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Health indicators for diagnostics and prognostics of composite aerospace structures

Georgios Galanopoulos
Dept. of Mechanical Engineering & Aeronautics
University of Patras
Patras, Greece
g.galanopoulos@g.upatras.gr

Dimitrios Milanoski
Dept. of Mechanical Engineering & Aeronautics
University of Patras
Patras, Greece
d.milanoski@g.upatras.gr

Agnes A. R. Broer
Structural Integrity and Composites Group
Faculty of Aerospace Engineering
Delft University of Technology
Delft, The Netherlands
A.A.R.Broer@tudelft.nl

Dimitrios Zarouchas
Structural Integrity and Composites Group
Faculty of Aerospace Engineering
Delft University of Technology
Delft, The Netherlands
D.Zarouchas@tudelft.nl

Theodoros Loutas
Dept. of Mechanical Engineering & Aeronautics
University of Patras
Patras, Greece
thloutas@upatras.gr

***Abstract*—In order to reduce aircraft downtimes Condition-Based-Maintenance (CBM) is a topic gaining increased popularity in recent years. However, to apply such maintenance policies reliable health monitoring techniques should be implemented. Two state of the art monitoring techniques, namely Fiber Bragg Gratings (FBG) and Acoustic Emission (AE) are used to monitor the fatigue behavior of single stiffened composite panels (SSCPs) subjected to variable amplitude compression-compression (C-C) fatigue. Advanced features, called Health indicators (HIs) are extracted from the raw sensor data to monitor the degradation behavior. It is crucial to have robust and reliable HIs that capture the degradation of the structures. This work focuses on providing capable HIs for monitoring degradation of composite structures.**

***Keywords*—Composites panels, Structural health monitoring, health indicator construction, fiber Bragg gratings, acoustic emission**

I. Introduction

Composite materials are being used in increasingly more safety critical applications, performing under harsh conditions, with very high safety and performance standards. In aeronautics, composite material's, especially Carbon Fiber Reinforced Polymers (CFRP), excellent mechanical properties combined with their low weight-high strength ratio, as well as remarkable resistance to corrosion, deem such materials great candidates for structural components. Many airplane components previously consisted of metals, such as parts of the fuselage, the tail fin and the wings, while composites were used for secondary non-essential structures. However, many of these metal components are now being replaced by composite materials. Nowadays, aircrafts may consist of more than 50% fiber reinforced materials. However, due to their inhomegenic nature, CFRP materials are dictated by complex failure mechanics, difficult to interpret and even more difficult to monitor. This is complicated even more by subsurface damage caused by impacts, especially barely visible impact damage (BVID), which can be easily missed during visual inspection, further reduces the load bearing capabilitiy of the structure.

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Structural health monitoring (SHM) is a constantly evolving concept over the last decades. Utilization of SHM systems in more demanding applications, such as intelligent diagnostics and prognostics of structures has been a focus of several researchers [1], [2]. Strategically placed sensor networks can provide the ability to utilize SHM and lead to the implementation of Condition-Based-Maintenance (CBM), reducing aircraft downtimes and maintenance costs.

II. State of the art

A. Prognostics and health indicators

Two major categories can be identified in the implementation of prognostics. First, there are model based or physical approaches, which focus on creating a prognostics model given the physical equations governing the system and can capture the system's degradation. Such models can be found in [3], [4]. Then, there are the data-driven methods, which rely on historical data from which useful information are extracted in the form of health indicators (HIs). HIs are features capable of capturing the structure's degradation information. As discussed in [2], [5] the quality of the HI's evolution through time affects the performance of diagnostic systems and prognostic algorithms. HIs, as stated in [6], can be categorized into physical HIs (pHI) and virtual HIs (vHI). PHIs are linked to a physical property of the system, e.g. static or dynamic strain, ultrasound, etc. Eleftheroglou et al. [7] used axial strain as an HI to predict the Remaining Useful Life (RUL) of open-hole composite coupons using a variation of semi-hidden Markov models. Liu et al. [8] used strain reading from strain gauges as indicators to monitor composite coupons during both uniaxial and biaxial loadings using gaussian processes. VHIs on the other hand, are created solely to provide good prognostic attributes such as monotonicity and prognosability. Usually these HIs are combinations of multiple pHIs or other metrics with no physical meaning. Baraldi et al. [9] used binary differential evolution algorithms to fuse raw data, with monotonicity and prognosability as objective functions, to create HIs. These HIs were used to predict the RUL of aircraft engines. Loukopoulos et al. [10] used Principal Component Analysis' (PCA) metrics as HIs, more specifically Q index and hotelling's T2, to predict RUL in reciprocating compressors. Zhang et al. [11] also used PCA to reduce the dimensionality of a wavelet decomposition analysis in rotating machinery. The PCA extracted features were used in a neural network for fault diagnosis.

