Improving condition indicators for helicopter health and usage monitoring systems

Elasha, F & Mba, D

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Faris Elasha[1*], David Mba[2]

[1] School of Energy, Environment and Agrifood, Cranfield University (UK)

[2] School of Engineering, London South Bank University (UK)

Abstract

The helicopter Health and Usage Monitoring System (HUMS) is an essential component for rotorcraft flight operations. This system was introduced in the early 1990's in response to high accident rates experienced by helicopters operating in the North Sea. However despite the success of this system in reducing helicopter accident rates, recent accidents have raised questions about the efficacy and limitation of HUMS. Given the significant enhancements in advanced signal processing techniques this paper aims to examine the feasibility of employing signal separation techniques for improving the effectiveness of Condition Indicators (CI) employed by HUMS.

1   Introduction

Health and Usage Monitoring Systems (HUMS) are commonly used for fault detection of helicopter transmissions in which detection is based on extraction of predefined features of the measured vibration, such as FM4, NA4, etc. [1-3]. HUMS was developed in North Sea operations, motivated in part by the crash to a Boeing Vertol 234 in 1986 which was caused by disintegration of the forward main gearbox. After development in the 1990s the UK's Civil Aviation Authority CAA mandated fitment of HUMS to certain helicopters. One article suggested that HUM system "successes" are found at a frequency of 22 per 100,000 flight hours [4]. A HUM system consists of two complimentary subsystems; health monitoring and usage

monitoring. Health monitoring is a process of diagnosing incipient damage or degradation that could ultimately lead to a system failure. Usage monitoring is a process by which the remaining life of different gearbox components and auxiliary systems are determined by assessing operation hours, current components condition and load history [5; 6]. Several vibration analysis methods are developed and applied in the commercial HUM systems to detect faults in bearings, gears and shafts. For the vibration data Condition Indicators (CI) are extracted in order to identify and/or reflect the health and mechanical integrity of components within the gearbox (bearings, gears and shafts) [7]. Numerous condition indicators are calculated from vibration data to characterize component health and these indicators are often determined based on the statistical measurement of the energy of the vibration signal, such as r.m.s, kurtosis and crest factor. However, recent accident investigations showed inability of these condition indicators to detect some bearing faults due to the complexity of helicopter transmissions [8].

The majority of helicopters utilises epicyclic reduction modules in their transmission systems due to their high transmission ratio, higher torque to weight ratio and high efficiency [9]. These characteristics also mean this type of gearbox is widely used in many industries such as aerospace, wind turbines, mining and heavy trucks [10-14]. Different planetary gearbox configurations and designs allow for a range of gear ratios, torque transmission and shaft rotational characteristics. The planetary gearbox generally operates under severe conditions, thus the gearbox components are known to suffer different kinds of fault conditions such as gear pitting, cracks, etc. [15-18]. Recent investigations on applications of planetary gearboxes have shown that failures initiate at a number of specific bearing locations, which then progress into the gear teeth. In addition bearing debris and the resultant excess clearances can result in gear surface wear and misalignment [18]. More recently the accident to a helicopter (G-REDL) [8], resulting in the loss of 16 lives, was caused by the degradation of a planet gear bearing. In this instance the on-board HUM system's Condition Indicators did not offer any evidence of degradation prior to the accident. This paper suggests new method for improving the condition indicators used in HUM system based on signal separation of gears.

2   HUM Condition Indicators (CI)

Helicopter HUM system is a sophisticated system developed to inform condition based maintenance strategy applied to helicopters. It aims to ensure helicopters safe operation and reduce unnecessary repairs cost.   A typical helicopter HUMS system monitors the health of the rotor system, engines, airframe, and transmission [1; 5]. HUM condition indicators commonly used to quantify the health of the helicopter, especially the gearbox where the vibration analysis is commonly used for health assessment. HUM condition indicators are estimated by processing measured vibration signal.

