A Review of Gearbox Condition Monitoring Based on vibration Analysis Techniques Diagnostics and Prognostics

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ABSTRACT

This paper provides a review of the literature on condition monitoring of a gearbox. The progress and changes over the past 30 years in failure detection techniques of rotating machinery including helicopter transmission are reviewed. Vibration Analysis techniques, indicators and parameters used in condition monitoring are arranged in a historical perspective. The use of vibration-based analysis damage detection techniques is classified and discussed in details. The capability of each technique to sense failure and damage in rotary equipments is addressed. These diagnostics techniques in gearbox condition monitoring are organized and regrouped in this review paper in a better approach so they can be easily recognized.

Keywords: Condition monitoring; rotating machinery; gearbox; transmission; vibration-based; time-statistical; RAW; RMS; crest factor; energy ratio; energy operator; kurtosis; enveloping; demodulation; TSA; FM0; residual signal; NA4; NA4*; difference signal; FM4; FM4*; M6A; M6A*; M8A; M8A*; Band-Pass Mesh Signal; NB4; NB4*; Time-Frequency; Short-Time Fourier Transform; Winger-Ville Distribution; Wavelet Transform; NP4.

1. Introduction

Over the past 30 years, many researches have been extensively studied and focused on failure and damage detection techniques in mechanical equipments. Fault can take place at any time on rotating machinery which lead to harmful results or delays in production. It is important to detect any problems at an early stage to stay away from unexpected breakdown. Therefore, condition monitoring process was involved to detect such problems in rotating machinery in order to have an early notice of damages and to avoid unexpected failure. Condition monitoring system minimizes machines downtime. It also saves money and time in maintenance by recognizing the damaged elements without calling for shutdown or inspection.

The field of condition monitoring of rotating machinery is wide. There are hundreds of researches have been extensively studied and focused on failure and damage detection in mechanical equipments. These researches and works, have many different techniques and approaches applied to all rotating machinery in order to detect any damage way before it happens. The main goal of these techniques is to minimize the cost and time in machines repairs and also to enhance the ways of detecting failures. Since the techniques in condition monitoring in rotating machinery where stared long time ago, many approaches have been improved in damage detection and diagnostics field. Some of these approaches have a basic failure detection process such as oil debris analysis techniques. On the other hand, most of the recent work are focused on more advanced techniques such as angular motion analysis, vibration-based analysis, model-based analysis and mathematical

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modeling. This paper focuses on Vibration-Based Analysis techniques. Vibration-Based Analysis techniques are classified into two main groups and they are discussed in details in the following sections.

2. Vibration-Based Analysis

Vibration analysis is the most common and popular technique used in the field of condition monitoring of rotating machinery and it is also called feature extraction techniques. Most of the recent work are focused on vibration based techniques. In these techniques, accelerometers are used to acquire vibration signals that come from a defective part in a machinery system. Vibration-based techniques can be divided into two main different processing groups. These two main processing group are: Time-Statistical Analysis and Time-Frequency Analysis. Furthermore, each one of these processing groups are also divided into subgroups as shown in figure 1 below. Each individual technique is explained and addressed in details below.

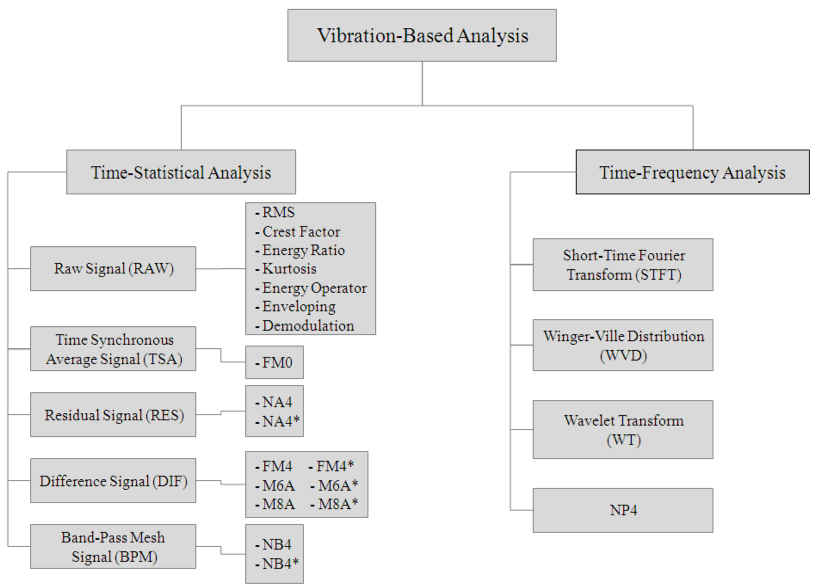

Fig.1 Classification of Vibration-Based Analysis Techniques and Parameters

2.1. Time-Statistical Analysis

Time-statistical analysis is one of the traditional methods used in rotating machinery failure detection and condition monitoring. This type of traditional analysis is typically based on some statistical measurement of vibration energy [1]. There are five different processing subgroups fall in this category of analysis: Raw Signal, Time Synchronous Average Signal, Residual Signal, Difference Signal, and Band-Pass Mesh Signal. Figure 2 below shows the processing flow for feature extraction techniques.

