SEMI-REAL TIME CLASSIFICATION OF ACOUSTIC EMISSION SIGNALS FOR DRIVE SYSTEM COUPLING CRACK DETECTION

Valery Godinez[1], Fong Shu[1], Athanasios Anastasopoulos[2], Apostolos Tsimogiannis[2], Richard Finlayson[1], and Bruce O'Donnell[3]

[1]Physical Acoustics Corp., 195 Clarksville Road, Lawrenceville, NJ 08648, USA, sales@pacndt.com
[2]Envirocoustics S.A., El. Venizelou 7 & Delfon, 144 52 Athens, GREECE, info@envirocoustics.gr
Naval Air Warfare Center, Patuxtent River, MD 20670 USA, Odonnellbw@navair.navy.mil

ABSTRACT

Early detection of mechanical failure in helicopter drive train components is a key safety and economical issue with both military and civil sectors of aviation. Of these components, couplings are particularly critical. The objective of this work is to demonstrate the feasibility of designing and developing a reliable, real time monitoring methodology based on Supervised Pattern Recognition (SPR) for early detection of cracks in couplings used in helicopter and engine drive systems. Within this framework, a portable Acoustic Emission (AE) system was used, equipped with a semi-real time SPR software package.

Results from AE tests performed in a gearbox-testing bench at different speeds and different torque values are presented. These results indicate that the energy content of different frequency bands in the AE signals power spectra is strongly correlated with the introduction of EDM notches in the main gear. Further tests indicate that a strong shift in the frequency of the AE signals is observed after spalling occurred in the pinion gear. The variation of displacement and velocity between signal classes are discussed as a potential feature in characterizing crack severity. Finally, a scope of the work for optimizing the methodology in detecting and evaluating coupling cracking in real time will be presented.

1. INTRODUCTION

Early detection of mechanical failure in aircraft drive train components is a key safety and economical issue with both military and civil sectors of aviation. The ability to monitor, detect, identify, and isolate coupling cracks on an operational aircraft is required in order to provide sufficient advance warning to preclude catastrophic failure. Vibration based mechanical diagnostics and debris monitoring are two types of techniques in use today for health monitoring of drive systems. The initiation and early stages of fatigue crack propagation do not usually change the component vibration and therefore, are not detectable by typical vibration sensors[1]. Generally speaking, both of these methods have had limited success in detecting either gear tooth breakage or fatigue cracks in diaphragm-type couplings.

It is known that metallic structures generate characteristic Acoustic Emission (AE) during crack growth/propagation cycles[2,3]. However, discrimination AE from crack growth in the presence of continuous background noise is a difficult process. In most cases, positive signal classification requires experienced personnel and post-test data analysis, which tends to be a time-consuming, laborious, and expensive process. Automated classification methods[4,5] have been proposed aiming to solve such problems. In addition to that, with further development and validation of automated classifiers, AE can become a fully autonomous fault detection technique requiring no human intervention after implementation. AE has the potential to be fully integrated with automated query and response mechanisms for system/process monitoring and control.

