Networked Modular Technology for Integrated Aircraft Health Monitoring: Application to Rotary Structures

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ABSTRACT

The largest variable cost to aircraft's manufacturers and flying companies is unscheduled maintenance. Therefore, developing efficient and modular PHM system capable to scale different architectures topologies for in flight and on ground health monitoring could be cost effective, since it brings indication and warning prior to damage occurring.

In this paper, we propose an innovative diagnostic and prognostic health system based on a combination of modular acquisitions interfaces and processing units.

An embedded JTFA (Joined Time-Frequency Analysis) method based on STFT (Short-Time Fourier Transform) or Wigner-Ville transforms are used to extract a relevant signature. The proposed algorithms and PHM system technology are applied for diagnosis of mechanical flows in a high speed rotating gear of a demonstrator machine. A detailed description of data management and rooting from vibration sensors to the processing unit will be exposed.

Finally, a proof-of-concept experiment will be designed to demonstrate the integration of all the described system elements to detect any damage or anomaly into the monitored structure.

1. INTRODUCTION

Health management and damage assessment of rotary structures is one of the major issues that face Helicopter's and turbofan's manufacturers. In this context, PHM applications can actually provide a wide range of benefits for complex systems such as transmission gear boxes or jet engine turbine.

For the time being, main and engine accessories are systematically replaced either upon failure or after a pre calculated time of use. These maintenance procedures which are typified in many reports (FAA report DOR/FAA/CT-92/29) create huge cost of maintenance and materials (Cf. Figure 1).

Therefore, forecasting the remaining useful life of these subsystems can improve flight safety and reduce exploitation cost by reducing unscheduled events and regular maintenance (Heng et al 2009). Moreover, a constant monitoring of critical subsystems reduces preventive aircraft grounding which increase airplanes readiness.

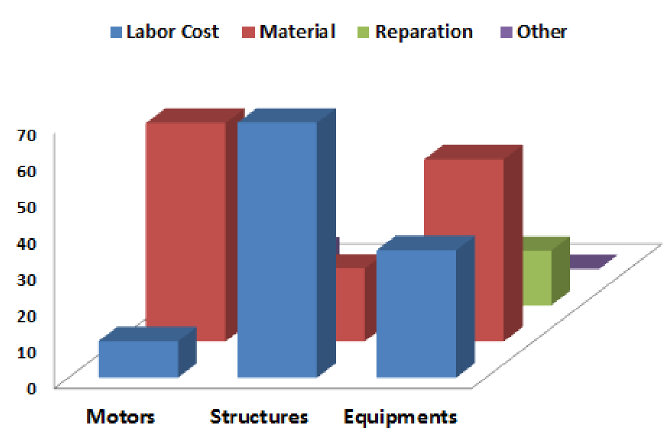

Figure 1. Maintenance, repair, and operations (MRO) cost distribution in (%) (PIPAME report)

In aircraft industries, real time monitoring of vibration (Lastapis et al 2007, Dempsey et al. 2007) is systemically used to detect machine faults including structure flaws, impacts, cracked rotors or oil degradation. Due to the complex nature of the inspected systems, analytical studies based on predictive behavior models show their limit quite quickly. Additionally, it has been shown by Lewicki et al. 2010 and Bechhoefer et al. 2011 that there is no single condition indicator (CI) which is sensitive to every failure mode.

So, in most methods, the diagnostic is simply based on comparison of vibration amplitudes or frequencies to a baseline. However, in the case of some complex machines, such as helicopter blades or turbofan, the detection of abnormal behavior is in essence complicated by the fact that changes in operational conditions makes acquired vibration non stationary. Because of that, classical vibration based diagnostics techniques which focus either on time domain or frequency domain are not suitable. In such cases an efficient approach to monitor (CI) condition indicator may be based on (JTFA) Joined Time-Frequency Analysis (Klein 2013).

The current paper proposes an automated solution for feature extraction. Health indicators such as temperature, pressure or vibration are acquired using on board sensors through avionics buses or analog interfaces. Hence, there is no need to plug external non-qualified sensors. To inform operators of needed repairs, the system is capable through embedded processor to evaluate the global health using evaluative and dynamic thresholds.

For the purpose of this article, We focused our studies, on the joined time frequency analysis of abnormal vibration behavior thought the instrumentation of piezoelectric sensors. Using an embedded processor, an analysis algorithm based on smart comparisons between different signatures will be exposed. Damage assessment approach is in fact based on a smart differentiation between classified signatures acquired prior and after to the damage. The healthy signature, in the other hand is extracted using a statistical characterization of the studied machine.