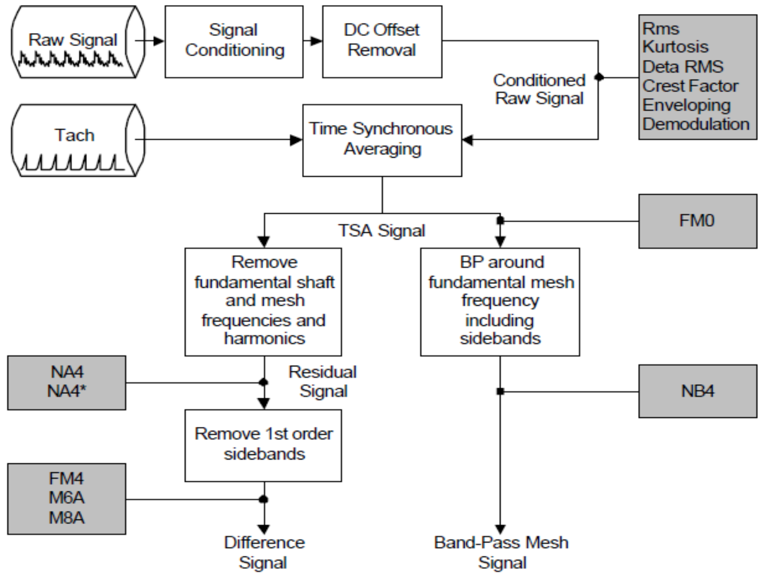

Fig.2 Processing Flow for Feature Extraction Techniques [2]

2.1.1. Raw Signal (RAW)

The RAW preprocessing indicates elements that are computed from the raw or trained signal collected by the sensor. Training the signal or eliminating the mean of the signal is the only preprocessing required for these elements. Training the signal can be done by multiplying all the data points by a calibration constant that is based on the accelerometer used. There are seven techniques fall in this subgroup: Root Mean Squared, Crest Factor, Energy Ratio, Kurtosis, Energy Operator, Enveloping and Demodulation [2].

2.1.1.1. Root Mean Squared (RMS)

The is the simplest method in detecting and measuring defects in the time domain. It is good for tracking the general noise level. It is also very useful for detecting unbalanced rotating elements. The root mean squared, also is called a quadratic mean, is a statistical measure of the magnitude of a varying quantity. RMS was initially developed to describe a temperature of a resistor subjected to sine wave alternative current. "The root mean squared value of vibration signal is a time analysis feature that is the measure of the power continent in the vibration signature."[2] It is very useful in sinusoidal waves. The RMS for a sine wave can be defined to be 0.707 times the amplitude of the signal [3]. RMS can be defined as the square root of the average of the sum of the squares of the signal samples [4, 5].

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

where,

x the original sample time signal

N the number of samples taken

i the sample index

The Delta RMS is the change between the present and the previous RMS values [2].

2.1.1.2. Crest Factor (CF)

This method gives better measurements than RMS in detecting defects in rotating machinery. "It is used to detect changes in the signal pattern due to impulsive vibration sources such as tooth damage in a gearbox or a defect in the outer race of a bearing." The crest factor can be defined as the ratio of the positive peak value of the input signal x to the RMS level. The value of the crest factor is affected by the numbers of peaks in the time series signal. Crest factor can be calculated to be between 2 and 6 in normal operation. However, any value higher than 6 is usually related to machinery problems [2]. A signal that has a less number of high amplitude peaks can generate a larger crest factor value as the numerator increases (high amplitude peaks), as the denominator decreases (few peaks means lower RMS) [6].

$$CF=\frac{\text{Peak level}}{\text{RMS}}=\frac{x_{0\text{-pk}}}{\text{RMS}} \tag{2}$$

where,

pk the sample index for the maximum positive peak of the signal

x_{0-pk} the value of x at pk

Crest Factor (CF) is a normalized measurement of the amplitude of the signal and is calculated to increase even when a small number of high amplitude peaks, such as a signal resulted from local tooth damage, occurs [5].

2.1.1.3. Energy Ratio (ER)

This is a useful technique for detecting heavy uniform wear [3]. It can be defined as the ratio of the RMS of the difference signal (d) and the RMS of the signal of the regular meshing component (r) [5].

$$ER=\frac{RMS_d}{RMS_r} \tag{3}$$

The energy in the regular component signal (r) is compared to the energy in the difference signal (d). The theory in this technique is that the energy moves from the regular signal to the difference signal [6].

2.1.1.4. Kurtosis

This technique provides a measure of the size of the tails of distribution. It can be used as an indicator of major peaks in a signal [2]. The kurtosis can be defined as the fourth normalized moment of the signal. The fourth moment is normalized by the square of the variance [3]. It is useful measurement of the peakedness of a signal [5]. "As gear wears or breaks, this feature should signal error due to the increased level of vibration."[7] Simply, it can be said that kurtosis is a statistical measure of the number of amplitude of peaks in a signal. when there are more peaks in a signal, kurtosis value become larger. A signal of Gaussian noise has a kurtosis value close to 3. A gearbox in a good condition is associated with a Gaussian distribution and have a kurtosis around 3. It should be noted that researchers subtract 3 from the calculated value and they end up with a value of near zero for a healthy gearbox [8]. Kurtosis equation is given by

$$\text{Kurtosis}=\frac{N\sum_{i=1}^{N}(x_i-\bar{x})^4}{\left[\sum_{i=1}^{N}(x_i-\bar{x})^2\right]^2} \tag{4}$$

where,

x	the signal
$\bar{x}$	mean value of the signal
i	the index of data points in time record
N	the total number of data points in time record

2.1.1.5. Energy Operator (EO)

The Energy Operator can be simply calculated by making the input signal of each point squared, and then subtracting the product of the point before and after from squared signal as follows

$$x_i^2-(x_{i-1}*x_{i+1}) \tag{5}$$

"For the end points, the data is looped around." The Energy Operator is calculated by taking the normalized kurtosis of the resultant signal [9].

2.1.1.6. Enveloping

Enveloping is a useful technique in monitoring high frequency response of rotating elements faults such as bearing and gear. An impact is generated when there is a fault on the inner or outer race of the bearing. Also, a damaged gear tooth produces impact when meshing with the other gear [10]. "Impacts in time domain generate many harmonics excite resonance to very high frequency in frequency domain". Figure 3 below shows the vibration and fault frequencies caused by amplitude modulation. The red curve shows the envelope that is caused by impacts of the defected elements. The enveloping technique can be applied by extracting the frequency of the envelope, and then the damaged part of the bearing or gearbox can be detected [11].

