Fault diagnosis using acoustical and vibration signal processing has received strong attention from many researchers over the last two decades. In the present work, the experiment has been carried out with a customized gear mesh test setup in which the defects have been introduced in the driver gear. Classical statistical analysis including higher-order statistics, namely bispectrum analysis, has been incorporated to detect the defects. However, in order to improve the signal-to-noise ratio of the captured signals for accurate defect detection, an adaptive filtering has been proposed. Active noise cancellation (ANC) has been applied on the acoustical and vibration signals as a denoising filter. The least mean square based ANC technique has been implemented considering the signals from healthy gear meshing as the background noise. The focus of this experimental research is to evaluate the appropriateness of the ANC technique as a denoising tool and the subsequent bispectrum analysis for identifying the defects. The performance of the ANC filtering was evaluated with most widely accepted standard filters. A synthetic signal, close in nature to the actual signal, has been investigated to ascertain the adequacy.

1. INTRODUCTION

Safety, reliability, efficiency, and performance of rotating machinery are major concerns in the industry. In this situation, the task of condition monitoring and fault diagnosis of rotating machinery has significant importance. Many methods have already been widely used in a variety of industries for predictive maintenance. It has been widely accepted that the structural defects in rotating machinery components can be detected through monitoring acoustical and/or vibration signals. The machine condition monitoring process consists of three stages of signal processing: (1) acquisition of acoustic or vibration signals, (2) signal pre-processing and extraction of the fault feature, and (3) diagnosis of the defect.

Various signal processing techniques have been identified and proposed by many researchers in this context. The most common method is the fast Fourier transform (FFT) to obtain the power spectrum to investigate the frequency components of the entire signal. However, it is a well-known fact is that the acoustical or vibration signals from a rotating system is composed of a large number of non-stationary signals, particularly in the presence of a localized, defect such as bearing pitting or gear tooth fracture. Short-time Fourier transform and related time-frequency and time-scale techniques have often been used to detect such non-stationary defect signatures. Another fact is that typical defects in machinery components have been characterized by particular vibration patterns. Loutas et al. have reported that the acoustical emission (AE) technique is more effective in the early stages of defect identification compared to vibration monitoring, particularly in the case of a crack in the gear. Regionally linear behaviour of AE parameters has been observed by them where the associated gradients change proportionally with the crack propagation rate. Some potential defects, namely spalling of the gears and bearings, clearances, etc., induce periodic impulses in acoustical and vibration signals of rotating machines. Such impulses may excite the eigenmodes of the structure and the sensor. The statistical parameters such as the root mean square (RMS) value, kurtosis, crest factor, skewness, peak value, and signal-to-noise ratio (SNR) are most widely used to detect the defect. These indicators are easy to implement; however, the complexity of the mechanisms involved may give rise to serious errors in interpretation. A detailed study was conducted by Dron et al. on the influence of certain parameters on the value of the crest factor, kurtosis, and RMS value. In order to carry out condition monitoring of the gear meshing using acoustical and vibration signals analysis, the selection of such statistical indicators needs to be well suited to the impulsive nature of the excitatory forces generated by the defects. Thus, reliability in fault diagnosis can be achieved if, and only if, the acquired signals are free from any background noise. Therefore, the major challenge is to remove background noise from acoustical and vibration signals captured at the faulty condition using appropriate signal processing. The intention of signal denoising is to minimize the influence of the unwanted noise without affecting the defect signatures.

Over the last decade, the performance of active noise cancellation (ANC) systems has been improved primarily due to the integration of digital signal processing. The merging of active noise cancellation techniques and digital signal processing has enabled the control of noise dynamically and adaptively. In practice, active noise control is mainly used for duct-like systems such as blowers, ventilation systems, or enclosures like aircraft and vehicle cabins, headphones, and control rooms.
The adaptive filtering deals with a least mean square (LMS) algorithm and an approach with reference signals with fixed length of filter coefficients. The LMS algorithm is widely used in adaptive filtering due to its computational simplicity and unbiased converging nature in a stationary environment. Adaptive digital filters consist of two distinctive parts: (1) a digital filter to perform the desired signal processing and (2) an adaptive algorithm using a reference signal and a residual error to adjust the coefficients (weights) of that filter. Based on a finite impulse response (FIR) structure, an adaptive digital filter with a filtered-x least mean square algorithm has been widely implemented in ANC applications due to its relative simplicity in design and implementation. Gonzalez et al. have investigated the attenuation of engine noise using active noise cancellation. They have demonstrated that ANC can be considered a useful tool to reduce the sound pressure level of low-frequency noises for improving the acoustical comfort. On the other hand, the use of higher-order spectral (HOS) analysis is an emerging area of interest, particularly when the nonlinear system analysis is of interest. HOS analysis demonstrates the groups of frequencies and their interrelationships. This technique is also capable of explaining the origins of spectral peaks at certain values in the frequency spectrum. An HOS, especially bispectrum analysis, has been used by many investigators for machinery condition monitoring. HOS has the potential to quantify nonlinearities using the time series signal. As a result, HOS methods have been applied with partial success to rotating machinery condition monitoring and fault diagnosis. In summary, bispectrum analysis can identify the non-Gaussian processes. Collis, White, and Hammond have reported the basic principles of HOS and also have demonstrated the capability of HOS in yielding information which is unavailable through inspection of second-order statistics such as the spectrum or correlation function.