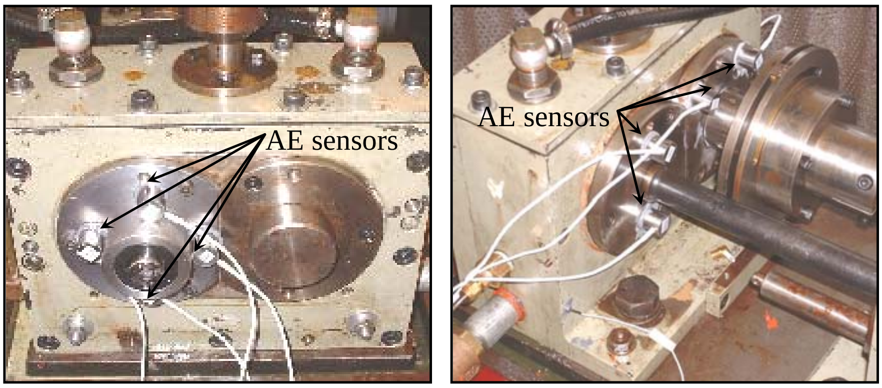
This paper presents the results obtained in the SBIR Phase I project "Acoustic Emission Monitoring for Drive System Coupling Crack Detection" sponsored by NAVAIR. One of the most important aspects of this research was the design of a Supervised Pattern Recognition Classifier (SPR) with the ability to discriminate between normal operation background noise and legitimate AE signals produced by cracking or other damage mechanisms occurring in the system under study. Results showed that the SPR was capable of correctly identifying six different classes of AE signals corresponding to different gearbox operation conditions. Also, semi-real-time classification software was developed. This software includes functions that allow the user to view and classify AE data from a dynamic process as they are recorded at programmable time intervals. The software is capable of monitoring periodic statistics of AE data, which can be used as an indicator of damage presence and severity in a dynamic system.

2. EXPERIMENTAL SET-UP

AE signals were collected in order to establish a baseline of a gear-testing fixture background noise and its variations due to rotational speed and torque. Also, simulated cracking signals immersed in background noise were collected. EDM notches were machined in the driving gear and the load on the gearbox was increased until damaged was induced. Data, were acquired during AE testing of a gear-testing fixture at the Gear Dynamics and Gear Noise Research Laboratory (GearLab) of the Mechanical Engineering Department of The Ohio State University (OSU). The gear-testing fixture at the OSU GearLab had the capability to test sets of driving and pinion gears at two different rotational speeds, 2700 and 5400 RPM. The fixture also has a clutch mechanism that was used to introduce variable loads on the shaft in order to apply controlled torque to the gearbox.

AE data sets were collected using an eight-channel, portable AE acquisition system (PAC micro-DiSP) controlled with a laptop computer through a PCMCIA connector. Wide band sensors (100-1000 kHz frequency response) were connected to the eight AE acquisition channels with PAC wide band (100-1200 kHz), 0dB preamplifiers. Smart threshold function, was used in all eight channels of the AE acquisition system. Under this threshold setting, the system maintains a constant AE hit rate on each of the channels by changing the detection sensitivity according to variations in the noise level generated in the structure under. Figure 1 shows the OSU GearLab Testing bench and the location of the eight sensors used in the data collection. Two different tests were performed.

During the first test, the data collected included background noise from the gearbox running at 2700 and 5400 RPM with no load, and at 2700 RPM with three different loads that change the torque applied to the gearbox. No data were collected at 5400 RPM with added torque in order to avoid premature failure of the gearbox. The torque values were 741.0, 1,531.5, and 2,582.0 lb-in.



(a) (b)

Figure 1. Location of the AE wide band sensors on the gear-testing bench: (a) Channels 1-4. (b) Channels 5-8.

Acoustic pulses simulating cracking in the gears were introduced in the gearbox during the baseline test at 2700 RPM, using piezoelectric sensor connected to a waveform generator board. The repetition frequency of the signals was set to 45 Hz, which corresponds to 2700 signals per minute. In this way, one simulated cracking signal was produced every revolution of the driving gear, as would be expected when real cracking occurs during operation.

A second set of data, also necessary for development and validation of the SPR, was collected in the same gear-testing fixture at OSU Gearlab. Prior to this second test, two EDM notches were machined in the driving gear to act as potential crack initiation sites during a fatigue test. The data collected included background noise from the gearbox with the notched gear with no torque running at 2700 and at 5400 RPM. The data also included background noise from the gearbox with the notched gear running at 2700 RPM with three different torque levels. As in the previous test, no data were collected at 5400 RPM with added torque in order to avoid premature failure of the gearbox. The data collected in this test were intended to evaluate the changes induced in the background noise signal characteristics by the presence of the EDM notches in the driving gear.