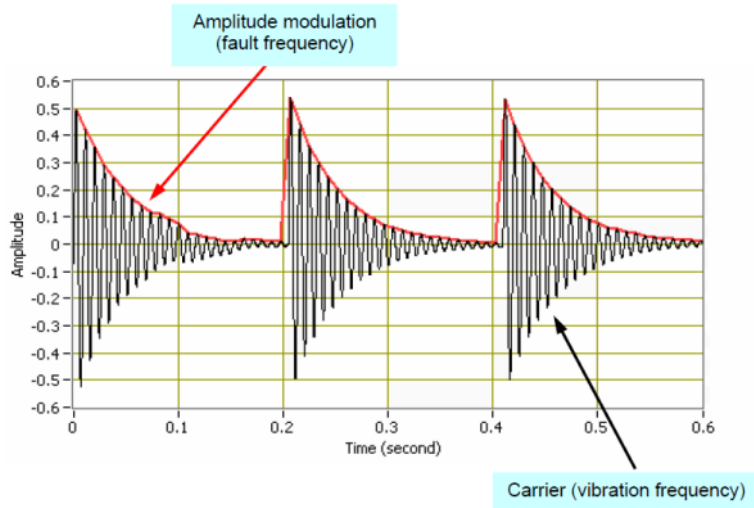

Fig.3 Envelope frequency caused by amplitude modulation [11]

The impact or impulse has a short duration compared to the interval between the pulse. The impact also excites a resonance in a mechanical system at a higher frequency than the vibration produced by the other elements in the system. the enveloping analysis has been extensively used in many applications. It has provided successful results in the early stage of damage detection in bearings. Furthermore, this technique helps finding the actual cause of bearing failure by analyzing the actual frequencies of the faulty rolling element bearing [2].

2.1.1.7. Demodulation

Demodulation techniques is functional in detecting and identifying the amplitude modulation factors stimulated by gear damage in the region of a single gear mesh frequency (GMF) and sometimes double gear mesh frequency (2GMF). Demodulation is different from enveloping techniques that is in demodulation techniques, the combined effect over a range of frequencies can be distinguish. demodulation technique can be applied by first high-pass filtering the raw data at 85 percent of the gear mesh frequency. Then, by low-pass filtering the raw data at 115 percent of the gear mesh frequency. The actual gear mesh frequency can be acquired by investigating the power spectral density of the filtered signal [2].

2.1.2. Time Synchronous Average Signal (TSA)

Time synchronous averaging is a signal averaging process and used to "extract repetitive signal from additive noise". TSA can be applied by dividing the raw signal into equal segments and averaged together. "before the signal is segmented based on the synchronous signal, the number of data points in the series is increased by means of interpolation. When Enough number of averages are taken, the random noise is canceled" [2]. Background noise can be removed using TSA analysis [12]. TSA can also be used to remove the periodic actions that are not synchronous with the monitored gears [13]. FM0 is the best technique would fall in this subgroup.

2.1.2.1. FM0

FM0 parameter was first proposed by Stewart in 1977. FM0 is a strong sign of major faults in a gear meshing [14]. However, it is not a good sign for minor tooth damage. FM0 is used for detecting major changes in the gear meshing pattern by comparing the maximum peak-to-peak amplitude of the signal to the sum of the amplitudes of the meshing frequencies and their harmonics. FM0 value increases when heavy wear occurs. This is because the peak-to-peak frequency stay constant and the gear meshing frequency shrinks [7]. FM0 equation is given as

$$\mathrm{FM0}=\frac{\mathrm{PP_x}}{\sum_{\mathrm{n=0}}^{\mathrm{H}}\mathrm{P_n}} \tag{6}$$

where,

PP_x the maximum peak-to-peak amplitude of signal x

P_n the amplitude of nth harmonics

H the total number of harmonics in frequency rang

2.1.3. Residual Signal (RES)

RES analysis can be applied by removing the shaft components and the gear meshing frequency with their harmonics in order to calculate the residual signal that contains the time synchronous averaged signal. The two techniques fall in this subgroup are: NA4 and NA4*.

2.1.3.1. NA4

The NA4 parameter was initially found by Zakrajsek, Townsend and Decker in 1993 at the NASA Lewis Research Center. NA4 is useful technique for detecting the onset of fault and the continuing development of damage in mechanical equipments [15]. Because FM4, which will be discussed later in this paper, was less sensitive in detecting damages, two changes were made to it in order to develop the NA4 parameter. These two changes made the NA4 a better indicator and more sensitive in detecting faults. The first change is that the difference signals were used to compute the FM4. On the other hand, the residual signals were used to compute the NA4. These residual signals have the first order sidebands which were removed from the difference signals. The second change is that the FM4 is the ration of the kurtosis of a data to the square of the variance of the same data record. However, the NA4 is the ration of the kurtosis of a data record to the square of the average variance which is the mean value of the variance of all previous data records in the run ensemble [1]. NA4 equation is given as

$$\mathrm{NA4}=\frac{\mathrm{N}\sum_{\mathrm{i=1}}^{\mathrm{N}}\left(\mathrm{r_i}-\bar{\mathrm{r}}\right)^4}{\left\{\frac{1}{\mathrm{M}}\sum_{\mathrm{j=1}}^{\mathrm{M}}\left[\sum_{\mathrm{i=1}}^{\mathrm{N}}\left(\mathrm{r_{ij}}-\bar{\mathrm{r}}_{\mathrm{j}}\right)^2\right]\right\}^2} \tag{7}$$

