Signal Processing Techniques to Improve an Acoustic Emissions Sensor

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ABSTRACT

Acoustic Emissions (AE) are stress waves produced by the sudden internal stress redistribution of material caused by changes in the internal structure of the material. Possible causes of these changes are crack initiation and growth, crack opening/closure, or pitting in monolithic materials (gear/ bearing material). Where as vibration can measure the effect of damage, AE is a direct measure of damage. Unfortunately, AE methodologies suffer from the need of high sample rates (4 to 10 Msps) and relatively immature algorithms for condition indictors (CI). This paper hypothesizes that the AE signature is the result of some forcing function (e.g. periodic motion in the case of rotating machinery). By using analog signal processing to demodulating the AE signature, one can reconstruct the information carried (e.g. modulation) by the AE signature and provide improved diagnostics. As most on-line condition monitoring systems are embedded system, analog signal processing techniques where used which reduce the effective sample rate needed to operate on the AE signal to those similarly found in traditional vibration processing systems. Further, by implementing another signal processing technique, time synchronous averaging, the AE signal is further enhanced. This allowed, for the first time, an AE signal to be used to identify a specific component within gearbox. This processing is tested on a split torque gearbox and results are presented.

1. INTRODUCTION

The promise of condition based maintenance (CBM)

systems is to produce maintenance saving by reducing unscheduled maintenance events. As confidence in CBM improves and systems mature, maintenance paradigms can be moved to a true, "On Condition" practice. Unfortunately, for many industries, CBM is an immature technology and has not proven itself in operational circumstances. The low penetration (3% of installed turbines) of condition monitoring systems (CMS) into the wind turbine industry is symptomatic of the lack of confidence in the ability of CMS to deliver their' promised performance. The industry needs better sensing and analysis capabilities in order to capture these markets.

One aspect of condition monitoring on wind turbines is the extraordinarily low frequencies of the environment. The main shaft rate on utility scales wind turbines range from 0.11 to .25 Hz. With typical planetary gearbox frequencies of 1:5, gear mesh frequencies in the range of 10 to 25 Hz are not uncommon. Because acceleration is the second derivative of displacement, gear mesh frequencies are on the order 0.005 to 0.02 G's, making gear fault detection difficult with tradition vibration condition monitoring systems.

Acoustic Emissions (AE) are the stress waved produced by the sudden internal stress redistribution of material caused by the changes in the internal structure of the material. Possible causes of these changes are crack initiation and growth, crack opening and closure, or pitting in various monolithic materials (gear, bearing material) or composite materials (concrete, fiberglass). Most sources of AE are damage related. Thus the ability to detect AE can be used to give diagnostics indications of component health.

AE is a direct measure of damages instead of the indicator of the result of damage (such as vibration). AE can potentially be a more sensitive of fault, especially in the low frequency seen on the planetary gearboxes of wind turbines.

However, AE systems tend to be more expensive and difficult to implement over vibration based non-destructive test or CMS.

From a development perspective, AE has a number of perceived disadvantages:

- AE signals are relatively high frequency, 1 to 4 MHz, thus the sample rates are high (4 to 10 MSPS),

- Processing of the data, needed for feature extraction, is made more difficult because of the high sample rates and large volume of data needed to be processed (consider 10 MSPS for 40 seconds, which would capture just 6 revolutions on a 2.5 MW wind turbine, is 400 million samples!),

- Typical AE analysis is limited in its "action ability", meaning that its can detect or count AE events, but does not tie the event to a component in the gearbox.

The ideal CMS would:

- Allow for fault detectability afforded the direct measure of damage in the AE signal, which is independent of rotation rate,

- The maturity of vibration processing techniques to provide actionable information by identifying the component which is damages,

- Reduce the computation burden of AE by sampling at the lower rate.

- Improve the detection of low frequency components which are now difficult to do with vibration based CMS.

We developed an analog Hilbert envelope circuit to demodulate the AE signal, which greatly reduced the sample rate typically needed for AE. This reduces the cost of a AE CMS system by allowing the use of lower end, audio analog to digital converts and low end microcontroller for processing of that data. Additionally, we applied time synchronous averaging of the demodulated signal to improve the signal to noise ratio of the signal which normally would be undetectable, but also allowed the identification of the damaged component (AE analysis typically only identifies that there is damage, but not what is damage). Finally, this new technique was compared against tradition vibration analysis, using similar algorithms, and was found to be significantly better and gear fault detection.