B. Fiber Bragg gratings

To implement CBM a capable Structural health monitoring (SHM) system is required to provide the degradation information. In the strain department, fiber optic sensors (FOS), is a state of the art sensing technology, able to provide a promising solution due to their high tolerance to environmental conditions, their immunity to electromagnetic interferences as well as great flexibility for use in various applications. Fiber Bragg gratings (FBGs) in particular, have been extensively used for localized strain measurements in various applications. Kahadndawa et al. [12] extensively studied the effects of loading conditions on FBG strain readings. The strains were used as input in an artificial Neural Network (ANN) to predict damage evolution. In [13] embedded chirped FBGs have been used to monitor disbond propagation in adhesive joints. The initiation of the disbond would cause a shift in the FBG wavelength when a sensor is affected. Milanoski et al. [14], used FBG strains to construct HIs and monitor skin/ stiffener disbond growth in composite stiffened panels. The strain based HIs managed to accurately capture the disbond propagation. Geuemes et al. [15] investigated damage detection in composites using PCA to reduce the dimensionality of several FBG sensors. Using T2 and Q, they managed to distinguish between different damage states. Airoldi et al. [16] studied damage evolution on a composite wing spar using FBG sensors. Sbaruffati et al. [17], [18] used FBGs to monitor crack growth on helicopter tail model. The damage detection method was based on Mahalanobis distance and provided accurate damage quantification.

C. Acoustic emission

Acoustic emission (AE) is another popular monitoring technique for composite structures. Zhou et al. [19] used AE to monitor the behavior of multi-delaminated composites under compressive loading. They managed to correlate amplitude, duration, and relative energy to damage propagation. Loutas et al. [1] and Eleftheroglou and Loutas [20] used windowed cumulative RA (rise time/amplitude) as a prognostic feature for RUL prediction in composite open-hole specimens. Liu et al. [21] used AE to monitor composite coupons degradation. A normalized damage index was proposed and used AE features to observe damage evolution. De Oliveira et al. [22] proposed a classification algorithm based on ANN and used AE signal to classify different damage mechanisms. Broer et al [2], [23], used AE to monitor localize damage initiation on composite single stiffened panels during compression- compression fatigue. A fusion with strain readings was also proposed to enhance the SHM system's monitoring capabilities. The damage progression has been successfully captured by the combined SHM framework.

In this work, data from two SHM techniques, i.e. FBG and AE will be utilized to construct HIs for use in diagnostics and prognostics. The HIs should be reliable, i.e. possessing a monotonic trend, and robust, i.e. resistance to outliers and erratic behaviors. A pHI and a vHI will be extracted from strain measurements from 10 FBGs as well as, windowed cumulative features from AE measurements. It will be shown that the proposed HIs are promising features for use in prognostics.

III. Experimental campaign

Single-stringered composite panels (SSCP) were manufactured from IM7/8552 unidirectional pre-preg CFRP by OPTIMAL solution (Portugal). The layups were [45/-45/0/45/90/-45/0]s and [45/-45/0/-45/45]s, for the skin and T-shaped stringered respectively. Two resin blocks were cast on the panels in order to ensure proper load introduction and uniform loading. Static compression tests were first conducted to determine the ultimate compression strength of the panels. The average collapse load was 100 kN and guided the decision for the selection of the variable fatigue loads.

