Fusion and Decision Making Techniques for Structural Prognostic Health Management [1,2]

数据融合和自动决策技术

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Abstract—There is a growing interest in fusing the wealth of data generated by aircraft sensors and airborne systems into prognostic information and automated decisions that lead to significant improvements in aircraft Management, Affordability, Availability, Airworthiness and Performance (MAAAP). Over the past five years, Smiths and BAE SYSTEMS have launched collaborative work to evolve a certifiable practical system that addresses this interest. The collaborative work has built on the BAE SYSTEMS vast advanced technology experiences and on the Smiths unique experience that has produced prognostic and decision support algorithms combining model-based and Artificial Intelligence (AI) techniques. This paper reports on certifiable techniques that fuse flight data into prognostic information. The techniques were blind tested on legacy data covering 15 years of military operations. The paper presents a fusion/decision support technique targeted at identifying sensor/system faults. The paper also presents preliminary collaborative work on a structural damage detection technology where AI and fusion methods have been used to mitigate technology risks.

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1. INTRODUCTION

Over the past five years, Smiths and BAE SYSTEMS have launched collaborative work to evolve a certifiable, affordable Structural Prognostic Health Management (SPHM) system. The collaborative work has built on the BAE SYSTEMS vast experience of operational load monitoring and on the experience of Smiths over the past 20 years that has produced affordable Flight and Usage Management System (FUMS™) technologies, e.g. [1] to [3].

Supported by the UK Ministry of Defence (MOD), FUMS™ has been evolving as an affordable Prognostic Health Management (PHM) tool. Affordability would be achieved through a stepped approach; at each step, the MOD users would benefit from some of the system capabilities. Each capability would be evaluated, tested and substantiated with the user. A capability that would successfully address a user need would be introduced in-

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service whilst maturing other capabilities, e.g. [4]. Affordability is also achieved by fusing available aircraft flight data into component loads, fatigue and other prognostic information and, hence, eliminating the need to directly measure these loads by strain gauges or other sensors that require high production and operational costs.

The main objectives of the Smiths and BAE SYSTEMS collaborative work included the following:

- Demonstrate the feasibility of using FUMS™ technologies for OLM and lifing to support the development of SPHM for modern aircraft.
- Demonstrate that sufficient configuration efforts of Smiths' models would eliminate concerns about FUMS™ technology risks.
- Demonstrate that the FUMS™ prediction methods can be qualified.

In order to address these objectives, legacy data were used to configure, optimise and test FUMS™ tools including the Mathematical Networks (MNs) that fuse flight data into prognostic information. The legacy data covered 2440 sorties, 4 aircraft, 4 configurations and a wide range of operations that spanned 15 years. Data covering 226 sorties of a modern aircraft were also used. The Smiths FUMS™ tools included data quality algorithms, MNs, rare event models, usage indices, signal processing tools, Artificial Intelligence (AI) tools and force life management software that enabled an efficient application of these tools on large datasets.

This paper briefly describes the Smiths tools and reports on some of the FUMS™ techniques that fuse flight data into loads and fatigue information. The paper describes in more details the blind tests of the most powerful FUMS™ fusion tools (the MNs), which were severely tested on legacy data covering 15 years of military operations.

2. The FUMS™ Tools

Data Quality Algorithms—The Smiths Automatic Data Correction (ADC) algorithm identified short period corruptions in flight data and strain measurements of three legacy systems. The identified short period corruptions were classified as spikes, multi spikes, spike-step transitions, steps, hesitant steps, step reversals, dropouts, DC signals, complex corruptions and jumps, **Figure 1**.

For a modern military aircraft application, BAE SYSTEMS requirements necessitated ADC reconfiguration, optimisation and revalidation to support airborne implementations. Revalidating the algorithm involved extensive testing using the legacy data to ensure the correctness of the reconfiguration/optimisation processes. Smiths reported the logic of the ADC algorithm in terms of inputs, outputs, configuration tables, functionality and descriptions of core processes. A code was also supplied to BAE SYSTEMS to allow rapid airborne implementation. The code was tested on data covering thousands of sorties.

The Smiths data quality algorithms identified long period corruptions caused by temporarily or persistently inoperative sensors and calibration problems. For a target sensor, long period corruption was identified by comparing the statistics of the sensor data across a number of sorties, and by cross correlating its data with other sensor data and/or with synthetic data generated by mathematical networks. The statistics of the sensor data were computed over the entire sortie, over its most probable data levels and at a number of predefined flight conditions referred to as 'hypercubes' or 'points in the sky'. A decision making process was implemented to fuse sensor health indicators derived from the above statistics. Generally, the decision making process could use logic, Bayesian belief networks, and/or fuzzy logic to fuse the derived heath indicators and increase the detection probability of sensor failures [4]. Examples of observed strain corruptions are shown in **Figure 2**.