2. AE: ACOUSTIC EMISSIONS

AE as phenomena, has been observed in many disparate fields of study. The earliest use of AE analysis was in geology and seismology. Here the analysis of elastic waves produced by an earthquake was used to find the location and depth of the event. Similarly, AE was proposed as a method to predict rockburst in mines. Tinsmiths have noted the "tin cry" associated with twinning deformation, and the clicks noted during heat treatment of steels is well documented (this is related to martensitic transformations of metals, which has been show to be a strong emitter of AE).

The general acceptance that AE is associated with dislocation and plastic deformation/crack propagation in metal was first proposed by (Liptai, 1969). The essential principles of AE where explored in (Liptai, 1970), by considering a grain of polycrytstalline material (steel, for example), where the grain boundary has a diameter of $d=5 \times 10^{-3}$in. During a strain event, the upper half of the grain slips over the lower half by a distance of $d=1 \times 10^{-3}$in. Given a shear modulus of $G=4 \times 10^{6}$ psi, then the stress driving the deformation is eq 1, and the energy change occurring with a deformation is eq. 2.

$$\sigma_s = {sG}\!/\!{d} \qquad (1)$$

$$\omega = {s^2GA}\!/\!{2d} \equiv 10^{-12}\,{in}\!/\!{lbs} \qquad (2)$$

where A is the sheared area. This allows one to estimate the frequency of an event as:

$$\omega = \sqrt{{2GA}\!/\!{dm}} \approx 5 \times 10^6 \,{rad}\!/\!{\sec} \approx 0.8\,MHz \quad (3).$$

where m is the half mass of the grain (assumed to be steal). While estimates vary with density, grain size, and material, this estimate serves to bound the AE frequency from 500 KHz to perhaps 40 MHz.

2.1. AE: State of the Art

Most AE products quantify five basic condition indicators (Figure 1): Amplitude, Duration, Rise Time, Counts and the mean area under the rectified signal envelope (MARSE). Other condition indicators (CI), such as average frequency (counts/duration), are function of the basic AE CIs and have been found to be useful in non-destructive test literature (Miller, 2005). Cumulative counts and cumulative absolute energy have also been shown to correlate to the fatigue crack growth process (Barsoum 2009).

More recent studies have focused on the use of wavelet to de-noise and enhance the AE signal. For example (Abouel-seoud 2012) used a continuous wavelet transform improve the signal to noise ratio for diagnostics on a wind turbine planetary gearbox. In (Gu, 2011), a signal processing method for AE signal by envelope analysis with discrete wavelet transforms followed by spectral analysis allowed visualization of the gearbox fault frequencies.

It most be noted that none of these analysis can directly tie the AE CI with a specific component within a gearbox. Instead, these techniques can give indicators that there is a

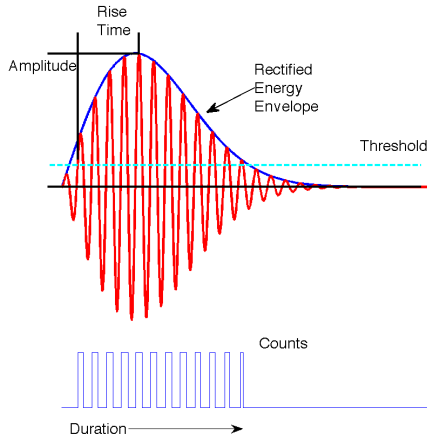fault present, and rely upon more tradition techniques such a Borescope to identify the damage component.

Figure 1 AE Condition Indicators

These methodologies, while successful in diagnostics, fundamentally do not address the hardware/software need to sample at lower data rates (needed for lower cost systems). Additionally, wavelets required off-line processing/ optimization techniques to select coefficients/levels to achieve successful diagnostics.

For a commercial product, the reapplication cost (e.g. off line analysis, configuration for the given application, etc.) and hardware costs are a large driving factor. This is the motivation to develop a system with the performance of AE fault detection, but without sacrificing the cost advantage of tradition vibration based systems.