2.1   Signal Processing

Time Synchronous Averaging (TSA) is one of the robust tools for analysis of machine and is used to separate the noise or random parts from the vibration signal of interest. TSA is performed by dividing the signal into segments using a synchronous signal. In the case of a rotating machine, the synchronous signal can be the pulses from the shaft tachometer. The technique is illustrated in figure 1 [15; 19].
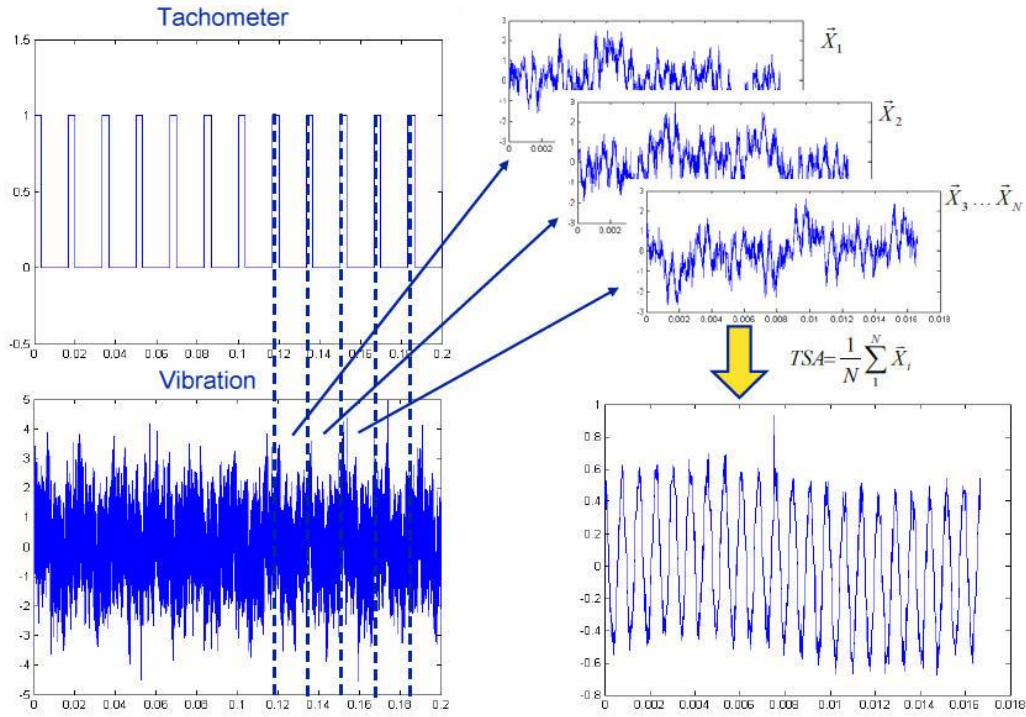
Figure 1   TSA layout [20]

Many parameters are used to extract useful information from the TSA signal; these parameters were developed recently to enhance vibration monitoring, especially for gears. To use these parameters further processing methods are required though this is dependent on the parameter considered. Details of the metrics extensively employed in helicopter gearbox condition monitoring are shown in

Table 1 and include residual signal processing (RES), difference signal processing (DIF) and Band-Pass filtering (BP). The residual signal is obtained by eliminating the shaft and gear meshing components, and their harmonics, from the TSA signal. The DIF signal is obtained by removing sidebands from the RES signal. In addition, the TSA signal is filtered around the dominant gear mesh frequency to obtain the BP signal.

Comparisons of the metrics listed in table 1 show that there is no single parameter that can provide robust alternative for fault detection. Therefore, a combination of

these parameters is required for effective monitoring. Among these parameters, the NB4*, NA4* and FM4* can be considered as the most robust metrics for fault detection. For the purpose of this paper only four indicators were investigated in an attempt to achieve enhanced fault detection improvements; these indicators were FM4, NA4, FM4* and NA4*. A description of these indicators is presented in the next section.

Table 1: Vibration Condition Indicators (CI)

Metrics	Signal processing required	Normal value	Advantages	Limitations
FM0 [21]	TSA	2.8	- Increase significantly in the majority of the gear tooth faults	- React differently to same pitting damage in different types of gears. - Also, the FM0 level under normal conditions has been found to be different in different tests [3]
NA4 [22]	TSA, RES	3	- Identify initiation of the damage	- Sensitivity tends to decrease as damage progresses
NA4* [22]	TSA, RES	3	- Detects damage in the majority of faults in different types of gears. - Indicate the fault progression and severity - React to different gear failure modes starting from failure in single tooth to failure in a number of teeth [22]	- More sensitive to the load and speed variation [22]
FM4 [2]	TSA, RES, DIF	3	- Relatively consistent results for detecting the majority of gear damage - The value of FM4 related to damage progression and severity [22]	- Tend to be insensitive for detection of new damage - Failure to detect light pitting of spur gears and partial fracture of face gear tooth - Decrease in value when the damage spreads to more than one tooth [2]
FM4*[1]	TSA, RES, DIF	3	- Can detect damage even in multiple gear teeth [1]	- Sometimes provides inconsistent results [1]
M6A [23]	TSA, RES, DIF	15	- Detect surface damage - It is sensitive to peaks in the difference signal [5]	- Tend to be insensitive for detection of new damage - Decrease in value when the damage spreads to more than one tooth
M6A* [6]	TSA, RES, DIF	15	- More sensitive to peaks in the difference signal	- Estimation of the variance in good conditions involves