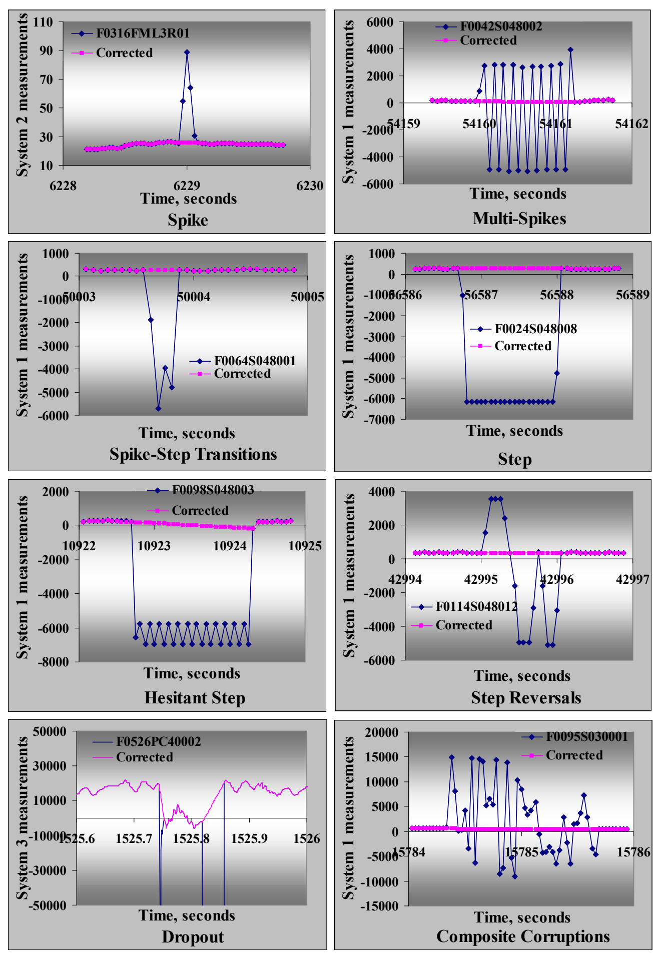

Figure 1 – Examples of Short Period Corruptions

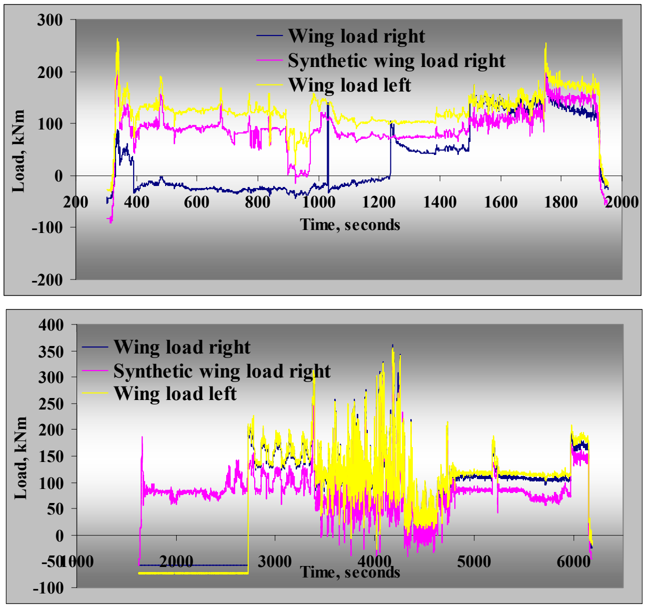

Figure 2 – Examples of Long Period Corruptions

The Smiths data quality algorithms identified, as if it was blindly tested, several shifts in legacy-measured strains and estimated the dates of shifts. They identified changes in calibration factors required to compute loads from measured strains and changes in equation coefficients required to compute stresses from loads. At a later stage, BAE SYSTEMS endorsed the results of the data quality algorithms: for example, the changes in the equation coefficients had been introduced in sympathy with structural modifications.

For the legacy data, it was found that under the same loading conditions, the measured strains varied by more than ±10% around mid strain values over the 15 years; e.g. the strain-truth margins (errors) were wider than ±10%. Nevertheless, a decision was made to use the legacy data. It turned out that using the data in their raw format provided Smiths and BAE SYSTEMS with challenging real life environments, which blind tested the Smiths data quality algorithms, highlighted the problems that could face SPHM systems, and consequently, enabled the development of realistic qualification guidelines for prediction methods. It is worth noting that the results of the Smiths models presented in this paper could have been much better if the models had been calibrated using data with narrow truth margins.

The strain truth margins were determined by defining several hypercubes to identify ground operations and airborne flight conditions over which similar loading conditions could be assumed. The results of the hypercube analyses were fused with other statistics to confirm the wide strain truth margins. For example, **Figure 3** shows ground load averages over calibration periods. The figure indicated the practical difficulties facing electrical calibration procedures that might not bring the strain responses to the same level under the same ground loading conditions.

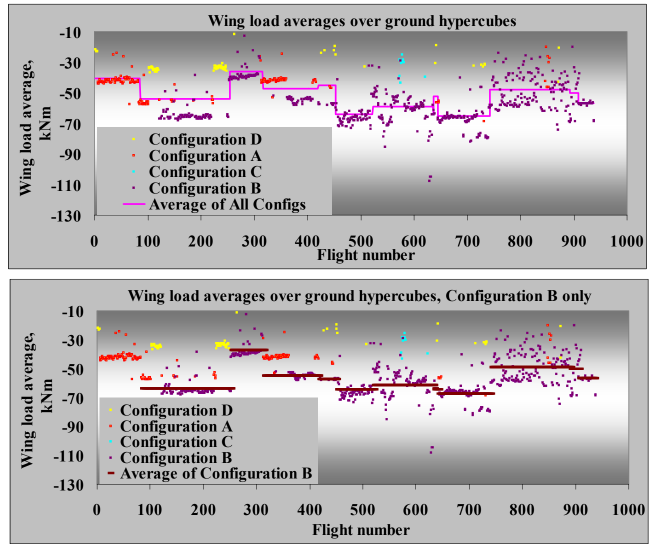

Figure 3 – Strain-Truth Seen by Ground Load Averages

The strain gauge data corruptions observed in legacy aircraft data could have occurred for a variety of reasons. Short term failures in power supplies can cause sudden drops in strain measurements to values close to zero. The strain voltage levels are usually very small (millivolts), and, therefore, the strain signals are amplified hundreds of times (e.g. 200 times). The signal amplifiers can suffer failures leading to intermittent gain changes and signal corruption. Whilst the strain system cables are screened to prevent electromagnetic interference, operating in high radio fields can cause signal corruption, especially for aging strain gauge systems. Dry joints and soldering that fails to achieve perfect contacts can cause erratic strain behaviour characterised by the signals being stuck at a wrong strain levels for a period of time. Changes in resistance due to ingress of moisture can cause corruption. Failures in temperature compensation mechanisms can lead to sensitivity to local temperature changes and signal drifts. Strain gauge sensitivity can be influenced by changes in bonding characteristics. Errors can also occur during strain signals multiplexing, synchronisation and recording. The corruption patterns of a strain gauge system are influenced by the system maintenance status; they can vary with time and can be at variance with those of other systems [5].

Therefore, the truth as seen by strain gauges is not absolute and perfect. The accuracy and the resolution of strain measurements must be assessed to determine strain-truth margins. The strain-truth margins should encompass the accumulative effect of variability factors such as placement/orientation precision, bonding, age, environments (sand, temperature, humidity) along with inherent characteristics such as measurement accuracy, resolution and drift that cause scatter in strain measurements for the same loading conditions. The strain-truth margins of an exposed strain gauge are expected to be wider than those of an embedded one. The strain variability is expected to increase close to moving parts and control surfaces, especially for lightly loaded conditions where the structure can be more sensitive to factors such as vibration induced by engines and preloading conditions, which add to the noise and increase the noise to signal ratio without any significant effects on structural integrity. The strain-truth margins depend on the data quality and the magnitude of scatter in strain gauge data.