The specimens were tested under variable amplitude compression-compression (C-C) fatigue in an INSTRON 8802 with up to 250 kN loading capabilities. The load was periodically increased to introduce harsher working conditions. A frequency of 2 Hz and a constant ratio of 10 were used. The extent of the initial damage was measured using a dolphicam, portable phased array camera. Every 500 cycles the fatigue was paused, and quasi-static (QS) loading was performed from the minimum to the maximum absolute fatigue load. The load was arbitrarily increased after a few tens of thousands of cycles.

A variety of 4 different sensor networks was employed to monitor the panels' degradation behavior, namely FBG, distributed FOS, AE, and lamb wave detection system (LWDS). In this work only data from FBG and AE are used for the development of the HIs. Two micro-200HF AE sensors from Physical Acoustics Corporation with an operation frequency range of 500 – 4500 kHz were used, clamped on the skin of the panel. Two optical fibers with 5 FBG each were enclosed in a SMARTape™, provided by SMARTEC Switzerland, and bonded on the stiffener's feet using a co-polyamide based non-permanent adhesive. The spacing between the FBGs was 20 mm and the total monitoring length was 140 mm, focusing mostly in the middle section of the panel. AE recorded constantly over the course of the fatigue experiment, while FBG recorded only during the quasistatic with a measurement rate of 5 Hz via a two channel sm130 dynamic interrogator from Micron Optics.

A representative specimen, with dimensions and sensor locations, as well as initial damage extent and position is shown in Fig. 1. The FBG sensors are depicted by the black bars on the black optical fiber, while the black circles indicate the location of the AE sensors.

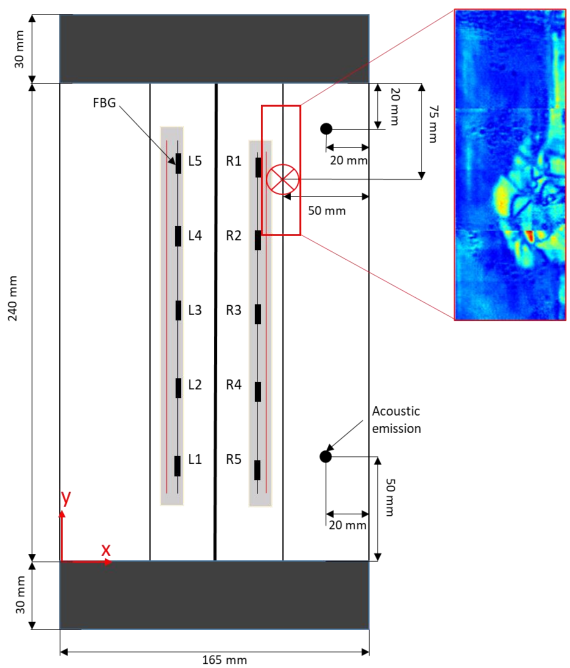

Fig. 1: SSCP geometry, sensor positions and initial impact damage of a representative panel.

IV. Results

A. Data pre-processing

The raw SHM data, especially the strain data, are quite complex and uninformative. Hence, novel data processing methods were used to pre-process the data before constructing the HIs. To both simulate a more realistic data acquisition situation, with unknown loading conditions and measurement sequences and deal with the different loading condition from SSCP to SSCP, the FBG data were processed using a random sampling method. This method samples n random points during the QS and calculates the average of these samples. A uniform sampling method is used. This is also a great tactic to deal with possible missing data. The processed data are then smoothed and used to construct the HIs. Applying this pre-processing, method helps deal with the variable loading conditions, by eliminating increasing load effect, and focusing on the increase of strain due to the accumulation of damage. This method is only applied to the FBG data. For the AE data, a simple cleaning of the data is performed, discarding events occurring during the pauses to change the loads, the PZT measurements, or other uninformative events. Then the Rise Time to Amplitude ratio (RA) is calculated.

The proposed HIs will be displayed for a representative specimen and their behavior will be discussed. In the final subsection, the resulted HIs for all SSCPs will be jointly displayed and discussed for comparative purposes.