3. ANALOG PROCESSING TO IMPROVE THE AE SENSOR

The AE signal is generated by an impulse or forcing function, which causes a dislocation in the material. For rotating components such as gears, that force and the resulting damage is periodic. With this view, we hypothesized that the AE signal is the carrier signal on which the forcing function is modulated. The forcing function information content relates to the damage it is exciting (e.g. the AE signal). For nominal gears, there should be no AE signal, while a damaged gear should generate a period AE response.

In the fault case, the information of interest is not the AE signal, but the modulated force/load that is causing the AE burst. This type of information process is similar to the information in an amplitude modulated (AM) radio frequency signal, where the information is recovered by demodulating the radio signal.

In an AM radio, the carrier is demodulated using an analog signal conditioning circuit. This allows the system to be designed at audio frequencies (10s of KHz vs. MHz of the carrier signal). In the proposed analysis, the AE signal is demodulated with an analog circuit, and the result acquisition system is designed to performance at tradition vibration processing frequencies (100 KHz vs. MHz). The signal processing can then be performed on low cost embedded microcontrollers instead of higher end computers.

A demodulator shifts the carrier frequency to baseband, eq(4), followed by low pass filtering and enveloping.

$$\cos(a) \times \cos(b) = 1/2[\cos(a-b) + \cos(a+b)] \quad (4)$$

The envelope is the absolute value of the Hilbert transform. In frequency domain, the Hilbert transform is defined in the Fourier domain as: $2X(f)$, for $f>0$, and $X(f) = 0$, for $f<0$, which easily computed in software. As stated, one of the objectives is to perform this signal processing in an analog circuit, such as in (Figure 2). The raw, time domain signal from the AE sensor is defined as x(t). x(t) is quadrature demodulated by convolving the signal x(t) with a frequency near the carrier frequency (cos(ft)) and then low pass filtered to remove the image. The carrier frequency is generated by a voltage-controlled oscillator (VCO) or through low pass filtering a pulse width modulated (PWM) signal. This allows one to configure the demodulation process for different materials (which may have different AE carrier frequencies) or for different AE sensors, which may have different frequency responses.

After low pass filtering to remove the image (e.g. $\cos(a+b)$) of the baseband signal, the quadrature is create by phase shifting the baseband signal by $\pi/2$ radian. The quadrature signals are then squared, summed and the square root is taking. This circuit can be built at low cost using operational amplifiers (op amps) per (Horowitz, 1995) or by using a monolithic multiplier/divider such as the AD532. This transforms the AE signal to its demodulated envelop.
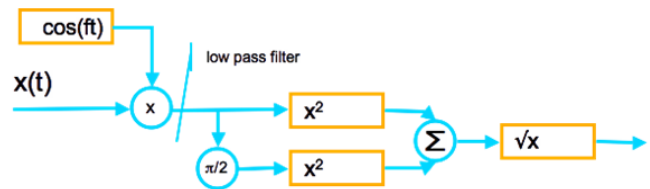

Figure 2 Analog Signal Process for the AE Sensor

The advantage of using an analog/hardware solution instead of the using a digital approach is a greatly simplified acquisition and processing system. Instead of designing a system to sample at potentially 10 MSPS (which includes increased memory, a high performance processor, high speed ADC, increased capacity of the power supply, increased heat dissipation), more modest 100 KSPS system can be designed. Note that the limit of the system is no longer the sample rate of the ADC, but the bandwidth of the analog devices, typically on the order to 2 GHz.

While other researchers have "enveloped" the AE signal by low pass filtering the rectified AE signal (Miller, 2005), this does capture the modulation rate of the forcing function. This is because a rectified/low pass enveloping technique does not heterodyne the AE signal to base band, as does the presented technique.

For rotating machinery, e.g. a gearbox, where the load is periodic the, the envelope of the AE sensor contain the information related to any gear faults within the gearbox. This has the advantage of giving actionable information as to the faulted component, as the AE signal is generated as a result of the periodic load of a specific component. As such, the modulation rate is the same as the damaged component rate. This in turn is easily identified through spectral analysis.