However, analysis using a bispectrum technique has been used predominantly for condition monitoring purposes. The bispectrum of a signal is the decomposition of the third moment skewness of the signal over frequency, which supports the analysis of systems with asymmetric nonlinearities. Similarly, another powerful technique known as trispectrum represents a decomposition of kurtosis over frequency. The bispectrum of acoustical, vibration, or current signals has been extensively investigated by many researchers and reported suitable in fault diagnosis of rotating system components, such as a damaged gear or bearing. Montero and Medina have demonstrated the theoretical approach of implementing a bispectrum technique to identify a rolling bearing element defect. Li et al. have presented fault detection and diagnosis of a gearbox in marine propulsion systems using bispectrum analysis and artificial neural networks. Incipient gear fault vibration signals often have non-stationary features, are usually heavily corrupted by noise, and are often strongly coupled with the faults of other components. Li et al. have demonstrated that the features of the gear fault vibration signals can be extracted effectively using bispectrum analysis. Both the amplitude and phase information can be preserved, and distinguished features can be extracted along the parallel lines of the bispectrum diagonal.

Time-frequency analysis has been used by many investigators to analyse the non-stationarity of the signal. Sung, Tai, and Chen have employed wavelet transform to detect the location of tooth defects in a gear system precisely. They have implemented wavelet analysis on vibration signals for locating gear defects and advantages of multi-resolution property of the wavelet. Jena, Panigrahi, and Kumar recently investigated adaptive wavelet transform for analysing non-stationary vibration response from a faulty gear mesh system. Another important aspect of condition monitoring is establishing a reliable online system to offer accurate fault diagnostic information for mechanical systems to prevent machinery performance degradation, malfunction, or even catastrophic failures. Moreover, machinery fault diagnosis information can also enable the establishment of a maintenance program based on an early warning of incipient defects.

In the present work, an experiment has been carried out with a customized gear-meshing test setup in which defects have been introduced in the driver gear teeth. Two different defect conditions have been analysed: (1) a defect in one tooth and (2) a defect in two teeth. The acoustical and vibration signals are captured both in healthy conditions and with faulty gears. The ANC has been proposed for denoising purpose. An LMS-based adaptive filtering technique has been used on acoustical and vibration signals to improve the SNR of the signals in defect scenarios. The acoustical and vibration signals at healthy conditions have been used as reference signals for the adaptive LMS filter. The statistical and bispectrum analysis have been incorporated to evaluate the performance of the filtering technique. A synthetic signal simulation analysis has been carried out to understand the capability of the proposed method followed by experimental validations, which are explained and presented in subsequent sections.

### 2. UNDERLYING THEORY

#### 2.1. Hunting Tooth Frequency

It is a well-known fact that gear-mesh frequency can be computed by multiplying the number of teeth \((T)\) of a gear by the speed of the gear \((G_s)\). The number of teeth on the drive gear multiplied by the speed of the drive gear must equal the number of teeth on the driven gear multiplied by the speed of the driven gear. The fractional gear-mesh frequencies generated may be caused by the common factor and the eccentric gear. Hunting tooth frequency (HTF) occurs when the same tooth on each gear comes into mesh again. The HTF can be determined by dividing the least common multiple of the teeth on the two gears by the uncommon factor of the gear of interest. The product equals the number of revolutions the gear must make before the HTF occurs and can be expressed as

\[
\text{HTF} = \left[ \frac{1}{(L/U)} \right] \times (1/G_s);
\]

where \(L\) is the least common multiple and \(U\) is the uncommon factor of the gear. The HTF is not normally measurable because it occurs infrequently; however, one can notice the same situation occurring in the time domain signal. The broken tooth on each gear generates a pulse each time when it goes into mesh. In the case of two broken teeth, consecutive pulses are

---

generated. The frequency of such impulse events observed in a time-domain signal is called HTF. Amplitude modulation of gear-mesh frequency and harmonics reveals useful information about the mesh (e.g., misaligned gears, improper backlash, loading, eccentricity, etc.). Gear-mesh frequency does not usually reveal a broken, cracked, or chirped tooth except in rare cases when natural frequencies are not measurable. Gear-mesh frequency and amplitude can be modulated by the speed of the problem gear. Some ghost frequencies may also be present due to errors during gear manufacturing.

2.2. Active Noise Cancellation Using an LMS Algorithm

Acoustical and vibration signals acquired from the machines for diagnostic purposes may be either deterministic or random. Deterministic signals can be further classified as periodic and non-periodic, whereas random signals can be classified as stationary and non-stationary. Useful information can be extracted from these signals by appropriate signal processing techniques. However, these acoustical and vibration signals often contain a lot of noise, which may also lead to incorrect conclusions. In such cases, techniques that enhance the SNR are highly desired. Adaptive noise cancellation is one such technique that enhances SNR. An adaptive digital filter consists of two stages of signal processing. The first stage is a digital filter, which processes the expected output signal, and second one is an algorithm to adjust weighting coefficients of the digital filter. Two kinds of digital filters can be used in ANC, namely infinite impulse response or FIR filters. In the present study, an FIR filter is used as the controller of the system.

Mathematically, if a linear FIR filter (discrete-time) has a series of coefficients \( w_l(n) \); \( l = 0, 1, \ldots, L - 1 \) and a series of continuous inputs \( \{ x(n) \ x(n-1) \ldots x(n-L+1) \} \), then an expected output, \( d(n) \), occurs, and the output signal is used to reduce noise from filter.

Briefly, the procedures for the ANC system can be described as follows:

1. Optimal selection of the order of filter coefficient \( L \), step size \( \mu \), and the initial filter coefficients \( w_0(n) \)

2. Evaluation of the output signal from the adaptive filter:

\[
y(n) = \sum_{l=0}^{L-1} w_l(n)x(n-1)
\]

3. Measurement of the error signal as:

\[
e(n) = d(n) - y(n)
\]

4. Updating of the adaptive filter coefficient using LMS algorithm

\[
w_l(n+1) = w_l(n) + \mu x(n-l)e(n);
\]

where \( l = 0, 1, \ldots, L - 1 \).