Where,

r the residual signal

$\bar{r}$ the mean value of residual signal

N the total number of data points in time record

M the number of current time record in run ensemble

i the index of data points in time record

j the index of time record in run ensemble

2.1.3.2. NA4*

NA4* was developed by Decker, Handschuh and Zakrajsek in 1994 to be an enhanced version of NA4 [15]. "As damage grows from localized to distributed , the variance of kurtosis increases dramatically. Since the kurtosis is normalized by the variance, this result in the kurtosis decreasing to normal values even with damage present. To counter this effect, NA4* was developed" [3]. In NA4 analysis technique, the kurtosis of a data record is normalized by the squared average variance for the run ensemble. However, in NA4* analysis technique, the kurtosis of a data record is normalized by the squared variance for a healthy gearbox. NA4* is given as

$$NA4^{*}=\frac{N\sum_{i=1}^{N}\left(r_i-\bar{r}\right)^4}{(M_2)^2} \tag{8}$$

where,

r the residual signal

$\bar{r}$ the mean value of residual signal

N the total number of data points in time record

M_2 the variance of the residual signal for a healthy gearbox

i the index of data points in time record

The variance value in a damaged gearbox is greater than the one in a healthy gearbox. The variance for a healthy gearbox can be estimated by selecting a less number of data records in order to guarantee "a statistically significant sample size." The residual signal and the mean and standard deviation of the variances are calculated in order to make the decision that is based on the upper limit L, which is given by

$$L=\bar{x}+\frac{Z}{\sqrt{n}}\,\sigma \tag{9}$$

where,

$\bar{x}$ the mean value of previous variances

Z the value of a normal distribution

n the number of samples, $n \geq 30$

σ the standard deviation of previous variances

The judgment can be made based on the variance value. For instance, when the current variance value goes over the limit L. then it is considered that the gearbox is not healthy any more [16]. This modification makes NA4* more sensitive than NA4 in detecting a growth of damage in gearbox.

2.1.4. Difference Signal (DIF)

In the operation of a gearbox, the shaft frequency and its harmonics, the primary gear meshing frequency and the first order sidebands and its harmonics are the main elements of the regular gear meshing signal. The preprocessing technique is initially applied by removing that regular gear meshing signal from the time synchronous average (TSA) signal. The actual processing technique can be applied by removing only the sidebands of the primary gear meshing frequencies from the residual signals which resulted from the elimination of the shaft and primary gear meshing frequencies and harmonics [2]. Techniques would fall in this subgroup are: FM4, FM4*, M6A, M6A*, M8A and M8A*.

2.1.4.1. FM4

FM4 was initially developed by Stewart in 1977. It was calculated to detect faults only for limited number of gears. FM4 is defined as the ratio of the kurtosis and the square of the variance of the difference signal. It is given as

$$\mathrm{FM4}=\frac{N\sum_{i=1}^{N}(d_i-\bar{d})^4}{\left[\sum_{i=1}^{N}(d_i-\bar{d})^2\right]^2} \qquad (10)$$

where,

d the difference signal

$\bar{d}$ the mean value of difference signal

i the index of data points in time record

N the total number of data points in time record

Like NA4, FM4 is nondimensional and will have approximate value of three if the difference signal is purely Gaussian. When damage grows up, the peaks in the difference signal increase which affect the kurtosis value to go over three [14].

2.1.4.2. FM4*

FM4* parameter has a similar calculations that are done in the parameter NA4* which was discussed earlier in this paper. "The diagnostic parameter FM4* is an addition of the run ensemble averaging, and also a statistical limitation of the growth of the square of the variance". The calculation of the numerator of FM4* stays the same as the numerator in FM4. However, "the denominator has the averaging effect of NA4*, and also determine if the current variance is of sufficient probability to be contained in the previous samples" [3].

2.1.4.3. M6A

M6A was initially proposed by Martin in 1989. It was calculated to detect surface damage on mechanical components. The theory applied in M6A is the same as the one applied in FM4. Both M6A and FM4 parameters are applied to the difference signal. However, M6A is expected to be "more sensitive to peak in the difference signal". This is because M6A uses the sixth moment normalized by the variance to the third power [17]. M6A is given as

$$M6A=\frac{N^2 \sum_{i=1}^{N}(d_i-\bar{d})^6}{\left[\sum_{i=1}^{N}(d_i-\bar{d})^2\right]^3} \tag{11}$$

where,

d	the difference signal
$\bar{d}$	the mean value of difference signal
i	the index of data points in time record
N	the total number of data points in time record

2.1.4.4. M6A*

M6A* parameter has a similar calculations that are done in the parameter NA4* and FM4* which were discussed earlier in this paper. "The diagnostic parameter M6A* is an addition of the run ensemble averaging, and also a statistical limitation of the growth of the square of the variance". The calculation of the numerator of M6A* stays the same as the numerator in FM4. However, "the denominator has the averaging effect of NA4* and FM4*, and also determine if the current variance is of sufficient probability to be contained in the previous samples."[3, 4]

2.1.4.5. M8A

Like M6A, M8A was initially proposed by Martin in 1989. It was calculated to detect surface damage on mechanical components in a better way than M6A . The theory applied in M8A is the same as the one applied in FM4 and M6A. M8A, M6A and FM4 parameters are applied to the difference signal. However, M8A is expected to be more sensitive than M6A and FM4 to peak in the difference signal. This is because M8A "uses the eight moment normalized by the variance to the fourth power."[17] M8A is given as

$$M8A=\frac{N^3 \sum_{i=1}^{N}(d_i-\bar{d})^8}{\left[\sum_{i=1}^{N}(d_i-\bar{d})^2\right]^4} \tag{12}$$

where,

d	the difference signal
$\bar{d}$	the mean value of difference signal
i	the index of data points in time record
N	the total number of data points in time record

2.1.4.6. M8A*

M8A* parameter has a similar calculations that are done in the parameter NA4*, FM4* and M6A* which were discussed earlier in this paper. "The diagnostic parameter M8A* is an addition of the run ensemble averaging, and also a statistical limitation of the growth of the square of the variance". The calculation of the numerator of M8A* stays the same as the numerator in FM4. However, "the denominator has the averaging effect of NA4*, FM4* and M6A*, and also determine if the current variance is of sufficient probability to be contained in the previous samples" [3, 4].