Metrics	Signal processing required	Normal value	Advantages	Limitations
			- Sensitive to new damage and damage progression - Insensitive to torque fluctuation	some mathematical complexity
M8A[23]	TSA, RES, DIF	105	- More sensitive to peaks in the difference signal	- Tend to be insensitive for detection of new damage - Value decreases when the damage spreads to more than one tooth
M8A* [23]	TSA, RES, DIF	105	- More sensitive to peaks in the difference signal - Insensitive to torque fluctuation	- Estimation of the variance in good conditions but involves some mathematical complexity
NB4 [2]	TSA, BP	3	- Can monitor the damage progression and severity across other teeth - Increases significantly due to faults causing load fluctuation or due to surface cracks and fatigue	- Sensitive to noise in the signal - Unable to detect the single tooth fracture
NB4* [23]	TSA, BP	3	- Consistent performance for damage detection	- Estimation of the variance in good conditions but involves some mathematical complexity

2.2 Condition Indicators

2.2.1 NA4

NA4 was proposed by Zakarjesk in 1994 [22]. This metric is used to identify the initiation and progress of damage. This CI is determined after the frequency component of the shaft; the meshing gears and its harmonics are removed from the TSA signal. However, sidebands remain in the residual signal. This process is known as residual signal analysis (RES). The NA4 is computed as the ratio of the fourth moment signal (kurtosis) to the square averaged variance of the residual signal and the average variance is the mean variance value for all previous records. NA4 is given as:

$$NA4 = \frac{N \sum_{i=1}^{N}(r_i - r')^4}{[\sum_{i=1}^{N}(r_i - r')^2]^2} \tag{1}$$

where N = total number of samples, r_i = residual signal and r' = average of residual signal. NA4 increases as the fault increases and in normal conditions the value of NA4 is less than three.

2.2.2 NA4*

This metric was also proposed by Zakarjesk et al. to improve the NA4 indicator [22]. This parameter is computed as the ratio between the kurtosis of the residual signal to the square variance for a healthy gearbox:

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

Zakarjesk's research proved the ability of NA4* to detect damage in the majority of faults in different types of gears and to react to different gear failure modes starting from a failure in a single tooth to a failure over a number of teeth. NA4* indicates the fault progress and severity although it is sensitive to the load and speed variation [22]

2.2.3 FM4

To estimate FM4, the residual signal is processed further by removing sidebands. This results in a signal free from all shaft meshing frequencies and harmonics and is known as the difference signal (DIF). FM4 is used to detect faults in a limited number

of gear teeth by observing change in patterns [2]. FM4 was defined by Stewart in 1977 [2] as the ratio between kurtosis to the variance square of the difference signal:

$$FM4 = \frac{N \sum_{i=1}^{N}(d_i - d')^4}{[\sum_{i=1}^{N}(d_i - d')^2]^2} \qquad (3)$$

where d_i= difference signal, d'= mean of difference signal and N = total no. of points. In normal conditions, FM4 has an approximate value of 3 and when damage occurs and progresses, the value of FM4 increases above 3. The value of FM4 is related to damage progress and severity but FM4 tends to be insensitive for detection of new damage. Moreover, FM4 fails to detect the light pitting of spur gears and the partial fracture of a face gear tooth. Also, FM4 decreases when the damage spreads to more than one tooth [22].

2.2.4 FM4*

FM4* is a relatively simple method used to detect changes in the vibration pattern resulting from damage to gear teeth. The FM4* parameter is the ratio between the kurtosis of the difference signal to the squared variance of a healthy gearbox's difference signal. The difference signal is computed by extracting gear mesh, shaft frequencies, their harmonics and the associated sidebands from the vibration signature. As a defect progresses on a tooth, vibration peaks will increase in the difference signal and, as a consequence, the kurtosis value will exceed 3 which will lead to an increase of FM4*. This metric is calculated as [6; 24]:

$$FM4^* = \frac{\frac{1}{N} \sum_{i=1}^{N}(d_i - d')^4}{M_2^{\ 2}} \qquad (4)$$

where d is the difference signal, d' is the mean value of the difference signal, N is the total number of the samples and M_2 is the variance of the difference signal in good condition. This metric has been applied in the vibration diagnosis of helicopter gearboxes even during torque variation [6; 25; 26].