Finally in the last section, we will demonstrate the flexibility that network embedded modular system architecture may bring to PHM in aerospace.

2. JOINED TIME-FREQUENCY ANALYSIS AND FEATURE EXTRACTION METHODS :

Based on JTF analysis, feature extraction methods can be computed using different techniques of signal processing. This section provides a short description of the considered methods:

1. **Short-Time Fourier Transform**: STFT is widely used for JTF analysis. It splits a time domain signal *f(t)* into small segments and applies a window function *W(t)* to each one before computes a FFT (Fast Fourier Transform) of each segment :

$$STFT_f^u(t',\omega) = \int_f [f(t)\cdot W(t-t')]\cdot e^{-i\omega t}\cdot dt \quad (1)$$

Since it uses a typical Fourier transform, this method requires a stationary signal over each segment interval. So to analyze semi-transient signals, the required segments lengths could be adapted dynamically to the observed system. In this case, the major consideration is to correctly balance between time and frequency resolution (Qian et al 1999). In fact, due to Heisenberg-Gabor uncertainty principle, a wide window *W(t)* gives good frequency resolution and poor time resolution. In opposite a narrow time slice gives a good time resolution and poor frequency resolution. These two cases could be problematic for fast transient signals.

2. **Wavelet Analysis** is mostly used to localize the exact time of a specific vibration event. This approach is widely used as a JTFA technique for Lamb wave triangulation and feature extraction (Boukabache et al. 2013). Basically, Wavelet Transform (WT) contains informations similar to STFT. However due to the special proprieties of the used wavelet, the resolution in time is much higher at high frequencies. The resolution difference between STFT and Wavelet Transform is shown in Figure 2.

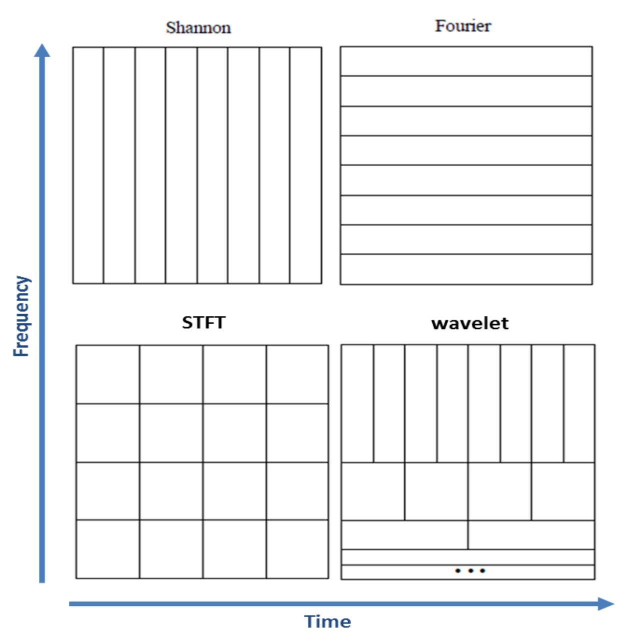

Figure 2. Time-Frequency sampling resolution representation of different JTF methods

3. **Bilinear Time-Frequency Distribution** using Cohen's Class Distribution Function: (CCDF) was firstly proposed in 1966 in the context of quantum mechanics (see Cohen 1966). It is a generalized time-frequency representation method that utilizes bilinear transformations thought the use of a kernel function :

$$C_x(t,f) = \iint_{-\infty}^{\infty} A_x(\eta,\tau)\Phi(\eta,\tau)e^{-i2\pi(\eta t-\tau f)}d\eta d\tau \qquad (2)$$

   Where A_x is the ambiguity function and Φ is the kernel function which could include Choi-Williams Distribution (Lazorenko 2006) Wigner-Ville Distribution (Boashash 1987) or Zhao-Atlas-Marks (Rajagopalan et al. 2006). The main primary advantage of CCDF is its capability to analysis non stationary signals. This technique could therefore be applied to transient vibration data collected through high speed transition conditions. However, the bilinear-transformation needs a careful investigation of used window function otherwise it suffers from inherent cross-term contamination which degrades the clarity for most practical signals.

Therefore based on these points and the study of (Byington et al, 2011) the authors chose a STFT as a JTFA method. Compared to the other techniques, STFT offers the best compromise between resolution performance and embedded computational time. In fact, efficient FFT algorithms already exist for embedded CPU or FPGA which makes STFT time calculation quite efficient. In addition, small amount of data is needed to computes the algorithm which lighten aircraft data bus traffic.