2.1.5. Band-Pass Mesh Signal (BPM)

The Band-pass mesh signal technique is applied by band-pass filtering the TSA signal around the primary gear meshing frequency. Then, the Hilbert transform is applied to the filtered signal which generates a complex time series of real and imaginary parts. Techniques fall in this subgroup are: NB4 and NB4*

2.1.5.1. NB4

The NB4 parameter was initially found by Zakrajsek, Handschuh and Decker in 1994 to be used as a useful technique for localized tooth damage. NB4 and NA4 are similar and have the same technique of analysis and exact way of calculation by using quasi normalized kurtosis. However, NB4 and NA4 have only one difference that is the residual signal is used in NA4 analysis while the envelope of the band-passed segment of the time synchronous averaged signal is used in NB4 Analysis [18]. NB4 is defined as the fourth statistical moment of the envelope signal divided by the current run time averaged variance of the envelope signal which is raised to the power two. NB4 is given as

$$\mathrm{NB4}=\frac{N\sum_{i=1}^{N}(E_i-\bar{E})^4}{\left\{\frac{1}{M}\sum_{j=1}^{M}\left[\sum_{i=1}^{N}(E_{ij}-\bar{E}_j)^2\right]\right\}^2} \qquad (13)$$

Where,

E	the envelope signal
$\bar{E}$	the mean value of envelope signal
N	the total number of data points in time record
M	the number of current time record in run ensemble
i	the index of data points in time record
j	the index of time record in run ensemble

The theory behind NB4 is that when there is a few damage on gear teeth, a transient load fluctuations are created. These transient load fluctuations are different from the ones that are created by healthy gear teeth, and it can be recognized by using the envelope signal. To calculate NB4, the envelope signal first has to be calculated using the Hilbert transform which given as

$$E(t)=\sqrt{\left(A(t)\right)^2+H[A(t)]^2} \qquad (14)$$

where,

$E(t)$	the envelope of the band-passed signal
$A(t)$	the band-passed signal
$H[A(t)]$	the Hilbert transform of the band-passed signal

The Hilbert transform generates a complex time signal with two parts: real and imaginary. The real part is the band-passed signal and the imaginary part is the Hilbert transform of the signal. "The envelope of the band-passed signal is the magnitude of the complex signal or the analytical signal which is $|A(t) + iH[A(t)]|$" [2, 19].

2.1.5.2. NB4*

NB4* parameter has a similar calculations that are done in the parameter NA4*, FM4*, M6A* and M8A* which were discussed earlier in this paper. "The diagnostic parameter NB4* is an addition of the run ensemble averaging, and also a statistical limitation of the growth of the square of the variance". The calculation of the numerator of NB4* stays the same as the numerator in FM4. However, "the denominator has the averaging effect of NA4*, FM4*, M6A* and M8A*, and also determine if the current variance is of sufficient probability to be contained in the previous samples."[3, 4, and 20]

2.2. Time-Frequency Analysis

Time-frequency analysis has become a popular and useful technique for gear fault detection. It was recognized that gear faults can generate a sharp transients in the vibration signals of gearboxes. Therefore, the exploration of time-frequency features started in the late 1980s [21]. The vibration signature from a gearbox consists of three significant components: "a sinusoidal component due to time varying loading, a broad-band impulsive component due to impact, and random noise."[5] The sinusoidal component dominates in a healthy gearbox. on the other hand, the sinusoidal component shows signs of modulation and reduction in amplitude[22, 23]. In addition to that, "both the broad-band impulsive component and the random noise become more prevalent."[24] The trend displayed by the sinusoidal components are more observable in the frequency domain while the trends displayed by the broad-band impulsive components are more observable in the time domain. Therefore, to capture these trends, time-frequency analysis is considered as a proper technique [25]. There are four different processing subgroups fall in this category of analysis: Short-Time Fourier transform, Winger-Ville distribution, Wavelet transform, and NP4.

2.2.1. Short-Time Fourier Transform (STFT)

The short-time Fourier transform can be considered as a typical time-frequency analysis technique. It useful technique for detecting gear faults by studying the energy distribution signal over a time-frequency domain [26]. The frequency domain of the signal $x(t)$ can be studied by multiplying that signal by a window function $h(t)$. The squared magnitude of the short-time Fourier transform $|X(\omega)|^2$ gives the spectrogram. The spectrogram $P_{sp}(t,\omega)$ calculates the energy density range of the signal as function of time [27], and given as

$$P_{sp(t,\,\omega)}=|X_t(\omega)|^2=\left|\frac{1}{\sqrt{2\pi}}\int e^{-j\omega\tau}\ x(\tau)\ h(\tau\text{-}t)\ d\tau\right|^2 \tag{15}$$

2.2.2. Winger-Ville Distribution (WVD)

Different from STFT, WVD can be obtained by taking the "sum of the product of the signal before time t, $x(t-{\scriptstyle 1/2\tau})$ and the reversed signal after time t, $x(t+{\scriptstyle 1/2\tau})$. The reversal of the signal after time t ensures that at time t, the point being multiplied are equidistant in time from t, specifically $\pm\frac{1}{2}\tau$" [5]. Thus the WVD is given as

$$\tfrac{1}{2}\tau W(t,\tau)=\frac{1}{2\pi}\int x^*\left(t\text{-}{\scriptstyle 1/2\tau}\right)x(t+{\scriptstyle 1/2\tau})e^{j\tau\omega}\ d\tau \tag{16}$$

