Development of data mining based prognostic models for condition monitoring of carbon fibre coupons

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1. PROBLEM

In the presence of aging aircraft fleets, there is a desire among the aerospace industry to reduce costs associated with the maintenance of airframes. In this respect, there is an increasing need for Structural Health Monitoring (SHM). The focus of SHM is to perform *in-situ* and continuous on-line monitoring of aircraft structural components. Currently, many researchers are developing SHM systems for aircraft structural components using small ultrasonic lead-zirconate-titanate (PZT) transducers. These transducers are ideal for monitoring of aircraft structural components due to their compact size and low power consumption needs and also with more recent wireless sensor advances continuous in service monitoring using these transducers is possible.

On top of aging aircraft fleets, airframe manufacturers are increasingly depending on the strong use of composites in airframe fabrication due to their phenomenal strength to weight ratios leading to high fuel economy savings. Although there are many advantages to using composite materials as opposed to aluminum for aircraft fabrication, their behavioral characteristics are less understood. Inspection of composite materials is thus required more regularly. With detection and localization of airframe failures using PZT transducers in SHM, further possibilities in maintenance cost and down-time minimization can be conceived. This means that in the presence of damage, decision support systems can be employed to supplement a built-in intelligence which is currently lacking from SHM systems at least in civil transport. The decisions of the system can then be evaluated by fleet managers and maintenance personnel and further action can be pursued. Sweeping benefits of such an advanced SHM system can be observed especially with composite airframes where maintenance and inspection intervals can be reduced.

2. EXPECTED CONTRIBUTION

The objective of this work is to provide decision support to ultrasonic SHM systems that use PZT transducers for monitoring of composite airframes. In order to satisfy this requirement, this problem can divided into three separate tasks.

Currently, there are no commercial SHM systems on-board aircraft. Without the existence of pre-gathered data, training and testing data sets are required prior to the development of predictive models. These datasets are built using input data gathered from a number of observations in a dataset defined by a set of parameters useful for prediction. The first contribution to this work therefore involves defining a robust data gathering methodology. Obtaining a thorough knowledge of ASTM standards with respect to both fabricating aerospace grade carbon fibre composite coupons and inducing damage into these specimens is therefore important. Prior to inducing damages, a list of parameters or significant metrics needs to be defined based on what data can be gathered and the probability that tendencies could be extracted from these data parameters which would be useful in prognostics.

The second task focuses on the SHM system itself. Much of the research in PZT transducer technology for damage detection and localization is performed on already damaged specimens. In the presence of impacts, the adhesive interface between the PZT transducer and composite coupon degrades completely and the transducers de-bond thus complicating the data gathering process. Therefore, the second contribution relevant to the data gathering methodology investigates the use of a variety of adhesives that would survive common impacts thought to be experienced by aircraft. Not only can reliable data be gathered but also, damage to the SHM system and the structure itself can be distinguished. Acquired signals can then be adjusted to compensate the Remaining Useful Life (RUL) estimates determined by the machine learning algorithms that have been biased due to a damaged SHM system.

Finally, in the third task the data gathered from the two previous contributions is analyzed using machine learning algorithms to determine 1) How early premature damage can be detected? and 2) How accurately the RUL following premature damage detection can be predicted

3. PROPOSED PLAN

The approach is demonstrated on ASTM carbon fibre composite coupons under drop-weight impact loading. This strategy controls through standardization the types of induced damages and assures realistic aircraft operating conditions in a simulated environment. The coupons will be instrumented with two 5mm PZT transducers in a pitch-catch configuration. In this configuration, one transducer (T_x) will transmit an ultrasonic guided wave packet into the composite specimen through the damage site. The other transducer (R_x) will receive the transmitted wave packet.

3.1 Parameter Identification

Through analysis of the transfer function between the two transducers a series of parameters can be extracted. Variations in the time-of-flight (ToF) and amplitude of the injected wave packet when compared prior to and following impact can reveal trends with increasing damage. A Normalized Least Mean Squared (NLMS) adaptive filter can be derived from the wave packet signal. The error of the adaptive filter coefficients will increase linearly with increasing damage if the coefficients are kept constant. Using "dispersion" a phenomenon that exists when injecting guided wave packets into materials where the frequency components that compose a wave packet do not all travel at the same velocities, dispersion indexes can be calculated for specific materials. These indices can change with damage initiation and these changes may be significant in machine learning. Parameters relating to the impact system can also be considered such as impact energy, and damage depth and area that change with increasing damage.

3.2 Prognostic Model Development

With a defined set of parameters, a series of repetitive experiments submitting several carbon fibre composite specimens to impact loading will be performed. The impact loading configurations may alternate between constant repetitive cyclic loads or increasingly larger damage loads to determine which type of loading is better for machine learning. With each impact, the identified parameters will be recorded in a database. Following experiments, the data will be analyzed for prognostics. Prior to data analysis using machine learning algorithms, changes to the gathered signals ($\Delta s(t)_n$, n=1,2,3,…) influenced by SHM system damage will be corrected. One of the key ideas in this work is to separate damage observed due to degradation of the SHM system piezo-electric transducers ($\Delta i_n^p(t)$) and damage observed due to degradation of the structure ($\Delta i_n^s(t)$). Damage to the SHM system will surely affect the RUL estimate of the prognostics system and may lead to premature inspection interval estimates thus yielding inaccuracies. One such parameter for separating these two systems is derived from electrical admittance measurements (ΔZ) on the transducers prior to and following impacts. This methodology will act as a preconditioning to the signals entering the machine learning system and follows equations 1 and 2.

$$\Delta s(t) = \Delta i_n^p(t) + \Delta i_n^s(t) \tag{1}$$

$$\Delta i_n^s(t) = \Delta s(t) - f^{-1}(\Delta Z) \quad \text{where } \Delta Z = f\left(\Delta i_n^p(t)\right) \tag{2}$$

After preconditioning the signals, the process for analyzing the gathered raw data is as follows. Further conditioning of the still raw signals via feature generation tools to calculate averages, means, mediums, standard deviations, variances, and quantization levels may be required to reveal trending in the data. Data clustering and filtering will then be performed to group similar instances that show similar trends in the presence of damage. The final dataset will be a collection of these similar instances and will be analyzed using a series of classifiers including binary, SMO regression, decisions trees, and random forests for a statistical calculation of the RUL.

4. CONCLUSION

This work emphasizes the deep integration of machine learning with research in PZT transducer technology. A robust data gathering methodology that feasibly simulates realistic flight conditions will be defined based on existing ASTM standards such that a valid parameter set can be collected and used with machine learning algorithms to estimate the RUL for carbon fibre composite specimens in damage conditions and improve PZT SHM systems.

Park, G., Farrar, C. R., Lanza di Scalea, F., Coccia, S. (2006). Performance Assessment and Validation of Piezoelectric Active-sensors in Structural Health Monitoring, *Smart Materials and Structures*, vol. 15 (6), pp. 1673-1683.

Quaegebeur, N., Masson, P., Langlois-Demers, D., Micheau, P. (2011). Dispersion-based Imaging for Structural Health Monitoring using Sparse and Compact Arrays, *Smart Materials and Structures*, vol. 20 (2), pp. 1-12.