3. THE PROPOSED PHM SYSTEM

In order to monitor several airplanes systems without overloading the weight with additional sensors, we developed new system architecture, capable to interact with existing embedded avionics and embedded sensing units (See Figure. 3).

The presented technology is built around harsh networked electronic modules (see Figure 3 and 4) where each one is dedicated to a specific task such as:

- Sensors instrumentation and acquisition (Temperature, Strain, Pressure, Acceleration and Deformation)
- Multiple avionics protocol communication interfaces (ARINC429, CAN, Ethernet, RS422 ….) to connect the PHM system with on board calculators
- Waveform and signal generation (current, voltage, resistive load …) to simulate avionics sensors behavior or to provide calibrated stimulus.

Based on embedded CPUs, each module has lightweight signal processing capabilities to execute basics algorithms such as filtering or buffering.

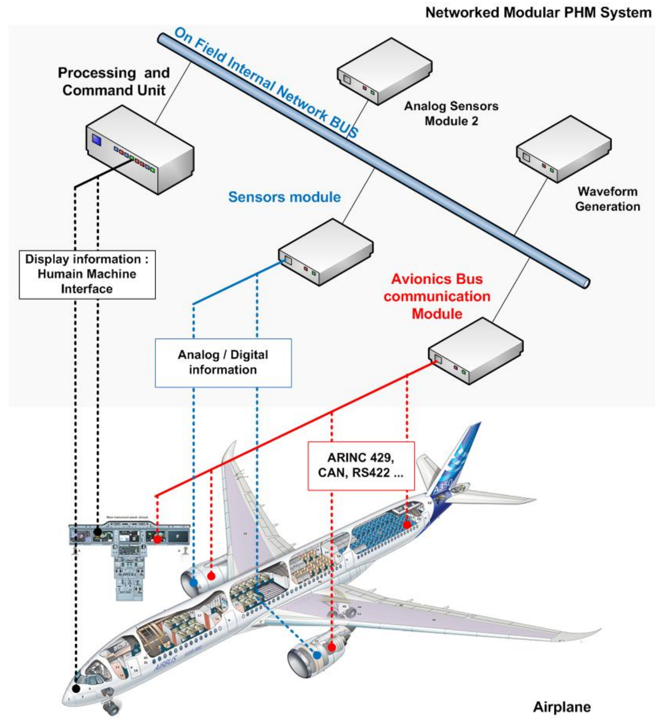

Figure 3. Synoptic of the proposed PHM modular system

Moreover using hot swap and reconfiguration capabilities, the modules can be plugged and unplugged freely without damaging the PHM System. The theoretical maximum number of plugged modules is in fact only limited by the internal network bus bandwidth. Hence, this architecture allows high level of scalability to manage aircraft life cycle.