The literature has supported the above conclusions and indicated that the strain-truth margin can be very wide. For example, during fatigue tests performed recently in Canada [6], it was observed that the strain scatter was much more than expected and the same load values produced different strains because of, for example, strain hysteresis, drift and strain gauge fatigue. Difficulties in developing a reliable strain calibration procedure have been encountered because similar gauges placed at nominally identical locations on different airframes could produce varying responses to nominally identical loads due to slight differences in airframe build quality, slight gauge alignment differences and variations in gauge factors or sensitivities [7]. For example, ground based calibration of F/A 18 vertical tail strains performed to validate analytical calibration approaches indicated up to 40% variations from one aircraft to another [8]; differences up to 35% in CF-188 wing root strains were also observed [9]. Responses of a strain gauge to a specific load could drift and vary over time. For example, the responses of an F/A 18 wing root strain gauge to a reference bending moment was found to increase with time and, eventually, reach a constant value [8], this drift was attributed to 'migration and wear of bushing within the lug'. 耳片衬套的移动和磨损

The above discussions and results suggested that strain gauge SPHM systems would not provide significant improvement in aircraft MAAAP for a number of reasons: The costs of fitting strain gauge systems in each aircraft and maintaining/operating them are very high and would not satisfy the affordability requirement. Failures of strain gauge systems would result in reduced availability or loss of load/fatigue data. The loss of data is likely to occur when the operational demands are high (e.g., during war) and when the fatigue monitoring is most needed because of the possibility of aggressive usage. Maintaining the system accuracy would require regular expensive calibration exercises. The operational accuracy of strain gauges suffers from the accumulative effects of factors such as placement/orientation precision, bonding, age, environments (sand, temperature, humidity) along with the inherent accuracy and resolution of the sensors. It may be argued that the strain error will move from positive to negative values during the lifetime of a component and, hence, the net effect on fatigue will be small. This argument implies that the strain system will be repaired/calibrated several times during the lifetime of the monitored component, which is undesirable. Furthermore, the impact of strain error on fleet management is unfavourable: When the error is positive, some of the normal flying practices and aircraft operations would appear to consume fatigue at a rate higher than normal and, consequently, fleet managers might discourage certain pilots or mission types. When the error is negative damaging flying practice and manoeuvres would appear to be undamaging leading to unfavourable impact on airworthiness. 阐述直接法的缺点，最终采用间接法

Therefore, Smiths and BAE SYSTEMS launched their collaborative work to accelerate the advent of a parametric SPHM where available flight data can be fused to produce load and fatigue information.

Mathematical Networks—The capabilities of mathematical networks combining model-based analysis, AI, knowledge extracted from measured data and engineering experience were demonstrated. Throughout the demonstration stages, the mathematical networks successfully predicted strains, stresses and fatigue by fusing flight parameters. Strains/stresses computed from flight parameters would allow health assessments to be made using a safe-life approach (fatigue) or a damage-tolerant approach (crack characteristics) without the need for dedicated strain gauges.

For an initial demonstration, data covering three aeroplanes were used to configure and blind test generic MNs that could compute stresses and fatigue from flight data for 4 configurations (referred to as Configurations A, B, C and D). The data covered 51 sorties spanning about 7 years. The flight data were cleaned using the Smiths ADC algorithm before using them. 数据清洗 The stresses/fatigue were computed at four locations chosen by BAE SYSTEMS: a fuselage duct referred to as 'Wing 1', a fuselage frame referred to 'Wing 2', a taileron spigot attachment lug referred to as 'Taileron' and a fin centre attachment bracket referred to as 'Fin'. Less than 503,000 training data records were selected from a total of 7,994,648 clean records to provide adequate coverage of flown flight envelopes and aircraft configurations.

The Wing 1 MN was tested on 7,838,867 records covering 46 flights. The test results indicated a 2.87% average error and a 0.996 correlation coefficient between measured and synthetic stresses. The MN synthetic fatigue agreed well with the fatigue calculated from strain gauge data; at the end of the 46 sorties, the error in the synthetic fatigue was less than 1.0%. The Wing 2 MN was tested on the 7,838,867 records. The test results indicated a 6.08% average error and a 0.995 correlation coefficient between measured and synthetic stresses. The MN synthetic fatigue agreed extremely well with the fatigue calculated from strain gauge data; at the end of the 46 sorties, the error in fatigue was less than 0.3%. The Taileron MN was tested on the 6,637,646 records covering 40 flights. The test results indicated a 3.11% average error and a 0.989 correlation coefficient between measured and synthetic stresses. The MN synthetic fatigue agreed well with the fatigue calculated from strain gauge data; at the end of the 40 sorties, the error in the synthetic fatigue was less than 0.41%. The Fin MN was tested on 7,994,648 records covering 48 sorties. The test results indicated average error in fin synthetic stresses higher than those of the other MNs, however, the synthetic fatigue of the Fin MN agreed with the fatigue calculated from strain gauge data; at the end of the 48 sorties, the error in the synthetic fatigue was less than 0.55%. **Figure 4** and **Figure 5** show samples of the MN good results.

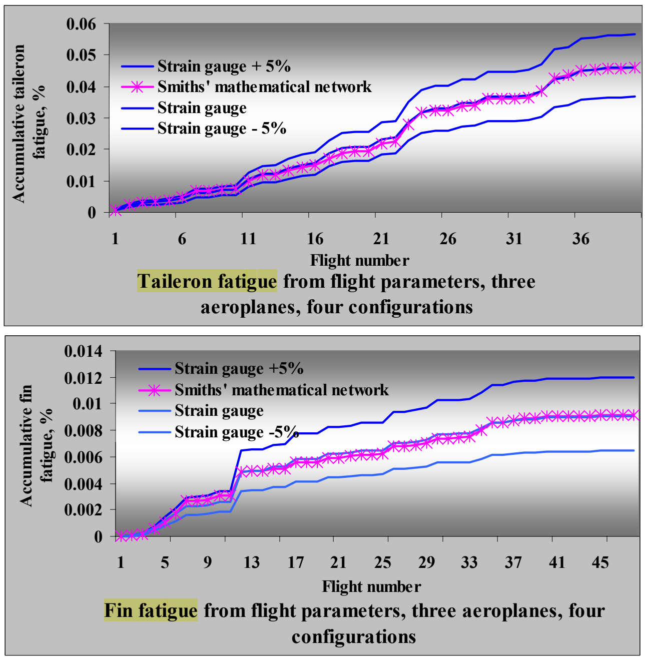

Figure 4 – Fatigue Computed by Fusing Flight Parameters

Thus, it was demonstrated that a 0.995 correlation coefficient between measured and MN strains could be achieved. Nevertheless, Smiths also demonstrated that for any parametric model, no matter how sophisticated, this correlation could deteriorate well below 0.995 during rare events such as turbulence, hard landings, buffeting, foreign object strikes and on-ground low-velocity impact caused by runway debris. Therefore, Smiths proposed the use of their rare event models to improve the prediction capability of parametric models during rare events.