3 Concept of HUMS CI enhancement

A recent report showed HUMS CIs have been known to reach levels above an alarm threshold under fault free condition, such false alarms were attributed to the effect of random components of the vibration signal [4]. Therefore isolation of these random

components can improve the effectiveness f the CIs and reduce any false alarms. The signal processing techniques proposed for HUMS CI's enhancements are summarized in figure 2**Error! Reference source not found.**. The TSA signal is separated into deterministic and non-deterministic parts; the non-deterministic part refers to the vibration signal from the bearings and the deterministic part refers to the vibration associated with the gears. The vibration signal corresponding to the gears is then further processed to estimate the residual signal by eliminating the shaft and gear meshing components, and their harmonics, the residual signal used to estimate NA4 and NA4* condition indicators. Finally the residual signal is processed to estimate the difference signal by removing sidebands, then FM4 and FM4* is calculated**Error! Reference source not found.**.

Figure 2: Proposed process for improving robustness of HUMS CIs

The signal separation was performed with an adaptive filter using fast block algorithm least mean square algorithm (FBLMS) described by Elasha et. al [27].; this has the added advantage of improved processing time [28] and as such is more suitable for online diagnostics where an instant response is required. The fast block LMS algorithm uses the fast Fourier transform (FFT) to transform the time series signal to the frequency domain. This algorithm also updates the filter coefficients in the frequency domain. Updating the filter coefficients in the frequency domain can save computational resources. Details of the procedure have been summarised [29].

4   Comparative analysis of enhanced CI's

This section defines the test conditions for which a comparative performance analysis was undertaken on the four selected CIs for normal and enhanced analysis. The aim of this case study is to examine the performance of enhanced condition indicators in the detection of gears faults using the deterministic part of measured vibration. The signal separation was achieved using FBLMS adaptive filter algorithm on four CIs including FM4, FM4*, NA4, and NA4*. All CI's were estimated for the vibration data collected from gearbox shown in Figure 3. The gearbox used was a generic industrial gearbox with a fixed set of gears [30]. The data set extracted for different fault conditions included 16 recordings of 4 seconds each. Figure 4 shows the location of the vibration accelerometer and tachometer. The bearings used in the gearbox are of type MB Manufacturing ER-10K. All the bearings were similar and the gearbox was of 'spur' configuration. Data was collected at 30 and 50 Hz shaft speeds under constant load. The data was sampled synchronously from accelerometers mounted on both the input and output shafts. The tachometer generated 10 pulses per revolution and the vibration data was collected at a sampling rate of 66.66 kHz.