As the final step in the test, a fatigue test with six increasing torque levels was performed. It was estimated that the minimum duration necessary for the fatigue test to produce fatigue damage in the gearbox was one million cycles, or approximately 6.5 hours at 2700 RPM. Table 1 shows the progression of the torque level increase during the fatigue test.

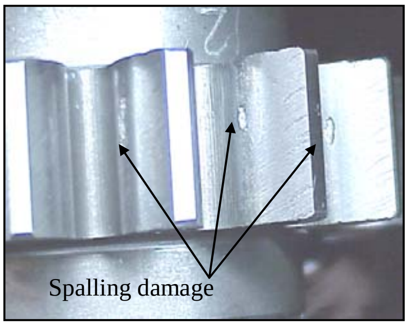


Figure 2. Spalling damage on pinion gear after one million cycles fatigue test.

Torque [lb-in]	Time [min]	# of Cycles	Accumulated # of cycles
1531.5	45	121,500	121,500
2582.0	45	121,500	243,000
3207.1	105	283,500	526,500
3893.0	60	162,000	688,500
4639.6	180	486,000	1,174,500

Table 1 Torque and time parameters used during the fatigue test of a notched gear at OSU Gearlab.

During the fatigue test, the gearbox was opened before each torque increase in order to perform a visual inspection of the gear. There were no signs of crack growth from the EDM notches even after the fourth torque increase. However, after the last increase in torque, the pinion gear showed severe spalling, which, according to OSU Gear lab, is a precursor of more severe damage and failure of the gear. Dramatic changes in the AE signals caused by the spalling damage in the gear, shown in Figure 2, were observed during the last part of the fatigue test.

3. CLASSIFICATION OF AE SIGNALS

3.1 FEATURES SELECTION: Effect of torque, rotational speed, and EDM notches

Using the first data set (base-line data and simulated crack using pulser) it was determined, that the frequency features better reflected the difference between background noise, simulated cracking signals, and legitimate AE produced by damage in the gearbox. The following frequency features were calculated in real time: Partial Powers 1, 2, 3 and 4, measuring the fraction of energy in the signals power spectrum between 100-200 kHz, 200-300 kHz, 300-400 kHz and 400-1000 kHz respectively. In addition to that, Frequency Centroid and Peak Frequency were measured. Among the different frequency domain features measured, Partial Power 2, and the power spectrum Frequency Centroid exhibited the smallest changes with variations in the gearbox torque and rotational speed.

Statistical analysis and visual examination of 2D scatter plots, revealed that for practical purposes the Partial Power 2 and Frequency Centroid are invariant to changes in torque or speed conditions for both tests (simulated crack signal and EDM notched gear tests).

Among the six frequency domain features, partial power 1 and frequency centroid found to be highly correlated. On the other hand partial power 2, found to be uncorrelated with all remaining features. Therefore Partial Power 2 and Frequency Centroid were selected as basic features for the classification process.

3.2 CLASSIFIER FEASIBILITY: Discriminating background noise from pulser signals.

The feasibility of discriminating crack like signals in excessive background noise was investigated using a pulsing sensor simulating cracking signals. The data collected with and without load, data set 1 - without EDM and at 2700 RPM, were used for the classifier design. The aim of such classifier design is to discriminate pulser (used as crack simulation) from background data. The definition of training data set i.e. data to be used as examples for the classifier design is the key issue in this process. All data recorded during background noise monitoring formed class 1 while part of the data recorded during crack simulation formed class 2 (since the pulser is not pulsing continuously and thus there exist time periods of background noise in these data). In addition to that the class 2 data were enhanced with the addition of AE data from simulated source (pulser) recorded with the gear box not running. Such data enhance the pulser signature training set.

The data were split at random in two parts. One part was used to train the classifier while the other part was used to test the classifier performance. Two different classification schemes were examined using NOESIS[6] software: k-Nearest Neighbor Classifier and Back Propagation Neural Network with 1 hidden layer.