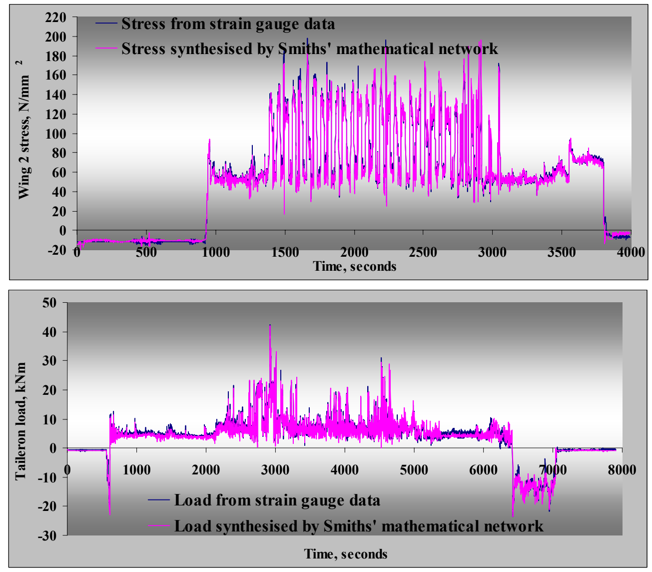

Figure 5 – Loads Computed by Fusing Flight Parameters

Rare Event Models—The Smiths rare event models would condense finite element and modal structural analysis into model-based equations that could be incorporated within mathematical networks to improve their predictions during dynamic events. Smiths demonstrated that a wide range of dynamic events could be identified from measured flight parameters and that their high frequency effects could be simulated from flight parameters sampled at low rates. This concept was demonstrated for the fin, which could suffer from high frequency damaging buffet loads [3].

Usage Indices (UIs)—The concept of UIs was proposed and implemented by Smiths to provide concise summaries of recorded flight data and, at the same time, indicate the impact of usage on component condition and life. It was demonstrated that the fatigue of engine and structural components could be accurately computed from UIs. The UIs could also summarise sensor data, strain data, vibration data and any data derived from measured flight data, and thus, provide further prognostic information that could be used to evaluate the condition/life of additional aircraft subsystems including electronic equipment. The UIs provide a high data compression ratio without a significant loss of aircraft condition/life information. Using UIs to summarise 1000 flight parameters, whether sampled at 1 or 10,000 samples/second over 1000 flights regardless of the duration of flights, would only require about 20 megabytes of airborne storage. Thus, the airborne system could carry the history of the aircraft. Storing UIs could have allowed UK and US military operators to review the thousands of sorties of the Iraq War in seconds. Storing the aircraft history in a concise UIs format would provide operational, management and safety benefits. For example, if improved damage computation methods or new knowledge from fatigue tests would emerge, cost-effective retro computations would be possible for each individual aircraft without the need for a large amount of historical flight data.

By simple data mining techniques, prognostic relationships could be derived to link aircraft usage patterns to equipment failures, unscheduled maintenance and operational arisings; see for example [4].

Intelligent Management Software—The FUMS™ software was demonstrated using legacy data. The software has been designed for efficient automatic analysis, fusion and mining of huge sets of aircraft data from different sources and to support openness and rapid configuration of diverse applications by the user. FUMS™ software can integrate with military/Design Authority (DA) logistic systems. It can provide retrofit and future management and prognostic applications. FUMS™ can support a range of platforms in a similar 'look and feel' software environment. The platforms considered to date include: Chinook, Apache, Tornado, Harrier and Typhoon. FUMS™ applications that have been demonstrated at TRL 6/7 include: a flight data tool to aid maintenance at first line, a usage tool allowing comparisons between individual aircraft usage and design/intended usage spectra, and a health indicator management tool that would handle health records downloaded from aircraft systems and provide a powerful fleet management capability. The FUMS™ tools also include the data integrity algorithms and structural models described above in addition to damage models and a suite of statistical, signal processing and AI tools, which could be configured to provide powerful force life management applications. FUMS™ tools have been configured to automatically check the adequacy and quality of flight data. Data coverage and data quality tools would be key affordability enablers that would mitigate schedule risks and allow quick analysis of huge volumes of flight test data; see for example [4].

3. Mitigating Technology Risks

Three concerns/questions regarding the Smiths models were addressed:

1. Would the models work for challenging components such as the fin?
2. Would a single model work across different aircraft, various configurations and a wide range of military operations? This concern was raised since the previous demonstrations were based on a limited number of flights.
3. How could the models be qualified?

Addressing Concern 1—In order to address the first concern, data from a modern aircraft was used to configure a fin rare event model. A mathematical network combined with the rare event model was trained to predict fin strains at 256 samples/second from flight parameters sampled at 16 samples/second. By applying the trained mathematical network alone on flight data from 26 sorties, the accumulative fatigue was underestimated by 48%; the combined models reduced the accumulative fatigue error to 5.7%, which was much less than the fatigue error produced by strain gauges with 2% strain error [1].

Addressing Concern 2 Through True Blind Tests—The second concern was addressed through true blind tests. The Smiths models were trained (calibrated) using real life strain data that contained shifts/anomalies from 3 operational aeroplanes flown in 4 configurations. The training data supplied by BAE SYSTEMS included strains, loads, stresses, flight parameters, aircraft configuration information and fatigue damages for each sortie. The models were calibrated for 4 structural locations chosen by BAE SYSTEMS: 2 fuselage locations called Wing 1 and Wing 2, a fin location called Fin and a taileron location called Taileron. After calibrating the models, BAE SYSTEMS supplied flight data covering 4 configurations and 15 years of operations of another aircraft. BAE SYSTEMS only provided flight parameters and did not supply fatigue information. Smiths applied their calibrated models to the supplied flight parameters and blindly predicted fatigue. After sending the blind test results to BAE SYSTEMS, the fatigue values computed from strains were supplied by BAE SYSTEMS to be compared with the true blind test results.

For the MNs, the differences from the BAE SYSTEMS accumulative fatigue after 15 years were found to be 3.16%, -2.71% and 0.86% for Wing 1, Wing 2 and Fin respectively. For these three airframe locations, the network accuracies were better than those of a strain gauge system with 1% error. The error of the Taileron network was -6.5%, which was less than the fatigue error produced from strains with 2% error. For the UIs models, the differences from the BAE SYSTEMS accumulative fatigue for Wing 1, Taileron and Fin were found to be 2.69%, 2.75%, -0.85%, which corresponded to UIs accuracies better than those of a strain gauge system with 1% error. The error of the UIs model for Wing 2 was -12.3%, which corresponded to an accuracy of a strain gauge system with 3% error. **Figure 6** to **Figure 9** illustrate the quality of load/stress predictions as well as fatigue predictions, both accumulative fatigue and yearly fatigue life consumptions.