Different fault cases were employed in this gearbox and the details of the faults combination are illustrated in Table 2. The data set, contained a number of various faults on the bearings and gears, provided ideal conditions to test the effectiveness of the enhanced CIs being proposed.
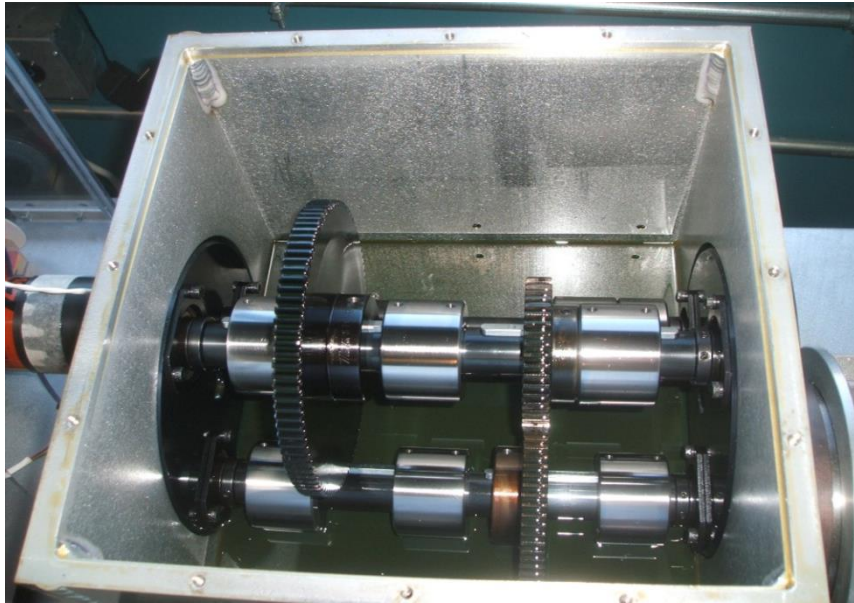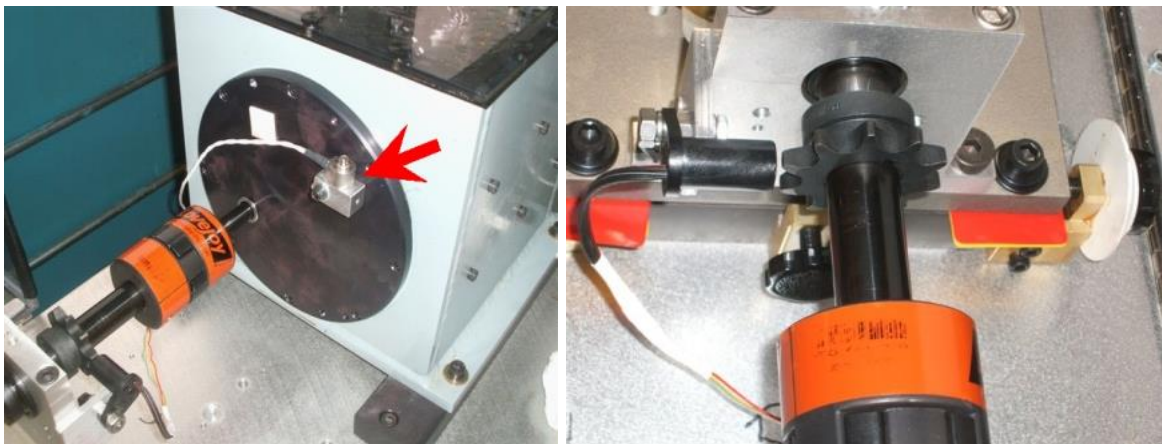
Figure 3: Gearbox Test Rig

Figure 4   Vibration accelerometer (left) and tachometer (right)

Table 2 Fault combinations considered for analysis (INSERT REFERENCE)

Case	Fault condition
1	Fault free conditions
2	Input shaft unbalance, bearing fault (Ball) on idler shaft input side.
3	Sheared keyway on output shaft, Bearing Fault (Inner race) input shaft input side
4	Eccentric gear 2nd stage pinion
5	1st stage pinion chipped tooth, Eccentric gear 2nd stage pinion
6	Broken tooth 2nd stage wheel, Bearing fault (Inner race) on input shaft input side, bearing fault (ball) on idler shaft input side, Bearing fault (outer race) on output shaft output side.
7	Eccentric gear 2nd stage pinion, broken tooth 2nd stage wheel, Bearing Fault (ball) input shaft input side
8	Eccentric gear 2nd stage pinion, broken tooth 2nd stage wheel, Chipped tooth 1st stage pinion, , Bearing fault (Inner race) on input shaft input side, bearing fault (ball) on idler shaft input side, Bearing fault (outer race) on output shaft output side.