3.1. Feature Extraction from the AE Envelope

Vibration signatures for machinery faults tend to be small relative to other vibration signatures. For example, in the typical gearbox, the energy associated with gear mesh and shaft vibrations will be orders of magnitude larger than a fault feature. This is also the the case in performing analysis on the AE envelope. Spectral analysis or root mean squares (RMS) of AE signal are not powerful enough CIs to detect an early fault, let alone provide information useful for prognostics. Additionally, since all rotating equipment has limits on the feedback controls driving it, there is some variation in speed. When taking the spectrum, this variation in shaft speed violates requirement of stationarity.

To improve the performance of the gear analysis and to control for variation in shaft rates, the analysis will based on operations of the time synchronous average (Bechhoefer, 2009). Time synchronous averaging (TSA) is a signal processing technique that extracts periodic waveforms from noisy data. The TSA is well suited for gearbox analysis, where it allows the AE signature of the gear under analysis to be separated from other gears and noise sources in the gearbox that are not synchronous with that gear. Additionally, variations in shaft speed can be corrected, which would otherwise result in spreading of spectral energy into an adjacent gear mesh bins. In order to do this, a signal is phased-locked with the angular position of a shaft under analysis.

This phase information can be provided through a n per revolution tachometer signal (such as a Hall sensor or optical encoder, where the time at which the tachometer signal crosses from low to high is called the zero crossing).

The model for vibration in a shaft in a gear box was given in (McFadden, 1985) as:

$$x(t) = \Sigma_{i=1:K} X_i(1 + a_i(t))cos(2\pi i\, f_m(t) + \Phi_i) + b(t) \quad (5)$$

where:

X_i is the amplitude of the kth mesh harmonic

$f_m(t)$ is the average mesh frequency
$a_k(t)$ is the amplitude modulation function of the kth mesh harmonic.
$\phi_i(t)$ is the phase modulation function of the kth mesh harmonic.
Φ_i is the initial phase of harmonic k, and
$b(t)$ is additive background noise.

The mesh frequency is a function of the shaft rotational speed: $f_m = Nf$, where N is the number of teeth on the gear and f is the shaft speed, with no reduction in the analysis performance. This is a general model, and it is hypothesized in this paper that the vibration signal can be replace by the AE envelope signal.

This TSA model assumes that f is constant. As noted, due to the finite bandwidth of the feedback control, there is some wander in the shaft speed due to changes in load or feedback delay. This change in speed will result in smearing of amplitude energy in the frequency domain. The smearing effect, and non synchronous noise, is reduced by resampling the time domain signal into the angular domain: $m_x(\theta) = E[x(\theta)] = m_x(\theta + \Theta)$. The variable Θ is the period of the cycle to which the gearbox operation is periodic, and E[] is the expectation (e.g. ensemble mean). This makes the assumption that $m_x(\theta)$ is stationary and ergodic. If this assumption is true, than non-synchronous noise is reduce by $1/\text{sqrt}(rev)$, where rev is the number of cycles measured for the TSA.

3.2. Condition Indicators based on the TSA

The TSA is an example of angular resampling (McFadden, 1985), where the number of data points in one shaft revolution (r_n) are interpolated into m number of data points, such that:

- For all shaft revolutions n, m is larger than r,

- And $m = 2^{\text{ceiling (log2 (}r\text{))}}$ (assumes a radix 2 Fast Fourier Transform).

Linear, bandwidth limited linear interpolation, and spline techniques have been used. In this study, linear interpolation was used as it is considerable faster than spline or bandwidth limited filtering, with no apparent reduction in analysis performance of the TSA.

The TSA itself can be used for CIs. Typically, a CI is a statistics of a waveform (in the case the TSA). Common statistics are RMS, Peak to Peak, Crest Factor, and Kurtosis.

3.2.1. Gear Fault Condition Indicators

There are at least six failure modes for gears (IS10825, 2007): surface disturbances, scuffing, deformations, surface fatigue, fissures/cracks and tooth breakage. Each type of failure mode, potentially, can generate a different fault signature. Additionally, relative to the energy associated

with gear mesh frequencies and other noise sources, the fault signatures are typically small. A number of researchers have proposed analysis techniques to identify these different faults (McFadden, 1985, Zakrajsek, 1993). These analyses are based on the operation of the TSA. In this study the fault is a broken tooth, and the following analysis where conducted (note the gear mesh frequency is found by: take the FFT of the TSA, take the absolute value of the number teeth + 1 bin):

- The common statistics of the TSA.