垂尾，应变信号：256HZ，飞参：16HZ

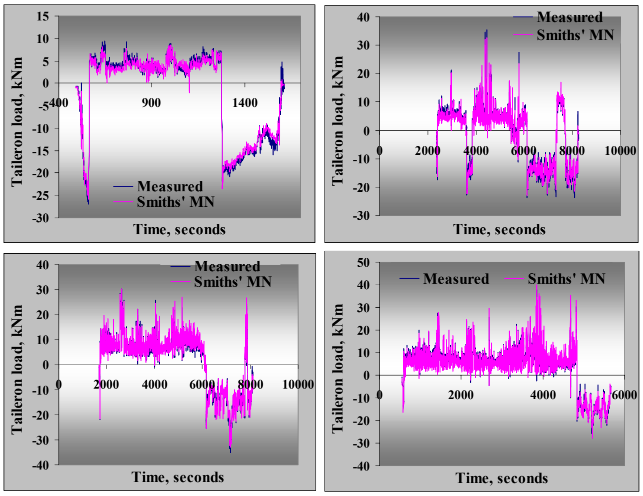

Figure 6 – Assessment of Predicted Taileron Loads

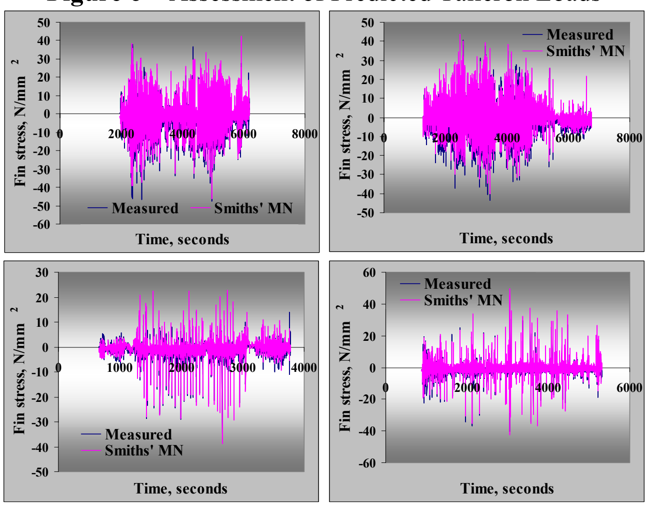

Figure 7 – Assessment of Predicted Fin Stresses

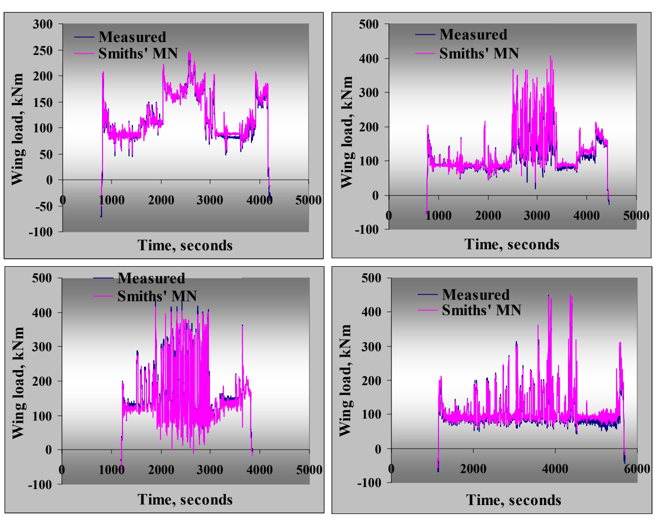

Figure 8 – Assessment of Predicted Wing Loads

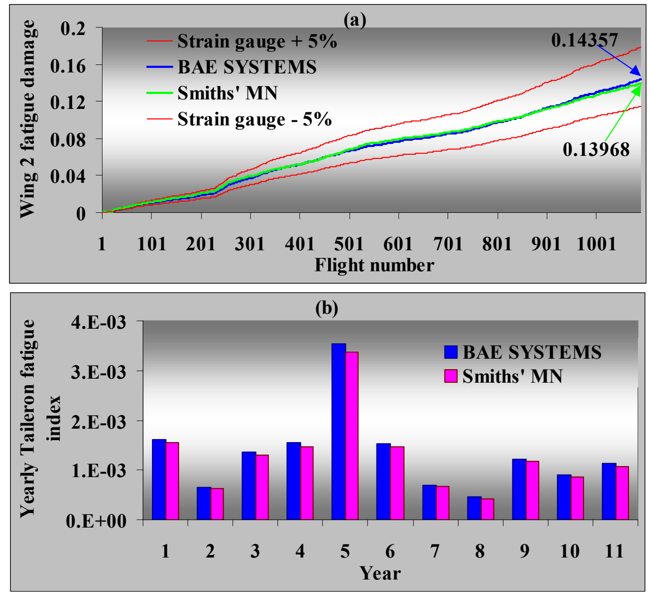

Figure 9 – Assessment of Predicted Fatigue

In light of operational data quality issues and from the above blind test results, it was concluded that the Smiths models could form the core of affordable, certifiable, and accurate SPHM systems. For each structural location, a single Smiths model accurately predicted fatigue for various configurations across potential structural repairs, different aircraft and for a variety of operations over 15 years without the need for mid life recalibrations.

Addressing Concern 3—The third concern was addressed by analysing huge volumes of flight data and strain measurements to establish guidelines to qualify SPHM non-adaptive prediction methods. A prediction method is defined as a set of coefficients (weights) and a set of transformation equations that operate on a set of inputs (flight parameters) to produce outputs that approximate the truth (target strain). Non-adaptive prediction methods use a fixed set of weights, which are evaluated through calibration (training) using truth data that contains examples of inputs and target outputs. After calibration, the coefficients of non-adaptive methods are fixed until the commencement of any further training. A prediction method may contain, for example, model-based equations, artificial intelligence tools such as neural networks and/or statistical tools. The qualification guidelines established by Smiths and BAE SYSTEMS for non-adaptive prediction methods include the following 11 steps [1]:

- Determine the Certification Level (Safety Target)
- Determine and Agree Truth Margins
- Check Data Quality
- Check Data Coverage
- Establish a Prediction Accuracy Model
- Prove the Generalisation Capability
- Establish and Agree Acceptance Criteria

- Perform Failure Analysis
- Establish an SPHM Management Procedure
- Apply Established Certification/Qualification Standards
- Collect and Document the Qualification Evidence