The step size and filter length are major parameters in adaptive filtering. The step size value affects the convergence speed, steady-state error, and stability of the adaptive filter. A small step size ensures low steady-state error and decreased convergence speed. Large step size improves the convergence speed but might cause instability.

The filter length affects the computational resource requirements, convergence speed, and steady-state error. The optimal filter length is decided by a trial-and-error process. However, simulation of adaptive filter is advised to be carried out to determine the most appropriate filter length. The filter length must be greater than the number of significant taps in the impulse response of the unknown system. A long filter length can reduce the steady-state error. Optimization of the filter length that satisfies the application is highly desired.

2.3. Statistical Parameters

To obtain useful information from the time-domain acoustic and vibration signals various statistical techniques have been developed over the years. One of the parameters, namely, the crest factor, which is defined as the ratio of maximum absolute value to the RMS value of the vibration signal, gives an idea about the occurrence of impulse in the time-domain signal. In real-time condition monitoring, an increased value of the crest factor over a period of time indicates the presence of wear or pitting. Another powerful parameter called kurtosis measures the degree of peakiness of a distribution compared to a normal distribution. In general, even statistical moments give information about spread. Mathematically, crest factor and kurtosis for signal \( x(n) \) with \( N \) number of samples in the time domain can be expressed as:

\[
\text{CrestFactor} = \frac{\text{CrestValue}}{\text{RMS value}} = \sup |x(n)| \sqrt{1/(1/N) \sum_{n=1}^{N} |x(n)|^2}
\]

and

\[
\text{Kurtosis} = \frac{M_4}{M_2^2} = \frac{1/N \sum_{n=1}^{N} (x(n) - \bar{x})^4}{[(1/N) \sum_{n=1}^{N} (x(n) - \bar{x})^2]^2};
\]

where \( M_4 \) and \( M_2 \) are the fourth-order and second-order statistical moment, respectively, and \( \bar{x} \) is the mean of the signal. The kurtosis and the crest factor parameters are very sensitive to the shape of the signal. The fourth-order moment of the signal gives a substantial weight to high amplitudes of the kurtosis. The crest factor attenuates the impact of an isolated event with high crest amplitude that only takes into account the crest amplitude of this event. The kurtosis therefore appears as a better indicator than the crest factor. But, in the case of severe defects or a multiple defect scenario, these statistical parameters only provide the indication of the presence of the defect but do not provide any information about the severity of the defect. One of the limitations of the kurtosis method is that the kurtosis value falls to 3 when the damage is well advanced. This may be due to the higher relaxation time of the impulsive response than the impulsive repetition period. Monitoring the overall RMS values can be more useful in such cases. Another limitation is that the kurtosis method can give
variable and misleading results if measurements are taken on machines in an unloaded condition.\textsuperscript{17}

SNR is a measure used to compare the level of a desired signal to the level of the background noise. SNR can be defined as the inverse of coefficient of variation ($C_v$), i.e., $\text{SNR} = 1/C_v$ and $C_v = \sigma/|\mu|$, where $\sigma$ is the standard deviation and $\mu$ is the mean of a discrete signal. The absolute value is taken for the mean to ensure $C_v$ will be always positive.

The mean-square error (MSE) is widely used for filtering performance analysis. MSE measures the average of the squares of the errors. The error is the difference between the observed and estimated values. MSE is the second moment (about the origin) of the error and thus incorporates both the variance of the estimator and its bias. For an unbiased estimator, the MSE is the variance.\textsuperscript{22} Mathematically, MSE can be expressed as

$$\text{MSE} = \frac{1}{n} \sum_{i=0}^{n-1} (x_i - y_i)^2; \quad (7)$$

where $n$ is the number of data points, $x_i$ is the $i$-th element of $x$ and $y_i$ is the $i$-th element of $y$.

### 2.4. Bispectrum Estimation

Higher-order statistics is effective in studying feature extraction of the non-stationary signal. Higher-order statistics usually refers to four major forms: (1) high-order moments, (2) high-order cumulants, (3) high-order moment spectrum, and (4) the high-order cumulant spectrum. The high-order cumulant of the random signal can be generated by the derivative of the second characteristic function. In practice, the higher-order spectra of a signal must be estimated from a finite set of measurements. Essentially, there are two broad non-parametric approaches: (1) the indirect method based on estimating the cumulant functions and then taking the Fourier transform and (2) the direct method based on a segment averaging approach.\textsuperscript{23} In the present analysis, indirect method is used to estimate the bispectrum.

Mathematically, for a random signal $x(t)$, the second-order spectral density (power spectrum) is given by

$$P(f) = \mathbb{E} \left[ X(f)X^*(f) \right]; \quad (8)$$

where $X(f)$ is the Fourier transform of $x(t)$, $\mathbb{E} \left[ \ldots \right]$ indicates the expectation value (or equivalently the average over a statistical ensemble) and $*$ denotes the complex conjugate. Mathematically, the bispectrum can be expressed as

$$B(f_1,f_2) = \mathbb{E} \left[ X(f_1)X(f_2)X^*(f_1 + f_2) \right]. \quad (9)$$

Due to the symmetries in the bispectrum, the region bounded by the lines $f_1 = 0$ and $f_1 = f_2$ contains all the available information. It is worth noting that if $X(f_1) = 0; X(f_2) = 0$; or $X(f_1 + f_2) = 0$, the bispectrum at $f_1, f_2$ is also zero, which is not obvious. In short, signals resulting from the nonlinear interaction of some excitation components have a specific phase relationship with the excitations that caused them. In the power spectrum, the phase information is lost, and hence, this phase relationship between different frequencies cannot be exploited.\textsuperscript{12,24}