4.1 Results of vibration analysis

4.1.1 CIs prior to enhancement

The vibration signal and tachometer signal were processed to construct the time synchronous averaging signal (TSA), and then the TSA signal was filtered to remove the primary meshing and shaft frequencies as well as their harmonics, yielding the residual signal. The residual signal was used to estimate the CIs NA4 and NA4*. The residual signal was filtered to remove first order sidebands to obtain the difference signal, and then the FM4 and FM4* CIs were estimated. All results are presented in figures 5 and 6. The results showed little variation between FM4* and NA4* for the different fault conditions (figure 6) whilst figure 5 showed variations in levels of NA4 and FM4 for the various fault conditions. In some instances the values increased relative to the fault free condition ('1), for instance cases 4 and 7, and decreased for all other cases. In practice it would be expected that the CIs would increase significantly for the gear fault conditions in comparison to fault free condition, however no differences were noted, see figures 5 and 6.
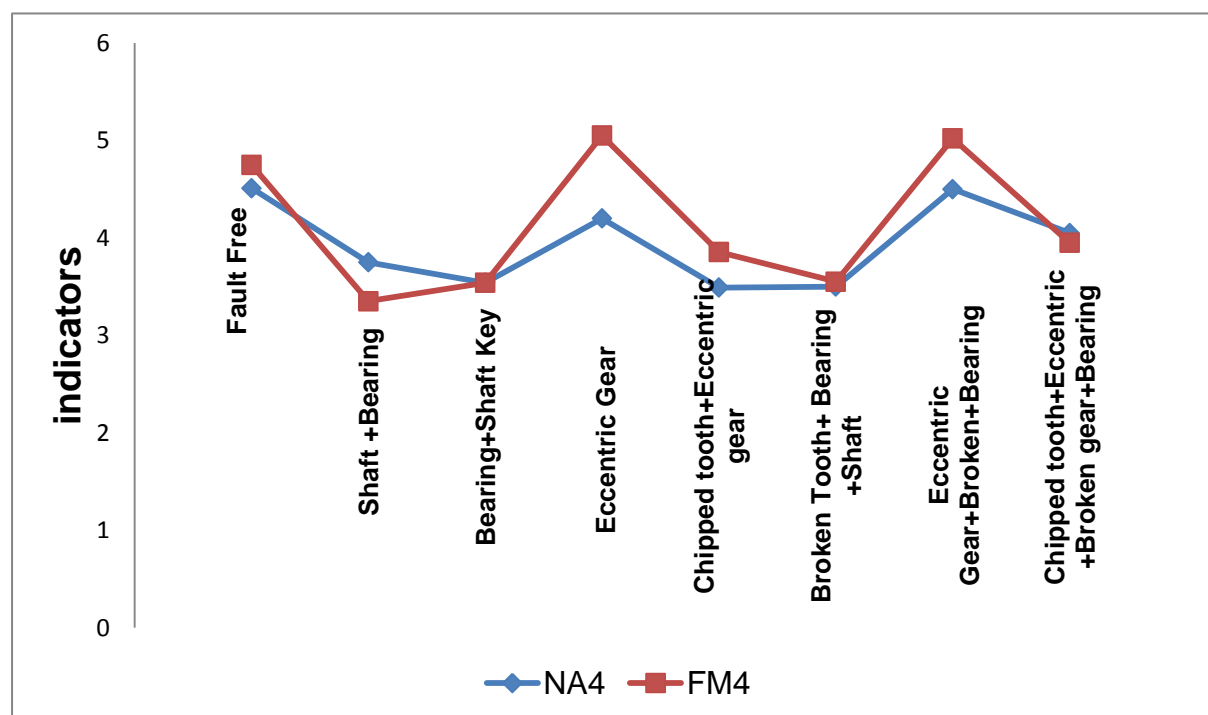

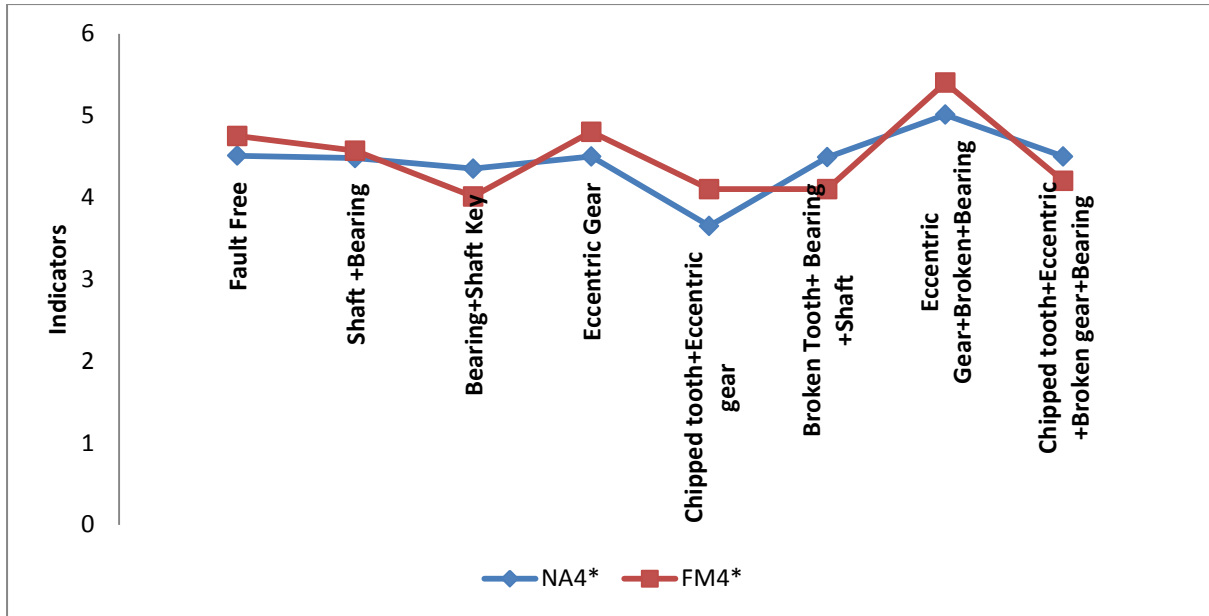**Figure 5   Results of NA4 and FM4 before signal separation**