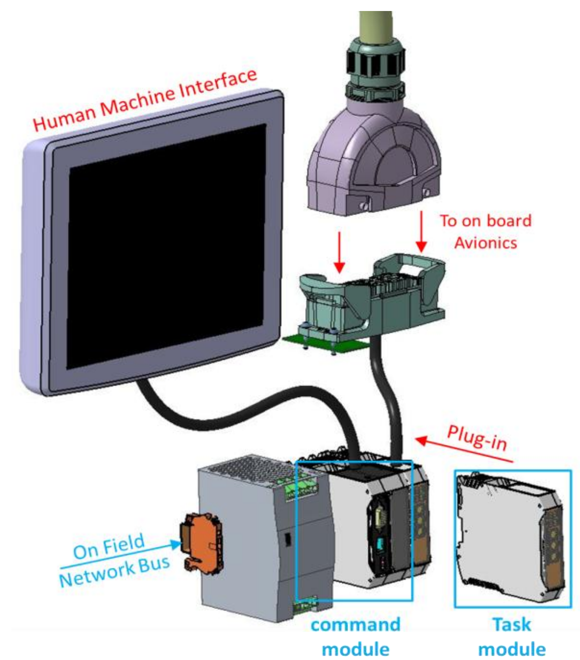

Figure 4. Synoptic of the proposed PHM modular system

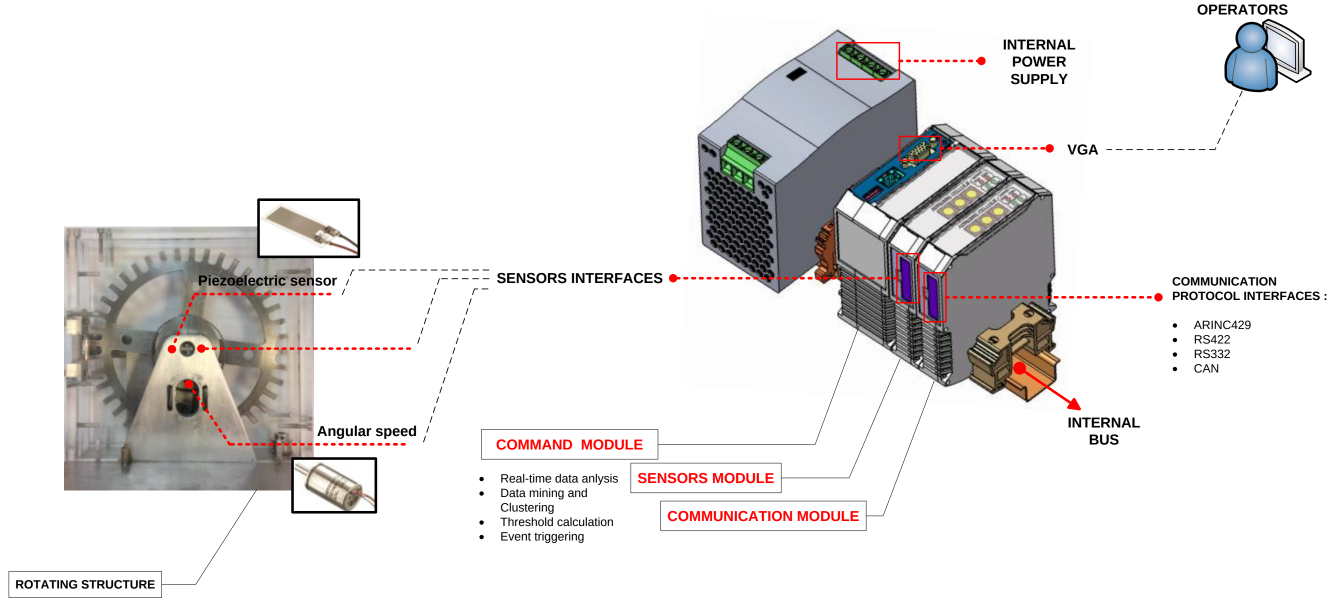

Figure 5. Experimentation setup

In addition, a central processing and control unit with advanced calculation capabilities manages the whole network scheduling and behavior. This command module is also responsible of sensors data collection, storage and processing as well as, the execution of JTFA diagnostic/prognostic algorithms. In fact, collected data could be exploited on ground with a post treatment for precise analysis or during flight using empiric thresholds for immediate alarm annunciations. The modular scalability of the proposed PHM architecture, allows immediate on flight installation to monitor in real time undesired events.

4. PROOF OF CONCEPT

4.1. Experimental setup

For the purpose of this article, we used as an experimental machine: a phonic wheel developed to characterize a turbojet engine rotating speed. During its operating, the produced vibration is measured using a PZT piezoelectric sensor of 5mm radius pasted directly onto the external frame of the demonstrator. In the meanwhile, rotating speed is acquired using an inductive sensor (See Figure 5).

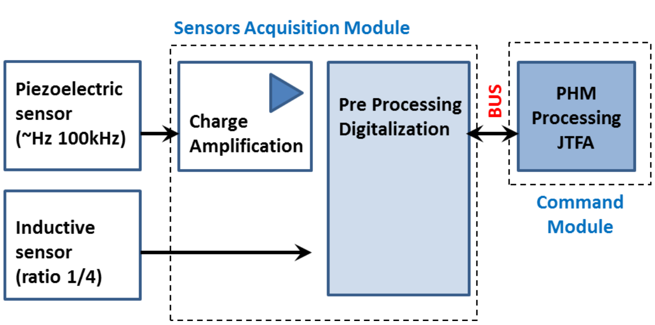

Figure 6. Data acquisition chain

The phonic wheel is actually driven by an electric brushless motor capable to reach a realistic rotating speed of 10000RPM. When activated, the rotation of the wheel generates vibrations signature that produces local micro deformations. Hence, according to the applied strain, the piezoelectric sensor generates charges Q(t). To be exploitable, these charges are converted into a voltage signal using a simple charge converter (See Figure 6).