## 3. SIMULATED ANALYSIS

This section is intended to evaluate the performance of the proposed method of analysis using synthetic test signals. A signal containing a number of sinusoidal bursts of progressively increasing frequency with respect to time was chosen for the analysis in order to observe the frequency resolution dependencies. The signal used can be mathematically written as

$$X[n] = x[n] + G_n; \quad (10)$$

where

$$x[n] = \sum_{m=1}^{m=10} \cos \left[ 2\pi nf_m(t - \tau_m) \right] [u(t - \tau_m) - u(t - \delta_m)];$$

where $f_m = 15 \text{ mHz}$; $\tau_m = 0.0006 + 0.002(m - 1)$; $\delta_m = \tau_m + 0.0006; G_n \sim N(0,0.25)$; and $f_s = 50 \text{ kHz}$ is the sampling frequency that is used to convert the continuous signal to a discrete one. The corresponding signals $x[n]$ and $X[n]$ are shown in Figs. (1a) and (1b), respectively. To understand the effect of Gaussian noise $G_n$ on the synthetic signal $x[n]$, the power spectrum density (PSD) has been extracted for both $x[n]$ and $X[n]$, as shown in Figs. (1c) and (1d), respectively. It is worth noting that from the PSD spectra, the impact of $G_n$ is not observed prominently.

Traditional correlation and power spectral analysis based on Fourier-transform could not extract useful information from the non-stable and nonlinear signals because the Fourier transform is based on the assumption that the signal is stationary. The bispectrum has been proven to be effective in this situation. It can capture characteristic frequency, identify the phase information, and extract nonlinearity. To demonstrate the effect of $G_n$ on synthetic signals, the bispectrum has been investigated for $x[n]$ and $X[n]$, as shown in Figs. (2a) and (2b), respectively. The bispectrum has been evaluated with 2048 numbers of frequency bins, 256 points of window length, and linear peak hold averaging with 50% overlapping. A large window generates a PSD with small bias but results in a coarse PSD plot.

A small window generates a smooth PSD plot but leads to large bias. Overlap specifies the overlap in percentage, of the moving window that applies to the time series. This parameter determines how much data of the signal will be used for space matrix. A large overlap reduces the variance of the resulting power spectrum but increases computation time. The resulting bispectrum can detect the asymmetric nonlinearities in the input time series. From Figs. (2a) and (2b), one can note that additional spectrum spikes are visible after introducing $G_n$. The bispectrum of $x[n]$ (see Fig. (2a)) explains the presence of periodic impulses at different frequencies, which creates the prominent side band spikes. The bispectrum of $X[n]$ has additional spikes due to well-known quadratic phase coupling with Gaussian noise $G_n$ and synthetic signal $x[n]$. It is well known that the nonlinear couplings, including quadratic phase coupling, can be identified using bispectrum analysis.

In line with the proposed technique, adaptive noise cancellation was implemented to improve the SNR of the signal. The periodic burst signal $x[n]$ is the desired signal, where Gaussian signal $G_n$ acts as the background noise. The resultant signal
Figure 1. Synthetic signal used for the performance analysis of the proposed method: (a) synthetic signal $x[n]$, (b) synthetic signal $X[n]$, (c) PSD of synthetic signal $x[n]$, and (d) PSD of synthetic signal $X[n]$.

$X[n]$ can be expressed as

$$ X[n] = x[n] + G_n. \quad (11) $$

The schematic of active noise cancellation process is shown in Fig. (3). Analogous to a real-time scenario, the Gaussian noise $G_n$ is treated as an acoustical signal or vibration signal at a healthy condition, and $X[n]$ is the impulsive noisy signal at the faulty condition.

In the present simulation study, the objective was to achieve $x[n]$ from $X[n]$. An ANC technique has been implemented as an adaptive denoising filter. The adaptive filter creates an FIR filter based on an LMS algorithm, as shown in Fig. (3). The adaptive filter considers the $G_n$ as background noise and filters out the noisy signal $X[n]$ using a filter size of 10 and step size of 0.1. When the output signal $y(n)$ becomes close to $G_n$, then the adaptive system can remove the background noise. In Fig. (3), the error signal $e(n)$ from the adaptive filter denotes the resultant signal, which needs to be similar to $x[n]$. The error signal from the adaptive filter and the denoised signal have been shown in Figs. (4a) and (4b), respectively. The overlapping of raw noisy signal on denoised signal has been shown in Fig. (4c). Now, one can note the suitability of the ANC technique as a denoising tool. Next, the bispectrum of the denoised signal has been extracted and is shown in Fig. (5). It is worth noting that the reduction of spectrum spikes. From the synthetic signal analysis, it is very clear that ANC can be used to remove Gaussian noise and that bispectrum analysis is an appropriate tool to understand the presence of different frequencies and nonlinearity of the signal. The adaptive filtering parameters for the synthetic signal are not optimal but explain the denoising capability of adaptive filter. The optimal filter size and step size parameters have been extracted for real-time
Figure 4. Denoising by ANC: (a) adaptive filter output $y(n)$, (b) error signal $e(n)$, i.e., denoised synthetic signal, and (c) denoised signal overlapped with original noisy synthetic signal $X[n]$.

Figure 5. Bispectrum of denoised signal (i.e., error signal from adaptive filter $e(n)$).