The k-NNC is a simple distance-based algorithm. This type of algorithm, classifies the unknown hit to the data class most frequently occurring among the k-nearest prototype vectors. It is a simple but powerful method, whose performance depends mainly on the completeness and accuracy of the data sets that are used to train the classifier.

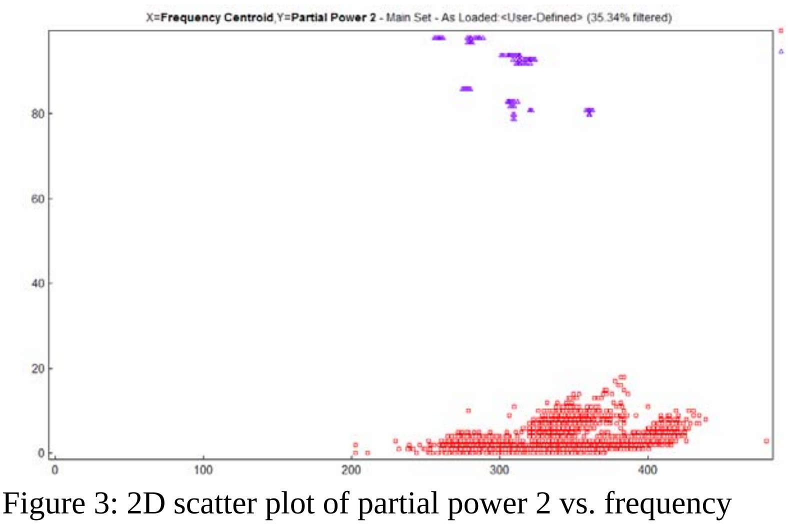


Figure 3: 2D scatter plot of partial power 2 vs. frequency centroid for the 2 classes of interest (background noise & pulser)

The error rate found in all cases (using different training parameters or different AE features) less than 0.05%. Closer examination of the training data at certain 2D and 3D projections (as shown in Figures 3) showed that the classification problem seems to be a Linearly Separable one. Thus a Linear classifier trained resulting in 0.12% error.

3.3 DEVELOPMENT OF A GENERALIZED SIGNAL CLASSIFIER

Further to the successful discrimination of simulated crack like signals from the excessive background noise, a six classes problem considered aiming to discriminate the following signal classes:

- Low speed baseline no notch,
- Low speed baseline notch,
- High speed baseline notch,
- Simulated cracking,
- Extraneous noise.
- Spalling damage

The data files used and the conditions under which they were collected are summarized in Table 2. Using these data files listed in Table 2, a k-Nearest Neighbor Classifier (k-NNC) was implemented in NOESIS software. The six class problem is considerably more complicated compared with the two class one based on the simulated signals.

Condition	Speed [RPM]	Torque [lb-in]
Notched Gear	2700	0
Notched Gear	5400	0
Simulated cracking	2700	0
Unnotched gear	2700	0
Unnotched gear	2700	2582.0
Notched gear	2700	3207.1
Notched gear under fatigue	2700	variable

Table 2. Data files collected under different conditions used to implement the k-NNC

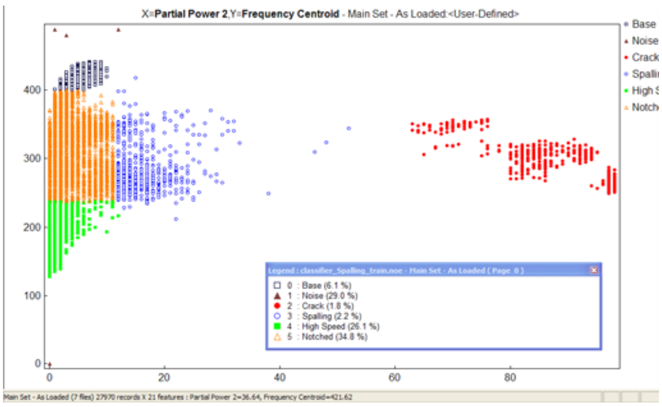


Figure 4: Partial Power 2 vs. Frequency Centroid correlation plot for the six different data classes