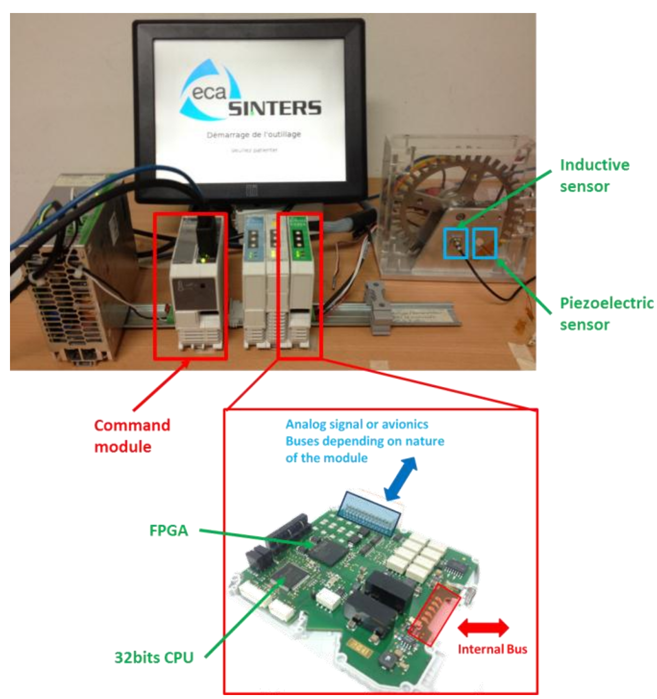

Figure 7. Photo of the experimental setup

Analog acquired values are digitalized using a Delta Sigma 24bits ADC inside the sensors module (See Figure 6), then buffered, eventually filtered using a low pass FIR filter and finally transmitted when the command module requests it. At the last stage of the process, the data is buffered into a hardware FIFO synthetized into an FPGA and finally handled by the processor to compute an STFT based JTFA analysis.

To synchronize the global system and schedule each task of the process, the command module controls the wheel speed using short time impulse orders and acquires the rotation speed using the inductive sensor. Hence, the command module applies to the mechanical system a strictly similar operating condition which allows the extraction of a relevant signature.

4.2. Experimental results

To demonstrate the detection capabilities of the described PHM system, in steady states conditions and pseudo stationary operational conditions, we performed two representatives' experiments.

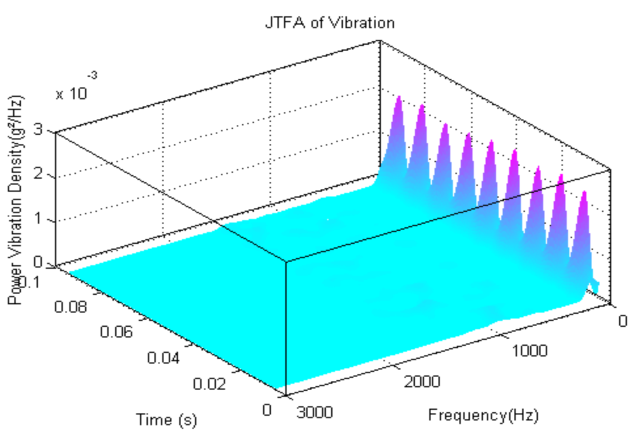

Figure 8. Healthy vibration baseline at 1000RPM

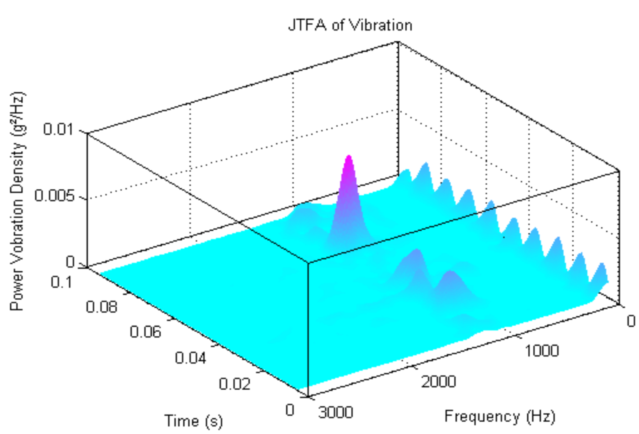

Figure 9. Abnormal vibration signature at 1000RPM

4.2.1. Abnormal behavior in steady state operation mode

In this configuration, the command module stabilizes the phonic wheel around fixed speed and acquired generated vibrations using the PZT sensors after 5s.

