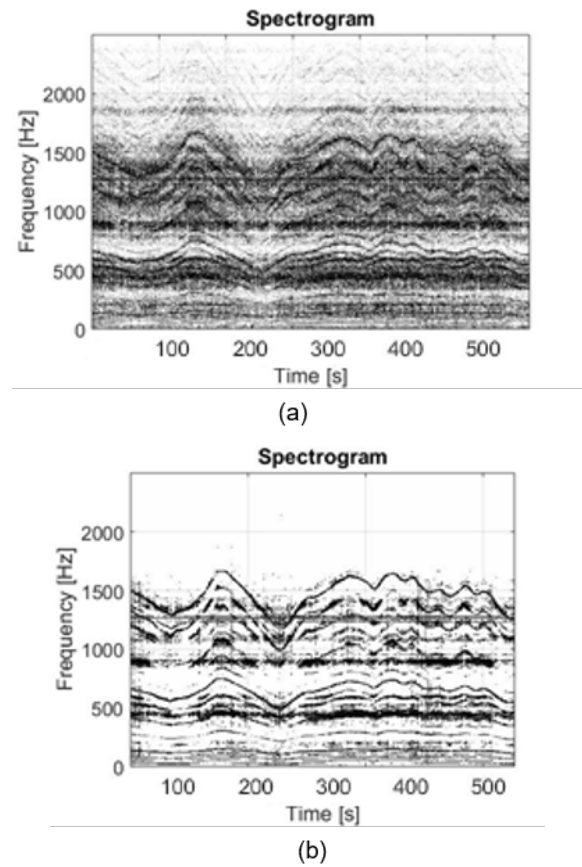


Fig. 15: Spectrogram of wind turbine vibration signal: (a) without and (b) with spectral de-noising using Mean Shift Clustering

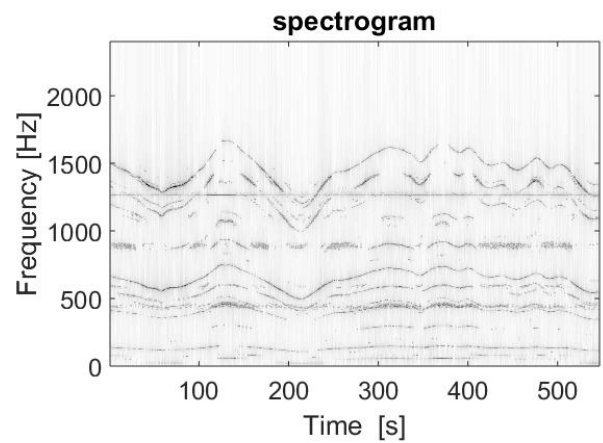


Fig. 16: Spectrogram of wind turbine vibration signal with spectral de-noising using Sliding SSA

shows the decomposition spectra corresponding to the smallest and largest bandwidth values for the wind turbine data, respectively. In the case of the smallest bandwidth, the over-decomposition of the noise component is apparent, leading to the minimum noise power level shown in Fig. 19a. In the case of the largest bandwidth, the decomposition is unable to separate harmonic components from noise, resulting in

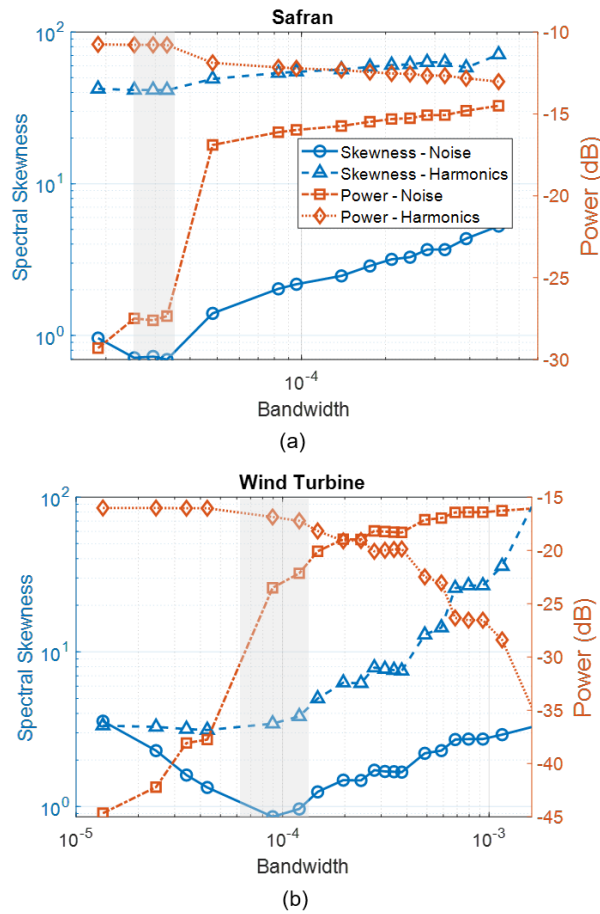


Fig. 17: Effect of bandwidth on skewness and power of MSC decomposition spectra (a) Safran (b) Wind Turbine

