Accelerated Aging Experiments for Prognostics of Damage Growth in Composite Materials

ABSTRACT

Composite structures are gaining importance in the aerospace industry; however, uncertain structural integrity due to fatigue under continuous usage is a big concern. It is arguably possible to detect precursors of failures as damage progresses and can be used to predict impending failures. Prognostic algorithms require large amounts of training data to build damage model for making useful predictions. One of the key aspects in these data is the trends of damage progression. Since these data are rarely available from actual systems an accelerated aging platform is the next possible resource to collect such data. A fatigue cycling experiment was designed to stress carbon-carbon composite coupons with various layups. Piezoelectric disc sensors were used to periodically interrogate the system. Analysis has shown distinct differences in the signatures of growing failures between data collected at conditions. Periodic X-radiographs were taken to assess the damage ground truth. Results from signal processing shows clear trends of damage growth in these coupons that were correlated to damage assessed from the X-ray images. Results from the analysis are presented in this paper.

INTRODUCTION

Use of carbon based composite materials in aerospace structures is increasing due to their superior properties of strength, stiffness, weight, performance, excellent corrosion resistance, etc. to name a few. A dramatic rise is seen in the application of advanced composite materials for aircraft in the last two decades. Current predictions estimate that over the period of next ten years the manufacturing of composites will quadruple at an increasing usage rate of 7% annually [1]. However, due to lack of dependable Structural Health Monitoring (SHM) techniques these systems are currently overdesigned to avoid failures and hence are less cost-efficient. In the Structural Health Management context, prognostics can be defined as predicting the Remaining Useful Life (RUL) of a structure based on a continuous health monitoring since the inception of a fault to avoid catastrophic failures through advance warnings.

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Augmented with the understanding of damage progression model, condition monitoring data can help generate growth trajectory that the damage is expected to take and provide an estimate of the RUL [1]. Damage growth model may be physics based or derived from historical data, detailed understanding of the intrinsic material properties, structure geometry, loading environment, etc. For composites these factors are not as well understood as for metals. Internal anisotropic structure of composites is significantly more complex to study and any model or theoretical development based on a particular composite material rarely generalizes to other variants. There is a barrage of theoretical models for composite failure but hardly any consensus on a single candidate. Thus for any given material a significant model adjustment and fresh validation is required before one could use these models with confidence.

Prognostics estimates expected RUL of a structure that leads to more informed decisions for future actions such as launch/abort decisions, near term repairs, or maintenance schedules. Data required for studying fault growth and subsequently develop models for prediction algorithms are rarely available from real applications, especially for composites where the applications are relatively new. Therefore, the scientific community relies on customized accelerated ageing experiments to collect detailed run-to-failure data. From prognostics point of view such experiments address several key issues such as (i) allowing collection of relevant failure data in reasonable timeframe, (ii) ability to control various competing stress factors and in-situ measurements for desired parameters, (iv) develop fault growth models and relate model parameters to identified stress factors, and (v) validation of prognostics and SHM methods.

The analysis presented in this paper builds on existing understanding of the fault modes in composites. This paper investigates faults in laminated ply composites. Such structures mainly suffer from two damage types: matrix micro-cracks and inter-laminar delamination. When subject to fatigue loading matrix micro-cracks develop in the matrix through the ply thickness direction, creating high stress concentration at the ply interfaces. As more cracks form, an increased interfacial stress leads to initiation of delamination, which then starts to propagate further. Delamination significantly degrades the strength of the structure and is generally the ultimate cause of failure in composite structures. This implies that the two damage modes co-exist, which should be perceivable from the sensor measurements from the controlled experiments and, therefore, motivates this effort.