Using equation (1) a simple spectrogram is computed through the calculation of the squared STFT magnitude.

$$\text{Spectrogram}\,\{x(t)\}(t',\omega) = \left|STFT_f^u(t',\omega)\right|^2 \qquad (3)$$

A relevant signature baseline (See Figure 8) is therefore extracted using Eq. 3 then compared to an abnormal signature acquired for the same operating conditions. For this experience, we simulated a machine degradation using a faulty contact with the shaft. In this case, data analysis shows a clear spectrogram response modification. Beside to the initial low frequencies (<500Hz) shown clearly in figure 8, the mechanical default add to the spectrogram higher spikes frequencies around 1kHz. In addition, it is interesting to notice that magnitudes of low frequencies are the same in the two figures 8 & 9.

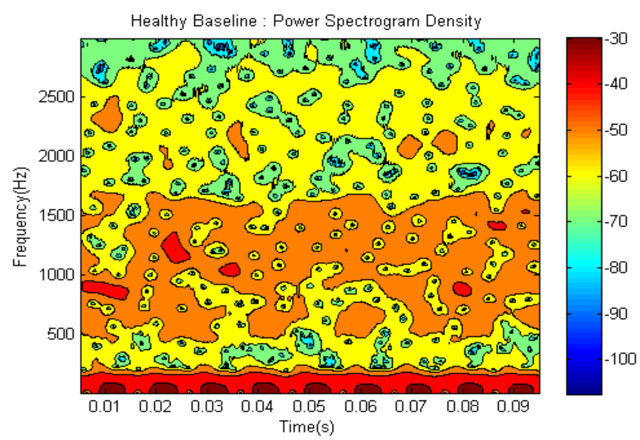

Figure 10. Healthy baseline: Power Spectrogram Representation (dB/Hz) in 2D at 1000RPM

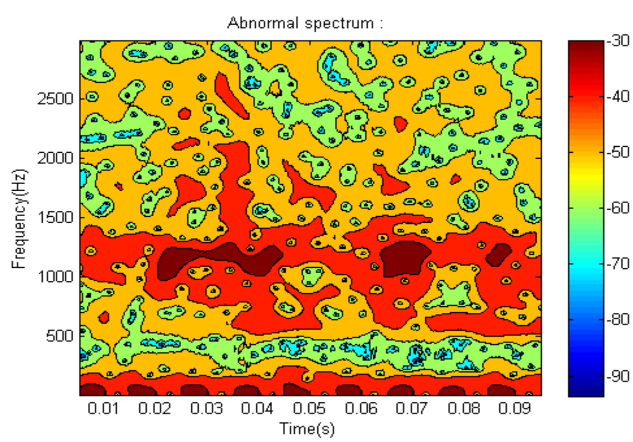

Figure 11. Abnormal signature: Power Spectrogram Representation (dB/Hz) in 2D at 1000RPM