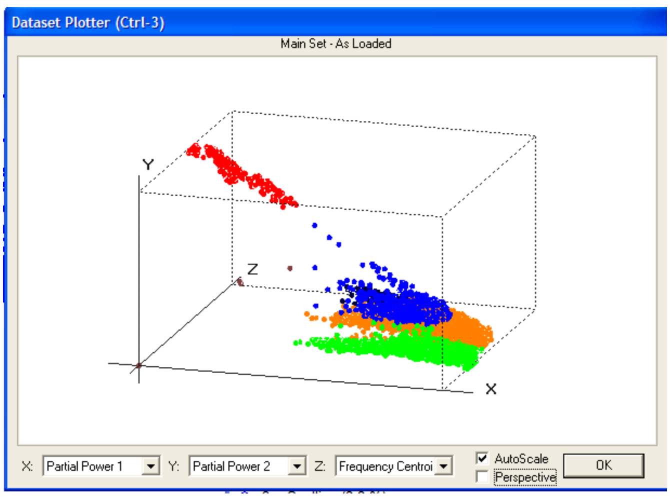


Figure 5: 3D graph of Partial Power 1 vs. Partial Power 2 vs. Frequency Centroid

Some of the data classes included data collected under different conditions resulting in class overlap on the Partial Power 2-Frequency Centroid plane, as it is the case of baseline notched gear with high torque and no torque at 2700 RPM data, which are included in the low speed baseline notch class. Also, the baseline unnotched gear with high torque and no torque at 2700 RPM data were included in the low speed baseline no notch class. The high speed baseline notch class includes data from both notched and unnotched gear running at 5400 RPM. Figures 4 shows the Partial Power 2 vs. Frequency Centroid correlation plot for the six different data classes while figure 5 shows a 3D graph of Partial Power 1 vs. Partial Power 2 vs. Frequency Centroid.

As can be seen from the 3D plot of figure 5, the class ovelap shown in Figure 4 is an artifact of projecting high dimentional space on a plane. Thus by proper selection of AE features, a reliable classification scheme was designed. The classifier overall error was 0.16% (or 22 AE hits misclassified out of 13895 hits). The within class error was considerably low in all cases, except for 8 misclassified hits from the spalling class which were classified as notched data resulting in within class error of 2.7%.

In order to test further the performance of the classifier, the k-NNC was applied to data files which were not used during its development but contained similar information. The results produced by the k-NNC on these data are listed in Table 3. In the table, each data file is classified as containing a certain percentage of AE signals that are identified as belonging to a particular data class. According to the results shown in Table 3, the classifier correctly identified the high speed notched with no load data file as containing high speed baseline notched data. Also, identifies the data from the notched gear at low, medium, and high torques as containing high speed notch data. These results are consistent with the previous observations that torque did not have a strong effect on the selected frequency features. The data corresponding to notched gear at low speed and no torque were classified correctly as containing mostly baseline notch signals at low speed. The simulated cracking signals were classified correctly in 92.8% of the cases. The 7.2% of the signals that were missclassified are signals that are located in the upper and lower boundaries of the simulated cracking signals distribution where some of the features overlap between data classes. Because 6% of these missclassified signals were identified within the spalling damage class, this indicates that some of the simulated cracking pulses show features similar to those of the spalling damage signals.