B. Strain-based Health Indicators

1) Strain based health indicators: HI_1 and HI_{fused}

Two strain-based pHIs will be introduced in this section. The concept of the first HI was introduced in [24]. HI_1 is slightly altered to suit fatigue experiments and measures the deviation of strain at time t compared to the reference stage. In our case, where the pristine condition and load are unknown, as reference, the first SHM measurement (t=0) is considered. The higher the values of HI_1 the larger the deviation from the reference stage, meaning higher damage accumulation in the specimen. HI_1 is defined in (1):

$$\mathrm{HI}_1^i(\mathrm{t}) = \left| \frac{\varepsilon_{ref}^{(i)} - \varepsilon_t^{(i)}}{\varepsilon_{ref}^{(i)}} \right| \tag{1}$$

Where i=1,...,10 denotes the FBG sensor number and t the operational time. Sensors closer to the damage should display higher values. HI_1 displays increasing values throughout time, capturing the specimen's degradation as shown in Fig. 2-a. Sensor R1, which is closer to the initial damage shows higher initial values, while the rest of the sensors increase gradually over time.

To create an HI more suitable for prognostics a fusion of HI_1 is proposed which fuses the 10 HI instances into 1, with a weighted summation. As weights the monotonicity of each curve is used since a monotonic trend is a desirable attribute in prognostics. The higher the monotonicity the higher the impact of the sensor. $\mathrm{HI}_{\mathrm{fused}}$ is denoted in (2):

$$\mathrm{HI}_{\mathrm{fused}}(\mathrm{t}) = \sqrt{\sum (\mathrm{m}_i \mathrm{HI}_i(\mathrm{t}))^2} \tag{2}$$

The sum is squared and rooted to ensure non-negative values. As expected, a monotonic instance is created with increasing behavior (Fig. 2-b). Creating a single instance of the indicator also provides the ability to compare it more easily to other degradation histories, unlike having 10 different curves for each specimen.

2) Virtual health indicators: Q index

A vHI based on PCA is introduced in this subsection. The HI is Q index, namely the squared sum of residual reconstructed error, and has been previously used in [10]. A PCA model is constructed from a portion of the data $\mathbf{X}_{\mathrm{ref}}$, and the transformation coefficients $\mathbf{P}$ are then used to transform the entire data $\mathbf{X}$ into a new PCA space. Only the vectors $\mathbf{P}_{\mathrm{r}}$ attributing to 90% or more explained variance are kept for the transformation. Q index is explained by (3) .

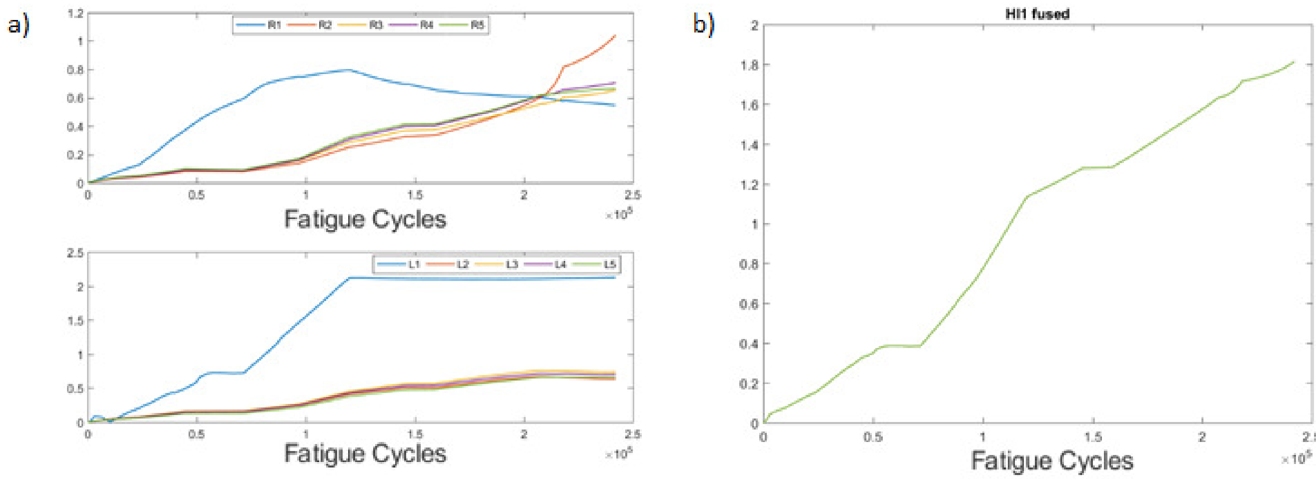

Fig. 2: a) HI_1 vs fatigue cycles for right (top) and left (bottom) foot and b) HI_1 fused vs fatigue cycles.