Funded by the UK MOD Aircraft Structural Integrity branch, QinetiQ had been tasked to undertake a similar but smaller task to independently evaluate qualification guidelines for non-adaptive prediction methods. As intended by BAE SYSTEMS and Smiths, a meeting between the main bodies involved in developing the qualification guidelines was held to compare the results of the two developed methodologies. At the end of the meeting all parties agreed in principle to the wording, which would be proposed to modify the relevant defence standards that would incorporate new regulations for non-adaptive prediction methods. The agreed qualification guidelines will be presented to the UK Military Aircraft Structural Airworthiness Advisory Group in the near future for incorporation within the UK defence standards.
It is worth emphasising that the Smiths prediction methods were trained on strain data selected from operational data with wide strain-truth margins exceeding ±10%; the true blind test results indicated that the Smiths prediction methods would generalise across a wide range of operations and configurations. The Smiths prediction methods were designed by combining neural networks with other model-based and engineering knowledge tools to provide a practical life management approach that would cope with real life calibration problems and data corruptions. Training pure neural networks on strain data with wide strain-margins or with insufficient data coverage would produce unpredictable results. Therefore, the qualification guidelines should not be developed only for the Smiths practical prediction methods. They should be developed to ensure that commissioning any prediction method would be based on data with narrow strain-truth margins. They should ensure the presence of a continued airworthiness process that would maintain adequate fatigue (or crack extension) predictions at low costs throughout the life of the fleet.

The airworthiness process should include a management approach where the prediction methods would be routinely or periodically assessed by comparing their results with those of strain gauge systems fitted on a fleet sample (for example, 1% to 2% of the aircraft of the fleet). Whilst adequate performance of prediction methods on a fleet sample would confirm their validity, unexpected comparisons would prompt further investigations of both the strain gauges and prediction methods. The supplier of the life management system should demonstrate the effectiveness of the continued airworthiness process, which should include the following:

- Tools to efficiently evaluate the strain-truth margins of the strain systems fitted on the fleet sample; Smiths has demonstrated a suite of FUMS™ tools that would address this requirement.
- Data coverage tools to identify new operations or configurations, and to assess their effects on fatigue; Smiths has demonstrated a suite of FUMS™ tools that would address this requirement.
- Intelligent, user-friendly software to allow cost effective investigations of anomalies; Smiths has demonstrated a suite FUMS™ tools that would address this requirement.

The continued airworthiness tools should be made available to the military operators and should be used along with structural integrity and maintenance databases to ensure cost effective assessments.

The adequate performance criteria of prediction methods should be 'accumulative fatigue predictions within the truth margins seen in the strain data used for training'. For example, if the strain-truth margins seen in the strain data are ±1%, which introduce fatigue errors of about ±5%, the adequate performance criteria should be prediction errors less than ±5%.

声发射

4. Damage Acoustic Emission

The collaborative work between BAE SYSTEMS and Smiths, reported in the above sections of this paper, was targeted at demonstrating the feasibility of a certifiable, affordable SPHM for evaluating damages caused by repeated stresses and over-loads. Damage in any aircraft component occurs as a result of component use/misuse, exposure to environments and/or component interactions with other components/objects. Understanding and tracking these three damage causes would lead to powerful diagnostics and prognostics. Damages caused by repeated stresses or high over-loads are examples of the use/misuse damage. The exposure of aircraft to salty water and sandstorms can cause corrosion/erosion leading to loss of material strength and damages caused by exposure to environments. Accidental damage, rubbing, foreign object strikes and damaging effects of vibration induced by unbalanced rotating aircraft components on neighbouring components are examples of interaction damages.

Work carried out at the BAE SYSTEMS Advance Technology Centre (ATC) over the last five years has been focusing on technologies for corrosion and damage detection. These technologies along with the affordable SPHM technology would provide full tracking and coverage of the three causes of damage. Acoustic Emission (AE) is one of the damage detection technologies considered by ATC [10].

AE is the sound emitted by stressed structures due to a rapid release of energy caused by events such as crack formation. AE, according to the American Society for Testing and Materials (ASTM), refers to the generation of transient elastic waves during the rapid release of energy from localised sources within a material. The causes of these emissions in metals are dislocation movement accompanying plastic deformation and crack extensions; plastic deformation is the primary source of AE in loaded metallic structures. Other causes of AE include melting, phase transformation, thermal stresses, cool down cracking and stress build up, twinning, fretting, undesirable sliding of two surfaces, and fibre breakage and fibre-matrix debonding in composites. AE types are mainly classified as continuous types and burst types. The waveform of the continuous type is similar to Gaussian random noise, but the amplitude varies with AE activity. In metals and alloys, this form of emission is mainly associated with the motion of dislocations. Burst type emissions are short duration pulses and are mainly associated with discrete release of high amplitude strain energy. In metals, the burst type emissions are generated by twinning, micro yielding and crack developments. The classification of AE sources is usually based on activity and intensity. A source is considered to be active if its event count continues to increase with stimulus. A source is considered to be critically active if the rate of change of its count or emission rate consistently increases with increasing stimulation. The AE technology is based on the detection and conversion of the emanating source high frequency elastic waves to electrical signals. AE technologies extract signal parameters and correlate them with the defects and failures. Some of the parameters used include: AE burst, threshold, ring down count, cumulative counts, event duration, peak amplitude, rise time, energy and root mean square voltage. When more than one sensor is used, the AE source (damage) can be located by measuring the signal arrival time at each sensor; from the arrival times at different sensors, the source location can be calculated through triangulation or other methods.

Traditional AE methods for locating the source of damage include using a first hit sensor and triangulation methods. By identifying the first sensor at which an AE signal arrives, a damage origin region can be established. If a more accurate approximation is required, triangulation methods can be used. Triangulation involves multiplying signal arrival times to three or more sensors by a bulk longitudinal AE wave velocity and using the known distances between sensors to locate the damage. Arrival time is defined by, for example, the time at which a threshold is exceeded or a peak amplitude reached. Problems can occur due to effects of attenuation and dispersion, which can result in misleading arrival times and, hence, inaccuracies in the location of the damage. The wave velocities in anisotropic materials also vary with direction. **Figure 10** illustrates a deterministic triangulation model for two-dimensional materials. For three-dimensional materials, a minimum of four sensors are required. Smiths proposed the use of such deterministic models combined with AI models and measured data to overcome the problems listed above; an AI model (e.g. neural network) can capture non-linear relationships and, at the same time, act as a least square tool that minimises the errors due to noise. The measured data along with model-based information about materials and wave characteristics can reduce the errors induced by attenuation, dispersion, etc.