Several efforts have characterized composite failures due to fatigue; however, most approaches focused on statistically estimating S-N curves by recording the number of cycles to fail under different loads. i.e. no failure progression data was collected [2]. Many non-destructive inspection techniques are available for hidden damage characterization but most of them require structure disassembly for inspection. SHM, on the other hand, uses a network of sensors attached to the structure that are able to rapidly inspect the structure. Apart from many other techniques active PZT-sensor networks have been shown to be very good for guided Lamb waves based interrogation of composite structures [3, 4]. A review of existing guided Lamb waves techniques for composite structural health monitoring clearly indicates that majority of the research conducted to date has focused on damage localization [4-6]. Also these approaches mostly just refer to damage detection without isolating a particular damage type. Others simulate damages by attaching mass, or drilling a through hole. Some research papers [7, 8] have reported results on the effect of matrix micro-cracks on Lamb wave propagation, in particular how it affects wave velocity, but has not directly quantified matrix micro-cracking density or developed a matrix micro-cracking diagnosis. Other papers look at methods to study delamination effects using lamb waves [6, 9]. Overall, not many efforts are seen on fatigue damaging a coupon with in-situ damage state estimation or looking for signatures of cracks and delamination separately. Therefore in this effort a run-to-failure experiment is used to collect data and analyze growth patterns for damage types typical of laminated sheet composites.

EXPERIMENTAL SETUP

The fatigue cycling experiments serve several objectives– (i) ability to collect run-to-failure data with periodic system health data using health monitoring sensors, (ii) ability to collect ground-truth data for the damage to validate measurement data analysis, (iii) account for variations between samples of same internal structure (layup), and (iv) characterize variations between sample of different internal structures. Three symmetric layup configurations were chosen to account for the effect of ply orientation: *Layup 1*: $[0_2/90_4]$, *Layup 2*: $[0/90_2/45/-45/90]$, and *Layup 3*: $[90_2/45/-45]_2$. Torayca T700G uni-directional carbon-prepreg material was used for 6in x 10in coupons with dogbone geometry and a notch to induce stress concentration. Two six-PZT-sensor SMART Layer® from Acellent Technologies, Inc (Figure 1(a)). were attached to the surface of each sample. This configuration allows six actuators and six sensors to monitor wave propagation through the samples, Figure 1(a) shows one such path from actuator 5 to sensor 8 (path 5→8) that will be used as an example throughout this paper. Strains of about 0.3-0.4% were estimated at the sensor location. Off the shelf data acquisition software and hardware was used to actuate and receive the corresponding signals for the 36 actuator-sensor paths at various actuation frequencies in the range of 150-450 KHz, with an average input voltage of 50 volts and a gain of -20dB. These frequencies were selected so that the fundamental symmetric and anti-symmetric modes can be as distinguishable as possible based on the differences in their phase velocities.

Static failure load (σ_s) was determined through static tests run-to-failure for two or three samples of each layup to determine maximum fatigue load (σ_f) that was set to 75-85% of σ_s. All tests were performed on an MTS machine with a load ratio (R) of approximately 0.14, following ASTM Standards D3039 and D3479 [10, 11]. The fatigue tests followed a sinusoidal load profile at a frequency of 5Hz. The fatigue cycling tests were stopped every 50,000 cycles to collect PZT sensor data for all paths and interrogation frequencies. X-rays of the samples were taken using a dye-penetrant to enhance X-ray absorption. The main goal of this test procedure is to be able to acquire sensor data as a function of damage progression; which is clearly visible from X-ray images Figure 1(c).

DATA ANALYSIS

The approach taken in this effort is to understand the damage progression characteristics through experimental run-to-failure data and seek following goals:

- Understand how faults grow in composites under fatigue environments.
- If multiple failure modes co-exist, then how to isolate and characterize their individual growth characteristics from the monitoring data.
- Identifying relevant Condition Indicators (CIs) from the monitoring data.

- Understand the effects of material geometry, construction, and loading sequences.
- Identify and distinguish between various sources of uncertainty in the experimental set up and incorporate them for more accurate predictions.
- Develop empirical models describing fault growths for prognostic modeling.

CIs or features were extracted from monitoring data and the trends observed thereby were compared to those obtained from assessment of X-rays, which is regarded as measured ground truth. This validates the CIs and also helps identify useful features of damage (area, length, intensity, etc.) in the X-rays. Once a good set of CIs is obtained that correlate well with the damage growth observed from the X-rays, an empirical model can be developed for prognostics. X-ray images were processed to extract damage quantifiers like matrix crack density and delamination area. Visible growth in damage was observed for both fault modes (Figure 1(b)). Delamination area grows significantly with fatigue cycling (Figure 1(c)). Delamination areas were measured and plotted against corresponding cycle index. Number of cracks was counted on the path between a sensor-actuator pair and normalized by path length to obtain the estimate of the crack density. To reduce the uncertainty in the measurements this process was repeated multiple times.