$$\mathrm{Q(t)} = \sum_{i=1}^{10} (x_i(t) - x_{r_i}(t))^2 \tag{3}$$

Where x_i the original strain data of FBG_i, x_{r_i} are the reconstructed data of FBG_i back from the PC space and t is the operational time. This procedure helps reducing the dimensionality of our data from 10 to 1. Fig. 3 shows the behavior of Q index. A monotonically increasing behavior throughout time is observed, much like the previously proposed HIs, providing a great candidate for a prognostic feature.

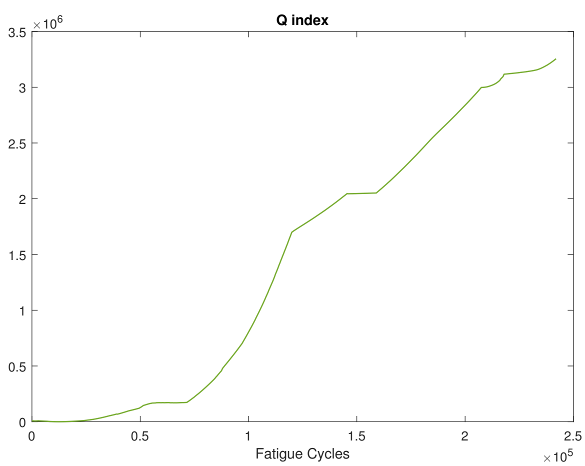

Fig. 3: Q index progression vs fatigue cycles.

C. AE based Health Indicators

A simpler approach is followed to create HIs from the AE data. The easier method would be to use the cumulative features through time as a HI. However, due to the nature of the cumulative sum the HI would constantly increase providing little information regarding the actual degradation. Instead a windowed cumulative sum is used, i.e. the features are summed in time (cycles in our case) windows as in [20]. This provides information on how AE has grown through time in a specific time window. After evaluating a number of windows, a 500-cycle window is proposed firstly because it displays a satisfactory increasing trend and also provides common measurement periods with the FBGs for a possibility of feature level fusion in later works. Two AE features are used, namely Hits and RA, which has been successfully used in prognostics in [20]. The general equation governing the AE based HI is:

$$\mathrm{HI_{AE}(t)} = \sum_{i=t-T}^{t} \mathrm{F(t)} \tag{4}$$

Eq. 4 starts calculating the HI at t>T, F is the AE feature and T denotes the fixed window.

Both windowed cumulative hits and RA (Fig. 4) show a progressively increasing behavior though time. Near the end of life (EOL) the increase is much larger, giving clear indication of the imminence of failure.

D. Discussion and comparisons

In the previous subsections we presented the proposed HIs for a representative specimen. In this subsection, we will show the comparison of the HIs for all specimens tested in the campaign. HI_{fused}, Q index and both AE based HIs are preferred for the visualiztion. HI_1 is not presented since HI_{fused} is proposed as an improvement of HI_1 for a clearer visualization of the degradation as captured by all FBG sensors.

It can be seen that the HIs for all specimens display an increasing trend, highly monotonic and with good trendability. Both HI_{fused} and Q index (Fig. 5-a, b), however, display low prognosability, i.e. the scatter of the failure values is high. In the AE based HIs (Fig. 5-c, d) the prognosability is much better. A common failure threshold can be easily set, with most of the specimens being able to adhere to it. There is still some