- Figure of Merit 0: the TSA peak-to-peak divided by the sum of the 1st and 2nd gear mesh frequencies;

- Side Band Modulation: the ration of the sum of the gear mesh side bands (+/-1 bin) divided by the gear mesh frequency.

- Residual Analysis: where shaft order 1, 2, and 3 frequencies, and the gear mesh harmonics, of the TSA are removed. Faults such as a soft/broken tooth generate a 1 per rev impacts in the TSA. In the frequency domain of the TSA, these impacts are expressed as multiple harmonic of the 1 per rev. The shaft order 1, 2 and 3 frequencies and gear mesh harmonics in the frequency domain, and then the inverse FFT is performed. This allows the impact signature to become prominent in the time domain. CIs are statistics of this waveform (RMS, Peak 2 Peak, Crest Factor, Kurtosis).

- Energy Operator: which is a type of residual of the autocorrelation function. For a nominal gear, the predominant vibration is gear mesh. Surface disturbances, scuffing, etc, generate small higher frequency values which are not removed by autocorrelation. Formally, the EO is: $TSA_{2:n-1}$ x $TSA_{2:n-1}$ x $- TSA_{1:n-2}$ x $TSA_{3:n}$. The bold indicates a vector of TSA values. The CIs of the EO are the standard statistics of the EO vector

- Narrowband Analysis: operates on the TSA by filtering out all frequencies except that of the gear mesh and with a given bandwidth. It is calculated by zeroing bins in of the Fourier transform of the TSA, except the gear mesh. The bandwidth is typically 10% of the number of teeth on the gear under analysis. For example, a 23 tooth gear analysis would retain bins 21, 22, 23, 24, and 25, and there conjugates in frequency domain. Then the inverse FFT is taken, and statistics of waveform are taken. Narrowband analysis can capture sideband modulation of the gear mesh frequency due to misalignment, or a cracked/broken tooth.

- Amplitude Modulation (AM) analysis is the absolute value of the Hilbert transform of the Narrowband signal. For a gear with minimum transmission error, the AM analysis feature should be a constant value. Faults will greatly increase the kurtosis of the signal

- Frequency Modulation (FM) analysis is the derivative of the angle of the Hilbert transform of the Narrowband signal. It's is a powerful tool capable of detecting changes of phase due to uneven tooth loading, characteristic of a number of fault types.

For a more complete description of these analyses, see (McFadden, 1985., Zakrajsek, 1993).

The analysis for the experiment used 17 CIs. In general, there is no consensus on which CIa are best, as different CIs seem to work better than other CIs depending on the fault type.

4. EXPERIMENTAL TEST

The test was conducted on a split torque gearbox (STG). While not a planetary gearbox, the TSG similarly splits the torque path from a drive pinion to a driven gear. A full description of the article is available in (Li, 2012). The test consisted of the comparison of the nominal gears, with a idler shaft pinions that was missing 100% of a tooth (e.g. the "Bad Gear"). The idler shaft rate was rate was 0.556 x the input shaft, on which a 1/rev tachometer takeoff was mounted (Figure **3**).