Figure 6. Test setup: (a) gear meshing test setup mounted with accelerometer and microphone, (b) driver gear of one defective tooth, and (c) driver gear of two defective teeth.

4. EXPERIMENT

In the present work, the experiments were conducted on a gear mesh assembly fabricated for the purpose as shown in Fig. (6). The pinion with 15 teeth was mounted on a driver shaft coupled with a Crompton© single phase 50 Hz AC induction motor of power rating 0.5 hp with the help of a belt drive. The driver shaft was supported on two P204 bearing blocks.

The gear on the driven shaft had 30 teeth. The other end of the driven shaft had means to apply the load on the shaft. The experiment was conducted by loading the driven shaft by different weights. From the experiment, it has been found that 2 kg load is suitable to carry out the experiment with adequate dynamic stability. The operating frequency observed was 7.62 Hz (457 rpm).

In order to acquire the acoustical signal, one microphone (Behringer ECM-8000©) was mounted near the gear meshing. A PCB© ICP-type accelerometer was mounted on the driven shaft bearing block, as shown in Fig. (6a), to capture the vibration signal. The acoustical signals and the vibration signals were acquired with the help of a National Instruments© SCXI-1530© data acquisition system and a customized LabVIEW-based application software. The signals were captured at sampling rate of 50 K samples per second. The data samples have been taken after running the system for 15 minutes to avoid initial dynamic instability and were processed offline.

The experiment was carried out in three phases. In the first phase, the healthy gears were mounted, and the corresponding acoustical and vibration signals were captured. Sample data of one second duration are shown in Figs. (7a) and (8a), and the corresponding PSD spectra are shown in Figs. (7b) and (8b). In the second phase, the defective driver gear (gear defect-1) was mounted on the driver shaft. One tooth of the driver gear was artificially damaged (defect-1) as shown in Fig. (6b). The corresponding acoustical and vibration signals were captured, and sample data of one second duration are shown in Figs. (9a) and (10a), respectively. From Figure, it is worth noting that the signal is modulated with the impulse generated by the defect. In the last phase of the experiment, the defective driver gear (gear defect-2) was mounted on the driver shaft. Two teeth of driver gear were artificially damaged (defect-2), as shown in Fig. (6c). The corresponding acoustical and vibration signals were captured, and sample data of one second duration are shown in Figs. (11a) and (12a), respectively.

5. RESULTS AND DISCUSSION

The gear meshing frequency (GMF) at 114.25 Hz was observed for an operating frequency of 7.62 Hz (457 rpm). One can note the HTF at 7.68 Hz from the raw acoustical and vibration time-domain signals at faulty conditions. From the PSD spectrum of the acoustical signal for healthy gear meshing, the GMF at 113 Hz was prominently visible along with
higher harmonics ($6^{th}$, $10^{th}$, etc.) of high amplitudes. Similarly, the PSD of the vibration signal for healthy gear meshing also carried $6^{th}$ and $16^{th}$ harmonics of the GMF prominently, as shown in Figs. (7b) and (8b), respectively. The PSD of acoustical signals for damaged driver gear meshing, namely one tooth defect (broken) and two teeth defects (broken), are shown in Figs. (9b) and (10b), respectively. The PSD spectrum of defect-1 carried the peak at GMFs predominately. However, in defect-2 condition, the $5^{th}$, $9^{th}$, and $10^{th}$ harmonics of the GMF were also visible prominently. Similarly, the PSD of vibration signals from the defective (defect-1 and defect-2) driver gear meshing was extracted and is shown in Figs. (11b) and (12b), respectively. In such situations, one can observe that the PSD spectra carried the spike at GMFs with very lower amplitude. The higher harmonics of GMFs ($5^{th}$, $16^{th}$, $19^{th}$, $25^{th}$, and $26^{th}$) were noticeable with higher amplitudes and with high side bands.

From the PSD spectra, it is worth noting that the acoustical signal carried high-frequency noise at smaller amplitudes and that the vibration signal carried high-frequency noise at a larger amplitude. Next, the statistical quantities such as RMS value, standard deviation, crest factor, SNR, and kurtosis for the acoustical and vibration signals were evaluated and have been tabulated in Tables 1 and 2, respectively. From Tables 1 and 2, it can be observed that the statistical parameters’ variations with respect to defect severity are inconsistent; only the kurtosis of acoustical and vibration signals varied significantly with respect to defect, but the variation shows a decreasing pat-
tern with severe defect condition. This is possible due to the sharpness of the burst visible for defect-1 condition.\textsuperscript{17}

For effective feature extraction of the nonstationary acoustical and vibration signals, we implemented bispectrum analysis, which computes the single-sided bispectrum of a univariate time series using the FFT method. The bispectra were extracted with 2048 frequency bins using 256 points of window length and linear peak hold, with parameters averaging at 50% overlap. The resultant bispectrum had 24.42 Hz frequency resolution.