the noise spectrum shown in Fig. 19b, which contains both harmonic and noise components. The over-decomposition of noise can also be seen in power trend of the decomposition spectra, as shown in Fig. 17. When considering the range of bandwidths below the optimal range, the power of both decomposition spectra can be seen to change rapidly with respect to the bandwidth, indicating a significant amount of frequency components (presumed to be noise) are transferred between the two spectra as the bandwidth increases. This behaviour continues until the bandwidth approaches the lower bound of the optimal region, at which point the skewness of the noise spectrum approaches a minimum, and the majority of the noise is assumed to be separated from the harmonic component. For bandwidths to the right of this optimal region, the skewness of the noise spectrum begins to increase, indicating that harmonic components are being clustered along with the noise. Hence, it is proposed that in the absence of *a priori* information, the minimization of the noise spectral skewness can be used as the selection criterion for the kernel bandwidth, which was found to be applicable to the types of spectra found in both of the signals considered.

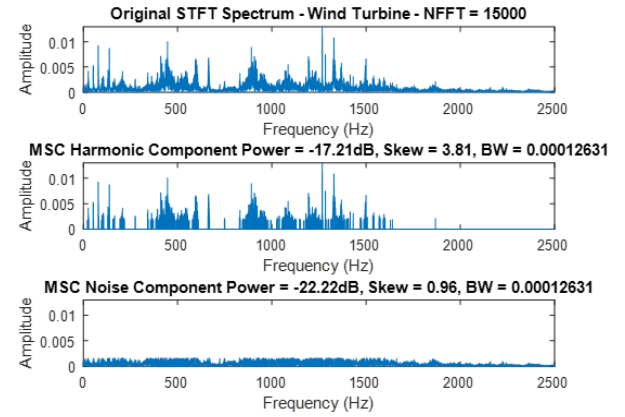


Fig. 18: MSC decomposition of wind turbine signal corresponding to optimal bandwidth

#### IV. CONCLUSION

The separation of time-varying harmonic and stochastic signal components is a fundamental pre-processing step in many current machinery diagnostic approaches that aim to extract diagnostic information buried in non-stationary signals. However, current approaches are often computationally demanding and require intensive parameter tuning or *a priori* information regarding the system to be effective, making these methods difficult to implement in online monitoring. This paper presents a model-free, blind spectral analysis approach for pre-processing non-stationary vibration signals. The approach consists of applying Mean Shift Clustering to the Short-Time Fourier Transform of vibration signals in order to simultaneously de-noise and separate time-varying harmonics from noise. It depends upon only a single parameter, the kernel bandwidth. A criterion is proposed to automatically select the bandwidth parameter based on minimizing the skewness of the MSC noise decomposition spectrum. Validation performed using real world, non-stationary data sets showed that the proposed approach is effective at separating noise from signal components in a variety of non-stationary conditions, providing comparable performance to more computationally intensive pre-processing methods. Most importantly, compared to the current state of the art, the proposed approach offers an effective, versatile, model-free tool for performing spectral analysis of non-stationary signals that is suitable for online monitoring of non-stationary machinery.

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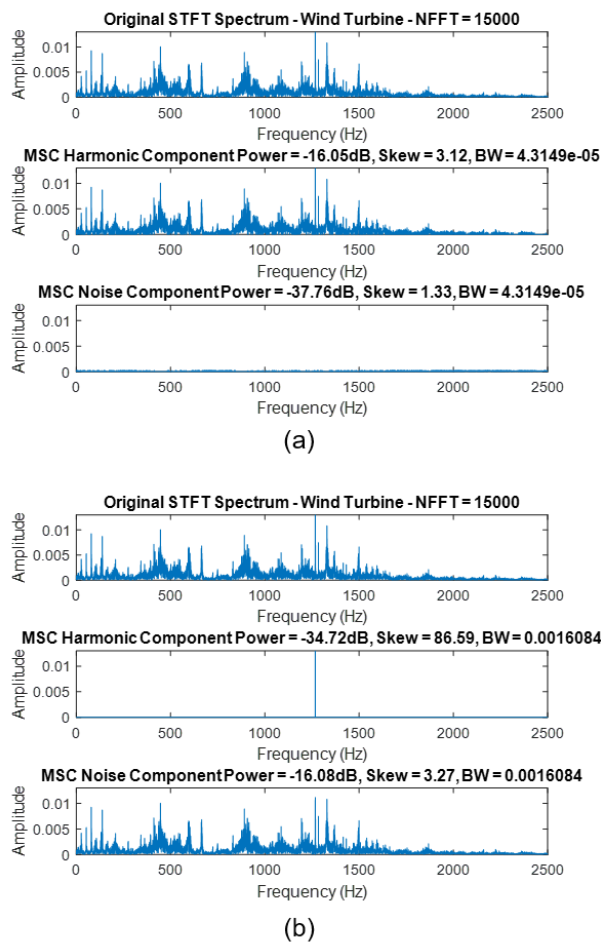


Fig. 19: Extreme cases for MSC decomposition of wind turbine signal using (a) low bandwidth (b) high bandwidth

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