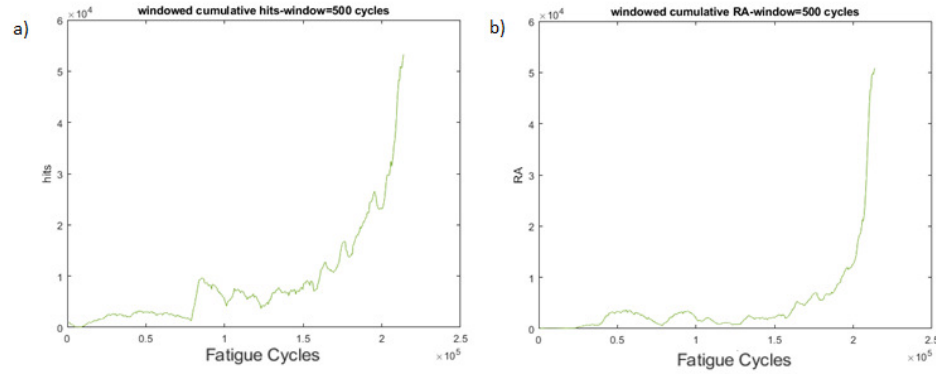

Fig. 4: Windowed cumulative a) hits and b) RA versus fatigue cycles for 500-cycle window.

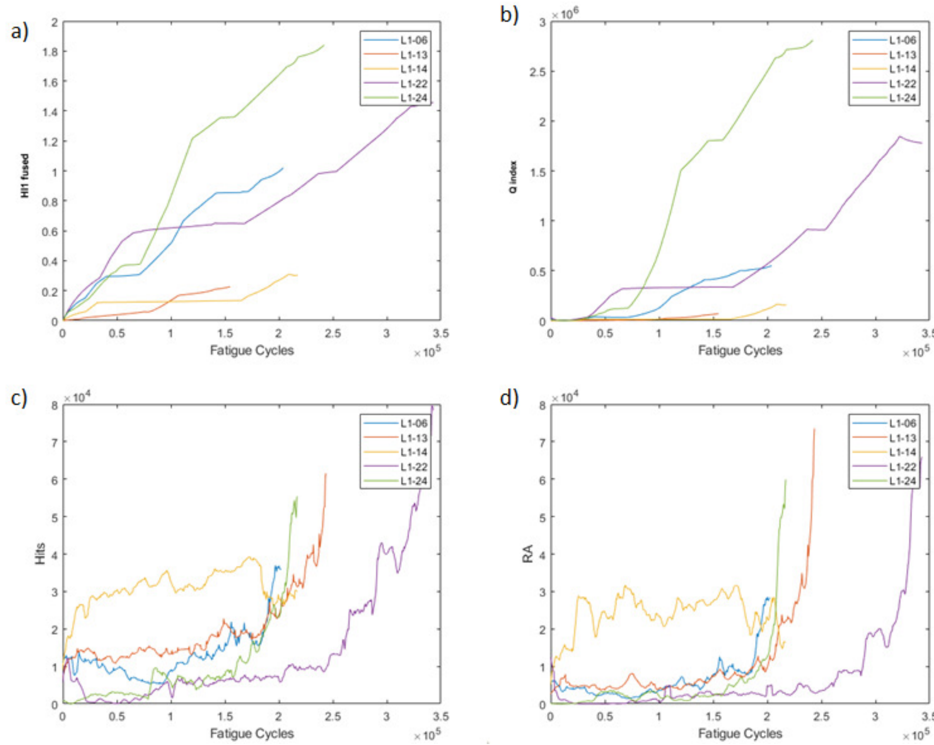

Fig. 5: a) HI_{fused} progression vs fatigue cycles, b) Q progression vs fatigue cycles, c) windowed cumulative hits progression vs fatigue cycles and d) windowed cumulative RA progression vs fatigue cycles.

variation, which sometimes may be useful for a more complete database. Overall, the developed HIs shows great promise as prognostic features.

V. Conclusions

In this work, a novel experimental campaign was conducted. Single stringered composite panels equipped with SHM sensors were subjected to variable amplitude compression-compression fatigue experiments. Health indicators from raw FBG strain data and raw acoustic emission data were proposed in an attempt to find suitable features for diagnostics and prognostics.

Four pHIs, namely HI_1, HI_{fused}, windowed hits and RA, as well as a vHI, namely Q index, were proposed. The HIs display monotonic trends able to successfully capture the degradation of the specimens. They also display high trendability, i.e. showing similar behaviors for all tested specimens. The developed HIs show great promise for use in prognostics, however, their prognosability, especially for the strain based HIs, needs further improvement.

In the future a more in-depth work will be conducted, studying the robustness of these HIs in more specimens and different loading conditions and the enhancement of the prognosability.

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