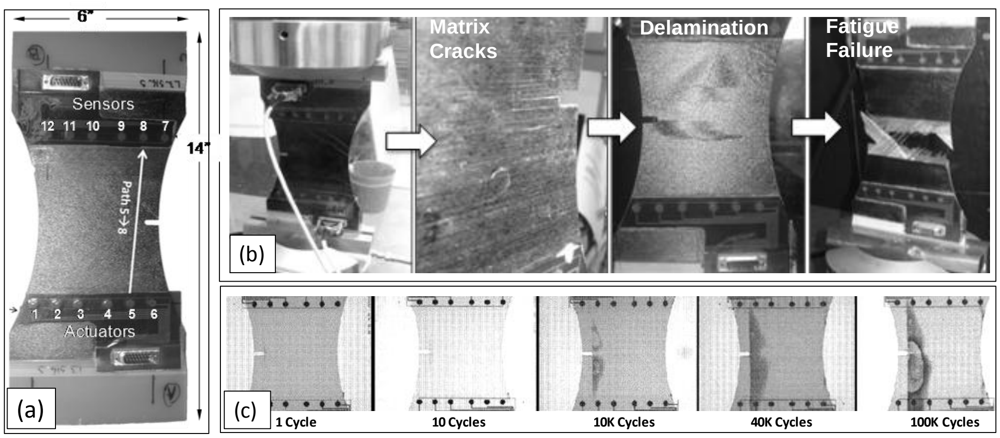

Figure 1(a) Coupon specimen, SMART Layers location, and diagnostic path from actuator 5 to sensor 8. (b) Development of cracks and delamination leading to fatigue failure. (c) Growth in delamination area during the course of fatigue cycling experiment.

Health monitoring data using Lamb wave propagation in pitch-catch configuration was collected from the PZT sensors to see effects of damage growth in the propagated signal. Separate CIs for matrix cracks and delamination were computed to track the growth of both damage types individually. Since the coupons are relatively small, it is hard to distinguish the fundamental anti-symmetric A_0 mode from edge reflections; therefore this work focused only on the fundamental symmetric S_0 mode. In order to distinguish the S_0 mode from the rest of the signal, theoretically calculated group velocity estimates and the known actuator to sensor path lengths were used to approximate an S_0 mode window as shown in Figure 2(a). Following CIs were computed from the windowed signals.

Change in Power Spectral Density - Power Spectral Density (PSD) as a function of time for the actuation frequency was extracted from Short Time Fourier Transform (STFT) for the signal. The peak value within the specified S_0 mode window decreases as a function of the matrix cracks that developed (see Figure 2(b)). Change in the PSD peak value normalized by the baseline PSD peak was computed. This feature, referred to as the ΔPSD throughout this paper, has been shown to correlated well to matrix micro-cracks on any given actuator sensor path [12].

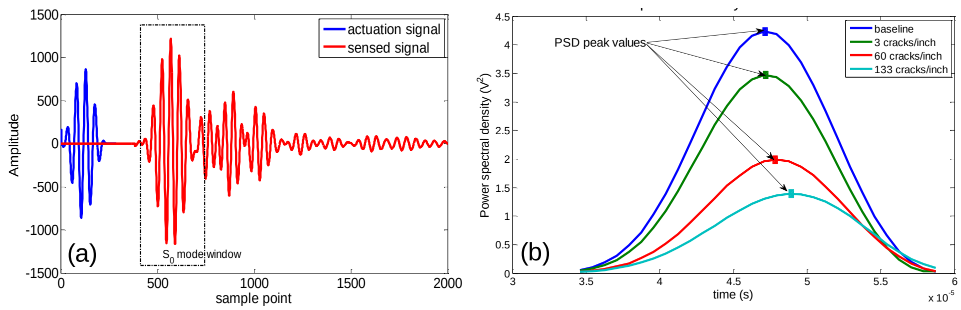

Figure 2(a) Isolating the first S_0 mode by windowing the sensed signal. (b) Change in Power Spectral Density curves with increasing matrix crack density.