A Physical Acoustic sensor, model: WD was used. This sensor is a wideband differential sensor with high sensitivity and bandwidth (100-900 KHz). The sensor was mounted on the output side of the gearbox, and after pre-amplification, was demodulate using a Analog Devices quadrature demodulator. The heterodyne frequency was 500 KHz. This frequency was optimized via testing using a Hsu-Neilsen source. The output of the demodulator and the tachometer 1/rev signal was sampled at 100 KHz using a 18 bit National Instruments data acquisition system. This represents an AE bandpass signal of 400 to 600 KHz, and an envelope bandwidth of 50 KHz. The gearbox was run at 60 Hz input shaft speed, where data was collected for 8 seconds per trail.
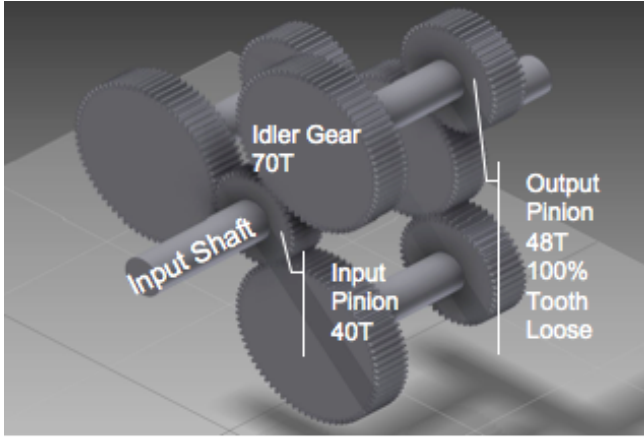
Figure 3 Split Torque Gearbox, Exploded View

4.1. Initial Results

The tachometer, shaft ratio and AE envelope signal was processed using the linear interpolation TSA algorithm presented in (Bechhoefer 2009). For the 8-second acquisition, the TSA had approximately 250 revolutions. The TSA length was 2ceil(log2(100000/(60*40/70)) = 4096 points. Some experimentation was performed where inline decimation was conducted to reduce the effective sample rate to 50000, with no loss in signal fidelity (Bechhoefer, 2012). Figure **4** displays the nominal vs. bad gear. The Bad Gear tooth fault is clearly visible when compared to the Nominal Gear.
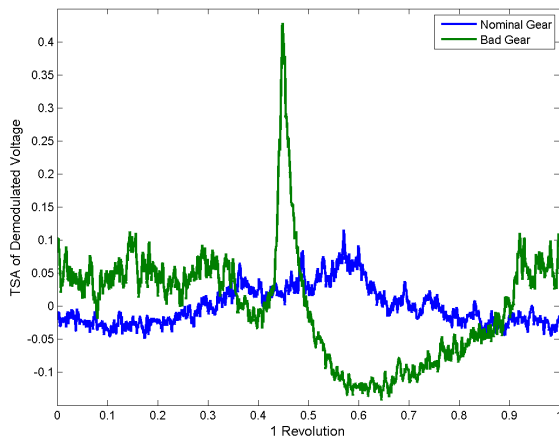

Figure 4 TSA of the AE Envelope: Nominal vs. Bad Gear

By removing the 1/Rev and gear mesh tone, the residual signal improves the fault visually (Figure **5**).
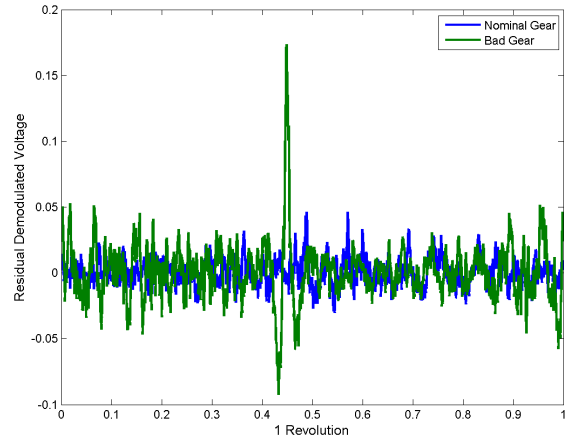

Figure 5 Residual of the AE Envelope

The one per revolution seems to be the result of an eccentric output gear, as the 1/Rev was present in both the nominal and damage gear TSA waveform. The Bad Gear fault is also clearly evident in the Energy Operator (Figure **6**). The waveform of the FM analysis shows a large phase reversal at the fault, which large Frequency modulation RMS/Peak to Peak (Table 1). The TSA, Residual, Energy Operator and Frequency modulation condition indicators are highly significant (Table 1).

It should be noted that without TSA, the raw spectrum of the demodulated AE signal indicated that the "Nominal Gear" was more damaged than the "Bad Gear", as evident by a large 50 Hz frequency associated with the shaft rate. This was likely caused by the eccentric pinion – the fault was not discernable without the use of the TSA.