The winger-Ville distribution (WVD) was first developed in the quantum correction for the thermodynamics equilibrium by Winger in 1932 [28]. Later, WVD was applied to signal processing by Ville in 1948 [29]. In the 1990s, more focus and research were applied to WVD in the field of gearbox damage detection analysis and diagnostics[30]. A great improvement was made by Forrester who applied the WVD analysis to investigate the averaged vibration signals of a faulty gearbox. Forrester found an incredible use of this technique in damage detection. The damage can be purely identified by a visual inspection of the different patterns in the WVD plots which are generated by different types of faults [31-34]. In figure 4 below, the WVD plot illustrates the disturbance at a shaft angle of 100°as a result of a fault in a helicopter gearbox [35].

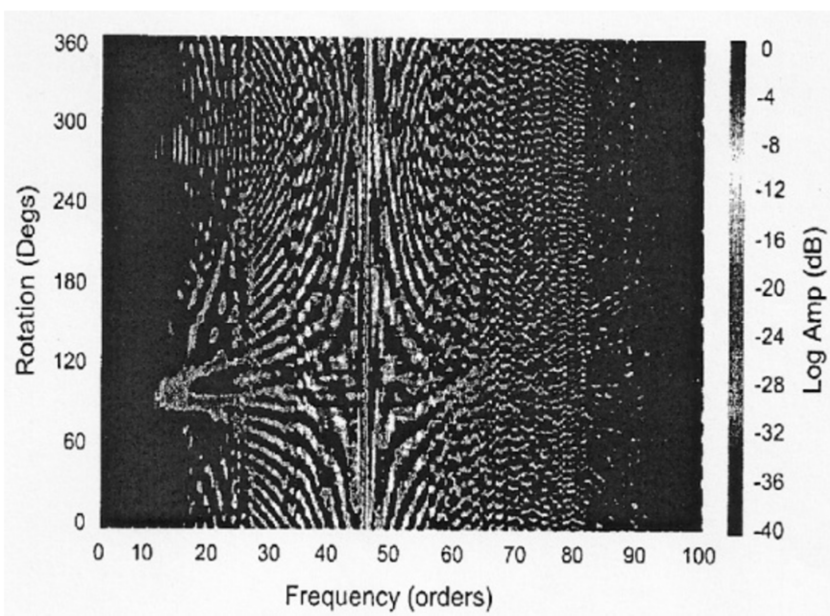

Fig.4 WVD plot of helicopter gearbox with cracked pinion gear [35]

In the early 1990s , McFadden continued the same great work by applying the properties of the continuous and discrete signals on WVD. He showed that the effect of the cross-terms can be minimized by using the sliding weighted functions to the WVD [36-38]. The work done by Choy, Huang, Zakrajsek, Handschuh, and Townsend at NASA Glen Research Center concluded that " the WVD provided vital information regarding the location and severity of gear tooth damage."[39]

2.2.3. Wavelet Transform (WT)

The investigation of wavelet transform (WT) analysis was started in the mid 1980's. WT was found to be a powerful technique for analysis of gearbox vibration signals. WT is a time-frequency analysis technique and has similar characteristics to WVD. However, WT differs from Fourier transform in the way that it "uses a new class of real and complex nonstationary basis function, termed wavelets, which can be independently dilate and shifted as a function of time". This technique has two advantages. The first advantage is that the time and frequency are independent which makes WT useful for describing the local behavior of the signals. The second advantage is that the frequency of the signal can be analyzed without losing the essential information of the time-domain.

Wavelet transform analysis can be applied by "convolving a signal with time shifted and dilated versions of a nonstationary wavelet basis function" [5]. To perform this analysis, the function $\psi_\lambda(t)$ is first defined as a wavelet, where λ belongs to some set of indices Φ. The basis Ψ is then given as

$$\Psi=\{\psi_\lambda|\lambda\in\Phi\} \quad (17)$$

Once the basis was chosen, the signal x is then signified as an arrangement of wavelets. The wavelet signal is given as

$$x=\sum_\lambda c_\lambda\psi_\lambda \quad (18)$$

Where the coefficient c is given as

$$c=\{c_\lambda|\lambda\in\Phi\} \quad (19)$$

In the process of continuous wavelet transform (CWT) which is a non orthogonal process, the coefficients c_λ are required to be computed over all time and frequency. However, in the process of discrete wavelet transform (DWT) which is an orthogonal process, the "dilation and position of the wavelets are chosen to be powers of two.

In 1993, Newland introduced both compact and smooth wavelets [40]. In 1995, Wang and McFadden performed a nice analysis for a transmission fault detection and they compared between the compact and smooth wavelets. Both compact and smooth wavelet were used with the DWT to analyze the vibration signal of a helicopter gearbox. It was found that smooth wavelet was a little better to damage detection than compact wavelet. However, Wang and McFadden reported that the nonorthogonal CWT used with a Gaussian was more efficient than the orthogonal DWT used with either compact or smooth wavelets [41, 42].