Composite Feature for Delamination – It was found that two signal parameters, scatter energy and change in the time of flight (ΔTOF), changes with the delamination growth. Scatter energy is calculated as the difference in the signal energy of first S_0 mode Figure 2(a) in the current signal and the baseline signal (damage free condition) whereas, ΔToF is estimated as the delay in the arrival of the first wave packet. Physically, delamination in the coupons degrades the mechanical properties, which in turn reduces Lamb wave velocity thereby increasing ToF. On the other hand, delamination also scatters the propagating Lamb waves in proportion to its size.

a.) Scatter Energy - It was observed that the scatter energy for L_2 Layup was relatively much higher than the scatter energy for L_3 layup. This can be due to multiple delaminations initiated on different ply interfaces through coupon thickness. Possibly delamination exists between 0/90, 90/45, and -45/90 ply interfaces whereas for L_2 layup the delamination initiation sites are only 0/90 interfaces.

b.) ToF - It was observed that the increase in ToF for L_3 Layup was relatively much higher than that for the L_2 layup. The reason for the higher ToF can be due to mechanical property degradation caused by delamination at 90/45 ply interface and matrix cracking in the outer 90° plies. For L_2 Layup, the increase in ToF is less due to less degradation in mechanical property due to the presence of 0º outer plies.

The trends of these individual parameters, scatter energy and ΔToF, did not match very well with the delamination area growth curves as observed through X-rays for either layups, but a composite signal feature (Scatter Energy x ΔToF) showed matching trends and is proposed for tracking delamination growth in the composite coupons.

RESULTS AND ANALYSIS

As shown in Figure 3, several comparisons can be drawn. First, the samples of the same layup type are compared. As shown in Figure 3 (a) and (b) delamination feature shows good correlations to the trends observed in the X-rays for L2 layups (L2S17 & L2S20). Likewise for L3 layups (L3S18 & L3S20) these trends look repeatable, for instance an increase in load at 600 cycle for L3S20 results in increased delamination area, which is also reflected in the corresponding feature. However, the magnitude of the delamination features does not correspond to same levels for the two layups, i.e. for very different magnitudes of delamination area the feature shows similar values.

These differences in the trend of the feature and delamination area curves could be due to several following reasons that require further investigation: (i) difference in layup types, (L2:$[0/90_2/+45/-45/90]_2$ vs. L3:$[90_2/+45/-45]_{2s}$) and hence effect of delamination geometry and orientation on sensor signals, (ii) discrepancies in the delamination area measurement from the conventional X-ray images, especially if the delamination appears on different interfaces which is not detectable from X-rays but still affects the signal significantly. Therefore, the layup type should be an important factor in interpreting the results and a good repeatability within a single layup type is desirable. Similarly, one can see from Figure 3(c) that the matrix crack density grows very quickly initially and then flattens out for both layup types. The cracks grow rapidly again when the loads are ramped up, e.g from 6 to 7 kips for L3S20 at cycle 450K and corresponding gains are visible from the ΔPSD feature in Figure 3(d). The differences between the two different layup types can be observed but also the repeatability between the same layup types.