Data File	NNSC Data Class					
	Low speed baseline no notch [% total hits]	Low speed baseline notch [% total hits]	High speed baseline notch [% total hits]	Simulated Cracking [% total hits]	Extraneous Noise [% total hits]	Spalling Damage [% total hits]
Notched gear no torque, high speed	0.0	2.6	69.3	0.0	28.1	0.0
Notched gear low torque, high speed	0.0	2.5	60.7	0.0	36.8	0.0
Notched gear, medium torque, high speed	0.0	1.6	63.5	0.0	34.9	0.0
Notched gear, high torque, high speed	0.0	1.5	59.5	0.0	39.0	0.0
Notched gear no torque, low speed	4.4	49.8	0.2	0.0	45.6	0.0
Simulated cracking, low speed	0.0	1.2	0.0	92.8	0.0	6.0
Fatigue low speed, high torque	0.0	33.9	49.5	0.0	7.8	8.8

Table 3: Classifier Validation. Classification Results

In the case of the fatigue at low speed data file, 8.8% of the hits were classified in the spalling damage class. Most of the data in this file was classified as baseline data for the notched gear at low, 33.9%, and high speed, 49.5 %. This result was expected since the spalling signals are immersed in the background noise of the gearbox. It is important to note that only the file that contained data corresponding to damage in the gearbox, simulated and real, were classified as such by the k-NNC. In all the data files analyzed, except for the simulated cracking at low speed data, the classifier detected a significant percentage of signals that were classified as extraneous noise. This class of data most likely corresponds to noise produced by the gearbox cooling system and static electricity spikes, which apparently increases at high speed operation, as indicated by the high percent of signals from the high speed data files classified within that class.

4. SEMI-REAL TIME AE CRACK MONITORING

In order to test the feasibility of on-line health monitoring, Live-Supervised Pattern Recognition (Live-SPR) software routines were implemented within NOESIS. The Live module uses previously trained algorithms which in turn are applied to the data read from the hard disk at predefined intervals during data acquisition. PAC-AE WIN s/w was used for controlling the AE system and the requested I/O on the hard disk. The classifying time interval can vary from 2 to 2,500 seconds, and it depends both on expected data volume and processor speed of the AE signal acquisition system.

A preliminary, version of Live-SPR was tested during the fatigue test data collection at OSU Gearlab, while the six class k-NNC classifier was applied in semi real time at 10 seconds intervals. During this trial, the Live-Semi Real Time classification software correctly identified the presence of simulated cracking signals produced with a piezoelectric sensor as described in section 2.

In addition to the semi-real time classification, periodic statistics were implemented in order to enhance further the on-line evaluation. This is a set of functions that can be used to monitor various statistics relating to the data classes typical of normal or abnormal system operation, and thus form the base of an advance alarming set-up. By tracking the changes in the periodic statistics, the onset and progression of damage can be monitored to avoid failure. Once the damage-related signals have been detected by the system, the periodic statistics of these data class are calculated and upgraded in semi-real time. If the periodic statistics show no change, the alarm will remain as a warning, showing that damage has occurred but is not progressing. If the periodic statistics show that the damage is increasing, the alarm level will be increased. The philosophy behind the periodic statistics is to select two data classes and monitor how the distance or velocity between them evolves. To achieve this, a reference class and a target class need to be defined. The former is the measurement origin and the latter is the point to measure to. Using this strategy, the distance and velocity of the moving data class can be tracked.

The concept of periodic statistics for the evaluation of cracking process was tested using simulated crack-like signals from a pulser and the two class classifier presented in paragraph 3.2, where one class corresponds to background noise of the gearbox while the second one corresponds to simulated cracking signals. In order to simulate variable crack growth rates, the frequency of the simulated cracking signals was initially at a pulsing rate of 250 kHz while it was decreased to 200 kHz and gradually increased to 300 kHz in a period of time of 200 seconds.

SPR-Live was simultaneously set to calculate the periodic statistics of the simulated cracking signals class using the background noise class as reference. The periodic statistics of the simulating cracking signals were calculated using three AE features: Frequency Centroid, Partial Power 2, and Peak Frequency. These three features defined a 3D space in which the distance between the background noise and simulated crack signals data classes was calculated. Also, the velocity at which the simulated cracking data moves in the 3D space was calculated.