The bispectrum for acoustical signals (healthy condition, defect-1, and defect-2) was extracted and are shown in Figs. (13a), (13b), and (13c), respectively. The bispectrum of the acoustical signal from healthy gear meshing had a major spike at the GMF frequency (at $\sim$110Hz). From Fig. (13), it can be noted that the bispectrum of faulty condition carries a prominent peak at about 1500 Hz with wide side band. In such cases, it can also be observed that the high-frequency signal components are introduced with a linear phase. So, the low-frequency peaks for HTF and GMF are not discernible. Similarly, the bispectra for vibration signals (healthy condition, defect-1, and defect-2) have been extracted and are shown

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|c|}
\hline
 & RMS & SD & Crest & SNR & Kurtosis \\
\hline
Healthy gear meshing & 0.23297 & 0.23297 & 4.29411 & 0.76149 & 4.25658 \\
Defective driver gear-1 & 0.14548 & 0.08068 & 5.15038 & 1.59379 & 31.71135 \\
Defective driver gear-2 & 0.12390 & 0.12080 & 5.74989 & 0.67445 & 13.76904 \\
\hline
\end{tabular}
\end{table
in Figs. (14a), (14b), and (14c), respectively. The bispectra of the vibration signals from healthy gear meshing shows major spikes at around 670 Hz, 1800 Hz, and 2100 Hz with wide side band. From Fig. (14), it can be noted that the bispectrum carries major peaks at around 2100 Hz, 2500 Hz, and 2800 Hz with wide side bands for faulty conditions. In such cases, another observation is that the high-frequency components are introduced with the linear phase. The low-frequency peak of HTF is visible for defect-1 condition but not prominently visible for defect-2. It is worth noting from the bispectrum that the three major spikes are visible, which dominates other low-frequency spikes in the faulty condition.

From statistical analysis and bispectrum analysis, it is understood that an adequate filtering is required to remove noise and make signals more informative. Next, in line with the proposed signal processing scheme, an ANC-based filtering technique was implemented. The filtering performance was compared with standard filters such as (a) FIR-based high-pass filter with a high cut-off frequency of 100 Hz with 51 taps; (b) FIR-based low-pass filter with a low cut-off frequency 5 kHz with 51 taps; (c) FIR-based band-pass filter with a high cut-off frequency of 100 Hz and low cut-off frequency of 5 kHz with 51 taps; (d) rectangular half the width of the moving average filter; and (e) wavelet denoising using undecimated wavelet transform up to decomposition level 3, using db-2 as the mother wavelet and soft thresholding at multiple levels using the SURE technique.

5.1. Acoustical Signal Analysis

Active noise cancellation has been implemented with an LMS-based adaptive filtering for acoustical signals from the defect conditions (defect-1 and defect-2). The acoustical signal from the healthy gear meshing was used as the reference background signal in the adaptive filter. The filtering was carried out with manual tuning of FIR filter length (200) and step size (0.093). The filtered acoustical signal of defect-1 and the corresponding PSD spectrum are shown in Figs. (15a) and (15b), respectively. Similarly, the filtered signal of defect-2 condition and the corresponding PSD spectrum are shown in Figs. (15c) and (15d), respectively.

From the PSD spectra of the denoised signals, it can be noted that the major low-frequency component is visible at 99.9 Hz (GMF − Operating Frequency + HTF). The high-frequency components are also visible, but their magnitudes have been reduced significantly. The denoised acoustical signal for defect-1 and defect-2 were overlapped with the corresponding raw acoustical signal and are shown in Figs. (16a) and (16b), respectively.

The statistical parameters, as discussed previously, were evaluated and have been tabulated in Table 3. In order to evaluate the performance of ANC-based filtering, well-established filters have been investigated. The statistical parameters of corresponding denoised acoustical signals were evaluated and are presented in Tables 4 and 5 for defect-1 and defect-2, respectively. It is worth noting from Tables 4 and 5 that the RMS and standard deviation decreased for the ANC-based denoised signal. However, the crest factor, SNR, and kurtosis values increased significantly compared to the raw acoustical signal and denoised signals from other standard filters. The MSE parameter was the lowest compared to other standard filters, which explains the retaining of the signal signature with minimal distortion after ANC-based filtering.

Next, the bispectrum of denoised acoustical signals for defect-1 and defect-2 conditions were extracted with the parameters in Tables 4 and 5. The corresponding spectra are shown in Figs. (17a) and (17b), respectively. Based on bispectrum analysis, it can be observed that the low-frequency component of HTF is clearly visible with high amplitudes. Other
Table 3. Statistical parameters of ANC-based denoised acoustical signals.

<table>
<thead>
<tr>
<th></th>
<th>RMS</th>
<th>SD</th>
<th>Crest Factor</th>
<th>SNR</th>
<th>Kurtosis</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Defective driver gear-1</td>
<td>0.13063</td>
<td>0.13044</td>
<td>6.0714</td>
<td>0.75175</td>
<td>5.63802</td>
<td>0.0367</td>
</tr>
<tr>
<td>Defective driver gear-2</td>
<td>0.18015</td>
<td>0.18001</td>
<td>4.46279</td>
<td>0.76608</td>
<td>4.20451</td>
<td>0.07234</td>
</tr>
</tbody>
</table>

Table 4. Statistical parameters of denoised defective acoustical signals (failure in one tooth) with standard filters.

<table>
<thead>
<tr>
<th></th>
<th>RMS</th>
<th>SD</th>
<th>Crest Factor</th>
<th>SNR</th>
<th>Kurtosis</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>High pass</td>
<td>0.19728</td>
<td>0.1972</td>
<td>5.04753</td>
<td>0.73888</td>
<td>5.61372</td>
<td>0.08663</td>
</tr>
<tr>
<td>Low pass</td>
<td>0.19314</td>
<td>0.19303</td>
<td>5.55174</td>
<td>0.74679</td>
<td>5.21144</td>
<td>0.08532</td>
</tr>
<tr>
<td>Band pass</td>
<td>0.18941</td>
<td>0.18932</td>
<td>5.60676</td>
<td>0.74436</td>
<td>5.34275</td>
<td>0.0836</td>
</tr>
<tr>
<td>Smoothing</td>
<td>0.19386</td>
<td>0.19376</td>
<td>5.61519</td>
<td>0.74545</td>
<td>5.25884</td>
<td>0.00429</td>
</tr>
<tr>
<td>Wavelet denoised</td>
<td>0.17696</td>
<td>0.17685</td>
<td>5.60978</td>
<td>0.73295</td>
<td>6.01631</td>
<td>0.00201</td>
</tr>
<tr>
<td>ANC denoised signal</td>
<td>0.13063</td>
<td>0.13044</td>
<td>6.0714</td>
<td>0.75175</td>
<td>5.63802</td>
<td>0.0367</td>
</tr>
</tbody>
</table>

Figure 15. Denoised acoustical signal of defective gear meshing: (a) defect in one tooth, (b) PSD in one tooth, (c) two teeth, and (d) PSD in two teeth.