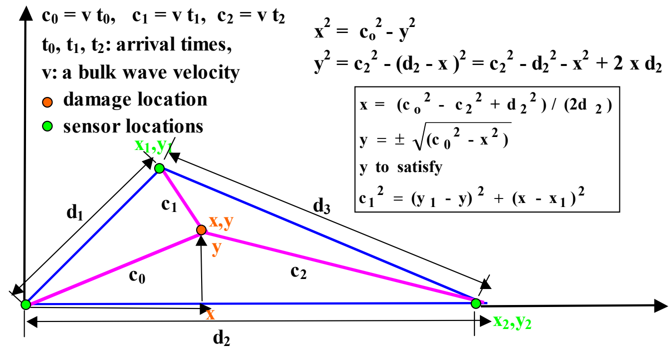

Figure 10 – A Deterministic Triangulation Model

ATC indicated that advanced AE techniques should overcome the challenges posed by signal attenuation and dispersion in a noisy background [10]. Each acoustic mode loses energy at a different rate and thus attenuation causes changes in burst characteristics with distance. Dispersion means that the travelling velocity of a particular stimulated mode depends on its frequency. For complex signals consisting of more than one stimulated mode, the signal characteristics will change with the distance travelled. This is also true for any burst containing different frequencies. Hence, the signal characteristics are highly dependent on the distance travelled; the signal characteristics close to the damage are not the same as the characteristics at a distance. The main challenge is to identify the acoustic emission event associated with damage against the background noise. Recovering acoustic emission signals in the presence of background broadband noise is a challenging task since the acoustic bursts tend to be of small energy content and can be lost in the background noise. Ideally, the identification of the following is required: unambiguous indication of damage occurrence, accurate damage location, and the nature and extent of the damage.

Following, the successful SPHM effort between BAE SYSTEMS and Smiths, ATC suggested that collaborative work taking advantage of BAE SYSTEMS and Smiths experiences should be targeted at addressing the challenges posed by signal attenuation and dispersion in a noisy background. In order to launch this collaborative work, ATC supplied Smiths with AE burst signals from several tests on Carbon Fibre Reinforced Plastic (CFRP) and Glass Fibre Reinforced Plastic (GFRP) specimens. During the tests some specimens were tested to failure, while other specimens were stopped in order to generate varying extents and types of damage. At this stage, the preliminary collaborative work concentrated on the following: investigation of existing AE signal processing and feature extraction techniques; investigation of the effect of AE sensor locations on noise to signal ratio; investigation of methods to characterise damages from extracted AE features; and investigation of methods to derive invariant AE features. The results of the preliminary collaborative work indicated the feasibility of developing automatic AI processes that could address the challenges facing AE technologies [11].

By analysing AE burst signals produced by delamination from various sensor locations, effects of attenuation and dispersion were highlighted. It was found that the commonly extracted AE parameters: peak amplitude, duration, rise time and AE counts (see **Figure 11**), varied in value and degraded in quality over distance. It was found that using a fixed threshold just above the background noise level caused significant deterioration in the quality of the AE parameters computed from signals of sensors placed beyond a distance of 300mm from the damage location; this conclusion would be only applicable to the material, damage extent and sensors studied.

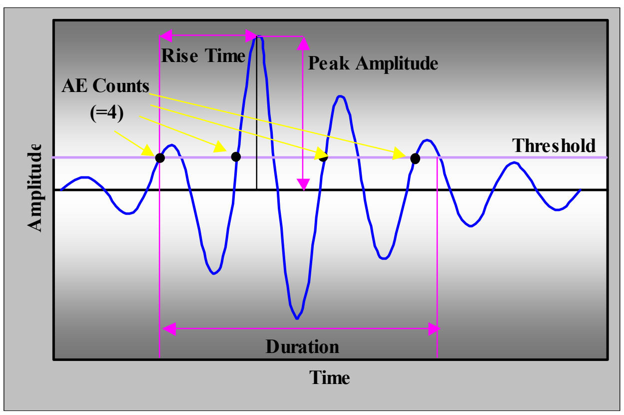

Figure 11 – Commonly Extracted AE Parameters

To improve the feature quality and allow for the investigation of invariant features, a number of signal filtering techniques were investigated to reduce background noise from the AE burst signals. With the noise reduced, much lower thresholds were used to calculate the AE parameters, which allowed the capture of the more signal characteristics. Filters applied to the Wavelet Transform (WT) of the AE signal were found to attenuate the background noise effectively. With the noise removed the calculated AE parameters have revealed patterns showing the effects of attenuation and dispersion over distance.

The preliminary collaborative work suggested that the derivation of invariant features would lead to improvements in the ability to classify the damage type and quantify the damage extent from AE burst signals recorded from different sensor locations on a structure. AE burst signal features can be invariant with regard to the following: the type of damage, the sensor distance/location from damage source and the extent of damage. Different types of invariant features were defined and derived, namely:

- Inherently invariant features – Features that are naturally invariant.
- Derived invariant features – Features that are generated by a mathematical formula using other features.
- Normalised invariant features – Features obtained by normalising (attenuating) effects of damage type, damage extent and/or damage location on them.

Principal frequency and normalised bin power were classified as inherently invariant features over distance and extent. By using combinations of standard AE parameters, a number of derived invariant features were computed. For example, features such as time ratio, average frequency and rise frequency were computed and shown to be invariant over distance and damage extent. The normalised invariant features, the third type, could be computed by normalising a feature over distance. A total of 73 features including invariant features were derived from the supplied AE burst signals [11] using various signal processing techniques.

The preliminary investigation indicated that the FUMS™ clustering/mining algorithms applied to fuse a number of AE extracted features could successfully classify the type of damage. Fusing features extracted from multiple AE sensors by using appropriate AI techniques would lead to an automated capability for detecting the damage extent and the damage location. At present, further AE data covering damage extents, damage types and damage location are being generated by ATC to enable investigations that can consolidate these preliminary conclusions. The results of these investigations will be reported by Bryant and Foote in the near future, [10] and [11].

5. CONCLUSIONS

Over the past five years, Smiths and BAE SYSTEMS have launched collaborative work to evolve a certifiable practical SPHM system. Recently, the collaborative work concentrated on addressing concerns regarding parametric SPHM technologies that fuse available flight data to predict aircraft loads and fatigue. One of these concerns posed the following question: Would a single Smiths parametric model work across different aircraft, various configurations and a wide range of military operations? This concern was addressed through true blind tests: The Smiths models were trained (calibrated) using real life strain data that contained shifts/anomalies from 3 operational aeroplanes flown in 4 configurations. The models were calibrated for 4 structural locations chosen by BAE SYSTEMS: 2 fuselage locations called Wing 1 and Wing 2, a fin location called Fin and a taileron location called Taileron. After calibrating the models, BAE SYSTEMS supplied flight data covering 4 configurations and 15 years of operations of another aircraft. BAE SYSTEMS only provided flight parameters and did not supply fatigue information. Smiths applied their calibrated models to the supplied flight parameters and blindly predicted fatigue. After sending the blind test results to BAE SYSTEMS, the fatigue values computed from strains were supplied by BAE SYSTEMS to be compared with the true blind test results.