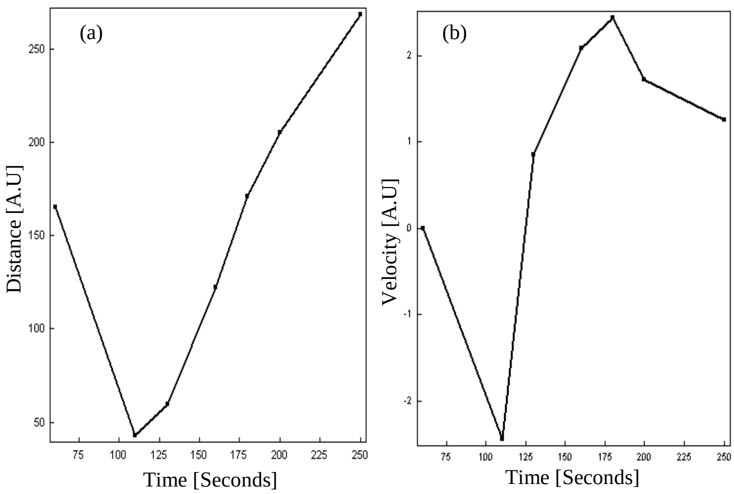


Figure 6. Periodic statistics calculated from the frequency changing simulated cracking signals: (a) Distance vs. time, (b) Velocity vs. time.

The results shown in Figure 6(a), Distance vs. Time, correctly track the movement of the simulating cracking data class, as it decreases from 160 to 45 and then gradually increases to 275 distance units. Figure 6(b) shows the Velocity vs. Time trace, calculated in the same AE feature space. This trace indicates how fast the simulated cracking class data is moving in the 3D space. The velocity decreases as the signal frequency was reduced from 250 to 200 kHz and then increases as it reaches 275, only to start decreasing again as the frequency goes up to 325 kHz.

6. CONCLUSIONS

Based on the results discussed in this paper, it has been demonstrated that is feasible to use Acoustic Emission for the detection of cracking in gearboxes. It is expected that this methodology will be expanded for monitoring in diaphragm-type couplings used in aircraft and engine drive systems. A Supervised Pattern Recognition Scheme based on the k-NNC Classifier using frequency domain Acoustic Emission signal features has been implemented. This classifier was capable of correctly identifying AE signals produced by a gearbox testing bench under six (6) different conditions.

The development of semi-real time classification software routines was implemented and tested. The Live-Supervised Pattern Recognition s/w, implements functions that allow the user to view and classify, at programmable time intervals using a SPR, AE data from a dynamic process as they are recorded by an AE system. Live-SPR is capable of monitoring periodic statistics of AE data, which can be used as an indicator of damage presence and damage severity in a dynamic system. A conceptual design for an acoustic emission on-line cracking monitoring system for drive systems couplings has been developed. Final development, design, and implementation of the system is planned to be carried out in consultation with aircraft maintenance experts and final users of the system.

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REFERENCES

1. Neubert C. G. and Wilson R., *Vibration Diagnostic Results of a several Degraded SH-60 Engine High Speed Shaft,* NAVAIR Interim Report, NAVAIRARCENACDIVTRENTON-LR-PPE-96-6, 1996.
2. Pollock A., *Acoustic Emission Inspection*, Physical Acoustics Corporation, TR-103-96-12/89.
3. Singh A., *Detecting Gear Tooth Breakage Using Acoustic Emission: A Feasibility and Sensor Placement Study*, Proceeding of 1998 ASME Design Engineering Technical Conference, 1998.
4. Almeida, A.F., W. D. Martin, D. J. Pointer, *Application of acoustic sensors for helicopter health monitoring,* Final Report, U.S. Army SBIR Phase I, contract number DAAJ02-95-C-0021, 1995.
5. Godinez, V., and Friesel, M., *Detection of Cavitation and Detonation in Diesel Engines*, Final Report, Project R00-706, Physical Acoustics Corporation, Princeton Junction, NJ, 1999.
6. NOESIS “Overview” & “Reference” Manuals, Envirocoustics S.A., 2004