The statistical parameters, as discussed previously, were evaluated and have been tabulated in Table 6. In order to evaluate the performance of ANC-based filtering, well-established filters were investigated. The statistical parameters of corresponding denoised vibration signals were evaluated and have

Figure 16. Denoised acoustical signal of defective gear meshing overlapped with raw signal: (a) denoised acoustical signal overlapped with the raw acoustical signal for a defect in one tooth and (b) denoised acoustical signal overlapped with the raw acoustical signal for a defect in two teeth.

5.2. Vibration Signal Analysis

In last phase of signal processing, the ANC was implemented on vibration signals from the defect conditions (defect-1 and defect-2) with LMS-based adaptive filtering. Similar to the acoustical signal processing, the vibration signal at healthy gear meshing was used as the reference background signal in adaptive filtering. The filtering was carried out with manual tuning of filter length 200 and step size 0.02. The filtered vibration signal of defect-1 condition and the corresponding PSD spectrum are shown in Figs. (18a) and (18b), respectively. Similarly, the filtered vibration signal of defect-2 condition and the corresponding PSD spectrum are shown in Figs. (18c) and (18d), respectively.

From the PSD spectra of denoised signals, it can be observed that the low-frequency component is visible at 98 Hz (GMF – [Operating Frequency + HTF]). The PSD of the ANC-based filtered vibration signal carried additional prominent frequency peaks (at 224 Hz, 687 Hz, and 1689 Hz, which is equivalent to 2nd, 6th, and 15th harmonics of GMF). The major spike at 2854 Hz with a wide side band was observed in both the defect conditions, which was introduced due to the defect. The denoised vibration signal for defect-1 and defect-2 were overlapped with the corresponding raw vibration signal and are shown in Figs. (19a) and (19b), respectively.

The statistical parameters, as discussed previously, were evaluated and have been tabulated in Table 6. In order to evaluate the performance of ANC-based filtering, well-established filters were investigated. The statistical parameters of corresponding denoised vibration signals were evaluated and have
Table 5. Statistical parameters of denoised defective acoustical signals (failure in two teeth) with standard filters.

<table>
<thead>
<tr>
<th>Filter Type</th>
<th>RMS</th>
<th>SD</th>
<th>Crest Factor</th>
<th>SNR</th>
<th>Kurtosis</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Pass (100 Hz)</td>
<td>0.27</td>
<td>0.27</td>
<td>3.58247</td>
<td>0.76</td>
<td>3.90218</td>
<td>0.18548</td>
</tr>
<tr>
<td>Low Pass (5000 Hz)</td>
<td>0.27</td>
<td>0.27</td>
<td>4.17771</td>
<td>0.77</td>
<td>3.78861</td>
<td>0.18355</td>
</tr>
<tr>
<td>Band Pass (100–5000 Hz)</td>
<td>0.26</td>
<td>0.26</td>
<td>4.22489</td>
<td>0.77</td>
<td>3.84271</td>
<td>0.1785</td>
</tr>
<tr>
<td>Smoothing (rectangular)</td>
<td>0.27</td>
<td>0.27</td>
<td>4.23522</td>
<td>0.77</td>
<td>3.79724</td>
<td>0.00785</td>
</tr>
<tr>
<td>Wavelet denoised (UWT)</td>
<td>0.25</td>
<td>0.25</td>
<td>4.28111</td>
<td>0.76</td>
<td>3.9837</td>
<td>0.00408</td>
</tr>
<tr>
<td>ANC denoised signal</td>
<td>0.18</td>
<td>0.18</td>
<td>4.46279</td>
<td>0.76</td>
<td>4.20451</td>
<td>0.07234</td>
</tr>
</tbody>
</table>

Table 6. Statistical parameters of the ANC-based denoised vibration signal.

<table>
<thead>
<tr>
<th>Gear Condition</th>
<th>RMS</th>
<th>SD</th>
<th>Crest Factor</th>
<th>SNR</th>
<th>Kurtosis</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Defective driver gear-1</td>
<td>0.147</td>
<td>0.065</td>
<td>3.7072</td>
<td>2.09</td>
<td>20.75317</td>
<td>0.00853</td>
</tr>
<tr>
<td>Defective driver gear-2</td>
<td>0.090</td>
<td>0.056</td>
<td>8.50815</td>
<td>0.74</td>
<td>11.54897</td>
<td>0.00869</td>
</tr>
</tbody>
</table>

Figure 17. Bispectrum of denoised acoustical signals by ANC: (a) bispectrum spectrum of the denoised acoustical signal at defect in one tooth and (b) bispectrum spectrum of the denoised acoustical signal at defect in two teeth.

![Figure 17](image1.png)

Figure 18. Denoised vibration signal of defective gear meshing: (a) one tooth, (b) PSD in one tooth, (c) two teeth, and (d) PSD in two teeth.