2.2.4. NP4

NP4 was initially found by Polyshchuk, Choy, and Braun in 2000. It was developed to be a novel technique in gear damage detection derived from WVD. "The novelty of the NP4 parameter is in application of the previously defined statistical parameter called kurtosis to the WVD data and its interpretation for gear fault detection". The calculation of NP4 does not required a comparison between a faulty and a healthy gear's signals. This makes NP4 a useful method for detecting the damage without tracing the vibration history of the gear. NP4 can be defined as the normalized kurtosis of the signal power P [43, 44]. NP4 is given as

$$NP4=\frac{N\sum_{i=1}^{N}\left(P_i-\bar{P}\right)^4}{\left[\sum_{i=1}^{N}\left(P_i-\bar{P}\right)^2\right]^2} \tag{20}$$

where,

P	the instantaneous signal power calculated using the WVD
$\bar{P}$	the mean value of the signal power
i	the index of data points in time signal
N	the total number of data points in time signal

3. Closure

The progress and changes over the past 30 years in failure detection techniques of rotating machinery were reviewed. Vibration Analysis techniques, indicators and parameters used in condition monitoring were arranged in a historical perspective. Also, they were organized and regrouped in a better way so they can be easily understood. The capability of each individual technique to sense the failure and detect the damage in rotary equipments was discussed in details. Many of these approaches and techniques have shown successful progress in detecting the damages. However, improvement in this field of analysis is still needed. Therefore, new techniques for damage detection will be investigated and the research will be continued.

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References

[1] Zakrajsek, J.J.: "An Investigation of Gear Mesh Failure Prediction Techniques," NASA TM-102340, AVSCOM TM 89-C-005, November 1989.

[2] Lebold, M.; McClintic, K.; Campbell, R.; Byington, C.; Maynard, K.: "Review of Vibration Analysis Methods for Gearbox Diagnostics and Prognostics," Proceeding of the 54th Meeting of the Society for Machinery Failure Prevention Technology, Virginia Beach, VA, pp. 623-634, May 1-4, 2000.

[3] Decker, Harry J.: "Crack Detection for Aerospace Quality Spur Gears," NASA TM-2002-211492, ARL-TR-2682, Prepared for the 58th Annual Forum and Technology Display, by the American Helicopter Society, Montreal, Canada, June 11-13, 2002.

[4] Decker, H.J.; and Lewicki, D.G.: "Spiral Bevel Pinion Crack Detection in a Helicopter Gearbox," in Proceeding of the American Helicopter Society 59th Annual Forum, Phoenix, AZ, pp. 1222-1232, 2003.

[5] Samuel, Paul D.; and Pines, DarryII J.: "A Review of Vibration-Based Techniques for Helicopter Transmission Diagnostics," Journal of Sound and Vibration. vol. 282, no 1-2, pp. 475-508, April 6, 2005.

[6] Swansson, N.S.: "Application of Vibration Signal Analysis Techniques to Signal Monitoring," in: Conference on Friction and Wear in Engineering, Institute of Engineering, Barton, Australia, pp. 262-267, 1980.

[7] Zakrajsek, J.J.: NASA Technical Memorandum 102340, Lewis Research Center, Cleveland, OH.

[8] Miller,; Irwin,; and Freund, J.E.: "Probability and Statistics for Engineering," 3rd Edition, Prentice-Hall, Inc., New Jersey, p.74, 1985.

[9] Ma, J.: "Energy Operator and Other Demodulation Approaches to Gear Defect Detection," Proceeding of 49th Meeting of the Society of Mechanical Failure Prevention Technology, Virginia Beach, VA, pp. 127-140, April 1995.

[10] Spectra Quest Tech Note,: "Analyzing Gearbox Degradation Using Time-Frequency Signature Analysis," March 2006.

[11] Spectra Quest Tech Note,: "Rotating Machinery Fault Diagnosis Techniques-Enveloping and Cepstrum Analyses," October 2006.

[12] Wang, Wilson Q.: "Rotary Machinery Health Condition Monitoring Fault Diagnosis and Prognosis," Thesis, University of Waterloo, Waterloo, Ontario, Canada, 2002.

[13] McFadden, P.: "A Technique for Calculating the Time Domain Averages of Vibration of the Individual Planet Gear and the Sun Gear in an Epicyclic Gearbox," Journal of Sound and Vibration, vol. 144, no.1, pp. 163-172, 1991.

[14] Stewart, R.T.: "Some Useful Analysis Techniques for Gearbox Diagnostics," Technical Report MHM/R/10/77, Machine Health Monitoring Group, Institute of Sound and Vibration Research, University of Southampton, July 1977.

[15] Zakrajsek, J.J.; Townsend, D.P.; and Decker, H.J.: "An Analysis of Gear Fault Detection Methods as Applied to Pitting Fatigue Failure Data," Technical Report NASA TM-105950, A VSCOM TR-92-C-035, NASA and the US Army Aviation System Command, Prepared for the 47th Meeting of The System Engineering Approach to Mechanical Failure Prevention, January 1993.

[16] Decker, H.J.; Handschuh, R.F.; and Zakrajsek, J.J.: " An Enhancement to the NA4 Gear Vibration Diagnostic Parameter," Technical Report NASA TM-106553, ARL-TR-398, NASA and the US Army Research Laboratory, July 1994.

[17] Martin, H.R.: "Statistical Moment Analysis As a Mean of surface Damage Detection," Proceeding of the 7th International Model Analysis Conference, Society of Experimental Mechanics, Schenectady, NY, pp. 1016-1021, 1989.

[18] Zakrajsek, J.J.: "A Review of transmission Research at NASA Lewis Research Center," Technical Report NASA TM-106746, ARL-TR-599, NASA and the US Army Research Laboratory, December 1994.

[19] Zakrajsek, J.J.; Handschuh, R.F.; Lewicki, D.G.; and Decker, H.J.: "Detecting gear Tooth fracture in a High Contact Ratio Face Gear Mesh," Proceeding of the 49th Meeting of the Mechanical Failure Prevention Group, Virginia Beach, VA, April 18-20, 1995.

[20] Zakrajsek, J.J.: "Transmission Diagnostics Research at NASA Lewis Research Laboratory," Technical Report NASA TM-106901, ARL-TR-748, NASA and the US Army Research Laboratory, April 1994.