Figure 6   Results of NA4* and FM4* before signal separation

4.1.2 CIs base on the deterministic component of the vibration signal

The deterministic part of TSA vibration data acquired was obtained for which the CIs were computed. The results of the condition indicators are shown in figures 7 and 8. The indicators NA4 and FM4 increased above good condition levels (~6) due to gear eccentricity and chipped tooth faults. However, these indicators were insensitive to broken gear faults. Indicators NA4* and FM4* responded to gear faults consistently depending on the fault severity. However all these metrics were unresponsive to bearing and shaft faults.
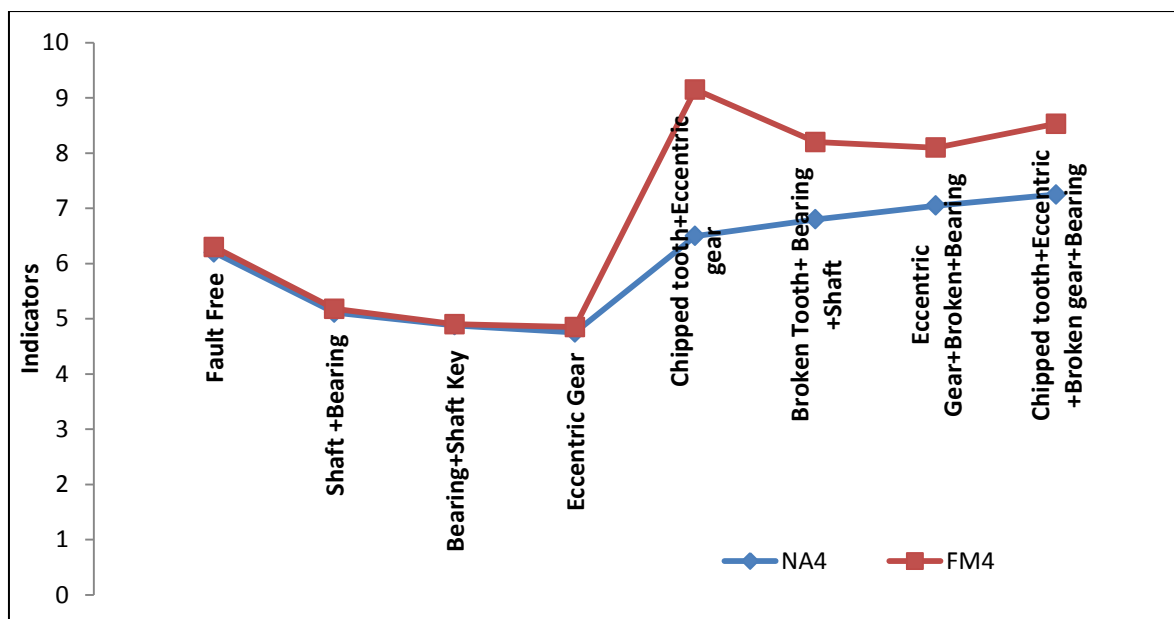
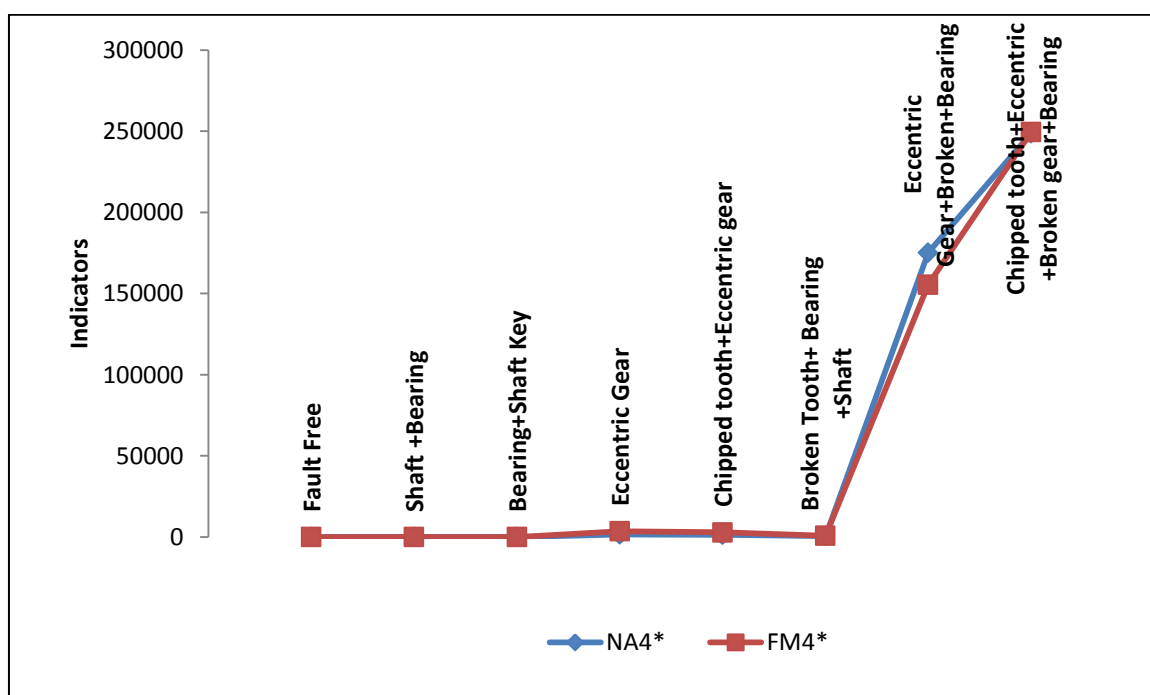**Figure 7 Results of NA4 and FM4 following signal separation**