4.2. Quantifying Result Performance

To quantify the performance, the measure of seperatbility was calculated using the pooled sample standard deviation. The sample size was 5 acquisitions per trail, where the populations for the null set came from the nominal gear (no damage) and the alternative set came from the damage gear population.
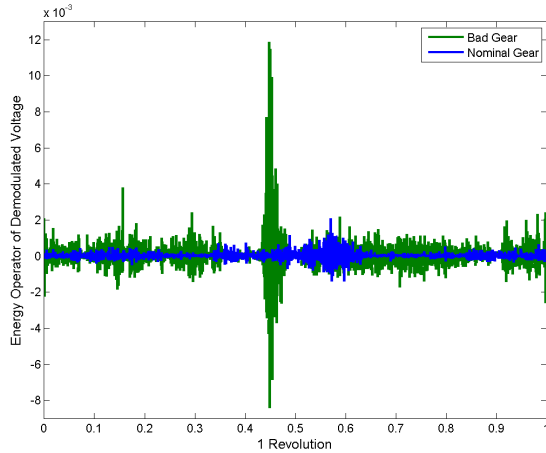
Figure 6 Energy Operator of the AE Envelope

The test statistics is then:

$$T = E[Y_1] - E[Y_2] \Big/ S_p \sqrt{\frac{2}{n}} \qquad (6)$$

where,

$$S_p = \sqrt{(n-1)S_1^2 + (n-1)S_2^2 / 2n - 2} \qquad (7)$$

A test statistic T greater than 3.58 is considered significant and would indicate that the CI could detect the fault (Wackerly, 1996). Note that AE is for the T statistics using the AE Envelope, while Vib is the T statistics from an earlier study using vibration data alone (Table 1).

Table 1. AE Envelop CI Algorithm Results

Condition Indicator	AE	Vib
TSA RMS	21.6	3
TSA Peak-to-Peak	9.2	4
FM0	3.25	
Sideband Modulation	3.14	4.3
Residual RMS	24.45	2.8
Residual Kurtosis	6.54	0.065
Residual P2P	15.4	2.75
Residual Crest Factor	6.91	1.24
Freq. Mod. RMS	6.65	0.22
Freq. Mod. P2P	4.14	0.616
Energy Operator RMS	33.26	3.5
Energy Operator P2P	7.74	2.4
Narrowband RMS	5.87	1.1
Narrowband P2P	6.6	0.1
Narrowband CF	5.24	7.1
Amp. Mod. RMS	6.04	1.1
Amp. Mod. P2P	6.9	3.1

These results are very encouraging. In general, the AE envelope T statistics is far more significant than the vibration based T statistic.

5. CONCLUSION

The AE envelope analysis show promises to be a powerful tool for gear fault diagnostics. By heterodyning the raw AE signal, it is possible to reduce the hardware resources and cost normally associated with AE processing. In this experiment, the acquisition-sampling rate of 100 KSPS was used on an AE sensor with a signal bandwidth of 600 KHz, using an analogy Hilbert transform circuit.

The AE envelope signal was then processed using time synchronous averaging (TSA). The TSA is commonly used with vibration-based diagnostics: this is the first time its use has been published using AE data. The TSA of the AE envelope was used to control for variation in shaft speed, and to reduce non-synchronous noise. The use of the TSA allowed the gear fault to be identified.

Condition Indicators, based on the TSA, were calculated for both the AE sensor and the for vibration sensor (accelerometer). The CIs for the AE enveloped signal were 3x more statistically significant than for the vibration sensor. This indicated that the combination of demodulated AE sensor data and the use of the TSA was superior for gear fault detection than traditional vibration/accelerometer sensors.

Currently, we are working on the deployment of a prototype AE sensor for application in wind turbines.

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BIOGRAPHIES

Eric Bechhoefer received his B.S. in Biology from the University of Michigan, his M.S. in Operations Research from the Naval Postgraduate School, and a Ph.D. in General Engineering from Kennedy Western University. His is a former Naval Aviator who has worked extensively on condition based maintenance, rotor track and balance, vibration analysis of rotating machinery and fault detection in electronic systems. Dr. Bechhoefer is a board member of the Prognostics Health Management Society, and a member of the IEEE Reliability Society.

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