![Figure 18](image2.png)

been presented in Tables 7 and 8 for defect-1 and defect-2, respectively. Similar to the statistics of the denoised acoustical signal, it is worth noting from Tables 7 and 8 that the RMS and standard deviation are decreased for the ANC-based denoised signal. However, the crest factor, SNR, and kurtosis values increased significantly compared to the raw vibration signal and denoised signals from other standard filters. The MSE parameter is was the lowest compared to other standard filters, which explains the retaining of signal signature with minimal distortion after ANC-based filtering.

Finally, the bispectrum of denoised vibration signals for defect-1 and defect-2 conditions was extracted, similar to the acoustical signal processing. The corresponding spectra are shown in Figs. (20a) and (20b), respectively. From the bispectrum, it can be observed that the low-frequency component of HTF is clearly visible with high amplitudes. Other high-frequency components were also observed but with significantly lower magnitude compared to the bispectrum of the raw acoustical signal (significant peak at \( \sim 2854 \) Hz, see Fig. (14)). With an increase in defect severity, other high-frequency components are introduced which dominate the HTF spike magnitude. The proposed method was tested with 20 test samples, and the observed results are repeatable. In summary, the pro...
Table 7. Statistical parameters of the denoised defective vibration signal (failure in one tooth) with standard filters.

<table>
<thead>
<tr>
<th>Filter Type</th>
<th>RMS</th>
<th>SD</th>
<th>Crest Factor</th>
<th>SNR</th>
<th>Kurtosis</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>High pass (100 Hz)</td>
<td>0.13635</td>
<td>0.09964</td>
<td>7.1434</td>
<td>1.48993</td>
<td>32.72079</td>
<td>0.01597</td>
</tr>
<tr>
<td>Low pass (5000 Hz)</td>
<td>0.14491</td>
<td>0.07976</td>
<td>7.38803</td>
<td>1.60825</td>
<td>30.62829</td>
<td>0.01584</td>
</tr>
<tr>
<td>Band pass (100-5000 Hz)</td>
<td>0.13611</td>
<td>0.07886</td>
<td>7.46802</td>
<td>1.56024</td>
<td>31.67959</td>
<td>0.01578</td>
</tr>
<tr>
<td>Smoothing (rectangular)</td>
<td>0.14399</td>
<td>0.07796</td>
<td>7.43385</td>
<td>1.64244</td>
<td>30.6741</td>
<td>0.00064</td>
</tr>
<tr>
<td>Wavelet denoised (UWT)</td>
<td>0.1436</td>
<td>0.07723</td>
<td>7.41479</td>
<td>1.65786</td>
<td>34.98493</td>
<td>0.00005</td>
</tr>
<tr>
<td>ANC denoised signal</td>
<td>0.14762</td>
<td>0.06516</td>
<td>7.37072</td>
<td>2.09151</td>
<td>20.75317</td>
<td>0.00453</td>
</tr>
</tbody>
</table>

Table 8. Statistical parameters of the denoised defective acoustical signal (failure in two teeth) with standard filters.

<table>
<thead>
<tr>
<th>Filter Type</th>
<th>RMS</th>
<th>SD</th>
<th>Crest Factor</th>
<th>SNR</th>
<th>Kurtosis</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>High pass (100 Hz)</td>
<td>0.12066</td>
<td>0.11801</td>
<td>8.19805</td>
<td>0.66558</td>
<td>14.50472</td>
<td>0.02853</td>
</tr>
<tr>
<td>Low pass (5000 Hz)</td>
<td>0.12315</td>
<td>0.12004</td>
<td>8.23485</td>
<td>0.67596</td>
<td>13.41093</td>
<td>0.0291</td>
</tr>
<tr>
<td>Band pass (100-5000 Hz)</td>
<td>0.12019</td>
<td>0.11752</td>
<td>8.27487</td>
<td>0.66537</td>
<td>14.13218</td>
<td>0.02837</td>
</tr>
<tr>
<td>Smoothing (rectangular)</td>
<td>0.12107</td>
<td>0.1179</td>
<td>8.28729</td>
<td>0.67947</td>
<td>13.30746</td>
<td>0.00103</td>
</tr>
<tr>
<td>Wavelet denoised (UWT)</td>
<td>0.11854</td>
<td>0.1153</td>
<td>8.32403</td>
<td>0.66858</td>
<td>14.78804</td>
<td>0.00014</td>
</tr>
<tr>
<td>ANC denoised signal</td>
<td>0.10081</td>
<td>0.08566</td>
<td>8.59815</td>
<td>0.74104</td>
<td>11.54897</td>
<td>0.00869</td>
</tr>
</tbody>
</table>

6. CONCLUSIONS

Statistical parameters provide information about the presence of the defects. However, they cannot explain the severity of the defect. The HTF is not observed from the PSD spectra of the acoustical and vibration signals from faulty conditions. The experimental analysis reveals that the ANC is an appropriate denoising tool for these faulty conditions. Acoustical and vibration signals from the healthy gear meshing scenario can be used as the background noise for the LMS-based adaptive filter. The performance of the proposed denoising technique is superior to most of the well-established standard filters. The improvement in SNR, crest factor, and kurtosis are significantly noteworthy after the denoising of acoustical and vibration signals from the faulty condition (defect-1 and defect-2) as compared to the raw signal. The bispectrum of denoised acoustical and vibration signal carries prominent spikes at lower frequencies, which explains the presence of HTF in the faulty condition. From identification of HTF, one can ensure the presence of faulty teeth in gear meshing. In summary, the bispectrum of denoised (ANC-based) acoustical and vibration signals provides a clearer view about the presence of fault in gear teeth.

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Bibliography