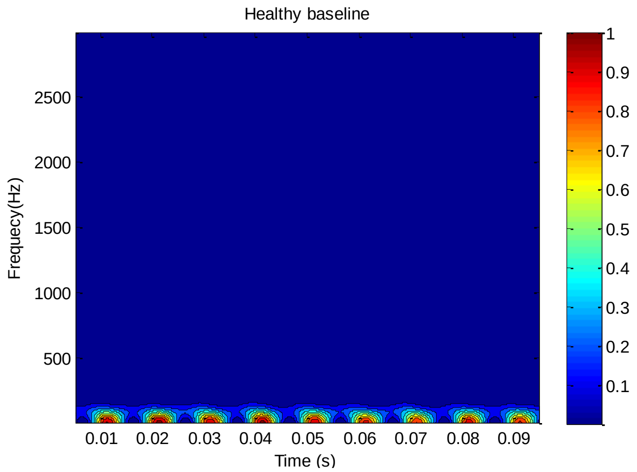

Figure 12. Normalized healthy baseline signature

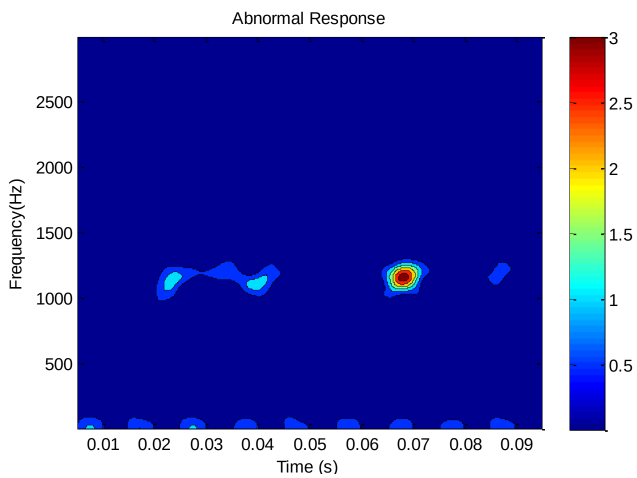

Figure 13. Normalized damage response

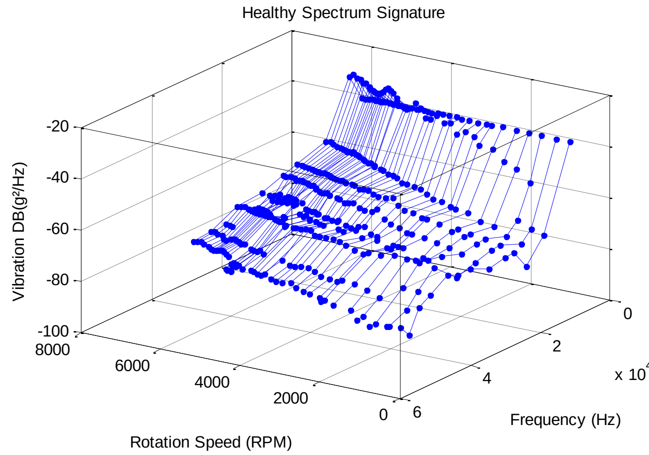

Figure 14. Healthy 3D baseline signature between 600 and 7000RPM

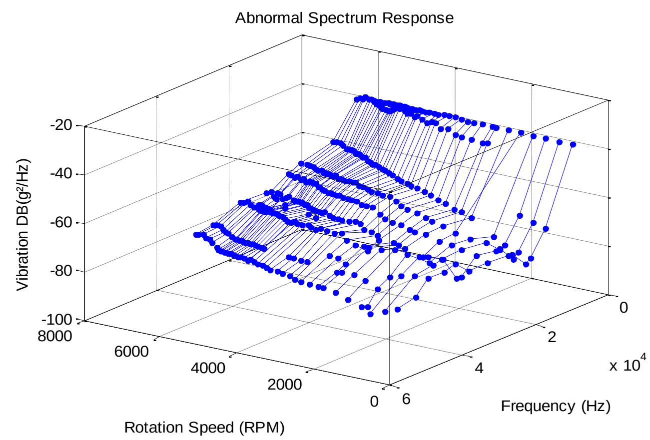

Figure 15. Damaged 3D signature between 600 and 7000RPM

In all the experimentations, we used a Hamming windowing to compute de DFT. The calculation of the power spectrogram representation presented in figures 10 & 11 shows the need to have same scaling. Actually, with this representation, the coloration map doesn't allow any thresholding. To solve this issue, we recalculate a common scale to both signatures using a simple normalization. The results are shown in figures 12 & 13. Using this simple algorithm, we are capable to detect any magnitude variation versus to the baseline (presented in figure 12) using a simple threshold fixed to 1.1.

4.2.2. Abnormal behavior in pseudo transient operation mode

In real operational condition, the speed or the load may vary with time. In this case, the previously presented algorithm does not suit. To simulate such behavior, the command module sends to the phonic wheel a series of orders to increment its speed by step of 2.5seconds to reach a maximum speed of 7000RPM.

In this configuration the command module verifies for each step that the needed speed was reached before acquiring 1second of vibration data. For these conditions, we may split the entire experimentation time into small segments where stationary conditions are verified. The segments intervals could be downsized depending on the acceleration capabilities of the motor. In other words, the more the acceleration is, the smaller the intervals are set.

While, semi-stationary conditions are verified for each segment, we computed for each interval, a simple power spectrum density algorithm; then we extracted for each rotation speed the location and the magnitude of the produced frequency peaks. The resulted data are plotted in figures 14 and 15. However, the 3D representations are quite difficult to analyze. To simplify and automatize the diagnosis, we extract statistically from the baseline (See Figure 14) a list of relevant frequency peaks. Then, we plot in 2D representation the magnitude of theses peaks versus the rotation speed.