Figure 8 Results of NA4* and FM4* following signal separation

5 Discussion

The condition indicators CIs employed by the HUM system are used as a measure of the peakedness of the vibration signal, with increasing CIs indicative of faulty gears. However existence of multiple faults can result in a reduction of CIs which can be mistakenly interpreted as normal condition. As presented earlier the CI's estimated based on TSA signal showed no distinctive difference between fault free and defective conditions. A signal separation technique was proposed to enhance the detection of gears failure within the gearbox. The enhanced CIs, particularly, FM4* and NA4*, increased significantly in the presence of gears faults. A comparative summary is presented in table 3. Improvements were noted for gear fault conditions only with the FM4* and NA4* indicators increasing from 4.8 and 4.5 respectively to 3569 and 1575 for eccentric gears faults. Similar significant increases in these CIs were noted for fault conditions 5 to 8. In addition the enhanced CIs were sensitive to combined fault conditions that included the bearing and gears. For instance values of NA4* and FM4* were above 150,000 for gear and bearing faults, however such sensitivity was not noted for combined defects that included the shaft. These indicators were not responsive to shafts and bearing failures.

The CIs employed were more sensitive to the gear eccentricity fault compared to broken gear teeth, FM4, FM4* and NA4* were increased significantly due to the gear eccentricity fault, NA4 was exception where the level was similar to good condition. In addition these indicators have responded to fault combination indicating the severity and fault type. Therefore enhanced FM4, FM4* and NA4* are recommended for gears fault detection and identification.

Table 3 comparisons of indictors prior and after improvement

Case	Indicators prior improvement		Indicators after improvement	
	NA4*	FM4*	NA4*	FM4*
Fault Free	4.51	4.75	4.51	4.75
Shaft +Bearing	4.48	4.57	3.5	4.57
Bearing + Shaft Key	4.35	4.01	4.35	4.01
Eccentric Gear	4.5	4.8	1575	3569

Chipped tooth + Eccentric gear	3.65	4.1	1430	2865
Broken Tooth+ Bearing +Shaft	4.49	4.1	578	789
Eccentric Gear + Broken + Bearing	5.01	5.4	175256	155468
Chipped tooth + Eccentric + Broken gear + Bearing	4.5	4.2	248695	249458

6 Conclusion

The ability of applied signal processing technique to identify the presence of gear faults is based on removing the random component of the vibration signal prior to post processing. Condition indicators estimated for the deterministic part of vibration signal show higher sensitivity to gears faults in comparison to indicators estimated based on the original signal. This method proposed could enhance early fault detection in gears, particularly for those applications where strong background noise from other sources in the machine masks the characteristics fault components.

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