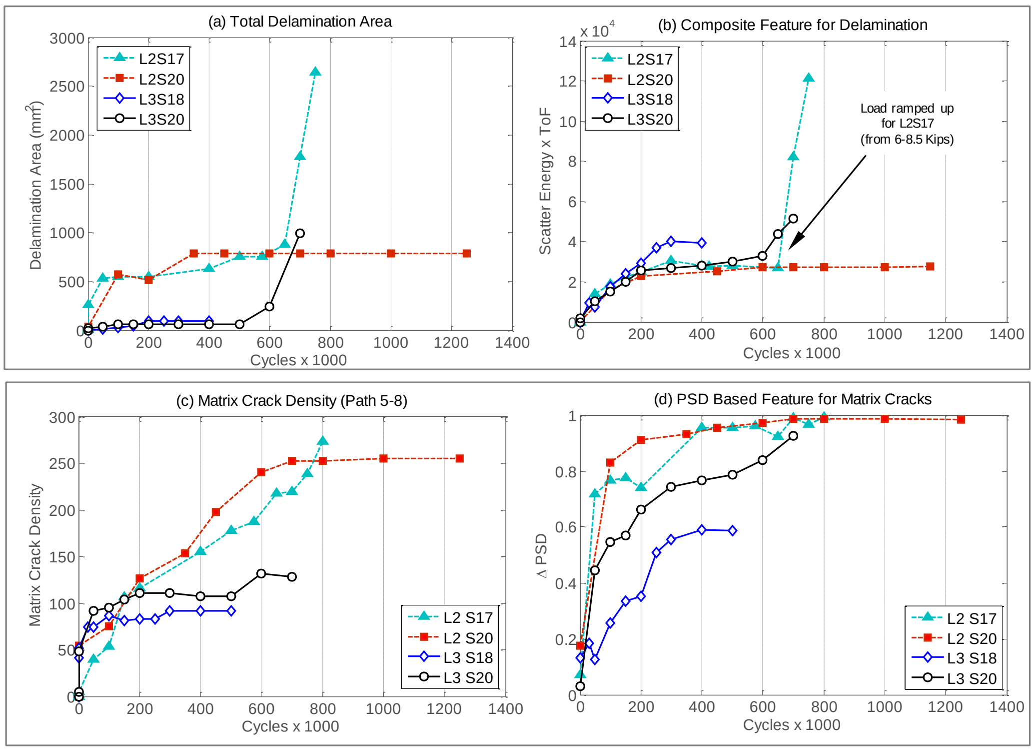

Figure 3. (a) Delamination area as observed from X-ray and (b) corresponding condition indicator from measurement data. (c) Matrix Crack density from X-ray and (c) corresponding condition indicator.

There were several limitations in the experimental setup that posed technical challenges leading to various uncertainties in the process and are expected to have contributed to some of the differences that were observed above. It is important to consider these sources of uncertainty while interpreting the results from data analysis therefore, we present here some such aspects that have been identified and are currently under investigation.

X-Ray analysis – (1) The X-ray machine used in this project was analog and resulted in non-uniform digitization leading to variance in contrasts, brightness, scaling, and orientations leading to some uncertainty in ground truth estimation despite calibration steps. (2) X-ray images cannot pinpoint the exact ply interface where the delamination is present. Therefore a single delaminated layer shows same features in the image as for multiple delaminated layers. (3) Matrix crack counting process is a manual process and prone to errors. (4) Cracks appear in different orientations in different layups, and manual counting results in more uncertainties.

Data Collection Setup – (1) Due to high-strain fatigue test wiring connections, and the adhesive all degrade with fatigue cycling limiting our ability to collect high quality fatigue data towards the end of the tests [13, 14]. (2) Since the experiments required the samples to be taken out of the MTS for measurements, re-loading of sample resulted in slight changes in orientation of the coupon that may affect the fault growth as tensile axis changes with orientation. (3) Dye penetrant when wet significantly affected the signal. (4) Manufacturing variability between coupons of the same type also leads to different damage trajectories. (5) Determining optimal load such that coupons break in a reasonable timeframe has been a challenge. Data on single load levels is not yet available.

Prognostic Algorithm Development

Prognostic algorithm development can take various approaches that may be data-driven or model based. Data-driven approaches learn current damage estimate from condition indicators and damage growth rates from load factors, which then are used to extrapolate the damage to a preset damage threshold to compute estimated RUL. Model based methods make use of a damage progression model instead and extend the current damage estimate through the use of those models. It was determined that so far the collected data is not sufficient to train these models. But with more experiments planned two individual models for delamination growth and matrix crack density growth will be developed. These models will be used to estimate growth of both damages and then combined to produce a common end-of-life estimate through a recursive Bayesian filtering methods like Particle Filters (PF). PFs have been shown to represent and manage the uncertainty in the prediction process through Importance Sampling, thereby refining the current estimates of multiple damage growth model predictions using evidence from measurement data [15]. Furthermore, a data-driven Gaussian Process Regression approach will also be explored. GPR is a probabilistic technique for nonlinear regression that computes posterior degradation estimates by constraining the prior distribution to fit the available training data [16]. It provides variance around its mean predictions to describe associated uncertainty in the predictions, which will be extremely useful in incorporating the effect of various uncertainties listed above in RUL predictions.

CONCLUSIONS & FUTURE WORK

It was shown in this paper that it is possible to extract separate damage growth indicators that will be useful for prognostic model development. These indicators were compared to the observations from X-ray images and positive correlations were shown to be found. However the authors would like to conduct more experiments to establish statistical significance of these results. It is also planned to use strain gage rosettes at multiple locations to collect additional data in further tests. That will provide additional information about the strain levels during the fatigue tests and help refine data analysis and interpretation. Data analysis, model development, and algorithm work will continue to carry out damage prognosis on composite structures.

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