[21] Forrester, B.D.: "Use of the Wigner-Ville Distribution in Helicopter Transmission Fault Detection," Proceeding of the Australian Symposium on Signal Processing and Applications-ASSP 89, Adelaide, Australia, pp.78-82, 1989.

[22] McFadden, P.D.: "Detecting Fatigue Crack in Gears by Amplitude and Phase Demodulation of the Meshing Vibration," Journal of Vibration, Acoustic, Stress, and Reliability in Design, vol. 108, pp. 165-170, 1986.

[23] Brennan, M.; Chen, M.H.; and Reynolds, A.G.: "Use of Vibration Measurements to Detect Local Tooth Defects in Gears," Journal of Sound and Vibration, vol. 31, pp. 12-17, November 1997.

[24] Larder, B.: "An Analysis of HUMS Vibration Diagnostics Capabilities," Proceeding of the American Helicopter Society 53rd Annual Forum, pp. 1308-1315, Virginia Beach, VA, 1997.

[25] Samuel, P.D.; Pines, D.J.; and Lewicki, D.G.: "A Comparison of Stationary and Non-Stationary Transforms for Detecting Faults in Helicopter Gearboxes," Journal of the American Helicopter Society, vol. 45, pp. 125-136, February 2000.

[26] Wang, W.; and McFadden P.: "Early Detection of Gear failure by Vibration Analysis – I, Calculation of the Time – Frequency Distribution," Mechanical System and Signal Processing, vol. 7, no. 3, pp. 193-203, 1993.

[27] Cohen L.: Time-Frequency Analysis, Prentice-Hall, Inc., New York, 1995.

[28] Winger E.P.: "On the Quantum Correction for the Thermodynamics Equilibrium," Physics Review, vol. 40, pp. 745-759. 1932.

[29] Ville, J.: "Theorie ef Applications de la Naotion de Signal Analytique," Cables et Transmission, vol. 2A, pp. 61-74, 1948.

[30] Staszewski, W.J.; Worden, K.; and Tomlinson, G.R.: "Time-Frequency Analysis in Gearbox Fault Detection Using The Winger-Ville Distribution and Patter Recognition," Mechanical System and Signal Processing, vol. 11, no. 5, pp. 673-692, 1997.

[31] Forrester B.D.: "Use of the Winger Ville Distribution in Helicopter Transmission fault Detection," Proceedings of the Australian Symposium on Signal Processing and Applications-ASSPA 89, Adelaide, Australia, April 17-19, 1989.

[32] Forrester B.D.: "Analysis of Gear Vibration in the Time-Frequency Domain," Proceedings of the 44th Meeting of the Society of Mechanical Failures Prevention Group (MFPT) of the Vibration Institute, Virginia Beach, Virginia, pp. 225-239, April 3-5, 1989.

[33] Forrester B.D.: "Time –Frequency Analysis of helicopter Transmission Vibration," Technical Report 108, Aeronautical Research Laboratory, ARL Propulsion, Melbourne, Australia, 1990.

[34] Forrester B.D.: "Time –Frequency Analysis in Machine Fault Detection," Time –Frequency Signal Analysis, B. Boashash Edition, Longman Cheshire, Melbourne, Australia, 1992.

[35] Blunt, D.M.; and Forrester B.D.: "Health Monitoring of Blackhawk and Seahawk Main Transmission Using Vibration Analysis," Proceedings of the 6th Australian Aeronautical Conference, 2nd Pacific Conference on Aerospace Science and technology, Melbourne, Australia, 1995.

[36] McFadden P.D.; and Wang, W.J.: "Time-Frequency Domain Analysis of Vibration Signatures for Machinery Diagnostics (I) Introduction to the Winger-Ville Distribution," Technical Report OUEL 1859, Department of Engineering Science, Oxford University, 1990.

[37] McFadden P.D.; and Wang, W.J.: "Time-Frequency Domain Analysis of Vibration Signatures for Machinery Diagnostics (II) The Weighted Winger-Ville Distribution," Technical Report OUEL 1891, Department of Engineering Science, Oxford University, 1991.

[38] McFadden P.D.; and Wang, W.J.: "Analysis of Gear Vibration Signatures by the Weighted Winger-Ville Distribution," Proceedings of the 5th International Conference on Vibration in Rotating Machinery, Institution of Mechanical Engineers, University of Bath, Bath, UK, pp. 387-393, 1992.

[39] Choy, F.K.; Huang S.; Zakrajsek, J.J.; Handschuh, R.F.; and Townsend D.P.: "Analysis of the Effects of Surface Pitting and Wear on the Vibrations of Gear Transmission System," Technical Report NASA TM-106678, ARL-TR-520, NASA and the US Army Research Laboratory, July 1994.

[40] Newland, D.E.: "An Introduction to Random Vibration, Spectral, and Wavelet Analysis," 3rd Edition, Longman Essex, 1993.

[41] Wang, W.J.; and McFadden P.D.: "Application of Orthogonal Wavelets to Early Gear Damage Detection," Mechanical System and Signal Processing, vol. 9, no. 5, pp. 497-507, 1995.

[42] Wang, W.J.; and McFadden P.D.: "Application of Wavelets to Gear Vibration Signals for Fault Detection," Journal of Sound and Vibration, vol. 192, no. 5, pp. 927-939, 1996.

[43] Polyshchuk, V.V.; Choy, F.K.; and Braun, M.J.: "New Gear-Fault-Detection Parameter by Use of Joint Time-Frequency Distribution," Journal of Propulsion and Power, vol. 16, no. 2, pp. 340-346, 2000.

[44] Polyshchuk, V.V.; Choy, F.K.; and Braun, M.J.: "Gear Fault Detection with Time-Frequency Based Parameter NP4," International Journal of Rotating Machinery, vol. 8, no. 1, pp. 57-70, 2002.