For the MN models, the differences from the BAE SYSTEMS accumulative fatigue after 15 years were found to be 3.16%, -2.71% and 0.86% for Wing 1, Wing 2 and Fin respectively. For these three airframe locations, the network accuracies were better than those of a strain gauge system with 1% error. The error of the Taileron network was -6.5%, which was less than the fatigue error produced from strains with 2% error. For the UI models, the differences from the BAE SYSTEMS accumulative fatigue for Wing 1, Taileron and Fin were found to be 2.69%, 2.75%, -0.85%, which corresponded to UIs accuracies better than those of a strain gauge system with 1% error. The error of the UIs model for Wing 2 was -12.3%, which corresponded to an accuracy of a strain gauge system with 3% error. It was therefore concluded that the Smiths models could form the core of affordable, certifiable, and accurate SPHM systems. For each structural location, a single Smiths model accurately predicted fatigue for various configurations across potential structural repairs, different aircraft and for a variety of operations over 15 years without the need for mid life recalibrations.

The paper presented qualification guidelines for non-adaptive prediction methods. These guidelines along with guidelines independently developed by QinetiQ will be considered by the UK MOD for defence standard regulations that will cover the emerging non-adaptive prediction technologies. The paper also reported on a fusion/decision support technique targeted at identifying sensor/system faults and described preliminary collaborative work on a structural damage detection technology where AI and fusion methods have been used to mitigate technology risks.

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REFERENCES

[1] Hesham Azzam, Lou Gill, Frank Beaven and Malcolm Wallace, "A Route for Qualifying/Certifying an Affordable Structural Prognostic Health Management (SPHM) System," *2004 IEEE Aerospace Conference Proceedings*, April 2004.

[2] Frank Beaven, Hesham Azzam, Iain Hebden and Louis, Gill, "A Mathematical Network Approach to Structural Prognostic Health Management," *Proceedings of the First European Conference on Structural Health Monitoring, Paris, France*, July 2002.

[3] Malcolm Wallace, Hesham Azzam, Iain Hebden and Louis Gill, "Monitoring the Damaging Effects of Aircraft Rare Events," *Proceedings of the First European Conference on Structural Health Monitoring, Paris, France*, July 2002.

[4] Hesham Azzam, Jonathan Cook, Peter Knight and Nigel Wakefield, "FUMS™ Fusion For Improved Aircraft MAAAP," *2005 IEEE Aerospace Conference Proceedings*, 2005.

[5] Graham Venn, "Information Received through Private Communication," *Westland Helicopters Limited*, December 2003.

[6] H Roy, "Experience with ON-Line Data Trend Monitoring on a Full-Scale Aircraft Fatigue Test," *International Committee on Aeronautical Fatigue (ICAF)*, May 2003.

[7] B Aktepe, L Molent, A D Graham and D P Conser, "Buffet Loads and Structural Redundancy Considerations in Vertical Tail Fatigue Monitoring Programs." *International Aerospace Congress, Adelaide*, September 1999.

[8] L Molent, "A Review of a Strain and Flight Parameter Data Based Aircraft Fatigue Usage Monitoring System." *USAF ASIP Conference San Antonio, TX*, 3-5 December 1996.

[9] Y Caron and Y Richard, "CF-188 Fatigue Life Management Program," *RTO MP-7, RTO AVT Specialists' Meeting on "Exploitation of Structural Loads/Health Data for Reduced Life Cycle Costs, Brussels, Belgium*, 11-12 May 1998.

[10] Peter Foote, "Information Received through Private Communication," *The UK BAE SYSTEMS Advance Technology Centre (ATC)*, November 2003.

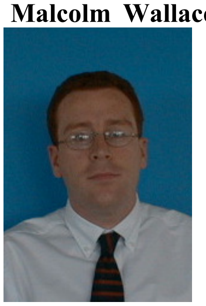
[11] Ken Bryant and Hesham Azzam, "Analysis of Multi-Sensor Damage Acoustic Emission Data," *Smiths Aerospace Electronic Systems – Southampton Report REP1630 Issue 1*, November 2004.

BIOGRAPHIES

Hesham Azzam *is the Research and Technology Development (R&TD) Director at Smiths Aerospace Electronic Systems - Southampton. He has been working within the aerospace field for 28 years. He is leading an R&TD team working on FUMS™ technologies, flight data analysis, information management systems, artificial intelligence, statistical methods, structural analysis, fatigue, fault simulations, prognostics and aircraft math models. He holds a BSc in Aeronautics and was awarded an MSc and a PhD from the University of Southampton.*

Lou Gill *is a specialist in Fatigue and Operational Loads Measurement (OLM) at BAE SYSTEMS. He has been working in the Structures field for over 30 years on a wide range of different military platforms. He has worked on a wide range of fatigue tasks including setting up Major Airframe Fatigue Tests (MAFT) and fatigue monitoring/management techniques for aircraft. Currently he is working on a specialist group to research, develop and deliver the skills, manuals, analytical tools and specialist advice in fatigue required by different Project Groups. He obtained his BSc degree in Mechanical Engineering at Salford University.*

Frank Beaven *is a senior R&TD engineer at Smiths Aerospace Electronic Systems - Southampton. Since joining the company in 1998 he has participated in the development of FUMS™ technologies including: artificial intelligence, mathematical models and data correction for fixed wing and rotorcraft operating on huge data sets. Before joining ES-S Frank worked as a senior research assistant at Swansea University where he researched Computational Fluid Dynamics (CFD). He also holds a BEng, an MSc in numerical methods in engineering and a PhD in CFD.*



Malcolm Wallace *is a senior R&TD engineer at Smiths Aerospace, Electronic Systems - Southampton. Malcolm was awarded a Master of Engineering (MEng) degree with distinction in Aeronautics and Astronautics from the University of Southampton. Since he has joined Smiths his general interests have covered helicopter mathematical models, artificial intelligence techniques and finite element analyses and he has participated in the developments of FUMS™ technologies.*

Iain Hebden *leads the Structures PHM team for the Joint Strike Fighter, responsible for development and validation of the on-board capability, and also for driving the design of the SPHM elements within the off-board PHM. He has experience in Smart Structures having previously been involved in the European DECODA program (damage detection in composites). Prior to JSF he was involved in the design, development and validation of the Eurofighter SHM system.*