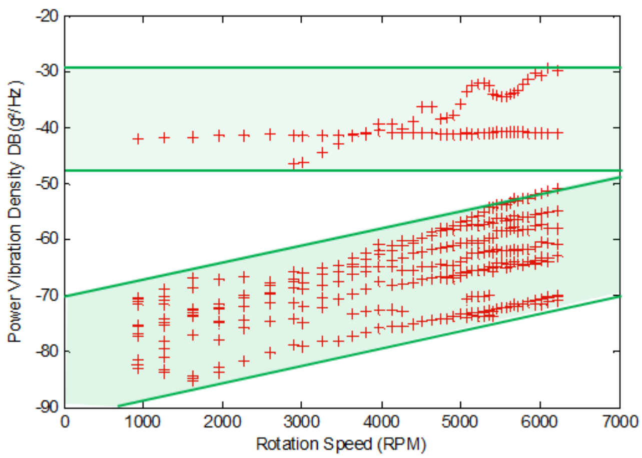

Figure 16. Healthy baseline between 700 and 6200RPM

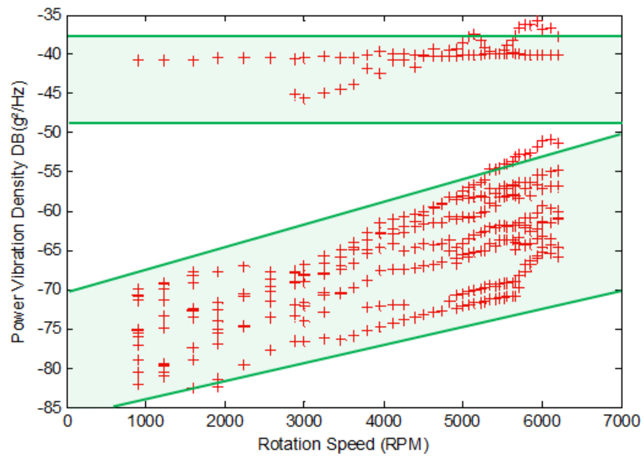

Figure 17. Abnormal signature between 700 and 6200RPM

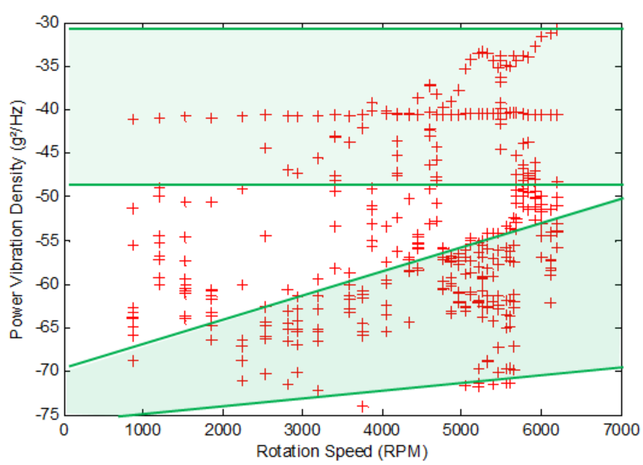

Figure 18. Damaged signature between 700 and 6200RPM

The produced signatures could therefore be quickly studied using a pre-calculated abacus (See. Figure 16). Using this simple representation, the diagnosis is quite quick to perform. The thresholds are calculated statistically for a healthy behavior then compared to degraded signatures. In the example of figure 17, the frame of the phonic wheel has been burden with 25g. The signature stills basically the same, even if we notice a thin shift of spikes magnitudes at high rotation speed. In the example of figure 18, a faulty contact has been introduced onto the shaft of the phonic wheel. The signature response has been completely modified.

5. CONCLUSION

A scalable aerospace PHM technology based on embedded networked modules was proposed. The system was designed for in flight and on ground aircraft health management. Beside its capacity to spy most of avionics buses, the system is capable to monitor mechanical machineries in order to detect an abnormal event and predict an eventual failure. In this paper the proposed system was successfully tested on a representative mechanical rotating machine.

In addition, we presented a method for analysis and diagnosis vibro-acousitic data acquired using piezoelectric sensor. The method was successfully demonstrated for stationary data and pseudo-transient variations. Using a 2D representation of RPM-spectrogram, we managed to diagnosis abnormal behavior onto a phonic wheel. Actually, the developed algorithms were specially studied to be suitable for an embedded integration.

NOMENCLATURE

CCDF	Cohen's Class Distribution Function
CI	Condition Indicator
CPU	Core Processing Unit
DFT	Discrete Fourier Transform
JTFA	Joined Time Frequency Analysis
FFT	Fast Fourier Transform
FIFO	First In First Out
FIR	Finite Impulse Response
FPGA	Field-Programmable Gate Array
PZT	Lead Zirconate Titanate
PSD	Power Spectral Density
RPM	Rotation per Minutes
STFT	Short Time Fourier Transform
WT	Wavelet Transform

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